

Power Systems

Xi Zhang · Chris Mi

Vehicle Power Management

Modeling, Control and Optimization

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Power Systems

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Preface

The world faces two important challenges nowadays: increased energy demand and serious environmental concerns. Global climate change due to green house gas emissions has brought worries about sea-level increase and severe climate damages that are afflicting people. However, the fact is that the vexations are brought about by the human-beings ourselves. The blind deforestation, large-scaled urbanization, and exponentially expanded consumption of fossil-fuel are key contributors to these social and environmental problems. Fortunately, we are more and more aware of these challenges and in the process of developing effective measures to tackle and mitigate these problems. The Kyoto Protocol, Copenhagen Accord, and Cancun Agreements are good proofs.

Automobiles as a major contributor for air pollution and greenhouse gases emissions are under deep innovation and brand-new definitions. Meanwhile the global energy shortage also offers new demands on alternative fuel applications to the automobile industry. Under such a background, development of electric vehicles, hybrid electric vehicles, plugin hybrid electric vehicles, and fuel cell vehicles has been the hottest topic across the automobile industry. New energy sources and energy storage systems (ESS) such as lithium-ion batteries, hydrogen fuel cell and ultra-capacitors are introduced to the design and production of electric and hybrid electric vehicles. Besides, high-performance alternators, electric motors and mechanical transmissions are incorporated in various hybrid architectures (e.g. parallel, series, series-parallel, complex, etc.).

Historically, studies have been concentrated on modeling, control and optimization of vehicle powertrain structure and components with the aim of fuel economy improvement, pollutant emission reduction, lifetime extension of ESS, vehicle drivability and reliability enhancement for various types of electric and hybrid electric vehicles. In the past two decades, new ideas about vehicle power management have been emerging exponentially, including dynamic programming (DP), analytical approaches and intelligent system approaches. Additionally, satisfactory test results when applied to real vehicles are considerable.

Unfortunately, although reasonable amount of literature exists in the area of vehicle power management, there always exists a feeling that the research results

are dispersive and not systematic. With such a consideration, the authors decide to write a book to systematically define, analyze and summarize the vehicle power management technology. Thus, this book is born.

The material of the book composition is mainly derived from many years of research experience of the authors and several colleagues and students. Some ideas from published references are introduced and quoted with their permissions. Three aspects for vehicle power management with modeling, control and optimization involved are focused on. Definitions, objectives, mathematical models, development tools, cases studies, and prospects related to vehicle power management are covered by the book. In addition, the system-level and component-level methodologies are both discussed. The book consists of 11 chapters, and reasonable configurations and stratified descriptions will bring in fresh and comprehensive understanding to the vehicle power management technology.

Similar to most publications, the book starts with an introduction in [Chap. 1](#). An overview of application fields and necessity of vehicle power management is provided in this chapter.

[Chapter 2](#) focuses on fundamentals and basic concepts of vehicle power management, including effects on vehicle performance, drive cycles and power demands, major applied software tools and so on.

In [Chap. 3](#), uniform model representations for vehicular components (i.e., energy sources, ESS, electric machines and mechanical devices) existing in the vehicle powertrain are described in detail.

[Chapters 4–7](#) describe the theoretical fundamentals and applications of state-of-the-art vehicle power management strategies. The analytical approach, dynamic and quadratic programming, and intelligent system approach employed for vehicle power management have already existed in various publications. However, the authors extend some new thoughts to their applications. These three strategies are introduced in [Chaps. 4, 6](#) and [7](#), respectively. The wavelet-based power management approach for multiple on-board energy sources and ESS is depicted in [Chap. 5](#). The theoretical system for applications of the wavelet technology on various types of vehicles is established, and the real-time analysis for employment in real vehicles is also given.

The battery is an essential factor for development of alternative fuel vehicles. At some point of view, the cost, volume, charging convenience and lifetime of the battery determines the marketization process of hybrid electric and all-electric vehicles. Consequently, the book specially gives one chapter's space to the management of energy storage systems with main focus on batteries. [Chapter 8](#) focuses on the energy management strategies for the purpose of battery lifetime extension and precise estimation of the battery status for powertrain controls.

Type selection, configuration, and design optimization of powertrain components in the early development stage for hybrid vehicles will represent significant impacts to running vehicles on dynamic performance, fuel economy and emissions. Therefore, [Chap. 9](#) discusses the component optimization issues for avoiding unnecessary losses on these aspects.

Hardware-in-the-loop (HIL) and software-in-the-loop (SIL) are delineated in [Chap. 10](#) since they can substantially lower the cost and the time for delivery of a vehicular product to market.

[Chapter 11](#) paints magnificent application prospects of vehicle power management for readers, and points out potential problems to be faced. Also, some advanced technologies of alternative fuel vehicles and accordingly powertrain components are introduced in this chapter.

The book can be used as a textbook to educate undergraduate and graduate students majoring in automotive engineering. Students majoring in mechanical engineering, electric engineering, and computer science and engineering may find this book useful when dealing with vehicle related design, optimization and control development. Besides, the book can be used as a reference for designers and engineers working in the automobile industry. Abundant case studies are beneficial for development of alternative fuel vehicular systems.

The authors wish to extend sincere thanks to several colleagues who made signification contributions for the successful publication of this book. In particular, Mr. Mengyang Zhang, a specialist in HEV, lent his idea to the authors to form the basis of [Chap. 4](#), Analytical Approaches for Vehicle Power Management. Students in the research group of Professor Chris Mi provided the original material and helped draft the manuscript of a few chapters: Dr. Zheng Chen for [Sects. 6.1 to 6.2](#), and [Sect. 7.5](#), Zhiguang Zhou for [Sect. 6.3](#) and [Sect. 7.6](#), Bingzhang Zhang for [Sects. 4.1 and 9.1](#), Yan Yang for [Sect. 4.2](#), Dr. Wenzhong Gao for [Sect. 9.2](#). Without their great efforts, the book would not have been possible.

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Chapter 1

Introduction

The objects under consideration in this book are automobile or motor cars, i.e., wheeled motor vehicles for transporting passengers or goods, which also carry their own engines or electric motors. Nowadays, most vehicles running on the road are propelled by spark-ignition (SI) or compression-ignition (CI) internal combustion engines (ICEs) that use gasoline or diesel as fuels.

Limited oil reserves, increased demand and costs for oil-based fuels, as well as air pollution and greenhouse emissions, are challenging the automobile industry. With fuel and emission reduction as the main objectives, alternative power systems for hybrid electric vehicles (HEV), electric vehicles (EV) and fuel cell vehicles are under development and production. Nevertheless, energy losses in vehicle operation and replacement of aged power sources, and pollutant emissions (in HEV) also exist in these new technologies. Regardless of the type of vehicles, it is essential to improve energy efficiency, reduce emission and extend lifetime of power sources without sacrificing vehicle performance, safety, and reliability.

First of all, to help readers comprehend the urgency of vehicle research for energy saving and emission reduction, we will start with the introduction to the above global problems which the automobile manufacturers are facing today.

1.1 Energy and Environmental Challenges

Gasoline and diesel used for vehicle propulsion are both refined from fossil oil. In 2008, the world oil reserves were 1.342 trillion barrels [1] and the daily consumption was about 85 million barrels [2]. Around 60% of the total oil consumption goes to transportation. Meanwhile, the world's population continues to grow at a quarter of a million per day [3], increasing the transportation demand and consequent oil consumption. The United States Energy Information Administration predicted that world daily oil consumption would increase to 98.3 million

barrels in 2015 and 118 million barrels in 2030 [4]. By using the Hubbert peak theory [5–7], the oil depletion situation can be predicted based on prior discovery rates and anticipated production rates. The American Petroleum Institute estimated in 1999 that the world's oil supply would be depleted between 2062 and 2094 [8]. Oil depletion curves are depicted in Fig. 1.1. The oil shortage will result in severe social and economic problems such as transportation and food crisis.

ICE powered vehicles rely on gasoline and diesel combustion during operation. Pollutions are generated during the combustion process inside the ICE. In addition, unburned fuel evaporates which forms the basis for another type of pollution—volatile organic compounds (VOC).

The emissions from the combustion include carbon dioxide, VOC, nitrogen oxides (NO_x), particulate matter (PM), and carbon monoxide (CO). These exhaust emissions occur during the following two modes [10, 11]:

- Cold Start—during cold weather, the catalyst which is used to control tailpipe emissions will not work until they have been warmed up to a certain temperature. Hence, starting and driving a vehicle in the first few minutes result in higher emissions.
- Running Exhaust Emissions—emissions are formed during normal operation of the vehicle-driving and idling.

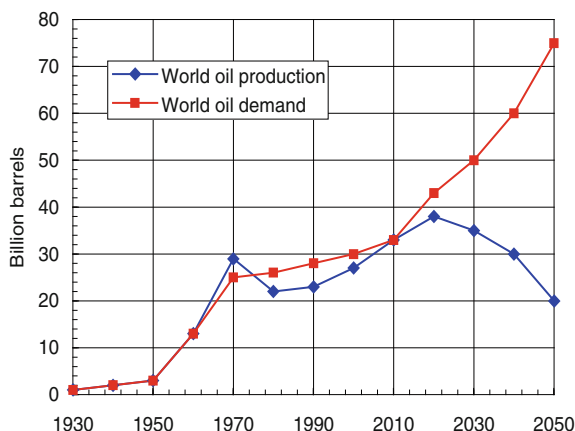
Through the fuel evaporation, the VOC leaves for the ambient air, which occurs in four ways as follows:

- Running Losses—During vehicle running, the gasoline is vaporized in the hot engine and exhaust system.
- Hot Soak—The engine remains hot for a while after the vehicle is turned off, and gasoline evaporation continues when the car is parked while cooling down.
- Diurnal Emissions—Even when the vehicle is parked for long periods of time, gasoline evaporation occurs due to the high ambient temperature.
- Refueling—While the tank is being filled, gasoline vapors escape from the vehicle's fuel tank and the refueling tubes.

In the United States, vehicles contribute 25 and 33% of the total VOC and NO_x respectively which combine to form ground-level ozone. Additionally, the combined direct and indirect contribution of vehicles amounted to 49 and 55% of national PM_{10} and $\text{PM}_{2.5}$ (both belong to particulate matter) emissions, respectively [12]. Unfortunately, ozone and particulate matter are identified as contributors towards worsening the health of people with asthma and other related public health impacts, e.g. increases in medication use, doctor and emergency room (ER) visits, and hospital admissions. Moreover, the possible contribution of vehicle pollution to the development of asthma, frequent respiratory infections and potential long-term effects of retarded lung growth and reduced lung function in children (which can lead to chronic lung disease later in life) may even have greater long-term public health significance [13].

Besides, vehicles play a disgraceful role in global climate change. Burning of fossil fuels contributes to the increase of carbon dioxide (CO_2) in the atmosphere.

Fig. 1.1 World oil demand and production. *Source* [9]



This will result in increased thickness and density of the atmosphere due to the action of carbon dioxide and other greenhouse gases (i.e., water vapor, ozone and methane) in the atmosphere. The thicker and denser atmosphere will trap heat inside the atmosphere to form the basis of the greenhouse effect [14–16]. It may increase the global air temperature and introduce global climate change due to disturbance to the eco system. The Intergovernmental Panel on Climate Change (IPCC) concluded in 2007 [17] by stating that: “Most of the observed increase in globally averaged temperatures since the mid-twentieth century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations.” The consequences including the widespread melting of snow and ice and rising global average sea level will bring disasters to the earth particularly to the maritime countries. Other consequences include increase flood and drought and extreme weathers in certain parts of the world which can cause disasters to many areas.

The global fossil carbon emissions and global air temperature since the nineteenth century are shown in Figs. 1.2 and 1.3, respectively. It can be observed from Fig. 1.2 that petroleum contributes the most fossil carbon emissions while most of the petroleum consumption comes from automobiles. Through contrast between Figs. 1.2 and 1.3, we can see that there really exists a relation between carbon dioxide emission and air temperature increase, as approved by most ecologists.

1.2 Energy Conversion Chain for Vehicle Energy Consumption

No matter what power sources are applied for vehicle propulsion, there exist at least three energy conversion processes [20]. The energy conversion chain from the primary energy sources to the eventual thermal energy generated in the vehicle

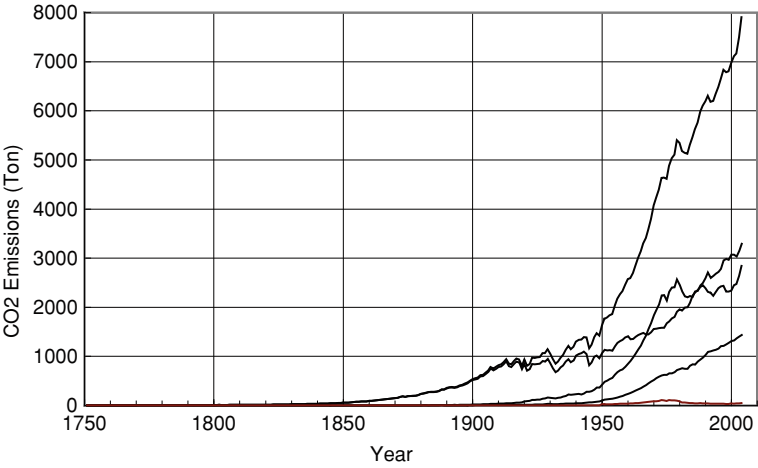


Fig. 1.2 Global fossil carbon emissions from 1800 to 2004 [16]. From top to bottom: total CO₂; CO₂ from oil; coal; cement production; other

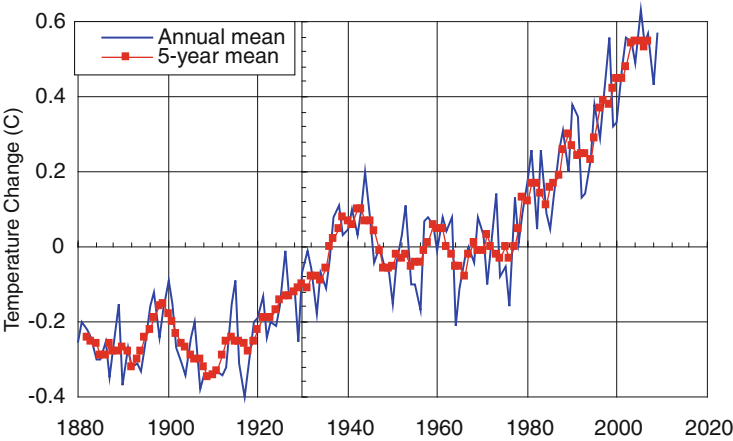


Fig. 1.3 Global air temperature since the year of 1850. *Source* [19]. *Courtesy* NASA Goddard Institute for Space Studies

operation is illustrated in Fig. 1.4. In the first step, the primary energy sources (chemical energy in fossil hydrocarbons, solar energy for generation of bio mass or electric energy, nuclear energy, etc.) transit energy to onboard energy carriers (battery, gasoline, hydrogen, etc.) in vehicles. Then the vehicle propulsion system transfers the energy from these energy carriers to mechanical components as the form of kinetic or potential energy in vehicles. Eventually, the mechanical energy is dissipated to thermal energy which is deposited to the ambient.

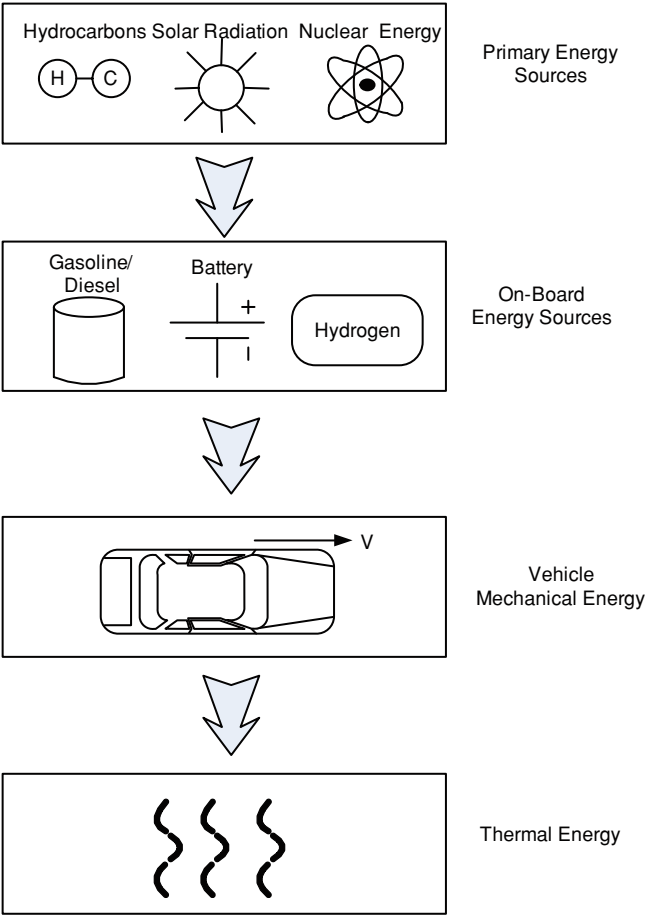


Fig. 1.4 Energy conversion steps for vehicle energy consumption

There exist energy losses in every junction of the energy conversion chain. Although the energy conversion efficiency and pollutant emissions in the first step have a great impact on the entire energy saving and environmental protection, large power plants, refineries, or other process engineering systems are beyond the scope of this book. The vehicle power management concept arises for the second energy conversion step (i.e., on-board energy carriers to vehicle mechanical energy) aimed at improving fuel economy, reducing pollutant emissions and maintaining power sources working properly, while the performance and safety are not impacted at all. For the ultimate step, energy conversion is natural and uncontrollable in a fixed driving profile, except that vehicle functional topology changes ahead of vehicle operation. In summary, the second energy conversion step, where vehicle power management strategies are embedded, acts as the main emphasis of this book.

1.3 Fuel Efficiency

Fuel efficiency of automobiles refers to the energy efficiency of a vehicle in terms of fuel consumption or fuel economy. In the United States, fuel economy is defined as the total distance travelled for a given amount of fuel, i.e., miles per gallon of fuel (MPG). In Asia and Europe, fuel consumption is defined as the amount of fuel required to move a vehicle over a given distance, whose unit is liters of fuel per 100 km (L/100 km), or (L/km). Since fuel consumption is reciprocal of fuel economy, to convert MPG to L/km or L/km to MPG, one first needs to convert them into the correct units and then take the reciprocal. From MPG to L/km:

$$x\text{MPG} = x \frac{1.608 \text{ km}}{3.785 \text{ L}} = \frac{x}{2.35} \text{ (km/L)} \Rightarrow \frac{2.35}{x} \text{ (L/km)}$$

From L/km to MPG:

$$y\text{L/km} = y \frac{0.2642 \text{ Gallon}}{0.6219 \text{ miles}} = \frac{y}{2.35} \text{ (GPM)} \Rightarrow \frac{2.35}{y} \text{ (MPG)}$$

Hence one can convert MPG to L/km by dividing 2.35 by the MPG numbers. Similarly one can convert L/km to MPG by dividing 2.35 by the L/km numbers. For example, to convert 33 MPG to L/km, one divides 2.35 by 33 to get 0.0712 L/km. To convert 7.5 L/100 km to MPG, one divides 235 by 7.5 to get 31.3 MPG.

Since different road conditions and driving patterns require different amount of fuel for a given distance, fuel economy or fuel consumption has to be evaluated upon different driving scenarios, also known as driving cycle tests, as further explained in [Chap. 2](#).

Once fuel economy is evaluated on standard driving cycles, they can be combined to form a composite fuel economy. In the United States, the composite fuel economy is evaluated over 55% urban driving (FUDS) and 45% highway driving (FHDS) as the following:

$$\text{composite MPG} = \frac{1}{\frac{0.55}{(\text{MPG})_{\text{FUDS}}} + \frac{0.45}{(\text{MPG})_{\text{FHDS}}}}$$

In this book, we will use fuel economy to evaluate the overall fuel efficiency of vehicles. But we will also refer to fuel consumption as needed when we discuss fuel savings. This is due to the fact that fuel consumption is more appropriate when calculating fuel savings. For example, fuel economy improvement from 30 MPG (0.07833 L/km) to 60 MPG (0.03917 L/km) seem to have 100% improvement in fuel economy but in fact the fuel saving is

$$\text{Fuel Savings} = \frac{0.07833 - 0.03917}{0.07833} = 50\%$$

1.4 Main Objectives of This Book

Although vehicle power management is familiar to related researchers and designers, this book, addressed to readers at various levels, describes and analyzes the basic concepts with respect to different vehicle configurations. The factors influencing the fuel economy and emissions are also discussed.

Today's advanced vehicles contain a significant number of components which consume a substantial amount of power. For vehicle designers, it's impossible to deal with the optimization of the entire system using heuristic methods. The model-based method has been proved to be the most efficient way for the initial-phase of vehicle design [20] (e.g. determination of vehicle structure and verification of control strategies in simulation). Consequently, this book also introduces the modeling of various devices and components in a vehicle which are involved in the vehicle power management system.

Although reasonable amount of literature exists in the area of vehicle power management [21], there always exists a feeling that the research results are dispersive and not systematic. To the authors' best knowledge, there do not exist comprehensive references that systematically define, analyze, and summarize this topic, which can be meaningfully applied to vehicle applications. This book is intended to bridge this gap. Specific algorithms and strategies including analytical approaches, optimal control, intelligent system approaches, wavelet technology, and optimizations, are theoretically derived and analyzed in this book for realistic applications towards vehicle power management. Optimal control, in particular the dynamic programming (DP) and the intelligent schemes (e.g. fuzzy logic control, neural networks, etc.), are existing popular power management methodologies for the purpose so far, while the wavelet technology is introduced for the first time to vehicle power management.

Electrification of the automobile is the current focus to shift fossil fuel based transportation to alternative energy based transportation. The fuel cell and battery are commonly regarded as two major alternative power sources for vehicle propulsion [22–38]. Equipped with these alternative power sources, various types of vehicles with low or zero emissions, pure electric vehicles (EV), plug-in hybrid electric vehicles (PHEV), hybrid electric vehicles (HEV), and fuel cell vehicles (FCV), have become research and development emphasis lately, which are within the scopes of this book. Despite of low or zero emissions, the problems of equivalent fuel economy improvement and power source lifetime extension in these alternative fuel vehicles or alternative drive train vehicles are still under consideration. So vehicle power management is beneficial and suitable for the above advanced vehicles.

In addition, the hardware-in-the-loop for vehicle power management research to emulate the realistic conditions is introduced with existing and potential real system designers in mind. Useful tools and devices, as well as some experimental results, can be found in this book to enlighten designers when establishing their own experimental platforms for vehicle power management research.

1.5 Issues in Research on Vehicle Power Management

Automotive industry is focusing on developing affordable vehicles with increased electrical/electronic components to satisfy consumers' needs on safety and comfort, while improving fuel economy and reducing emissions to comply with environmental regulations. With this in perspective, vehicle power management strategy that is employed to control power flow of power sources in vehicles was proposed during the last two decades to meet the above challenges [21].

Hybrid electric vehicles (HEV) are one of the leading technologies aimed towards sustainable mobility, and vehicle power management that is suitable for all types of vehicles has been more intensified by this emerging technology [21].

Mathematical models or human expertise are critical to the development of most of the power management approaches prior to real applications. Optimal control deals with the problem of finding a control law for a given system such that a certain optimality criterion is achieved. A control problem includes a cost function that is a function of state and control variables. An optimal control is a set of differential equations describing the paths of the control variables that minimize the cost function [39–41]. The optimal control strategy has been the most popular vehicle power management approach since the fuel consumption or emissions or other indexes can be considered as a cost function. The optimal control, especially dynamic programming (DP), has been widely applied to a broad range of vehicle models [42–44]. When using optimal control in vehicle power management, researchers usually assume that the entire driving cycle is available for analysis and algorithm development. This assumption can only provide off-line solution to the problem. Nevertheless, the off-line results provide a benchmark for performance of control strategies prior to real applications.

Recently, the intelligent system approaches including the artificial neural network (ANN), fuzzy logic, etc. have been introduced into vehicle power management [45–47]. The ANN, composed of artificial neurons or nodes, is a mathematical model or computational model. With the desire to incorporate the fuel consumption or emissions as design criteria, researchers used ANN models for prediction of vehicle behaviors [48]. The ANN models are trained using data from tests or simulations for different driving cycles.

Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than precise [45, 49]. In fuzzy logic, the degree of truth of a statement ranges between 0 and 1. In fuzzy-logic-based vehicle power management strategy, fuzzy rules were developed by researchers for the fuzzy controller to effectively determine the power split between various power sources in vehicles. The fuzzy controllers can be built based on some variables such as the driver command, the SOC of the energy storage system (ESS), the alternator speed, etc. The purpose of obtaining fuzzy rules is to optimize the operational efficiency of different power sources in all types of vehicles.

The analytical approach tries to reduce a system to its elementary elements in order to study in detail and understand the types of interaction between them.

General laws can be inferred to predict the system properties under various conditions. Laws of the additivity of elementary properties have to be invoked to guarantee the possibility of this prediction [50]. The analytical approach can take on the responsibility of meeting the objective (i.e., fuel consumption minimization) of the plug-in hybrid electric vehicle (PHEV). The simplified or unified analytical power solution to this optimization problem can be derived on basis of a realistic vehicle model comprised of individual power source components. Usually different PHEV operation modes such as the pure electric mode and blended mode need to be involved in discussion.

Besides, wavelets are introduced in this book for vehicle power management system applications. Wavelet transforms can be considered as forms of time–frequency representation for continuous-time signals, and so are suitable for harmonic analysis [50–52]. High-frequency transients can be identified from the real time power demand of the drive line. With the help of wavelet transform, a proper power demand combination can be achieved for power sources in all types of vehicles. The wavelet-based power management strategy helps improve system efficiency and life expectancy of power sources, usually in the presence of various constraints due to drivability requirements and component characteristics.

Details of the above state-of-the-art technologies for vehicle power management will be described from their fundamentals to specific applications for various types of vehicles in the later chapters of this book.

1.6 Book Organization

The entire composition structure and relations among various chapters are shown in Fig. 1.5.

Chapter 2 introduces the basic concepts of vehicle power management such that readers can have a clear global idea of what vehicle power management is. Due to the importance of modeling to development of vehicle power management strategies during the initial phase, Chap. 3 establishes mathematical or electrical models for vehicle propulsion systems where the internal combustion engine (ICE), battery, ultracapacitor, fuel cell, etc. may exist with respect to various vehicle types. Multiple vehicle power management strategies are described and analyzed in Chaps. 4, 5, 6, 7, 8, 9. Chapter 4 is devoted to the analytical approaches for the power management of hybrid and plugin hybrid electric vehicles. Chapter 5 introduces wavelets to the vehicle power management system. Chapter 6 introduces dynamic programming and quadratic programming for the power management of hybrid and plugin electric hybrid vehicles. Chapter 7 depicts two intelligent system approaches i.e., the fuzzy logic and neural networks, for vehicle power management. Chapter 8 briefly discusses the battery management in EV, HEV and PHEV. Chapter 9 discusses

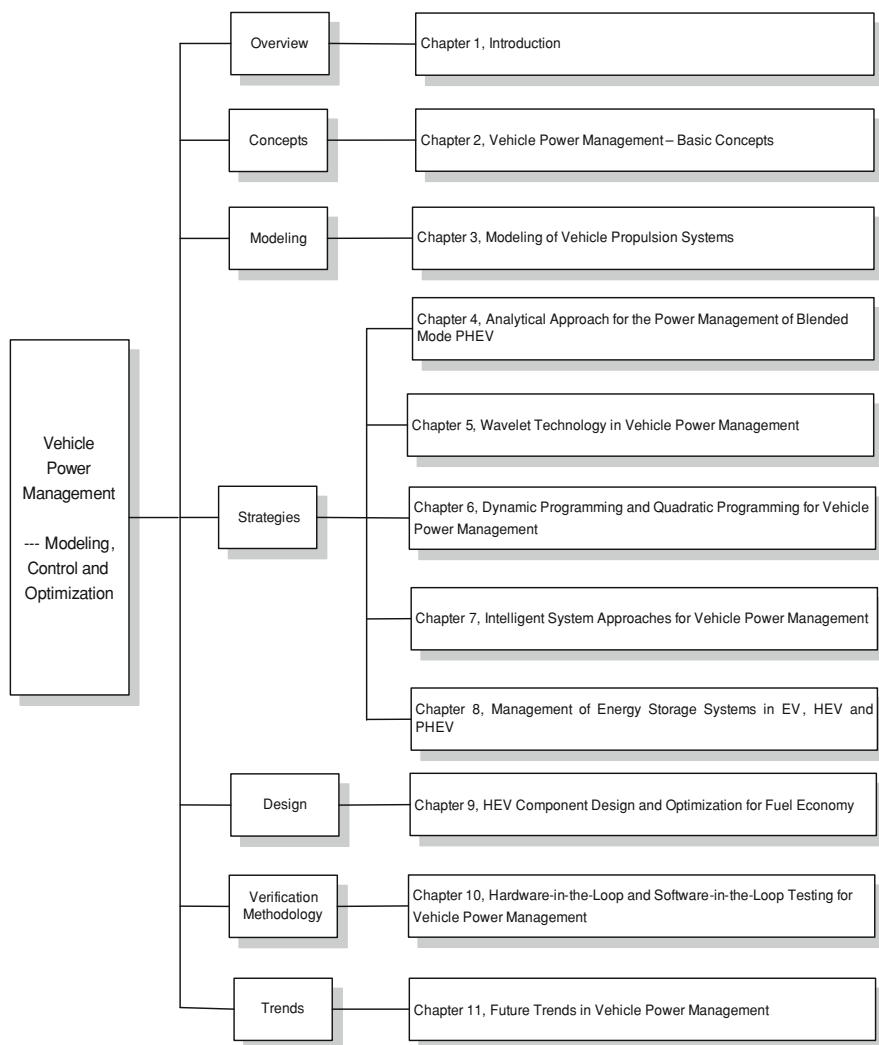


Fig. 1.5 Framework of the book organization

the component optimization which can also result in performance improvement of HEV and PHEV. In order to verify the validity of power management strategies prior to real applications in vehicles, experimental platforms are necessary. Thus [Chap. 10](#) describes the definition and structure of hardware-in-the-loop (HIP), and introduces relevant experimental devices and methodologies to enlighten the readers. Finally, [Chap. 11](#) gives an outlook on trends in future vehicle power management.

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Chapter 2

Vehicle Power Management: Basic Concepts

2.1 Vehicle Configurations

Since all types of vehicles including conventional, electric, and hybrid electric vehicles can be adapted to and benefited from the power management concept for improved fuel economy, reduced emissions, or extended power source life expectancy, a discussion of their configurations is important to help readers better understand how vehicle power management strategies cope with operations of various powertrain configurations and components.

2.1.1 Configuration of Conventional Vehicles

Figure 2.1 shows the configuration of a conventional vehicle. An internal combustion engine (ICE) provides all the vehicle propulsion power [1]. The drivetrain of a conventional vehicle includes clutches, gearbox, and final drive and differential. A speed-torque conversion is provided by the mechanical transmission for proper speed of the front or rear wheels. A multi-speed transmission is required due to the limitations of the ICE, such as incapable of running below 800 rpm, as well as incapable of providing large torque for low speed vehicle operations or maintaining high efficiency under certain operating conditions. Automatic transmissions, such as continuous variable transmission (CVT), automated manual transmission (AMT), dual clutch transmission (DCT) are developed to help transfer torque and power of the ICE to the final drive with better fuel economy and driveability. Many manufacturers capable of producing conventional vehicles exist around the world. On the other hand, conventional vehicles are major contributors to air pollution and green house emissions.

As alternatives to conventional vehicles, the new automobile propulsion technologies under development include electric vehicles, hybrid electric vehicles, plugin hybrid electric vehicles, and fuel cell vehicles.

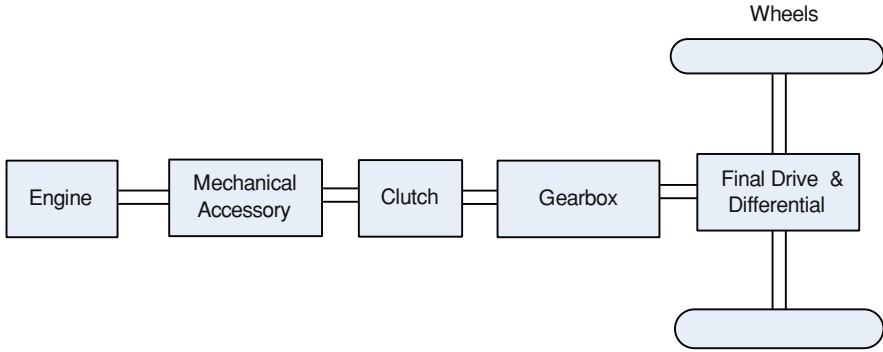


Fig. 2.1 Configuration of a conventional vehicle

2.1.2 Configuration of Electric Vehicles

Unlike a conventional vehicle driven by an ICE, an electric vehicle (EV) is propelled by electricity which is stored in an energy storage system (ESS), such as batteries, ultracapacitors, or flywheels. Electric vehicles are also referred to as pure EV or battery EV (BEV) in case the main energy storage is a battery pack. The configuration of a BEV is shown in Fig. 2.2.

The battery-powered electric vehicle is comprised of a battery for energy storage, an electric motor, and an inverter [2]. The battery is charged through a charger which can be either carried onboard or fitted at the charging point. The inverter is responsible for the direction and amount of power flow to/from the electric motor such that the vehicle speed and moving direction can be controlled. It has to be noted that during the braking process, the battery is charged by regenerative energy. The DC-DC converter is used to match the battery pack voltage and that of the DC bus of the inverter and can be optional. The mechanical transmission shown here is a generic term for gears and speed reduction. In contrast to conventional vehicles, EVs and other advanced vehicles do not have the need for automatic transmission as the case in conventional vehicles.

The limited travel range of BEVs (without recharging) prompted the research and development of fuel cell electric vehicles (FCEV) [3]. The fuel cell-powered electric vehicles have almost the same configuration as a BEV as shown in Fig. 2.3, except for the energy source. Hydrogen fuel is required and stored on board. The FCEV represents a true zero-emission vehicle for a long term. The Honda FCX was the first FCEV to be certified for use in the USA.

The traction motors used in electric vehicles are usually classified into DC motors, induction motors or permanent magnet motors [4]. Disadvantages of DC motors have forced EV researchers to turn their attention to AC motors. The maintenance-free and low-cost induction motors have attracted many EV developers. However, the problems of size and weight for high-speed operation

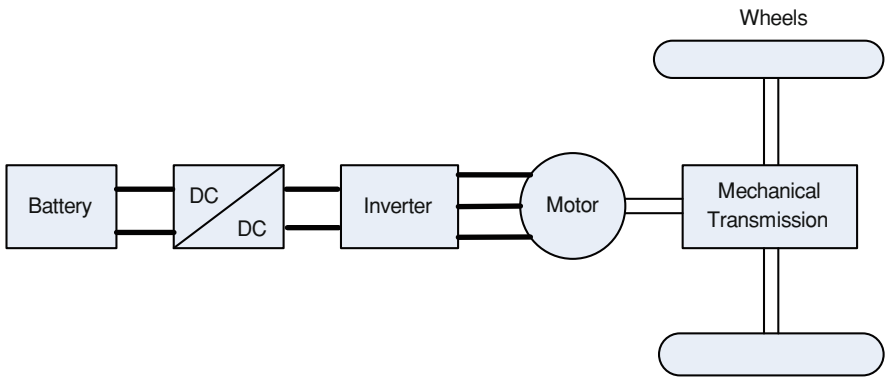


Fig. 2.2 Configuration of a battery-powered EV

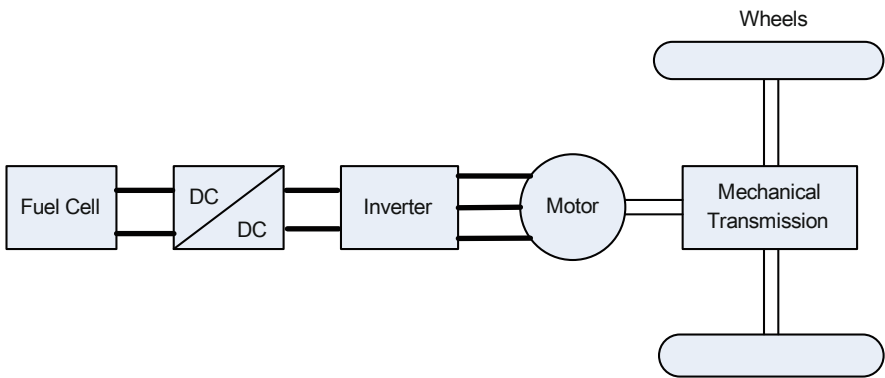


Fig. 2.3 Configuration of FCEV

exist in the meantime. High power density offers a major advantage by permanent magnet motors, which is attractive for EV propulsion solution in spite of the high cost of the motors.

2.1.3 Configuration of Hybrid Electric Vehicles

There are two or more power sources in a hybrid electric vehicle (HEV). Normally an ICE is combined with a battery, an electric motor, and/or an electric generator in the most common types of hybrid electric vehicles. Hybrid electric vehicles can be classified into four different types according to how the powertrain components are arranged: series, parallel, series-parallel, and complex hybrid.

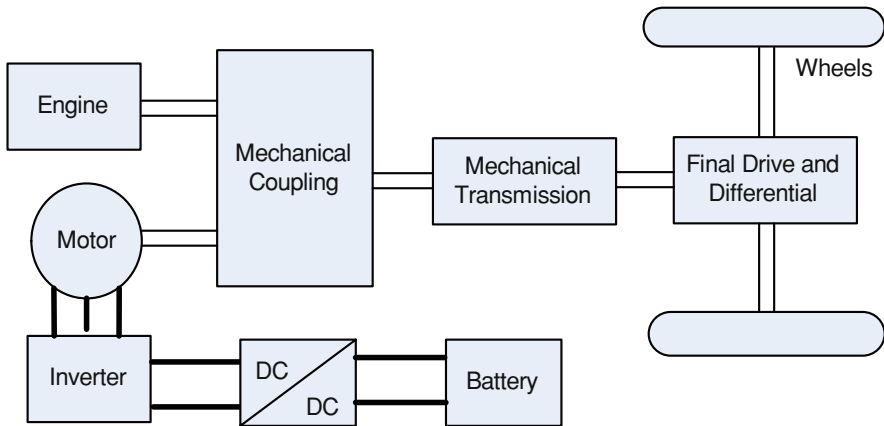


Fig. 2.4 Configuration of a parallel HEV

2.1.3.1 Parallel Hybrid

In a parallel HEV, an electric motor and an ICE are connected to the transmission through a mechanical coupling device, such as separate clutches, so that the vehicle can either be driven by the ICE, or by the electric motor, or by both [5]. The power requirements of the motor in a parallel HEV are lower than that of an EV with similar size. The configuration of the parallel HEV is shown in Fig. 2.4.

The parallel HEV has the following advantages. First, a parallel HEV needs only two propulsion components, ICE and an electric motor. The motor can be operated as a generator and vice versa. Second, the engine and the motor can be rated at reduced power levels for short-distance trips. For long-distance trips, the engine may be designed for maximum power, while the motor/generator may still be rated to half the maximum power. However, the mechanical structure and powertrain control is complex due to the necessity of power coupling for the ICE and the motor. It is also this complexity that gives more freedom for the powertrain control to optimize fuel economy and vehicle performance.

The mechanical coupling is realized through the use of pulleys, gears, clutches, or a common shaft for the engine and motor [5]. Mechanical coupling between motor and ICE can be configured to share a common transmission, or use separate transmissions or even separate axles. The mechanical transmission is also no longer restrained by the traditional automatic transmissions. For example, planetary gear sets have been introduced in parallel hybrids in place of the traditional CVT. The flexibility of configurations in parallel HEV offers the maximum advantage for fuel economy optimization in hybrid electric vehicles.

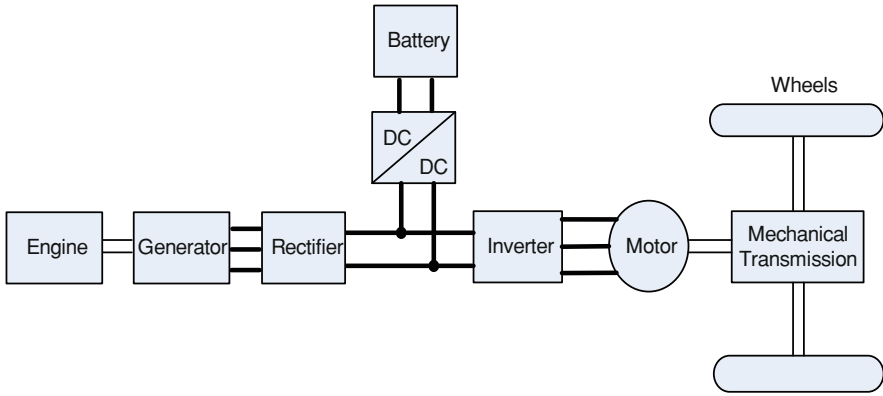


Fig. 2.5 Configuration of a series HEV

2.1.3.2 Series Hybrid

The configuration of a series HEV as shown in Fig. 2.5 is simpler than that of a parallel HEV. Only the electric motor provides all the propulsion power. An ICE on board drives a generator which can charge the battery when the state of charge (SOC) of the battery drops below a certain level [6]. Beyond the ICE and the generator, the propulsion system is the same as in an EV. The series HEV has advantages including flexibility of location of engine-generator set and simplicity of drivetrain, but meanwhile, due to its intrinsic structure, the series HEV needs more propulsion components (i.e., ICE, generator and motor). The fact that no mechanical link exists between the engine and mechanical transmission can have the engine operate in its most efficient region by adjusting its speed and torque. The electric motor has to be designed for the maximum power required by the vehicle. For long-distance missions, the three propulsion components need to be sized for maximum power.

2.1.3.3 Series-Parallel Hybrid

Considering the advantages of both series and parallel configurations, manufacturers and researchers have developed series-parallel hybrid electric vehicles. These HEVs can operate by either using electric motor alone or with the assistance of the ICE [7]. The configuration of the series-parallel HEV is shown in Fig. 2.6. In this configuration, power of the ICE and the electric motor is coupled to drive the vehicle in parallel operation. While power flow from engine to generator and then to the electric motor can be considered series.

There are many choices to design the “mode selection” device. The simplest one is clutches to select which shaft is connected to the ICE, i.e., to connect either the final drive or the electric generator to the ICE. Another choice is to have a

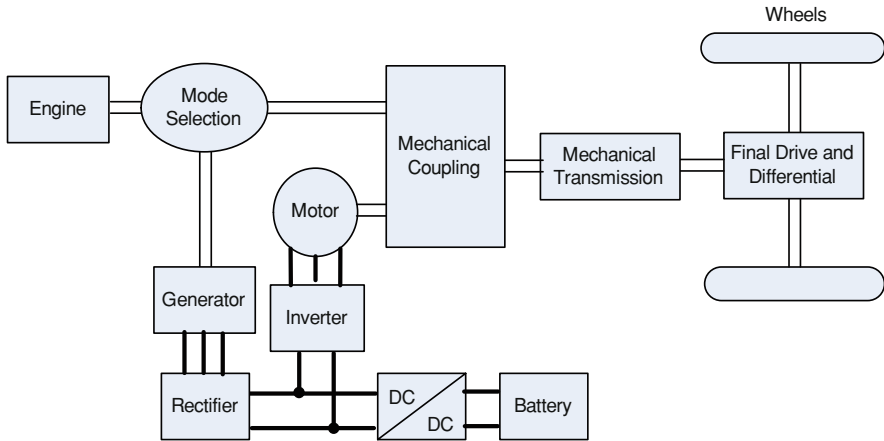


Fig. 2.6 Configuration of a series-parallel HEV



Fig. 2.7 Toyota Prius

power split device such as a planetary gear train to split the ICE power to the drive shaft and the electric generator.

The battery can be charged by the power of the generator. The electric motor can also supply power to the front wheels in parallel with the ICE. A control unit is in charge of driving mode selection. When short bursts of power are needed, the ICE and the electric motor together provide the power required by the vehicle demand.

The Toyota Prius, shown in Fig. 2.7, is a typical series-parallel HEV where a small series element is placed in addition to the primarily parallel HEV. In Toyota Prius, the battery remains charged in prolonged waiting periods such as traffic

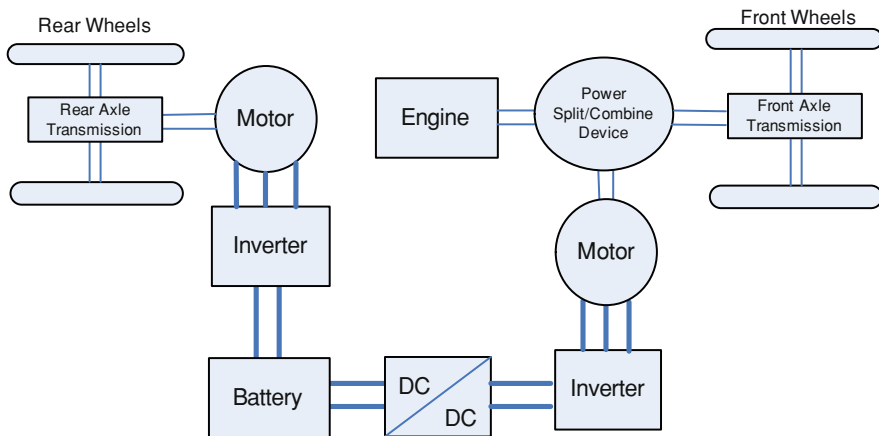


Fig. 2.8 Configuration of a complex HEV

lights or in traffic jam [8]. According to the report from the United States Environmental Protection Agency, the 2008 Prius is the most fuel efficient car sold in the U.S.

2.1.3.4 Complex Hybrid

There exist other configurations of HEVs which cannot be classified into the above three types. An example is shown in Fig. 2.8 which has dual-axle four-wheel drive capability with multiple electric machines and an ICE. It is very much similar to the series-parallel hybrid system. However, the main difference is that the electric motor connected to the power split/combine device in the complex hybrid allows for bidirectional power flow, while the generator in the series-parallel hybrid only permits unidirectional power flow. This bidirectional power flow results in the three propulsion power (due to the ICE and two electric motors) operating modes that are impossible in the series-parallel hybrid [9]. Another difference is that usually the series hybrid is propelled through front wheels by an engine and/or an electric motor. However, in the complex hybrid, the front-wheel axle and rear-wheel axle are separately driven by a hybrid powertrain and an electric motor, respectively. In normal operation mode, the power from ICE is split to propel the front axle and to drive the electric motor (as a generator) to charge the battery. When the load request is low, the battery supplies power to the front electric motor to drive the front axle and it is unnecessary to use both the ICE and rear electric motor. If the vehicle is running at heavy load (e.g. acceleration), both the engine and front electric motor provide power to drive the front axle and meanwhile the rear electric motor propels the rear wheels. Both the front and rear electric motors become generators to charge the battery in the regenerative mode (braking or deceleration). Another dual-axle complex hybrid system differs from the previous

one in terms of function exchange between front and rear wheels, i.e., icons of front and rear wheels exchange their positions. Other variations also exists, e.g. the Toyota Highlander, which employs three electric motors and an ICE to maximize the fuel economy of the vehicle, as well as to improve the vehicle driveability. Unfortunately, the complex hybrid suffers from the high complexity and cost, which is similar to the series-parallel hybrid.

2.2 Vehicle Fuel Consumption and Performance

2.2.1 Vehicle Energy Losses

Only about 15% of the energy from fossil fuel in the tank is used to move the vehicle or supply the accessories in a vehicle [10]. In other words, most of the energy is lost in the engine and drivetrain operations, and overcoming resistances such as aerodynamic drag, rolling resistance, inertia, etc. Reducing the overall vehicle energy losses is necessary and meaningful. The percentage for various energy losses within a vehicle is shown in Fig. 2.9.

2.2.1.1 Engine Losses

In an internal combustion engine (ICE), the combustion products, i.e., hot gases, have more available thermal energy than the original compressed fuel-air mixture. Thus the pistons in the engine are driven by the high-pressure hot gases. Then the remaining hot gases are vented and this allows the piston to return to its previous position. The piston then proceeds to the next phase of its cycle. The heat which is not translated into work is considered as a waste product. Generally speaking, the ICE is not efficient at converting the chemical energy to mechanical energy due to losing energy in engine friction, pumping air in and out of the engine, and wasted heat. More than 62% of the fuel's energy is lost in the gasoline ICE, while diesels are 30–35% more efficient than gasoline engines [10].

There have been great advances in engine efficiency improvement. However, in general, engines always have trade-offs between various characteristics such as efficiency, weight, heat, emissions or power. Discussion of issues related to achieving better fuel economy is one of the objectives in this book.

2.2.1.2 Drivetrain Losses

More than 5% of energy available in the fuel is lost in the transmission and other parts of the drivetrain. Two main causes of transmission losses include the sliding contact of the gears and oil fling and windage. The technologies, such as

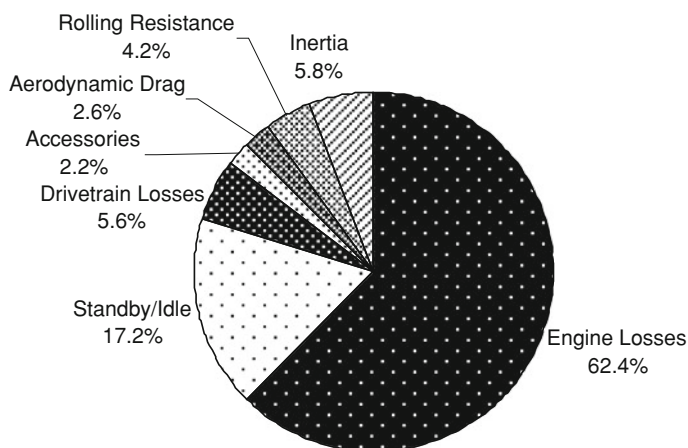


Fig. 2.9 Percentage of various energy losses in a conventional vehicle

automated manual transmission and continuously variable transmission, are developed to reduce these losses.

2.2.1.3 Standby/Idle

About 17% of fuel's energy is lost in idling at stop lights or in traffic in urban driving. The new technologies such as integrated starter/generator systems can reduce these losses by automatically turning the engine off when the vehicle comes to a stop and restarting it instantaneously when the accelerator is pressed.

2.2.1.4 Accessories

About 2.2% of total energy originated from fuel combustion is needed by air conditioning, power steering, windshield wipers, and other accessories. By using more efficient alternator and power steering pumps, fuel economy improvement of up to 1% is possible [10].

2.2.1.5 Aerodynamic Drag

The aerodynamic drag is caused by two factors. One is the viscous friction of the surrounding air on the vehicle surface, and the other is the pressure difference between the front and the rear of the vehicle generated by a separation of the air flow. The vehicle's shape plays an important role in deciding the degree of drag under the same surrounding conditions. The energy lost due to aerodynamic drag is about 2.6% of the total energy from the fuel. With new technologies in the future, such as streamline designed frontal, reductions of 20–30% of the energy

loss caused by aerodynamic drag are possible [10]. The equation to calculate the force of drag on a vehicle due to air is [11].

$$F_d = \frac{1}{2} \rho v^2 A C_d \quad (2.1)$$

where ρ is the density of air; v is the vehicle speed; A is the frontal area; C_d is the drag coefficient (0.25–0.45 for a vehicle).

2.2.1.6 Rolling Resistance

Rolling resistance is frictional force between tire and the road surface. It can be caused by the deformation of the tire, or deformation of the road surface. An improper inflated tire can cause more rolling resistance. The rolling resistance is directly proportional to the weight of the vehicle as expressed in Eq. 2.2 [12].

$$F_r = c_r \cdot m_v \cdot g \cdot \cos(\alpha) \quad (2.2)$$

where m_v is the vehicle mass; g is the gravity acceleration; $\cos(\alpha)$ represents the influence of a non-horizontal road; c_r is the rolling friction coefficient depending on vehicle speed, tire pressure, road surface conditions, etc. A wet road increases c_r by 20%. The vehicle speed influences c_r greatly. When the vehicle speed stays almost constant, the rolling friction coefficient can be considered as a constant. About 4.2% of the fuel's energy is lost because of the rolling resistance [10].

2.2.1.7 Inertia

The vehicle drivetrain must provide enough energy to overcome the inertia to change the vehicle's state of motion [13]. The inertia is directly related to the vehicle's weight. The more a vehicle weighs, the more energy it takes to move the vehicle. There are also many rotational parts in a vehicle which the vehicle has to overcome before the linear motion starts. Light weight materials or lighter-weight technologies such as automated manual transmissions have been developed to reduce vehicle's weight. Particularly, when the driver uses brakes, energy is used to overcome inertia. The total energy lost due to the inertia or braking is calculated to about 5.8% of the total original energy from the fossil fuel in the tank [10].

2.2.2 Vehicle Emissions

As discussed in Chap. 1, motor vehicles on the road emit significant quantities of carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NO_x), particulate matter (PM) and carbon dioxide (CO₂) which are by-products of the combustion process in an ICE. In addition, volatile organic compounds (VOC) escape through fuel evaporation [14]. These vehicle emissions result in adverse health effects and climate changes. As important as the improvement of fuel economy, reduction of

emissions is also one of the most important topics of vehicle power management. The descriptions for these emissions are provided below.

2.2.2.1 Particulate Matter (PM)

Particulate matter (PM) is the general term for the mixture of solid particles and liquid droplets in the air [15]. Particulate matter includes dust, dirt, soot, smoke and liquid droplets which can be man made or natural. Windblown dust, motor vehicles, construction sites, factories and fires all belong to the sources where particulate matter is emitted. Particles are also formed in the atmosphere by condensation or the transformation of emitted gases such as sulfur dioxide, nitrogen oxides, and volatile organic compounds. Particle emissions from motor vehicles are in the fine particle range. Fine particles are of health concern because they easily reach the deepest recesses of the lungs. PM pollution is estimated to cause 22,000–52,000 deaths per year in the United States (from 2000).

2.2.2.2 Carbon Monoxide (CO)

Carbon monoxide (CO) is a colorless, odorless and tasteless, yet highly toxic gas produced through the incomplete combustion of carbon-based fuels [16]. High-level exposures can lead to significant toxicity of the central nervous system and heart, often with long-term sequelae. The health threat from exposure to low-level exposure is very serious for those who suffer from cardiovascular disease.

2.2.2.3 Nitrogen Oxides (NO_x)

NO_x is a generic term for mono-nitrogen oxides (NO and NO₂) which are produced during combustion especially combustion at high temperatures [17]. In an ICE, combustion of a mixture of air and fuel produces high combustion temperatures to drive endothermic reactions between atmospheric nitrogen and oxygen in the flame, yielding NO_x. The amount of nitrogen oxides emitted into the atmosphere is significant due to the high vehicle traffic. NO_x emission is an important precursor to acid rain that may affect both terrestrial and aquatic ecosystems.

2.2.2.4 Volatile Organic Compounds (VOC)

Volatile organic compounds (VOC) are organic chemical compounds that have high enough vapor pressure under normal conditions to significantly vaporize and enter the atmosphere [18]. VOC include a wide range of carbon-based molecules such as aldehydes, ketones and other light hydrocarbons. VOC are emitted from the tailpipe and escape into ambient air through fuel evaporation. On hot days, the emission of the VOC is significant. Ozone is formed by a reaction of VOC (for

vehicles mainly hydrocarbons) and NO_x in the presence of heat and sunlight. Short-term exposures to high ambient ozone concentrations lead to respiratory problems. Repeated exposures to ozone exacerbate symptoms and the frequency of episodes for people with asthma. Long-term exposures to ozone may cause irreversible changes in lungs.

2.2.2.5 Carbon Dioxide (CO_2)

Carbon dioxide (CO_2) is an odorless, colorless gas. Carbon dioxide exists mainly in the gaseous form. It can only be solid when temperatures are below -78°C . Liquid carbon dioxide mainly exists when carbon dioxide is dissolved in water. Carbon dioxide is only water-soluble, when pressure is maintained. Besides, carbon dioxide is the main greenhouse gas whose amount has grown extensively since the industry revolution due to burning of fossil fuels. Greenhouse gas emissions cause the earth's climate to change, including rising temperature and extreme weathers. It is suspected that global climate changes due to greenhouse emissions may bring environmental problems such as increases in storm activity and melting of ice caps on the poles which will cause flooding of the inhabited continents.

2.2.3 Vehicle Performance and Drivability Analysis

Three metrics are often referred to, in order to describe the vehicle performance and drivability. They are maximum speed, gradeability (for vehicles with large loads) and acceleration performance (time from zero-speed to a reference speed).

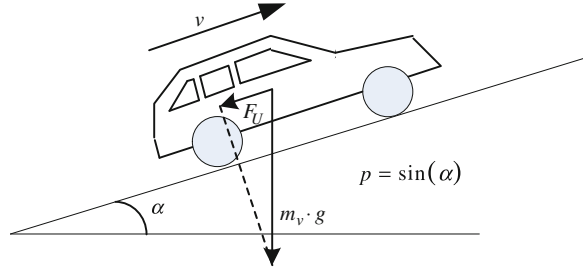
2.2.3.1 Maximum Speed

The maximum speed of a vehicle does not mean much for the speed limit on the public road. However, most drivers want to find the best deal for the speed when shopping for a car since the maximum speed is an important quantifier for vehicle performance [19]. To calculate the maximum speed $v_{\max}$ on a level road with ideal gearing, the parameters needed are: the density of air ρ , maximum traction power $P_{\max}$, frontal area A and drag coefficient C_d . The relationship of them is described as [11, 19]:

$$P_{\max} \approx \frac{1}{2} \cdot \rho \cdot A \cdot c_d \cdot v_{\max}^3 \quad (2.3)$$

However, the maximum vehicle speed in reality is limited by gearing because there is a correspondence between engine speed and vehicle speed for each gear. And the fact is most vehicles' top speed is in excess of speed limits of the public roads. The detailed discussion can be found in [Chap. 3](#).

Fig. 2.10 Sketch map for uphill driving



2.2.3.2 Gradeability or Uphill Driving

A relevant performance metric is the gradeability or uphill driving capability for trucks and other vehicles carrying large loads. The uphill drag is the force induced by gravity when driving on a non-horizontal road. The equation of the uphill drag F_U is shown below [20]:

$$F_U \approx m_v \cdot g \cdot p \quad (2.4)$$

where p is the incline gradient of the road (from zero to valid maximum value in percentage, i.e., 0.2); m_v is the vehicle mass; g is the gravity acceleration. The relationship of the parameters in Eq. 2.4 is shown in Fig. 2.10. Note that gradeability is measured by the vertical distance over a given horizontal distance. Hence, gradeability is equal to $\tan \alpha$, where $\tan \alpha$ is the slope angle.

The maximum traction power $P_{\max}$ can be expressed by the following equation [19].

$$P_{\max} \approx m_v \cdot v_{\min} \cdot g \cdot p_{\max} \quad (2.5)$$

where $p_{\max}$ is the maximum gradient of the road; $v_{\min}$ is the desired uphill speed. The maximum uphill driving angle can be obtained by this equation with a given rated power and a minimum speed.

2.2.3.3 Acceleration

The acceleration drag is the force generated by vehicle acceleration due to vehicle inertia. The following equation expresses the force needed for a given acceleration [20]:

$$F_A \approx m_v \cdot a \quad (2.6)$$

where $a = \frac{dv}{dt}$ is the vehicle acceleration magnitude. The energy required for vehicle acceleration from standstill to a reference speed v_r is expressed as:

$$E = \frac{1}{2} \cdot m_v \cdot v_r^2 \quad (2.7)$$

This energy has to be provided by the vehicle powertrain to accomplish the acceleration. Let t be the time for acceleration process, the mean power can then be calculated as

$$\bar{P} = \frac{E}{t}. \quad (2.8)$$

Considering the varying engine speed and neglecting losses, the approximate mean power is

$$\bar{P} \approx \frac{P_{\max}}{2} \quad (2.9)$$

So, by substituting Eq. 2.8 and 2.9 to Eq. 2.7, the relation between acceleration time and the maximum traction power can be obtained as

$$t \approx \frac{v_r^2 \cdot m_v}{P_{\max}} \quad (2.10)$$

In reality, if the maximum traction power is too low, the launching process lasts too long [21]. Consequently, the aerodynamic drag increases and vehicle performance will be degraded.

2.2.4 Vehicle Operation Modes

The vehicle traction force F_T on the wheel is the sum of the force accelerating the vehicle and the opposing forces in the powertrain. The expression of the traction force is shown as:

$$F_T = m_v \cdot a + F_R \quad (2.11)$$

Depending on the traction force, three various modes of vehicle operation are obtained [11, 22]:

- Traction mode: $F_T > 0$, i.e., the vehicle gets the force to move forward, overcoming inertia and resistive forces;
- Braking mode: $F_T < 0$, i.e., the kinetic energy of the vehicle is being dissipated by brakes or regenerative braking, and the propulsion system can either work or be cut off;
- Coasting mode: $F_T = 0$, i.e., the vehicle propulsion system stops working, and all the kinetic energy is decreased and transformed to the resistance losses.

Another definition for these three modes is based on the coasting speed. Suppose $F_T = 0$ and the vehicle is running on a non-horizontal road (the slope angle of the road α). The relationship between acceleration and all the resistances expressed in Eqs. 2.1, 2.2 and 2.4 can then be depicted as:

$$\frac{dv}{dt} = -\frac{1}{2m_v} \rho v^2 A C_d - c_r \cdot g \cdot \cos(\alpha) - g \cdot \sin(\alpha) = -k_1 v^2 + k_2 \quad (2.12)$$

where k_1 and k_2 are constants, $k_1 = \rho A C_d / 2m_v$, $k_2 = -c_r \cdot g \cdot \cos(\alpha) - g \cdot \sin(\alpha)$.

This formula can be solved with a solution for the coasting speed as a function of time shown below:

$$v(t) = \sqrt{\frac{k_2}{k_1}} \tanh \left\{ \tanh^{-1} \left(\sqrt{\frac{k_1}{k_2}} \cdot v(0) \right) - \sqrt{k_1 k_2} \cdot t \right\} \quad (2.13)$$

Starting with the same initial speed and for a given limited time interval, during this interval

- If the vehicle speed increases, then the vehicle operates in the traction mode.
- If the vehicle speed decreases but is more than the coasting speed shown above, then the vehicle also operates in the traction mode.
- If the vehicle speed decreases and is less than the coasting speed, then the vehicle operates in the braking mode.
- If the vehicle speed matches coasting speed with the same initial speed in a limited time interval, the vehicle operates in the coasting mode.

The above operation modes, depending on vehicle traction or coasting speed, are common for all types of vehicles. Another different classification standard for operation modes of hybrid electric vehicles is based on the power flow and combinations of various power sources [23].

For series hybrid electric vehicles, the operation modes are:

- Engine drive mode: the engine/generator drives the vehicle alone, with battery neither charged nor discharged. This mode is usually suitable to highway cruising when a moderate amount of power is demanded by the vehicle, while the battery SOC is within preset thresholds.
- Electric drive mode: the engine/generator is off, and the battery supplies all the power to the traction motor. This mode is suitable for city driving which is corresponding to low speed operations with gentle to moderate accelerations.
- Hybrid mode: the engine/generator is turned on to supply power to the traction motor together with the battery. This mode is suitable for heavy accelerations when a burst amount of power is demanded by the vehicle.
- Power split mode: the engine power is split to drive the vehicle and charge the battery at the same time. This mode is suitable for vehicle cruising in which a moderate amount of power is demanded by the vehicle but is less than the engine/generator power. The battery SOC needs to be lower than the high threshold in order to enter this mode.
- Braking mode: Depending on the control strategy, regenerative braking and frictional braking need to be coordinated to provide the maximum amount of regenerative braking energy while maintaining safe operation of the vehicle. The regenerative braking energy is stored in the battery during the braking process.

For parallel hybrid electric vehicles, the operation modes are specified below:

- Engine drive: the engine drives the vehicle alone with the battery/motor in idle. This mode is usually suitable to highway cruising when a moderate amount of power is demanded by the vehicle, while the battery SOC is within preset thresholds.
- Electric drive mode: the engine is off, and the battery/motor drives the vehicle alone. This mode is suitable for city driving when the vehicle power demand is relative low.
- Hybrid mode: the engine and the battery/motor together drive the vehicle. This mode is suitable for vehicle operations during heavy accelerations.
- Power split mode: the power from the engine is split to drive the vehicle and to charge the battery at the same time. In this mode, the motor becomes a generator.
- Braking mode: Depending on the control strategy, regenerative braking and frictional braking need to be coordinated to provide the maximum amount of regenerative braking energy while maintaining safe operation of the vehicle. The regenerative braking energy is stored in the battery during the braking process.

The operation modes of series-parallel hybrid electric vehicles and complex hybrid electric vehicles synthesize all the modes of series HEVs and parallel HEVs.

2.3 Power Demand in Drive Cycles

2.3.1 Definition and Standards of Drive Cycles

A drive cycle is a series of data points representing the speed of a vehicle versus time. Drive cycles are established by various countries and organizations to assess the vehicle performance [24]. As a result, the fuel economy and the emissions can be estimated. Chassis dynamometers can be employed to perform fuel consumption and emission tests, taking into account drive cycles required for replay of real world driving conditions. Additionally, vehicle simulations can be implemented using drive cycles. The vehicle propulsion system is regarded as an appropriate space where drive cycles play a very important role for simulation. The drive system can be modeled, and the performance of internal combustion engines, transmissions, electric drive systems, batteries and fuel cell systems can be predicted in the initial design phase.

Drive cycles were created in different ways. Some were derived theoretically, and others were obtained based on measurement data from real world driving tests [25]. The European Union prefers the former while the United States and Japan like the latter. Drive cycles are classified into two different types. One is the

Fig. 2.11 Speed profile of the UDDS cycle

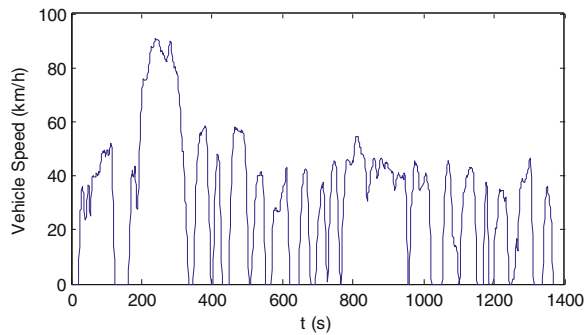


Table 2.1 Characteristics of the UDDS cycle

Time	1,369 s
Distance	11.99 km
Maximum Speed	91.25 km/h
Average Speed	31.51 km/h
Maximum Acceleration	1.48 m/s ²
Maximum Deceleration	−1.48 m/s ²
Average Acceleration	0.5 m/s ²
Average Deceleration	−0.58 m/s ²
Idle Time	259 s
No. of Stops	17

transient drive cycles. The speed changes a lot in these drive cycles based on typical on-road driving conditions. The American Urban Dynamometer Driving Schedule (UDDS) and Federal Test Procedure (FTP) drive cycles belong to this type. The other is modal drive cycles involving protracted periods at constant speeds. The official European New European Driving Cycle (NEDC) and the Japanese 10–15 Mode cycles are included in this type. Next, to make the description more visual and comprehensive, this section will briefly introduce the typical drive cycles i.e., the UDDS and NEDC drive cycles.

The UDDS is commonly called the “LA4” or “the city test”, representing complex city driving conditions. It is only suitable for light duty vehicle testing. The UN/ECE Regulation 53 refers to the UDDS as “Test Equivalent to Type 1 Test (verifying emissions after a cold start)” [26]. The UDDS cycle consists of two phases: the first phase lasts 505 s at 41.2 km/h average speed beginning with a cold start, and the second phase is the last 864 s. The two phases are separated by stopping the engine for 10 min. The speed profile for the UDDS drive cycle is shown in Fig. 2.11. The characteristics are listed in Table 2.1.

The New European Driving Cycle (NEDC) is a drive cycle consisting of four repeated ECE-15 drive cycles and an Extra-Urban drive cycle (EUDC). The ECE-15 cycle is an urban drive cycle which is employed to represent city driving conditions, e.g. in Paris or Rome, and characterized by low vehicle speeds, low engine load and low exhaust gas temperature. The EUDC cycle which has

Fig. 2.12 Speed profile of the NEDC cycle

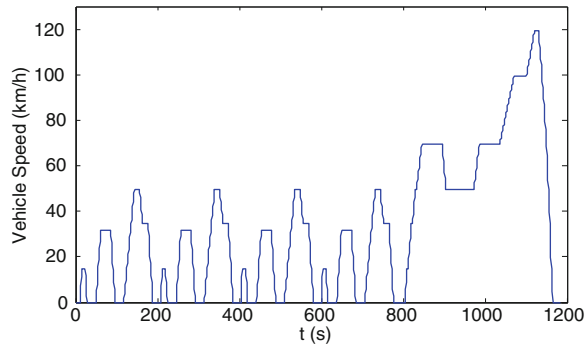


Table 2.2 Characteristics of the NEDC cycle

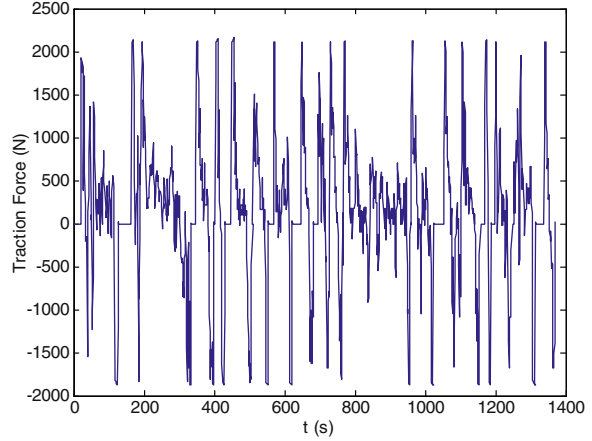
Time	1,184 s
Distance	10.93 km
Maximum speed	120 km/h
Average speed	33.21 km/h
Maximum acceleration	1.06 m/s ²
Maximum deceleration	−1.39 m/s ²
Average acceleration	0.54 m/s ²
Average deceleration	−0.79 m/s ²
Idle time	298 s
No. of stops	13

more aggressive and high speed drive modes is added after the fourth ECE-15 cycle to produce a NEDC cycle. The NEDC cycle is used for emission certification of light duty vehicles in Europe. The speed profile for the UDDS drive cycle is shown in Fig. 2.12. The summary of the NEDC cycle is shown in Table 2.2.

The drive cycles provide credible standards for vehicle optimization and simulation, although the real driving patterns are often more complex. A new technology called drive cycle recognition is under development for hybrid vehicles. The drive cycle recognition (DCR) uses the past driving information and the existing library of drive cycles to predict the future control parameters [27] used for vehicle optimization and control strategy development in a predictive manner. Since the control strategy has greater impact on performance of hybrid vehicles than that of conventional vehicles, the DCR is very beneficial to improve performance of hybrid vehicles.

2.3.2 Power Demand

When the vehicle is running, the on-board power sources supply the power required by both vehicle movement and auxiliary equipments. However, for description simplicity, this book only discusses the mechanical power demand

Fig. 2.13 Traction force in UDSS

related to vehicle kinetics, while neglecting items not considered being of significance. The UDSS drive cycle is employed here as an example for specific power analysis.

As described in Sects. 2.2.2 and 2.2.3, the traction force (considering the horizontal road, i.e., $\alpha = 0$) is the sum of aerodynamic and rolling friction forces and the force due to the acceleration. Based on Eqs. 2.1, 2.2 and 2.11, the traction force can be expressed as:

$$\begin{aligned} F_T &= F_m + F_r + F_d \\ &= m_v \cdot a + c_r \cdot m_v \cdot g + \frac{1}{2} \rho v^2 A C_d \end{aligned} \quad (2.14)$$

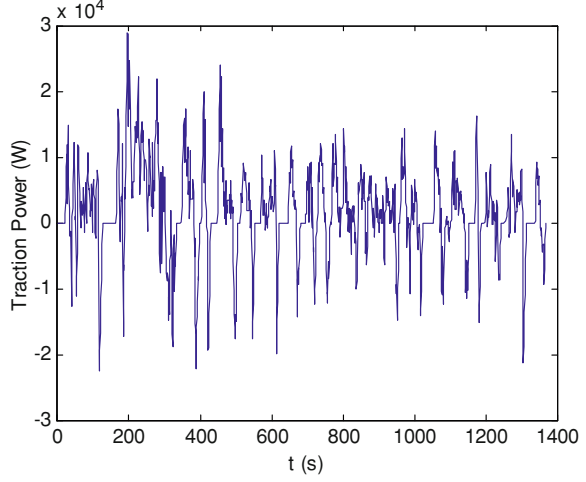
Consequently, the instantaneous traction power can be obtained as:

$$\begin{aligned} P_T &= F_T \cdot v \\ &= m_v \cdot a \cdot v + c_r \cdot m_v \cdot g \cdot v + \frac{1}{2} \rho v^3 A C_d \end{aligned} \quad (2.15)$$

Example 2.1 Given the following parameters for a parallel HEV, $c_r = 0.009$, $g = 9.81 \text{ m/s}^2$, $c_r = 0.009$, $\rho = 1.2 \text{ kg/m}^3$, $A = 2 \text{ m}^2$, and $m = 1350 \text{ kg}$. The traction force and power demand of the vehicle during the UDSS drive cycle can be obtained from the Advanced Vehicle Simulator (ADVISOR) [28], using default parallel HEV model in ADVISOR, as shown in Fig. 2.13 and 2.14, respectively.

On the other hand, power requirements from auxiliary equipments such as lights and indicators, acoustic equipments, windshield wipers, electric heaters and fans, etc. can be added to the total power demand for given driving conditions of the vehicle.

Fig. 2.14 Power demand in UDDS



The mean traction force plays an important role in calculation of the consumed energy during a drive cycle. The mean traction force is defined as follows [29]:

$$\bar{F}_T = \frac{1}{x} \int_{t \in \text{TM}} F_T \cdot v dt \quad (2.16)$$

where x is the distance of the drive cycle; TM means the traction mode. The reason why the traction mode is separated is that the vehicle does not need any mechanical energy in the braking mode and coasting mode. A discretization in time of the drive cycle is used for evaluation of the integral in Eq. 2.16. The time is divided into n segments, i.e., the time instants $t_i = i \cdot \delta$, $i = 0, \dots, n$, where δ is the segment time.

The speed and acceleration in a time interval $t \in [t_i, t_{i+1})$ are considered as the constant average values in this interval, expressed as

$$\bar{v}_i = \frac{v_i + v_{i+1}}{2} \quad (2.17)$$

and

$$\bar{a}_i = \frac{v_{i+1} - v_i}{\delta} \quad (2.18)$$

respectively. Consequently the mean traction force is determined by the following equation:

$$\begin{aligned} \bar{F}_T &= \bar{F}_m + \bar{F}_r + \bar{F}_d \\ &\approx \frac{1}{x} \cdot m_v \cdot \sum_{i \in \text{TM}} \bar{a}_i \cdot \bar{v}_i \cdot \delta + \frac{1}{x} \cdot m_v \cdot g \cdot c_r \cdot \sum_{i \in \text{TM}} \bar{v}_i \cdot \delta + \frac{1}{2x} \cdot \rho \cdot A \cdot c_d \cdot \sum_{i \in \text{TM}} \bar{v}_i \cdot \delta \end{aligned} \quad (2.19)$$

The mechanical energy needed to drive the distance x in the drive cycle is $E = \bar{F}_T \cdot x$. For the UDDS drive cycle, the total energy needed for vehicle movement is calculated to be 4,521 kJ.

2.4 Definitions and Objectives of Vehicle Power Management

It increased global energy demand and environment concerns are challenging the automobile industry. Under this background, the power management function of vehicles must be carefully designed to fully realize the potential of vehicle powertrains to meet the above challenges. The term, “power management,” refers to the design of the higher-level control algorithm determining the proper power level to be generated, and its split between various power sources [30]. Generally the power management control is implemented in the vehicle-level control system that can coordinate the overall powertrain to satisfy certain performance targets. Its commands then become the set-points for the servo-loop control (e.g. electric motor control) systems which operate at a much higher frequency. The servo-loop control systems can be designed for different goals, such as improved drivability, while ensuring the set-points commanded by the main loop controller are achieved reliably.

Power management for vehicle systems is desired for many objectives, such as improving fuel economy; reducing pollutant emissions; prolonging lifetime of some power sources, e.g. the battery, fuel cell, etc.; and enhancing vehicle drivability and reliability.

When accomplishing these objectives, items noted below have to be considered while developing the proper power management strategy [9].

- Optimal engine operating point—The optimal engine operating point on the torque-speed plane is decided by maximum fuel economy, minimum emissions, or a compromise between fuel economy and emissions.
- Optimal engine operating line—The engine operating line is constituted by optimal engine operating points related to different power demands.
- Optimal engine operating region—The engine has a preferred operating region on the torque-speed plane where the fuel economy is high.
- Minimum engine dynamics—The engine needs to be regulated at proper speed avoiding fast fluctuations and thus minimizing engine dynamics.
- Minimum engine speed—The engine has to be turned off when the speed is below a threshold level because the fuel economy is low at such a speed.
- Minimum engine turn-on time—The frequent turning on and off leading to additional fuel consumption and emissions should be avoided. The minimum engine turn-on time is considered as a metric to this.
- Proper battery capacity—The battery should be kept at a proper state of charge (SOC) level for both supplying sufficient power to acceleration and absorbing regenerative braking power.

- **Safety battery voltage**—The battery voltage may dramatically change during the processes of discharging, generator charging, or regenerative charging. The battery will be seriously and permanently damaged if severe over-voltage or under-voltage operation takes place.
- **Fuel cell maximum output power**—The distributed power demand from the fuel cell (in case of fuel cell based vehicles) cannot exceed its maximum output power constraint, otherwise the voltage will drop to an abnormal level and oxygen starvation will occur.
- **Geographical policy**—In some areas, HEVs need to be operated from the hybrid mode to the pure electric mode manually or automatically.

2.5 Power Management in Conventional Vehicles

Most automobiles today are conventional vehicles powered by either gasoline or diesel engines, with a small percentage also capable of running on bio-fuel, such as E-85. The power management of conventional vehicles can be in two different areas: powertrain torque-speed characteristic mapping, and electric power management.

In a conventional vehicle driven by ICE, the engine is only capable of delivering torque at some speed range, and there exists a range for the engine to offer better fuel economy. Hence, continuous variable transmission, automatic transmission, and dual clutch transmission, etc., have been developed to match the engine output (speed and torque) with the vehicle demand while optimizing the overall vehicle efficiency.

In general, automotive engineers and designers implement the improved vehicle fuel economy by utilizing advanced vehicle components. For example, the continuously variable transmission (CVT) technology is an automatic transmission with the ability to select any drive ratio available in the operating range whether the vehicle is accelerating or cruising. Nevertheless, a specific gear is selected like the third, fourth or fifth gear in a traditional automatic transmission. Consequently the CVT can provide better fuel economy than the traditional automatic transmission by enabling the engine to run at its most efficient speed. In addition, there are several driving tips for improving vehicle fuel economy. For instance, a driver can improve fuel economy if he keeps the tires inflated properly, and using cruise control can improve gas mileage by helping the driver maintain a steady speed, but only if he is driving on mostly flat roads. However, these aspects are not within the scope (vehicle-level power management strategies) of this book.

On the other hand, more and more mechanical systems in conventional vehicles are being replaced by electric systems, so called drive-by-wire systems, such as electric steering, electromechanical braking, and active suspension [31]. For example, an electronically controlled anti-lock braking system (ABS) has been used to prevent the wheels of a vehicle from locking up (or ceasing to rotate) during braking. A typical ABS is composed of a central electronic control unit

(ECU), four wheel speed sensors (one for each wheel) and two or more hydraulic valves within the brake hydraulics. When detecting a wheel rotating dramatically slower than the others, it actuates the valves to reduce hydraulic pressure to the brake at the affected wheel, thus reducing the braking force on that wheel. As a result, the wheel turns faster. On the contrary, if a wheel is detected turning significantly faster than the others, brake hydraulic pressure to the wheel is increased so the braking force is reapplied and the wheel slows. This process is repeated continuously, and can be detected by the driver via brake pedal pulsation. Therefore, ABS is capable of improving vehicle control, decreasing stopping distance on slippery surfaces, and increasing braking distance on loose surfaces such as snowy and gravel roads. Recent versions of ABS possess some new functions, such as electronic stability control (ESC), electronic brake force distribution (EBD), traction control system (TCS), and adaptive cruise control, due to the evolution that the front-to-rear brake bias can be electronically controlled.

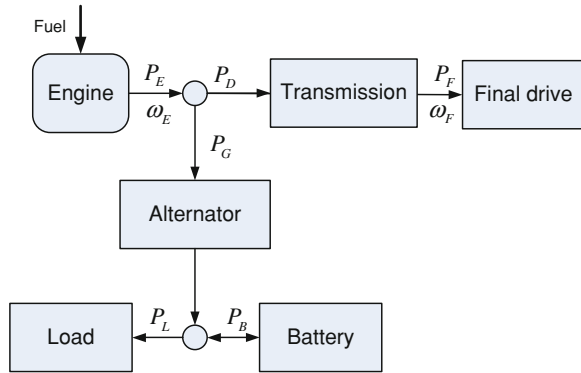
Increase of electric power demand in vehicles has prompted the use of high voltage bus, i.e., the 42 V system [31]. A typical passenger car today can easily experience 3–5 kW of electric power demand at its peak usage. Typical electric power demand includes power seats, windshield wipers, heated seats, headlights, entertainment systems, GPS, and drive-by-wire systems. This kind of power demand means a few hundred amperes of current needed from the traditional 14 V battery. Not only does this put pressure on the battery itself, but the heavy wiring costs more money in a vehicle. The introduction of 42 V powernet will ease the pressure on the battery and reduce overall vehicle system cost in the long term. However, initial cost will be high since it will affect the manufacturing of various components in the vehicle system. Hence, it will initially deter its introduction since cost is one of the dominant factors that drives or impedes technological change in the automobile industry. The real application needs to address issues involving existing manufacturing infrastructure, supplier base for various 42 V components, and other similar items, before the 42 V system becomes available and replaces the existing 14 V system.

As the electric power demand moving upwards kilowatts range, the proportion of electric power to overall vehicle power is no longer negligible. By properly controlling how the electric power is used, specifically, how the battery is charged and discharged, the overall vehicle fuel economy can be improved.

In a conventional vehicle, the alternator is directly coupled to the engine's crankshaft. By controlling the output electric power of the alternator, the operating point of the ICE can be somewhat manipulated, so the overall fuel economy can be improved [32, 33].

Figure 2.15 shows the power flow in a conventional vehicle. The nomenclatures of power flow in the vehicle are as follows: P_E Engine power; P_D Driver power demand; P_G Input power to alternator; P_F Power request at the axle; P_L Electrical power demand; P_B Power flowed into battery, ω_E engine speed, ω_F axle speed.

Fig. 2.15 Power flow of a conventional vehicle



The fuel rate of the engine F_E is a nonlinear function of the engine power P_E and engine speed ω_E , i.e., $F_E = F(P_E, \omega_E)$. The power from the engine is split to two components with a portion going to the drivetrain for vehicle propulsion and another to alternator, i.e., $P_E = P_D + P_G$. The alternator converts the mechanical power P_G to electric power to supply power to the electric loads and charge the battery. It is also possible for the battery to supply power to the electric loads, and in this case, the alternator power can be reduced to a lower level. Hence, fuel consumption can be modeled as a function of propulsion power P_D , battery power P_B , electric power demand P_L and engine speed ω_E .

One objective of power management is to minimize the power loss produced in the ICE, alternator and battery. Since P_D and P_L are determined by the driver's request, they can be considered given. Engine speed ω_E needs to match vehicle speed by properly controlling the transmission gear ratios. Since modern transmissions can offer many or infinite gear ratios for the powertrain, there exists a number of possible engine speed for a given vehicle speed by choosing different gear ratios for a given power demand.

Since only battery power and engine speed can be controlled, the fuel rate F_E can be expressed as a nonlinear function of P_B and ω_E i.e., $F_E = f(P_B, \omega_e)$, consequently. For a given power demand, by controlling P_B (magnitude and direction), the total engine power is controlled which will alter the engine operation. Hence, a better fuel economy is possible.

Although power management in conventional vehicles is important, it is beyond the scope of this book. Interested readers can refer to [32–34] and other related reference for further reading.

2.6 Power Management of Hybrid Electric Vehicles

A hybrid electric vehicle (HEV) combines a conventional combustion engine propulsion system with one or more electric propulsion systems. The presence of the electric powertrain is for the purpose of achieving better fuel economy than a

conventional vehicle. The control strategies of HEVs are more complicated than those of conventional vehicles because of the more-complex configurations and operation modes. Meanwhile it is commonly recognized that the power management for HEVs has more influence than in conventional vehicles on vehicle performance improvements such as fuel consumption, emission and lifetime extension of power sources, due to more freedom of power split between various power sources.

As introduced at the beginning of this chapter, there are four different types of hybrid vehicles, i.e., series hybrid, parallel hybrid, series-parallel hybrid and complex hybrid. A HEV power management controller is designed to meet the driver's power demand while optimizing fuel economy and reducing emissions, and to maintain the state of charge (SOC) of the battery at a desired level to enable effective delivery of power to the vehicle over a wide range of driving conditions.

The knowledge-based strategies, as the most popular methods, use rules or fuzzy logic for power management implementation in a real hybrid electric vehicle. The categories of this knowledge are [33]:

- Heuristic knowledge that is dependent on the efficiency map of an engine [35].
- Knowledge about the proper power split between two power sources for the minimization of the equivalent consumption cost, which is generated by optimal methods such as dynamic programming [36, 37].
- Prediction of driving environment using neural networks and fuzzy logic for vehicle power optimization [30, 33, 38].

Fuzzy logic and neural networks have been used in developing power management controllers for hybrid HEVs. In [39], a fuzzy controller was developed for a parallel HEV based on the driver command, the SOC of the energy storage system (ESS), and the motor/generator speed [39]. Fuzzy rules were derived to determine the proper power split between electric motor and internal combustion engine (ICE). The objective is to optimize the efficiency of the ICE, electric motor and battery.

The objective of HEV power management is typically a multi-objective non-linear optimization problem with multiple input variables and multiple constraints. It is not easy to decide the rules to meet all important trade-offs among multiple variables in the control system of a HEV with multiple variables and/or objectives. The study of optimal strategy such as dynamic programming (DP) is beneficial to comprehend the drawbacks of the rules, and achieve construction of better rules. The following three benefits result from the application of DP approach to establish rules in a parallel HEV [40].

- Optimal performance is known from the DP solutions.
- The rule-based algorithm is tuned to obtain near-optimal solution, under the pre-determined rule structure and number of free parameters.
- The design procedure is re-useable for other types of hybrid vehicles or other objectives.

In [30], a procedure for the design of a near-optimal power management strategy was proposed for a parallel hybrid truck. A cost function was defined

for minimizing the combination of fuel consumption and selected emissions. Dynamic Programming (DP) was utilized to find the optimal control. Hence the correct gear shifting and power split between engine and motor can be defined while maintaining the battery SOC in a certain preset thresholds. The optimization solutions are produced after two runs of DP, where one is with regeneration on, and the other is with regeneration off. The DP solutions in the first run result in the rules for the gear shift logic and power split strategy, and the DP solutions in the second run lead to the charge-sustaining rules. In addition, three variables, i.e., the power demand, engine speed and transmission input speed, can be selected as inputs to the neural network to predict the optimal motor power in a split mode [40]. After the training, the prediction results produced by the neural network are stored in a look-up table for possible real-time control.

Many power management strategies based on predefined drive cycles can not be implemented online due to the fact that they optimize fuel economy for known drive cycles. Driving situation, road condition, and the driving style of the driver are not part of the optimization process. An intelligent controller can predict the future condition therefore can further optimize the vehicle performance in real world driving. In [26, 37], an intelligent energy management agent (IEMA) was proposed to optimize the vehicle performance by predicting upcoming events [36, 37]. IEMA uses the information on roadway type and traffic congestion level, driver style, etc. to distribute the required torque between the electric motor and ICE.

More details of the power management strategies described in this section will be given in Chap. 4 through 7.

2.7 Software Tools

Simulation tools are critical for implementation and verification of these strategies ahead of real applications. So in this section we will introduce several effective vehicle simulators used in the initial phase for strategy development of vehicles. Effective and reliable software tools play a critical role in the optimization of vehicle structure, and verification of control strategies, especially the subject of this book i.e., power management approaches, in the initial phase for vehicle design and development. Numerical modeling and analysis for vehicle components are accomplished in these software tools where interconnection of vehicle powertrain components operating in different energy domains is permitted. The scaling of vehicle components is available for optimization of parameters; visual and numerical functions are well embedded. Next we will give an introduction of several popular vehicle simulation tools including MATLAB/Simulink, ADVISOR and PSAT, which have been widely and efficiently used in the field of vehicle research.

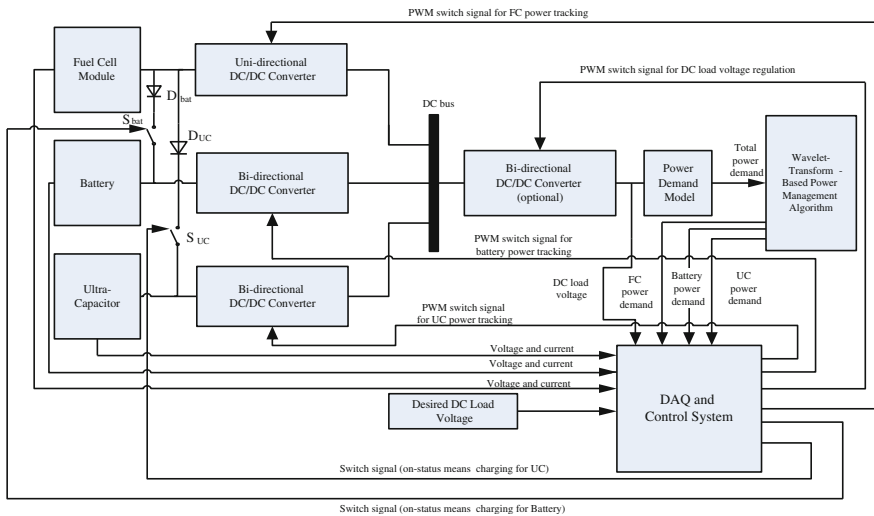


Fig. 2.16 Power system in a multi-source vehicle

2.7.1 MATLAB/Simulink

MATLAB (meaning “matrix laboratory”) by Mathworks is a high-performance language for technical computing and programming. Simulink, developed by The Mathworks, is a commercial tool for modeling, simulation and analysis of multi-domain physic systems. It contains a graphical user interface and a customizable set of block libraries. Simulink is widely used in control theory and digital signal processing for multi-domain simulation and design [41].

MATLAB/Simulink has proven to be a very effective software tool for vehicle modeling and relevant strategy verification. Several existing vehicle simulators such as ADVISOR, PSAT and VDMS have been developed and programmed with MATLAB/Simulink. Regardless of any professional software, users also can establish their own vehicle component models in terms of interests and specific system requirements. Figure 2.16 shows the block diagram of a hybrid power system consisting of multiple on-board power sources i.e., engine/alternator, fuel cell, battery and ultracapacitor. A hybrid electric vehicle is merely a particular case of this generic system, with only an engine and electric propulsion. The system shown in Fig. 2.16 has been studied by using Matlab/Simulink, and the results have been reported through publications [42].

The simulation results can be read through different ways, e.g. the “Scope”, “Workspace” variables, “Display”, etc. As an example of displaying vehicle simulation results in MATLAB/Simulink, the voltage on the 42 V bus of the above multi-source vehicle is displayed in a “Scope” (see Fig. 2.17), where the horizontal axis represents simulation time with the unit “second” while the vertical axis is the 42 V bus voltage magnitude with the unit “volt”. Users can easily

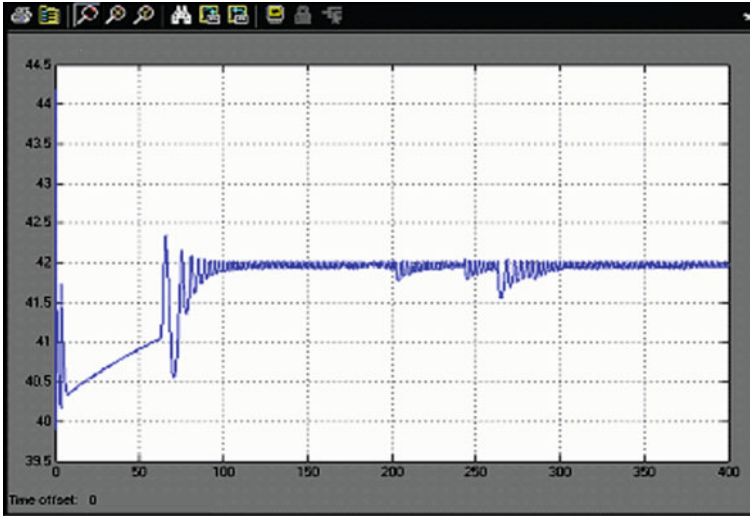


Fig. 2.17 The 42 V bus voltage shown in a “Scope” as an example for simulation results display methods

modify and try various power management algorithms and strategies for certain vehicle performance objectives in the MATLAB/Simulink environment.

2.7.2 ADVISOR

The U.S. National Renewable Energy Laboratory (NREL) worked with industry partners to develop a sophisticated systems analysis tool which can provide specific component and vehicle designs [43]. Thus the Advance Vehicle Simulator (ADVISOR) came out. ADVISOR is a model written in MATLAB/Simulink environment and used to simulate and analyze all types of vehicles. ADVISOR can predict the vehicle performance, energy consumption, emissions output, control strategy function and average component efficiencies over multiple drive cycles and test procedures. Users can alter simulation results by selecting vehicle component types, sizes and parameters.

As an example for description of relation between MATLAB/Simulink and ADVISOR, a parallel HEV model under the MATLAB/Simulink environment, developed by ADVISOR, is shown in Fig. 2.18. The component models representing real vehicle components in this figure are stored in libraries. The libraries provide the same component models to multiple vehicle configurations. Users can modify the models in the MATLAB/Simulink model and see the results in ADVISOR display interface.

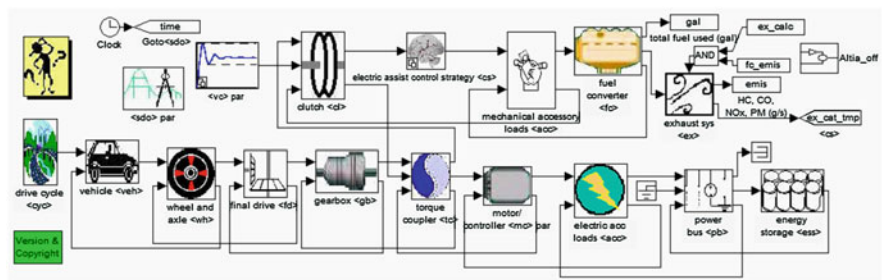


Fig. 2.18 MATLAB/Simulink parallel HEV model developed in ADVISOR

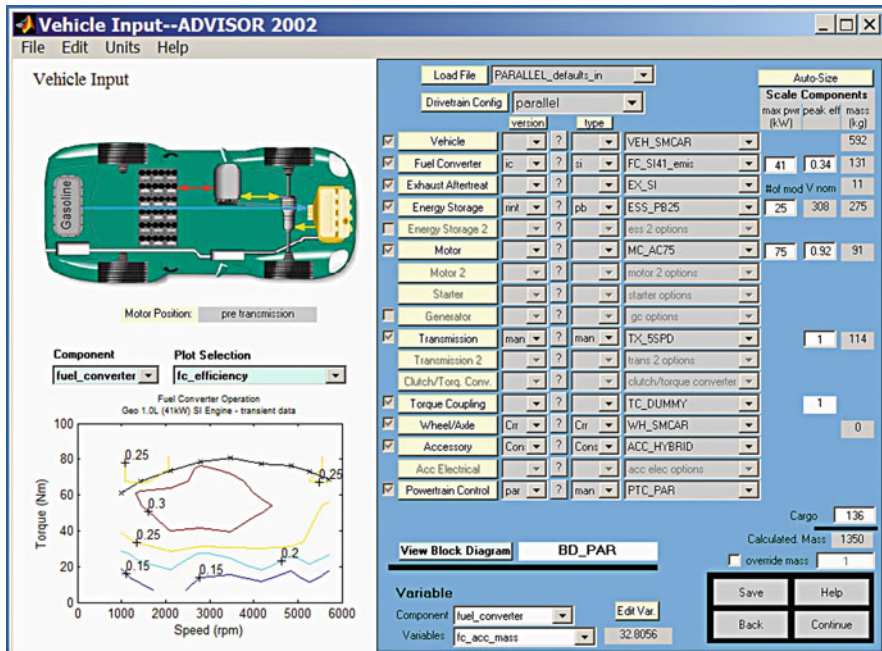


Fig. 2.19 Vehicle input window in ADVISOR

Users can “build” the vehicle of interest in the ADVISOR vehicle input window as shown in Fig. 2.19. A vehicle configuration as well as the components for the driveline can be selected. The size of a component can be modified in this window according to the desired value. Besides, any scalar parameter can be modified in the edit variable menu.

Users can define the drive cycles or test procedures for simulation in the simulation setup window (see Fig. 2.20). Users can also define the simulation

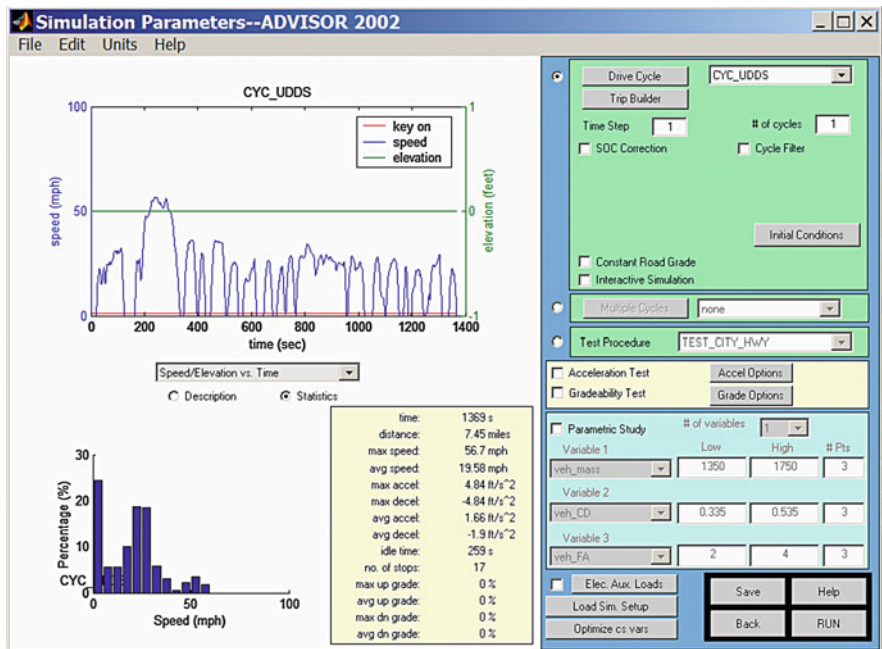


Fig. 2.20 Vehicle simulation window in ADVISOR

parameters on the right portion. Characteristics of a drive cycle or test procedure are provided on the left portion including the speed profile and statistical analysis.

The vehicle operation details (e.g. vehicle speed, battery SOC, overall ratio engine speed, etc.) throughout the entire drive cycle or test procedures can be displayed in the figures on the left portion of the results window (see Fig. 2.21). Summary results such as fuel economy and emissions are provided on the right portion.

A unique combined backward/forward-facing modeling approach is employed in ADVISOR, which allows ADVISOR to execute vehicle operation under a multitude of operating scenarios without the need to iterate.

2.7.3 PSAT

Sponsored by the U.S. Department of Energy (DOE), Argonne National Laboratory, has developed a Powertrain System Analysis Toolkit (PSAT) [44]. PSAT provides accurate performance and fuel economy simulations. Developed with MATLAB/Simulink, PSAT is a graphical user interface (GUI)-driven application, which makes it very easy to use. PSAT component interactions are “real world”

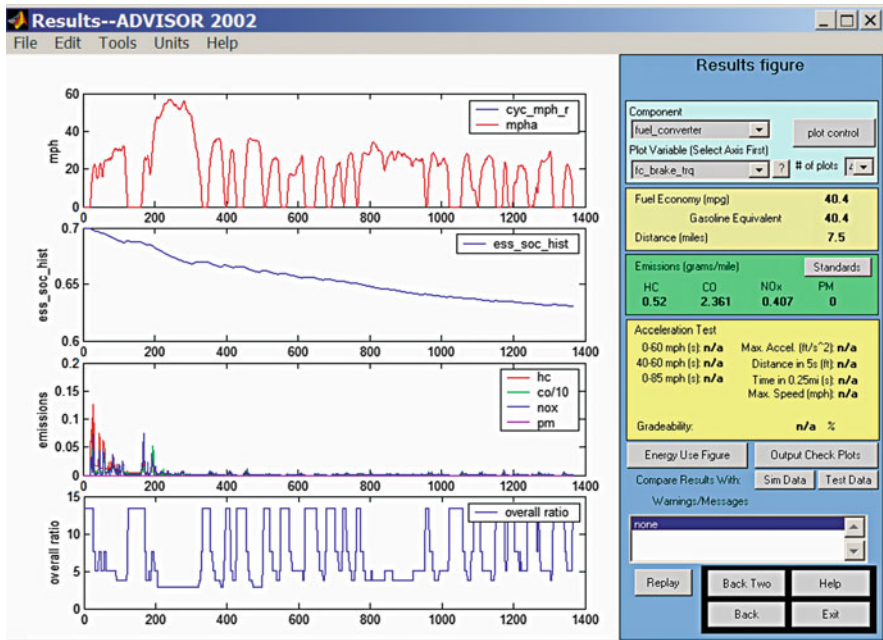


Fig. 2.21 Results window in ADVISOR

situations, because of its forward architecture. Control strategies can be directly realized and tested on the bench or in a vehicle. Users can have ideas of fuel economy, performance and gradeability, components' size, and can perform parametric studies, import test data, and animate and compare test and simulation data as well.

A MATLAB/Simulink parallel HEV model created by PSAT simulation execution is shown in Fig. 2.22. The vehicle components and controllers are involved. This created model can be directly run under the MATLAB/Simulink environment. Users can either modify the parameters or principles of the controllers inside the model.

The vehicle's configuration can be decided in the "Drivetrain Configuration" window shown in Fig. 2.23. The conventional vehicle, parallel HEV, series HEV, split HEV or fuel cell vehicle, is selected as the object to be studied and simulated in this step, and meanwhile the wheel drive mode is determined as well. PSAT provides the block diagram showing the vehicle configuration on the lower portion in this window.

The specific components selection is implemented in the "Drivetrain Components" window shown in Fig. 2.24. This step gives the type selections for the engine, motor, gearbox, final drive, battery, etc. Consequently the mass, size, power or

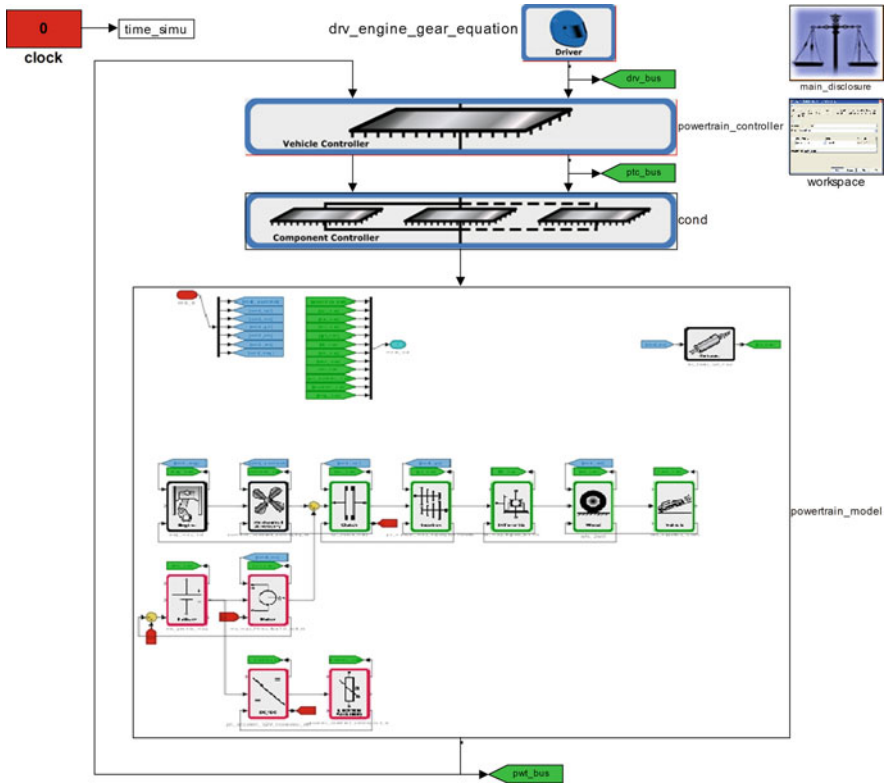


Fig. 2.22 MATLAB/Simulink parallel HEV model developed in PSAT

other parameters of these components are decided. All types of vehicle components are defined in the libraries provided by PSAT. Similar to ADVISOR, PSAT provides the drive cycle or test procedure selection in the “Simulation Setup” window shown in Fig. 2.25.

The main simulation results e.g. total fuel economy, fuel mass, emissions, battery initial and final SOC can be found in the “Main Results” window shown in Fig. 2.26. In the “Full Results” window next to it, more specific results such as volume of fuel consumed, maximum difference between the simulated and target vehicle speed, total time when positive or negative wheel torque occurred, and so on, are provided.

PSAT has been applied to a wide range of applications such as validating advanced vehicle models, simulating vehicles for industry, conducting fuel cell systematical requirements, well-to-wheel evaluation of advanced vehicles and research due to the flexibility of PSAT.

There are other simulation tools available for the purpose of validation of power management and control strategies in a vehicle but are not discussed further in this book.

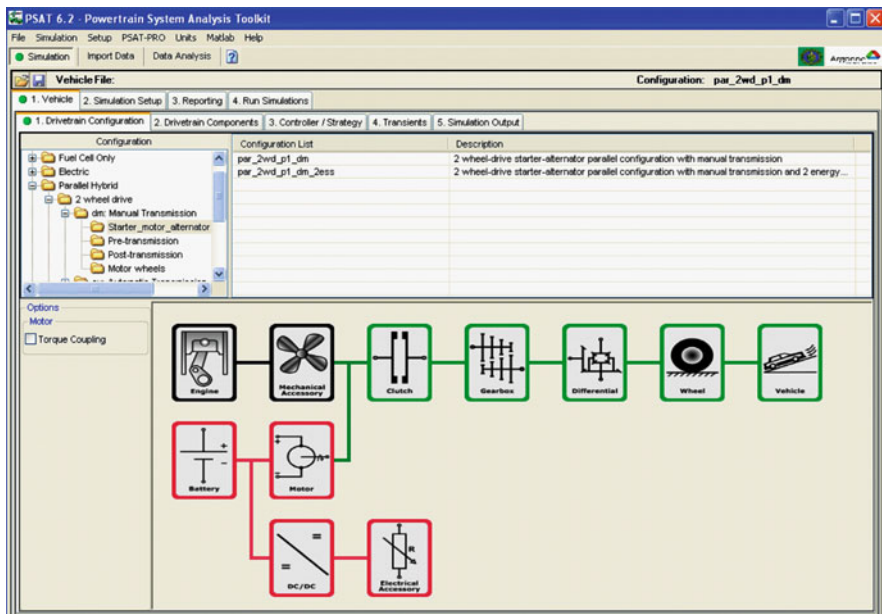


Fig. 2.23 PSAT vehicle drivetrain configuration window

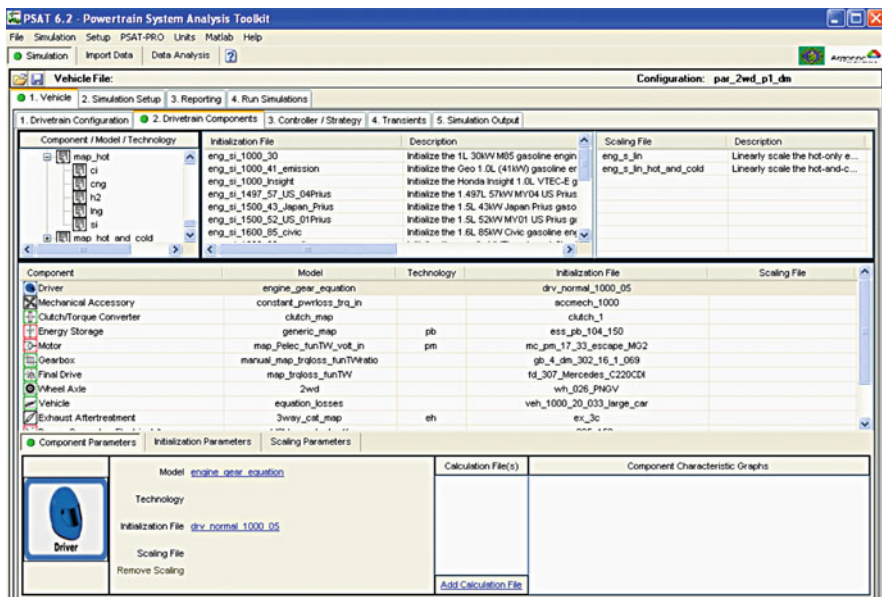


Fig. 2.24 Drivetrain component selection window in PSAT

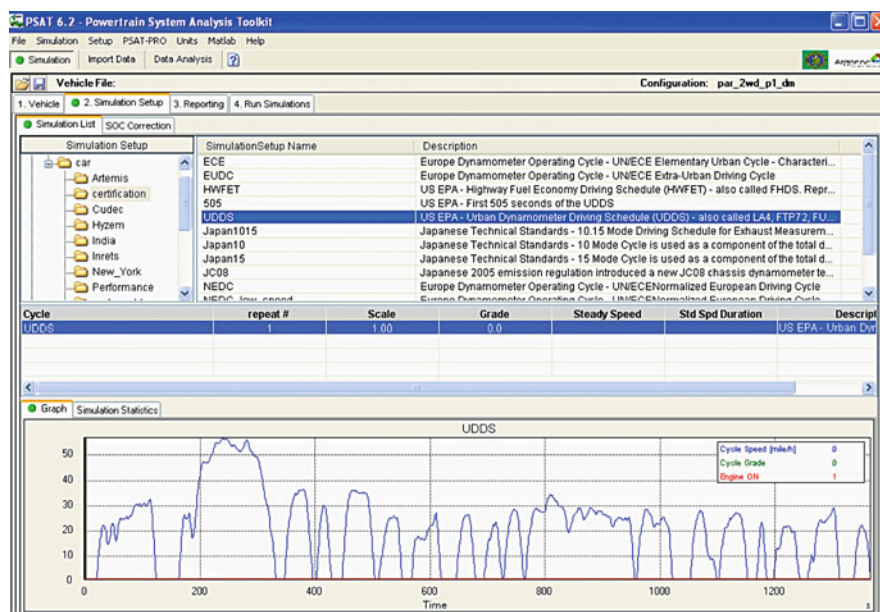


Fig. 2.25 Simulation setup window in PSAT

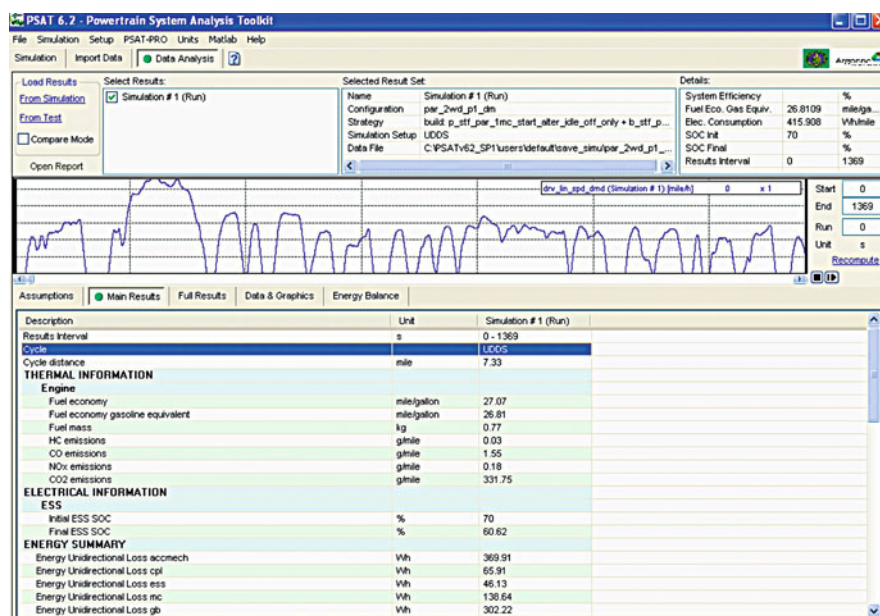


Fig. 2.26 Main results window in PSAT

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Chapter 3

Modeling of Vehicle Propulsion Systems

3.1 Internal Combustion Engine

The gasoline internal combustion engine (ICE) operating on a four-stroke Otto cycle, has been most successful for automobiles so far, while diesel engines are mainly used for trucks and buses. Recently, ICEs operating with Atkinson cycles have been successfully applied to various types of hybrid electric vehicles. The exothermic reaction of gasoline or diesel with an oxidizer produces gases with high temperature and pressure. The ICE is featured by the useful work that is performed by the expanding hot gases acting directly to cause movement of pistons.

Karl Benz was one of the inventors and leaders in the development of ICEs. He was granted patent in 1879 for his reliable two-stroke ICE design [1]. Later he designed and built his own four-stroke engine used in his automobiles. Thus the first automobiles in production appeared.

The continuation of the use of the ICE for automobiles is partly due to the improvement of engine control systems. All ICEs must have a way of ignition to initiate combustion. An electrical or a compression heating ignition system is utilized in most ICEs. A battery and an induction coil are applied to provide a high voltage electrical spark to ignite the air-fuel mixture in the engine's cylinders. Compression heating ignition systems such as diesel engines and HCCI engines depend on the heat created in the air by compression in the engine's cylinders to ignite the fuel. When the combustion begins, hot gases as the combustion products that have more available energy than the original fuel/air mixture drive the engine's pistons. Once the available energy has been removed, hot gases are vented. Then the piston returns to its previous position, waiting for the next phase of its cycle.

ICEs using the four-stroke Otto cycle have one power stroke for every four strokes (up-down-up-down). They are widely used in cars, larger boats, and many light aircraft and are generally quieter, more efficient and larger than their two-stroke counterparts. There exist a number of variations of these cycles, most

notably the Atkinson and Miller cycles [2]. The four-stroke cycle is also used in most truck and automotive diesel engines with a compression heating ignition system which will be separately discussed. Diesel engines are generally heavier, noisier and more powerful at low speeds than gasoline engines. Meanwhile diesel engines have the highest thermal efficiency of any ICE because of their high compression ratio. They are used in heavy road vehicles, some automobiles, ships, railway locomotives, and light aircrafts, due to their higher fuel efficiency, while gasoline engines are used in other road vehicles including most cars, motorcycles, and mopeds.

ICEs can have any number of cylinders with numbers between 1 and 12 being common. More cylinders mean two potential advantages. One is that the ICE can have a larger displacement with smaller individual reciprocating masses, which results in a smoother running engine (since the engine tends to vibrate due to moving up and down of pistons). The other is that more fuel takes part in combustion with a larger number of pistons, leading to more torque generated in such an engine than in a similar engine with fewer same-sized cylinders. On the other hand, more fuel is involved in combustion obviously if larger pistons are employed. However, the drawback of increasing the number of cylinders is that the engine's weight and internal friction will increase, which tends to the decrease of fuel efficiency and thus overall fuel economy. So at the present time, most car ICEs have four to eight cylinders. There seems to be a breakpoint around 10 or 12 cylinders for high performance gasoline engines using current materials and technologies.

3.1.1 Analysis of Normalized Engine Variables

When the engine operates in steady-state conditions, the thermodynamic efficiency η_E of ICEs is mainly decided by the engine speed ω_E and torque T_E . The relation of these parameters is described by

$$\eta_E = \frac{\omega_E \cdot T_E}{P_c} \quad (3.1)$$

where P_c is the enthalpy flow related to the fuel mass flow M_f defined in Eq. 3.2 and the subscript c represents “chemical” since the fuel carries the chemical energy.

$$M_f = \frac{P_c}{H_l} \quad (3.2)$$

where H_l stands for the fuel's lower heating value. The energy content in gasoline is 33.7 kWh/gallon for the lower heating value, or 36.6 kWh/gallon for the higher heating value.

The range of the variables ω_E and T_E depends on the specific engine to be modeled, though they have a clear physical interpretation. Thus this chapter

introduces and analyses normalized engine variables by which the engine size can be employed as a parameter to be optimized.

Two normalized engine variables, the mean piston speed C_m , and the mean effective pressure p_m , can depict the engine operating point in steady state conditions. These two variables are defined by [3]

$$C_m = \frac{\omega_E \cdot S}{\pi} \quad (3.3)$$

and

$$p_m = \frac{N \cdot \pi \cdot T_E}{S_d} \quad (3.4)$$

where S is the engine stroke and S_d the engine's displacement. In Eq. 3.4, $N = 2$ and $N = 4$ are for a two-stroke engine and for a four-stroke engine respectively.

The mean piston speed C_m is the average piston speed during one engine revolution, which is limited by the lower value (the idling speed), and the upper value associated with aerodynamic friction in the intake part and mechanical stresses in the valve train. The mean effective pressure p_m is the amount of constant pressure acting on the piston during one full expansion stroke to create the same amount of mechanical work produced by a constant engine torque T_E in one engine cycle.

The range of the normalized engine variables, C_m and p_m , is almost the same for all engines with the same type, and these two variables are not functions of the engine size. The engine maps are often shown through the engine speed in rpm n_E which replaces the average piston speed C_m because the engine speed boundaries vary less than torque boundaries for engines of similar type. For a given C_m and p_m , the mechanical power P_m is defined by

$$P_m = K \cdot \frac{\pi}{16} \cdot B^2 \cdot p_m \cdot C_m \quad (3.5)$$

where k stands for the number of cylinders and B is the cylinder bore. Consequently, once the rated engine power $P_{\max}$ is determined, it is available to estimate the engine size related to the number of cylinders and cylinder bore using Eq. 3.5.

3.1.2 Expressions of Engine Efficiency

The engine efficiency defined in Eq. 3.1 is often expressed in an engine map as shown in Fig. 3.1. This engine is a 41 kW SI type. Various colors indicate different equivalent-efficiency curves. The "Optimization Area" labels the operating region with the highest efficiency.

By using the normalization concept introduced in Sect. 3.1.1, the engine map can also be delineated by the mean piston speed C_m and the mean effective pressure p_m . Meanwhile it is available to simplify the engine model using the

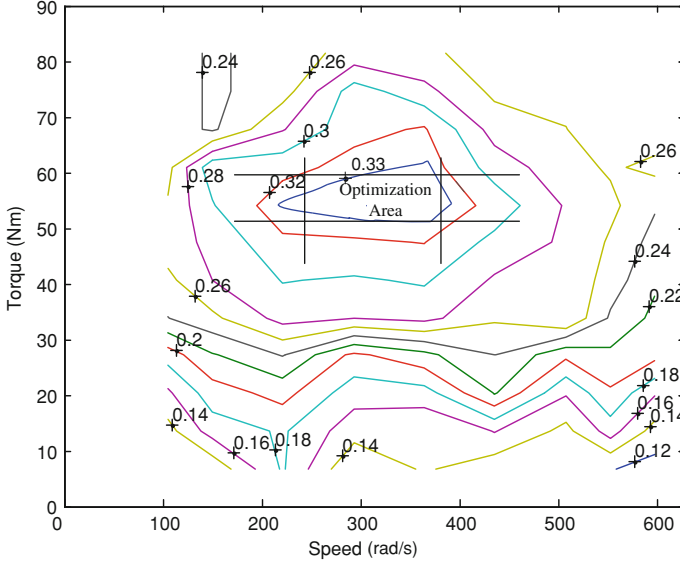


Fig. 3.1 Engine efficiency map

effective Willans description [4] where the engine mean effective pressure is approximated by

$$p_m \approx \eta(\omega_E) \cdot P_f - P_{me}(\omega_E). \quad (3.6)$$

where $\eta(\omega_E)$ is the efficiency of the thermodynamic energy conversion from chemical energy to pressure inside the cylinder at engine speed ω_E ; $P_{me}(\omega_E)$ represents all the mechanical friction losses in the engine at the speed ω_E . $\eta(\omega_E)$ and $P_{me}(\omega_E)$ are often considered as constants for preliminary computations. P_f , the mean fuel pressure, is the mean effective pressure that an engine with 100% efficiency produces by burning a mass m_f of fuel with a lower heating value H_l , which is expressed as

$$P_f = \frac{H_l \cdot m_f}{s_d} \quad (3.7)$$

3.1.3 State-Space Representation for ICE

The engine torque T_E can be computed by an empirical relationship depending on the mass of the air charge M_a , the air/fuel mixture ratio $\frac{A}{F}$, the spark advance (degrees before top-dead-center) σ and the engine speed ω_E as shown below [5]

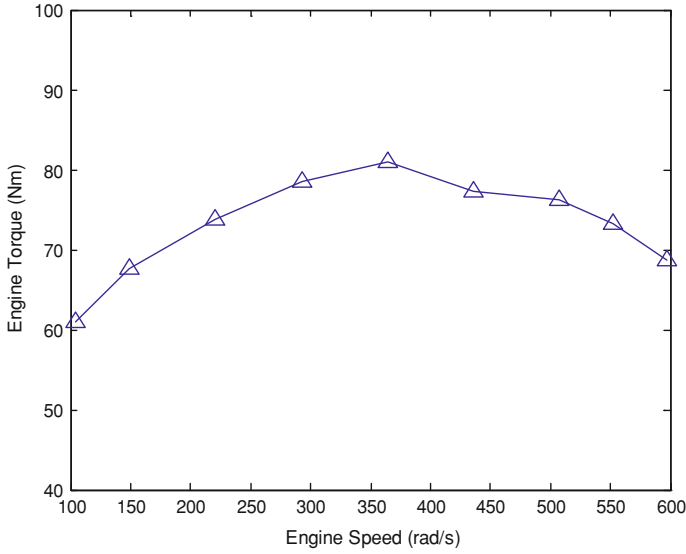


Fig. 3.2 Maximum torque curve

$$\begin{aligned}
 T_E = & -181.3 + 379.36 \cdot M_a + 21.91 \cdot \left(\frac{A}{F}\right) - 0.85 \left(\frac{A}{F}\right)^2 + 0.26 \cdot \sigma - 0.0028 \cdot \sigma^2 \\
 & + 0.027 \cdot \omega_E - 0.000107 \cdot \omega_E^2 + 0.00048 \cdot \omega_E \cdot \sigma + 2.55 \cdot \sigma \cdot M_a \\
 & - 0.5 \cdot \sigma^2 \cdot M_a
 \end{aligned} \quad (3.8)$$

The engine acceleration state equation can be described as:

$$\frac{d\omega_E}{dt} = \frac{1}{J_E} T_E - \frac{1}{J_E} T_L \quad (3.9)$$

where J_E stands for engine rotational moment of inertia, and T_L is load torque. The maximum engine torque can be obtained at the maximum throttle angle (100%). When the throttle angle u varies, the actual engine torque will change proportionally. Thus, the engine torque can be expressed as:

$$T_E = u T_{E \max} \quad (3.10)$$

where the throttle angle u is considered as the control variable for the state equation.

Based on the data provided by the engine manufacturer, the maximum engine torque is a function of engine speed depicted as (see Fig. 3.2, hot engine map):

$$T_{E \max} = f(\omega_E) \quad (3.11)$$

Consequently, by substituting Eqs. 3.10 and 3.11 into 3.9, the state equation of the engine can be rewritten as:

$$\frac{d\omega_E}{dt} = \frac{1}{J_E} u f(\omega_E) - \frac{1}{J_E} T_L \quad (3.12)$$

The high efficiency area (optimization area) shown in Fig. 3.1 represents the expected engine operation region. By constraining the engine torque and speed in such an area without degrading the engine output capacity, the engine shows high operation efficiency, which helps to improve fuel economy. The optimization area of this 41 kW SI engine is expressed quantitatively below:

$$237 \text{ rad/s} < \omega_E < 380 \text{ rad/s}, 52 \text{ Nm} < T_E < 60 \text{ Nm} \quad (3.13)$$

3.2 Electric Machines

Electric machines, generators and motors, are devices that transform mechanical power into electrical power, and vice versa. In conventional vehicles, electric machines are usually used as starters or alternators. The starter rotates an internal combustion engine at idle speed to cause the engine powering itself. The alternator is used to charge the battery with 12 V voltage and to provide power for vehicle's electrical loads when the engine is running.

Electric machines are essential to electric and hybrid electric vehicles [6]. In an electric vehicle (EV) or a parallel hybrid electric vehicle (HEV), a traction motor is usually used to perform the following functions: (1) convert the electrical power from the battery into mechanical power to drive wheels; (2) convert the mechanical power during the regenerative braking period into electrical power to recharge the battery; and (3) convert a portion of the mechanical power from the engine into electric power to charge the battery as needed in power split operations. In a series HEV, besides a traction motor with functions similar to those in electric or parallel HEVs, an electric generator is used to convert the mechanical power from the engine into electrical power to charge the battery or to supply the electrical loads the required power.

The electric machines in vehicles are required to have high efficiency since the electrical energy must go through two power converters and a generator (in series HEV) from the engine to the traction motor. The power losses in the electric machines and power converters have a multiplication effect on the vehicle propulsion system. Other primary requirements of electric machines in electric or hybrid electric vehicles include low cost, high power, small size, high reliability, fault tolerance, low noise, good controllability and stability.

Electric machines can be classified into Direct Current (DC) type and Alternating Current (AC) type. The former is referred as brushed DC electric machines and the latter includes induction and synchronous electric machines. Synchronous machines can be further classified to field excited synchronous machines and permanent magnet machines. Brushless DC motors is a type of AC machine whose stator current waveform is a trapezoidal other than sinusoidal. Induction motors, brushless DC motors, and permanent magnet synchronous machines are all

popular choices for EV and HEV. But brushed DC motors are not used due to many disadvantages such as reliability concerns, bulky size, and low efficiency. Since an electric generator acts as the reverse of an electric motor, and the principles are the same without requiring a separate discussion, this section will only introduce modeling methods of several electric motors such as brushed DC motor, induction motor, permanent magnet synchronous motor (PMSM) and brushless DC motor (BLDC) that are currently applied in EVs and HEVs.

3.2.1 Brushed DC Motor

The brushed DC motor generates torque directly from power received from the DC power supply. In general, there exist five major types of DC motors such as separately excited, shunt, permanent magnet, series and compounded types. The schematics for brushed DC motors with permanent magnets and field coils are shown in Fig. 3.3. In DC motors, the rotor is usually called armature since a back electromotive force (EMF) is induced in it. The equivalent circuit of the armature for a DC motor is shown in Fig. 3.4. The armature circuit is represented by a voltage source U_A , a back EMF E_A , a resistor R_A and an inductor L_A . Their relation can be expressed by a Kirchhoff voltage equation as:

$$U_A = E_A + I_A \cdot R_A + L_A \cdot \frac{dI_A}{dt} \quad (3.14)$$

where I_A is the armature current.

For the DC motors except permanent magnet DC motors, the equivalent circuit of field coils is shown in Fig. 3.5. The Kirchhoff voltage equation for this equivalent circuit is given by

$$U_F = I_F \cdot R_F + L_F \cdot \frac{dI_F}{dt} \quad (3.15)$$

where U_F is the field voltage; I_F represent the field current; R_F and L_F stand for the resistance and inductance of field coils, respectively.

For the shunt DC motor, the armature and field circuits are connected in parallel, sharing a DC power supply, i.e., $U_A = U_F$. For the series DC motor, the armature and field circuits are connected in series with the same current, i.e., $I_A = I_F$. The back EMF and armature torque in DC motors are expressed by the following two equations, respectively:

$$E_A = K_e \cdot \omega \quad (3.16)$$

$$T_A = K_T \cdot I_A \quad (3.17)$$

where ω is the rotor angular speed; K_e and K_T are called speed and torque constants, respectively. Usually these two constants are numerically equal to each other if international MKS units are used, i.e., $K_e = K_T = L_m \cdot I_F = K$, where L_m

Fig. 3.3 Schematic of DC motors. **a** DC motor with field coils. **b** Permanent magnet DC motor

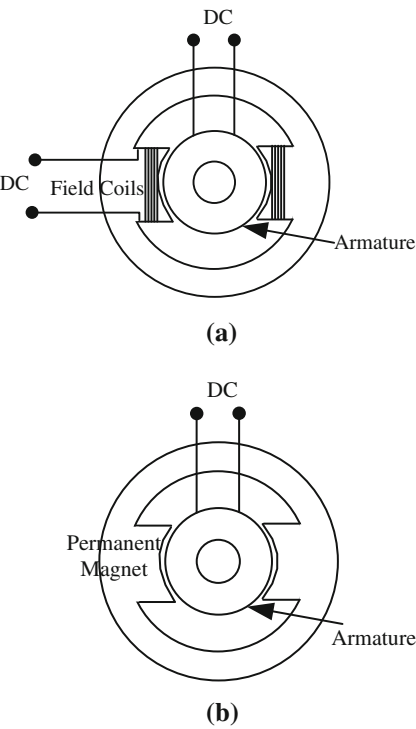


Fig. 3.4 Equivalent circuit of a DC motor

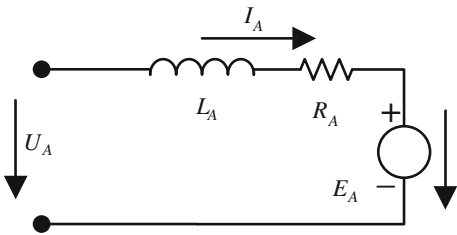


Fig. 3.5 Equivalent circuit of field coils of DC motor

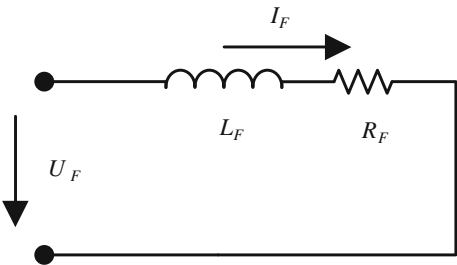
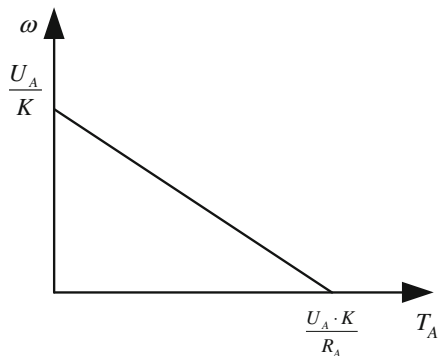


Fig. 3.6 Relation between the speed and torque



is the mutual inductance. Given a voltage source U_A , the steady-state relation between the angular speed and the torque is shown in Fig. 3.6.

According to Newton's second law, the shaft mechanical state equation is given by

$$J_{DC} \frac{d\omega}{dt} = T_A - T_2 \quad (3.18)$$

where J_{DC} is the moment of inertia of the DC motor; T_2 is the mechanical torque including the load torque, losses in the magnetic material, and losses due to frictional and windage.

When the DC motor runs in the steady state, the rotor speed is constant, so the armature torque completely supplies the mechanical load without shaft acceleration. Thus, one obtains:

$$T_2 = T_A = K \cdot I_A \quad (3.19)$$

In the quasi-stationary limit, the armature and field currents can be considered as constants, therefore Eqs. 3.14 and 3.15 become

$$U_A = E_A + I_A \cdot R_A = K \cdot \omega + I_A \cdot R_A \quad (3.20)$$

$$U_F = I_F \cdot R_F \quad (3.21)$$

Consequently, by substituting Eq. 3.20 to 3.19, the mechanical load torque can be expressed as

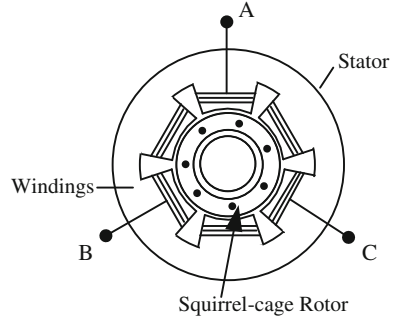
$$T_2 = K \cdot I_A = K \cdot \frac{U_A - K\omega}{R_A} \quad (3.22)$$

In DC motors, the input power P_1 is the product of armature current and voltage, expressed as follows:

$$P_1 = U_A \cdot I_A \quad (3.23)$$

By substituting Eq. 3.22 to 3.23, the input power can be rewritten as

Fig. 3.7 Schematic of a squirrel-cage induction motor



$$P_1 = T_2 \cdot \omega + \frac{T_2^2 \cdot R_A}{K^2} \quad (3.24)$$

The output power is computed by the multiplication of the mechanical load torque and the shaft speed, which is depicted by

$$P_2 = T_2 \cdot \omega = T_A \cdot \omega \quad (3.25)$$

Thus the efficiency can be calculated as

$$\eta = \frac{P_2 - p_{fw} - p_c}{P_1} \quad (3.26)$$

where p_{fw} and p_c are the friction and windage loss and core loss, respectively. If we neglect these two losses, then the efficiency can be written as $\eta = \frac{1}{1 + \frac{T_2^2 \cdot R_A}{K^2 \cdot \omega}}$, and the total power losses are obtained as

$$P_l = P_1 - P_2 = \frac{T_2^2 \cdot R_A}{K^2} \quad (3.27)$$

Therefore it can be observed that power losses in DC motors are due to the armature ohmic resistance. It should be noted that loss in the magnetic material of the motor, which is the armature core, loss of the field winding and the magnetic material of the field winding, and losses due to friction and windage, may not be negligible in most applications. But to keep the discussion simple, those losses will not be discussed in this section.

3.2.2 Induction Motor

An induction AC motor, whose schematic is shown in Fig. 3.7, is also called an asynchronous AC motor. It supplies power to the rotating device by means of electromagnetic induction. The stator current of an induction motor creates a magnetic field which interacts with the rotor to produce a resultant torque, thus

producing mechanical energy. The rotor of an induction motor may have a short-circuited winding or squirrel-cage construction. In this section we only discuss modeling of the three-phase squirrel-cage induction motor.

Using the Park's transformation, the three-phase (i.e., a, b and c phase) windings of the stator can be substituted by the two equivalent d - and q -axis windings, and the rotor can be analyzed also with two equivalent, short circuited d - and q -axis windings. The $dq0$ transform (often referred as Park's transformation) for electrical variables of the stator and rotor is described in the following two equations.

$$\begin{bmatrix} S_{ds} \\ S_{qs} \\ S_{0s} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} \cos(\theta) & \cos\left(\theta - \frac{2\pi}{3}\right) & \cos\left(\theta + \frac{2\pi}{3}\right) \\ \sin(\theta) & \sin\left(\theta - \frac{2\pi}{3}\right) & \sin\left(\theta + \frac{2\pi}{3}\right) \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} S_{as} \\ S_{bs} \\ S_{cs} \end{bmatrix} \quad (3.28)$$

and

$$\begin{bmatrix} S_{dr} \\ S_{qr} \\ S_{0r} \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} \cos(\theta_{sl}) & \cos\left(\theta_{sl} - \frac{2\pi}{3}\right) & \cos\left(\theta_{sl} + \frac{2\pi}{3}\right) \\ \sin(\theta_{sl}) & \sin\left(\theta_{sl} - \frac{2\pi}{3}\right) & \sin\left(\theta_{sl} + \frac{2\pi}{3}\right) \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} S_{ar} \\ S_{br} \\ S_{cr} \end{bmatrix} \quad (3.29)$$

where S represents one of the various electrical variables, e.g., current i , voltage u , flux ψ , etc.; the subscripts s, r stand for the stator and rotor, respectively; θ is the synchronous flux rotating angle, and θ_{sl} is the slip angle calculated by the difference between the synchronous flux rotating angle and the electric angle equivalent to the rotor angle θ_r , i.e., $\theta_{sl} = \theta - \theta_r$. The synchronous angular speed ω , the electrical angular speed ω_r that equals the multiplication of the rotor mechanical angular speed ω_2 and the number of pole pairs p , and the slip angular speed ω_{sl} are expressed as

$$\omega = \frac{d\theta}{dt}, \quad \omega_r = \frac{d\theta_r}{dt}, \quad \omega_{sl} = \omega - \omega_r \quad (3.30)$$

respectively. Kirchhoff's voltage laws for the stator and rotor are written as

$$u_{ds} = R_s \cdot i_{ds} - \omega \cdot \psi_{qs} + \frac{d\psi_{ds}}{dt} \quad (3.31)$$

$$u_{qs} = R_s \cdot i_{qs} + \omega \cdot \psi_{ds} + \frac{d\psi_{qs}}{dt} \quad (3.32)$$

$$u_{dr} = R_r \cdot i_{dr} - \omega_{sl} \cdot \psi_{qr} + \frac{d\psi_{dr}}{dt} \quad (3.33)$$

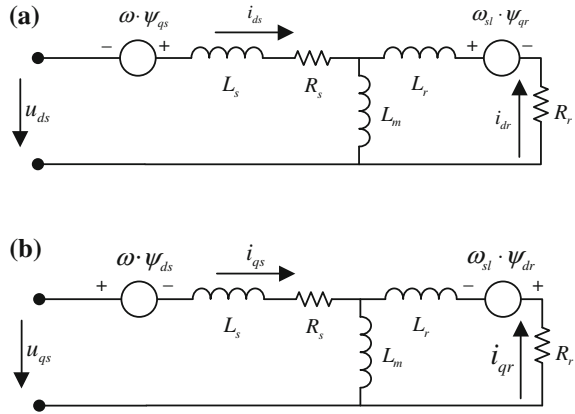
$$u_{qr} = R_r \cdot i_{qr} + \omega_{sl} \cdot \psi_{dr} + \frac{d\psi_{qr}}{dt} \quad (3.34)$$

where R_s, R_r are the stator resistance and equivalent transformed rotor resistance, respectively. For a three-phase squirrel-cage induction motor, $u_{qr} = u_{dr} = 0$. The flux equations described by dq0 transform are given by

Fig. 3.8 Equivalent circuit of an induction motor.

a d-axis equivalent circuit.

b q-axis equivalent circuit



$$\psi_{ds} = L_s \cdot i_{ds} + L_m \cdot i_{dr} \quad (3.35)$$

$$\psi_{qs} = L_s \cdot i_{qs} + L_m \cdot i_{qr} \quad (3.36)$$

$$\psi_{dr} = L_r \cdot i_{dr} + L_m \cdot i_{ds} \quad (3.37)$$

$$\psi_{qr} = L_r \cdot i_{qr} + L_m \cdot i_{qs} \quad (3.38)$$

where L_s, L_r are the stator and equivalent transformed rotor inductance; L_m is the magnetizing (or mutual) inductance. The d- and q-axis equivalent circuits are shown in Fig. 3.8.

The electromagnetic torque generated at the rotor shaft is expressed as

$$T_e = \frac{3pL_m}{2L_r} (i_{qs} \cdot \psi_{dr} - i_{ds} \cdot \psi_{qr}) \quad (3.39)$$

According to Newton's second law, the mechanical equation of an induction motor is given by

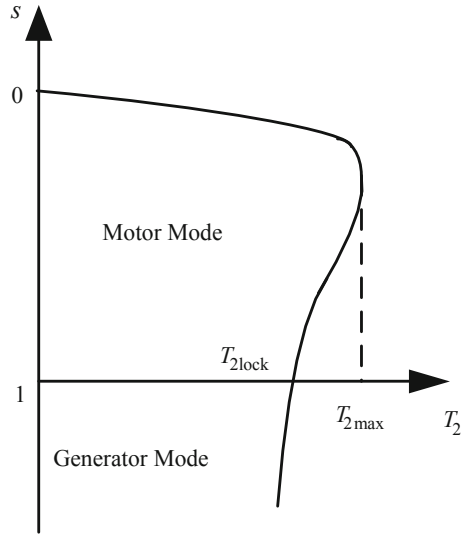
$$J_{IM} \cdot \frac{d(\omega_r/p)}{dt} = T_e - T_2 \quad (3.40)$$

where T_2 is the torque of the mechanical load; ω_r/p is the rotor mechanical angular speed; J_{IM} stands for the moment of motor inertia.

Within the quasi-stationary limit, by expressing i_{qs}, i_{ds}, i_{qr} and i_{dr} as a function of $u_{qs}, u_{ds}, \omega, \omega_r$ and ω_{sl} , the torque of the mechanical load can be written as

$$\begin{aligned} T_2 &= \frac{3p}{2} \cdot \frac{R_r \cdot L_m^2 \cdot \omega_{sl} \cdot (u_{ds}^2 + u_{qs}^2)}{(R_r \cdot L_s \cdot \omega + R_s \cdot L_r \cdot \omega_{sl})^2 + (R_r \cdot R_s - \omega \cdot \sigma \cdot L_s \cdot L_r \cdot \omega_{sl})^2} \\ &= \frac{3p}{2} \cdot \frac{R_r \cdot L_m^2 \cdot s \cdot (u_{ds}^2 + u_{qs}^2) / \omega}{(R_r \cdot L_s + R_s \cdot L_r \cdot s)^2 + (R_r \cdot R_s / \omega - \omega \cdot \sigma \cdot L_s \cdot L_r \cdot s)^2} \end{aligned} \quad (3.41)$$

Fig. 3.9 Curve of slip ratio versus load torque of an induction motor



where $s = \omega_{sl}/\omega$ represents the slip ratio; $\sigma = 1 - L_m^2/(L_s \cdot L_r)$. Fig. 3.9 shows the steady-state relation between the motor torque and the slip ratio. $T_{2\text{lock}}$ stands for the torque for the locked rotor and $T_{2\text{max}}$ represents the maximum torque.

The d-q stator voltages u_d , u_q and the synchronous angular speed ω are determined by the inverter that converts a DC power supply voltage or the AC power grid voltage to the variable-frequency three-phase AC voltage needed by the motor. Sinusoidal pulse-width modulation (SPWM) or space vector PWM (SVPWM) is often used in the motor drive as an advanced class of switching schemes to generate the required waveform of the three stator phase voltages.

The input power of an induction motor can be depicted as

$$p_1 = \frac{3}{2} (u_{qs} \cdot i_{qs} + u_{ds} \cdot i_{ds}) \quad (3.42)$$

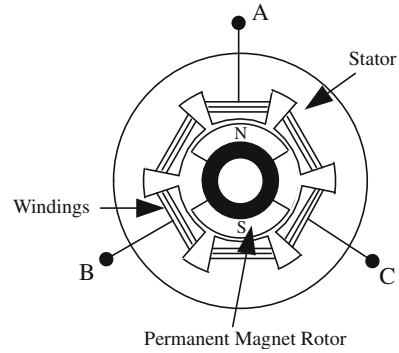
Meanwhile the output mechanical power P_2 can be expressed by the multiplication of the torque of the mechanical load and the rotor mechanical angular speed as

$$P_2 = \frac{T_2 \cdot \omega_r}{p} \quad (3.43)$$

Consequently, using the above equations, the induction motor efficiency can be obtained as

$$\eta = \frac{P_2}{P_1} = \frac{1}{\frac{\omega}{\omega_r} + \frac{R_r R_s}{L_m^2 \omega_{sl} \omega_r} + \frac{R_s}{R_r} \cdot \frac{L_r^2}{L_m^2} \cdot \frac{\omega_{sl}}{\omega_r}} \quad (3.44)$$

Fig. 3.10 Schematic of a PMSM or BLDC



Thus the expression for the total power losses in an induction motor operation is

$$P_l = P_1 - P_2 = \frac{\omega_r \cdot T_2}{P} \left(R_s \cdot \frac{R_r^2 + L_r^2 \cdot \omega_{sl}^2}{R_r \cdot L_m^2 \cdot \omega_r \cdot \omega_{sl}} + \frac{\omega_{sl}}{\omega_r} \right) \quad (3.45)$$

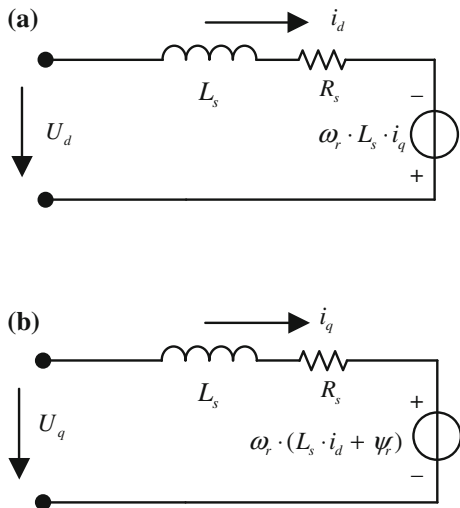
It can be concluded that the power losses in an induction motor are mainly contributed by two factors, i.e., the ohmic resistance and the slip. Here also it should be noted that in addition to the ohmic resistance loss, there is loss due to friction, windage, stray load loss, and some amount of loss in the magnetic material of the motor, which involves magnetic materials in both the stator and the rotor. But to keep the discussion simple, those losses are not discussed here.

3.2.3 PMSM and BLDCM

Synchronous motors operate at a constant speed in absolute synchronization with the line frequency. The permanent magnet synchronous motors (PMSM) can be classified into the surface permanent magnet and interior permanent magnet types according to the placement of permanent magnets on the rotor. Brushless DC motors (BLDC) were developed from conventional brushed DC motors with the availability of solid state power semiconductors that forms an electronically controlled commutation system. The PMSM and BLDC are identical as for torque generation principle. Both PMSM and BLDC (see their schematic in Fig. 3.10) are synchronous machines implementing excitation on the rotor with permanent magnets.

The stator of both machines has armature windings that connect the external three-phase voltage. The major difference between the two machines is that the waveforms of stator currents in BLDC are rectangular while that in PMSM are sinusoidal. Therefore, the back EMF in BLDC is trapezoidal-shaped while that in PMSM is sinusoidal-shaped. Additionally, both types of motors can be expressed in the following equations using the dq0 transform.

Fig. 3.11 Equivalent circuit of a PMSM. **a** d-axis equivalent circuit. **b** q-axis equivalent circuit



$$U_d = \frac{d\psi_d}{dt} - \psi_q \cdot \omega_s + R_s \cdot i_d \quad (3.46)$$

$$U_q = \frac{d\psi_q}{dt} + \psi_d \cdot \omega_s + R_s \cdot i_q \quad (3.47)$$

where U_d and U_q are the d-and q-axis stator voltages; i_d and i_q are the d-and q-axis stator currents; R_s is the stator resistance; ω_r , i.e., the synchronous angular speed ω in a PMSM or BLDC, stands for the electrical angular speed that equals the multiplication of the rotor mechanical speed ω_2 and the number of pole pairs p ; ψ_d and ψ_q are the d-and q-axis stator fluxes which are given by:

$$\psi_d = L_s \cdot i_d + \psi_r \quad (3.48)$$

and

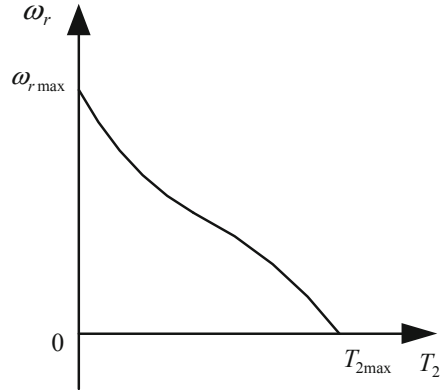
$$\psi_q = L_s \cdot i_q \quad (3.49)$$

respectively. In the above two expressions, L_s represents the stator inductance; ψ_r denotes the permanent magnet flux. The d-and q-axis equivalent circuits of the PMSM or BLDC are described in Fig. 3.11.

With the existence of the permanent magnetic field, the direct-axis stator current i_d could be controlled to reach zero, i.e., $i_d = 0$. Therefore, the electromagnetic torque generated at the rotor shaft is depicted as:

$$\begin{aligned} T_e &= \frac{3}{2}p \cdot (i_q \cdot \psi_d - i_d \cdot \psi_q) \\ &= \frac{3}{2}p \cdot \psi_r \cdot i_q \end{aligned} \quad (3.50)$$

Fig. 3.12 Speed-torque curve of a BLDC



Based on Newton's second law, the mechanical equation is

$$\frac{J}{p} \cdot \frac{d\omega_r}{dt} = T_e - T_2 \quad (3.51)$$

where T_2 represents the torque of the mechanical load, and J is the moment of inertia of the motor.

When the PMSM or BLDC gets to the steady state, the torque of the mechanical load can be derived from Eqs. 3.46–3.51

$$T_2 = \frac{3}{2} \cdot p \cdot \psi_r \cdot \frac{R_s \cdot U_q - \omega_r \cdot R_s \cdot \psi_r - \omega_r \cdot L_s \cdot U_d}{R_s^2 + \omega_r^2 \cdot L_s^2} \quad (3.52)$$

In the PMSM, the synchronous frequency can be chosen ahead of starting operation, while in the BLDC, the DC commutation frequency is decided by the magnetic pole detection. In essence, mechanical characteristics of the BLDC and brushed DC motor are the same. Figure 3.12 shows a typical steady-state speed-torque curve (voltage keeps unchanged) of a BLDC which looks similar to that of a brushed DC motor. The difference is due to the additional stator inductance for the BLDC compared with the brushed DC motor, otherwise Eq. 3.52 will have the same expression form as that in Eq. 3.22 for the DC motor.

Similar to the above analysis of the induction motors, the SPWM or SVPWM is utilized in the inverter to generate the various-frequency three-phase voltage required by the PMSM. The basic expressions of the input power P_1 and the output power P_2 are the same as those in Eqs. 3.42 and 3.43. Consequently, with the help of Eqs. 3.46–3.49 and 3.52, the efficiency of the PMSM or BLDC is calculated as

$$\eta = \frac{P_2}{P_1} = \frac{1}{1 + \frac{R_s}{\frac{3}{2}p\psi_r^2} \cdot \frac{T_2}{\omega_r} + \frac{L_s^2}{R_s} \cdot \frac{\omega_r \cdot T_2}{\frac{3}{2}p\psi_r^2}} \quad (3.53)$$

As a result, the term of power losses $P_l = P_1 - P_2$ is a quadrature function of the torque expressed as:

$$P_l = \frac{2T_2^2}{3\psi_r^2} \cdot \left(\frac{R_s}{p^2} + \frac{L_s^2 \cdot \omega_r^2}{p^2 \cdot R_s} \right) \quad (3.54)$$

Similar to discussion of induction and DC motors, the friction and windage loss, magnetic loss and stray load losses are not included in the above expression.

3.3 Batteries

Some of the salient features of the traction battery for vehicle propulsion are listed as follows:

- High energy density can be reached to provide a large mileage in one charge cycle;
- High energy density and high power density allow for vehicle acceleration and energy regeneration;
- High safety and long lifetime should be built into the battery for reliability and durability;
- Battery recycling should be considered for environmental protection.

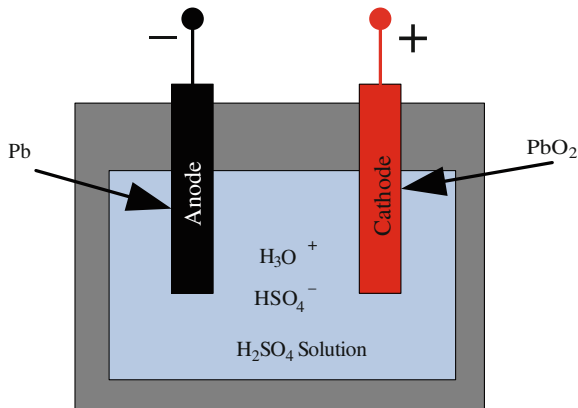
Flooded lead-acid batteries have been the commonly-used energy source in power systems for over a century. With the development and significance of advanced battery technologies, the user demand for nickel-metal hydride (NiMH) battery and lithium-ion (Li-ion) battery has been growing for traction battery applications at an exponential rate. This section starts from the description of lead-acid batteries.

3.3.1 Lead-Acid Battery

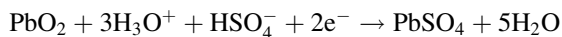
Lead-acid batteries, as the oldest type of rechargeable battery, were invented by Gaston Planté in 1859 [7]. In general, flooded lead-acid batteries comprise negative plates sandwiched between positive plates. The negative plates are made of lead (or a lead alloy) while the positive plates are made of lead (or a lead alloy) with calcium or antimony as an additive. A microporous material as the insulator can prevent the electrodes from shorting while allowing the chemical reaction to take place [8, 9].

Each cell contains electrodes of lead metal (Pb) and lead (+4 valence) dioxide (PbO₂) in an electrolyte of sulfuric acid (H₂SO₄). The schematic of a lead-acid battery is depicted in Fig. 3.13. When the battery is discharged, both electrodes turn into lead (+2 valence) sulfate (PbSO₄) and the electrolyte loses dissolved H₂SO₄ and becomes water. The electrolyte is likely to freeze because the water is reaching the freezing point and the concentration of H₂SO₄ reduces. When charging happens, the amount of PbSO₄ and water decreases for recovering the cell to the primary state. The chemical reaction equations are expressed as

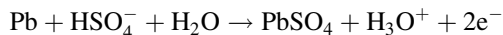
Fig. 3.13 Schematic of a lead-acid battery



Cathode:



Anode:



The above electrochemical reaction creates the cell's potential or voltage. The positive and negative plates have a potential difference (cell voltage). A float charge is placed on the battery to maintain a charge or polarization of the plates upon their assembly.

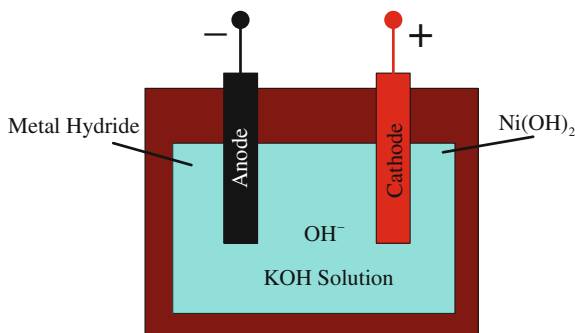
The valve regulated lead acid (VRLA) battery, as one type of lead-acid batteries, does not require (and make impossible) regular checking of the electrolyte level, since no watering is required. Thus, the efficiency of the VRLA battery is 95–99% [10]. However VRLA cells may experience “dry-out” as electrolyte is lost, so detection and measurements of regular internal resistance, conductance or impedance of cells are needed to avoid cells from losing capacity. The electrical characteristics of VRLA batteries differ somewhat from flooded lead-acid batteries, and caution should be exercised in charging and discharging them.

It has to be noted that overcharging of a lead-acid battery will cause emission of hydrogen and oxygen from each cell. Flooded cells have vents to release the gas while the VRLA batteries have valves fitted to each cell. Any hydrogen and oxygen are recombined into water in the VRLA cell, but malfunction or overheating may cause gas building up, so the valve in the VRLA cell works to vent the gas.

3.3.2 NiMH Battery

Nickel-metal hydride (NiMH) batteries are replacing the long-time market dominator, nickel-cadmium (NiCd) batteries, gradually due to the larger capacity. Compared with the NiCd battery, the NiMH battery uses a hydrogen-absorbing

Fig. 3.14 Schematic of a NiMH battery



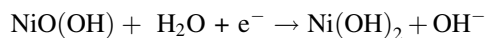
alloy for the negative electrode instead of cadmium. A NiMH cell has two to three times the capacity of an equivalent-size NiCd cell.

The consumer grade NiMH battery is a variation of the 1970s nickel hydrogen battery. Dr. Masahiko Oshitani from Yuasa Company developed the high-energy paste positive electrode [11]. Association of this work with discoveries of high-energy hybrid alloys for the negative electrode by Philips Laboratories and French CNRS labs in 1970s, resulted in the high-energy NiMH cell [9].

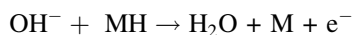
The active material for the cathode in the NiMH battery is actually hydrogen. The hydrogen ions (protons) are stored in the metal hydride structure which also serves as the cathode. The “M” of a NiMH cell is actually an intermetallic compound. The most commonly-used compounds belong to AB_5 , where A represents a rare earth mixture of lanthanum, cerium, neodymium praseodymium and B stands for nickel, cobalt, manganese, and/or aluminum. The electrolyte does not enter into the anode reaction so that conductivity stays at a high level throughout the usable capacity of the battery. In addition, the nickel active material is insoluble in the KOH electrolyte which leads to longer life and better abuse tolerance. Only a proton is involved in the charge/discharge reaction leading to very small density changes and improved mechanical stability of the anode during cycling. Figure 3.14 shows the schematic of a NiMH battery.

The chemical reaction equations are given by

Cathode:

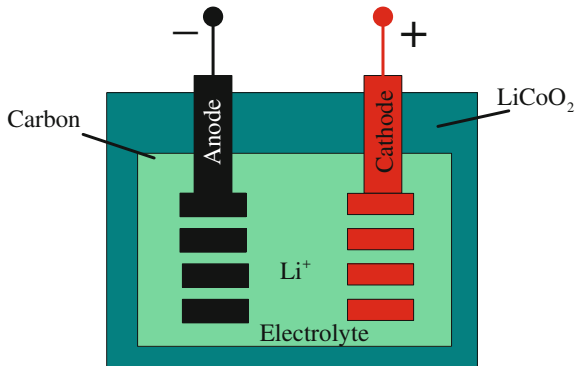


Anode:



Catalysts are used in NiMH cells to deal with gases generated due to over-charging with currents up to $C/10$ [12]. The NiMH batteries will heat up considerably, which means the charging process ends. However, the increase of hydrogen may cause the cell to rupture. Thus a vent is needed to allow hydrogen to be emitted from this vent during the serious overcharging process.

Fig. 3.15 Schematic of a Li-ion battery

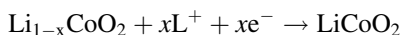


3.3.3 Lithium-Ion Battery

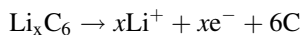
The lithium-ion (Li-ion) battery is a type of rechargeable battery where a lithium ion moves between the anode and cathode. During discharging, lithium ions are released from the anode and travel through an organic electrolyte towards the cathode. When lithium ions get to the cathode, they are quickly incorporated into the cathode material. When charging, the process is reversible. The lithium ions move from the cathode to the anode. The schematic of a Li-ion battery is shown in Fig. 3.15. It is observed that both the anode and cathode have layered structures for lithium ions to move in between layers.

The chemical reaction equations are depicted as

Cathode:



Anode:



Concepts of Li-ion batteries were proposed by Whittingham from Binghamton University in the 1970s [13]. The first consumer grade Li-ion battery was released by Sony in 1991 [14], thanks to John Goodenough's work on the cathode of the Li-ion cell where layered oxide chemistry specifically lithium cobalt oxide was employed.

In general, the anode materials are various forms of carbon, particularly graphite and hydrogen-containing carbon materials. Oxides of cobalt, nickel and manganese have been used for the cathode. The performance of cobalt oxide is the best among the three types while its cost is much higher than the nickel oxide and manganese oxide [15].

Li-ion batteries have an advantage on weight compared with other equivalent secondary batteries. In addition, Li-ion batteries have a high open circuit voltage in comparison to aqueous batteries (lead-acid, NiMH, etc.), and Li-ion batteries do

Table 3.1 Comparison of three types of batteries. Data are taken from [12, 16–18]

Characteristics/type	Lead-acid battery	NiMH battery	Li-ion battery
Specific energy	35 Wh/kg	70 Wh/kg	180 Wh/kg
Energy density	70 Wh/l	140 Wh/l	180 Wh/l
Energy/consumer-price	7 Wh/US\$	2.75 Wh/US\$	2.8 Wh/US\$
Electrical efficiency	90%	66%	85%
Self-discharge rate	20%/month	30%/month	5%/month
Durability	800 cycles	1000 cycles	1200 cycles

not suffer from the memory effect. Besides, the self-discharge rate of 5% per month is very low compared with over 30% per month for the NiMH battery. However, Li-ion batteries are not as safe as NiMH batteries. Several safety devices with the shut-down separator for over temperature, tear-away tab for internal pressure, venting for pressure relief and thermal interrupt for overcurrent have to be built into Li-ion batteries.

Table 3.1 shows the comparison of three types of batteries (i.e., a lead-acid battery, a NiMH battery and a Li-ion battery). One can see that the Li-ion battery has obvious advantages on most aspects.

3.3.4 State of Charge and Battery Capacity

State of charge (*SOC*) is the equivalent of a fuel gauge for the battery related to the nominal capacity.

$$SOC = \frac{Q}{Q_0}, \dot{Q} = -i \quad (3.55)$$

where Q is the electric charge; Q_0 is the battery capacity usually expressed in Ah (ampere-hours); i is the terminal current. An alternative for the state of charge, depth of charge (*DOD*), is often used and has the following expression

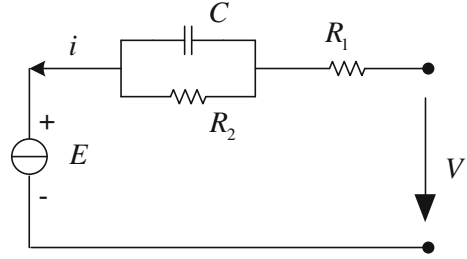
$$DOD = 1 - SOC \quad (3.56)$$

The battery is initially fully charged for a typical constant-current (denoted by i) discharge test, and the voltage at the beginning equals the equilibrium potential E . When the battery voltage drops to the cutoff voltage (e.g., $0.8 E$) after a certain time t_d , the battery can be considered as discharged. The discharge time t_d is a function of the discharge rate i . The relation between t_d and i can be described using the Peukert equation as:

$$t_d = K \cdot i^{-q} \quad (3.57)$$

where K is a constant; q is called the Peukert exponent having a range from 1 to 1.5 (for typical lead acid batteries, $q = 1.35$). Assume the battery capacity at a

Fig. 3.16 Equivalent circuit of a battery



given discharge rate i^* is known as Q_0^* , then the battery capacity Q_0 for a discharge current i can be expressed as

$$Q_0 = \frac{K_c \cdot Q_0^*}{1 + (K_c - 1) \cdot (i/i^*)^\delta} \quad (3.58)$$

where $\delta = q - 1$; K_c is a constant.

Let $i_0 = \frac{Q_0}{1h}$, and a non-dimensional value called C-rate is given by $c(t) = \frac{i}{i_0} = \frac{1}{k}$. The C-rate is often written as $\frac{C}{k}$ related to a current at which the battery is discharged to depletion or charged to full in k h.

3.3.5 Equivalent Circuit

In batteries, capacitive effects are derived from double-layer formation at the electrode/solution interface [8] including capacitance due to purely electrical polarization and pseudo-capacitance i.e., capacitance from diffusion limited space charges. When modeling batteries, a single lumped capacitance is used in parallel with a resistance to describe the aforementioned capacitive effects, especially when the rates of charge/discharge are high. A higher-order RC network can be employed to account for additional details of the transient dynamics of batteries. However, in most cases, a single capacitance is sufficient as describe in this chapter. Hence, the equivalent electrical schematic of the battery, consisting of an equilibrium potential E , an internal resistance R_{int} having two components R_1 and R_2 and an effective capacitance C characterizing the transient response of charge double layers, is shown in Fig. 3.16.

The equivalent electrical network yields the following equation that relates the transient terminal potential to the terminal current

$$i = \frac{1}{R_2} [V - E - R_1 \cdot i] + C \cdot \frac{d}{dt} [V - E - R_1 \cdot i] \quad (3.59)$$

The equilibrium potential (open-circuit voltage) E of the battery depends on the temperature and the amount of active material available in the electrodes which can be specified in terms of the state of discharge (SOD). To model the equilibrium potential, a two-step procedure is required as

- 1) Based on experimental data, a typical curve of battery voltage verses the depth of discharge, its discharge rate (i.e., the current) and battery temperature in such a situation are chosen as the reference discharge curve, reference rate and reference temperature, respectively. The equilibrium potential as a function of the *SOD* is expressed as an *n*th-order polynomial. The dependency of the *SOD* on rate is accounted for by a rate factor $\alpha(i)$, which has value unity for the reference curve. The dependency of the *SOD* on temperature is accounted for by a temperature factor $\beta(T)$ that has a value of unity for the reference value.
- 2) A potential correction term $\Delta E(T)$ is used to compensate for the variation resulting from the ambient temperature change.

Thus, we obtain the following equations [19] expressing the relation between the potential, terminal voltage and *SOD*,

$$E[i(t), T(t), t] = V[i(t), T(t), t] - R_{\text{int}} i(t) \quad (3.60)$$

$$V[i(t), T(t), t] = \sum_{k=0}^n C_k \text{SOD}^k[i(t), T(t), t] + \Delta E(T) \quad (3.61)$$

$$\text{SOD}[i(t), T(t), t] = \frac{1}{C_r} \int_0^t \alpha[i(t)] \cdot \beta[T(t)] \cdot i(t) dt \quad (3.62)$$

where C_k is the coefficient of the k th order term in the polynomial expression for the reference curve and C_r is the battery capacity. For $k = 0$, $E = C_0$ is the open-circuit voltage when discharge begins at the reference temperature for the reference curve.

It is necessary to resolve the temperature dynamically for computation of the equilibrium potential during each time step due to the fact that the equilibrium potential depends on the temperature. The battery temperature change is determined by the thermal energy balance [20] expressed as below

$$m \cdot c_p \cdot \frac{dT(t)}{dt} = i(t)^2 \cdot R_1 + \frac{1}{R_2} [v(t) - E[i(t), T(t), t] - i(t)R_1]^2 - h_c A [T(t) - T_a] \quad (3.63)$$

where m stands for the battery mass, c_p specific heat, h_c heat transfer coefficient, and T_a ambient temperature.

3.3.6 Battery Efficiency

The global efficiency of a battery is defined as the ratio of the total energy the battery delivers to loads to the energy required to fully charge the battery. Since the battery voltage equation is given in Eq. 3.60, the global efficiency can be

evaluated in the “Peukert” case with a constant charge/discharge current [10]. The total discharge time $t_d = Q_0/i$, thus the energy that the battery can deliver to loads is expressed as

$$E_{\text{dis}} = \int_0^{t_d} P_d dt = t_d(E - R_{\text{int}} \cdot i) \cdot i \quad (3.64)$$

The energy required to fully charge the battery at the same rate from depletion is obtained as

$$E_{\text{chg}} = \int_0^{t_d} P_c dt = t_d(E + R_{\text{int}} \cdot i) \cdot i \quad (3.65)$$

So the global efficiency defined as the ratio of E_{dis} to E_{chg} is given by

$$\eta_B = \frac{E_{\text{dis}}}{E_{\text{chg}}} = \frac{E - R_{\text{int}} \cdot i}{E + R_{\text{int}} \cdot i} \quad (3.66)$$

If the battery is charged/discharged at a constant power P (called Ragone case [10]), the analysis method for the battery efficiency is the same. According to the following equation

$$i = \frac{P}{V} \quad (3.67)$$

we can obtain the following formula by substituting Eq. 3.67 to Eq. 3.60,

$$V^2 - E \cdot V + P \cdot R_{\text{int}} = 0 \quad (3.68)$$

Therefore the terminal voltage can be expressed as a function of P :

$$V = \frac{E}{2} + \sqrt{\frac{E^2}{4} - P \cdot R_{\text{int}}} \quad (3.69)$$

Equation (3.66) can be converted to

$$\eta_B = \frac{E_{\text{dis}}}{E_{\text{chg}}} = \frac{E - R_{\text{int}} \cdot P/V}{E + R_{\text{int}} \cdot P/V} \quad (3.70)$$

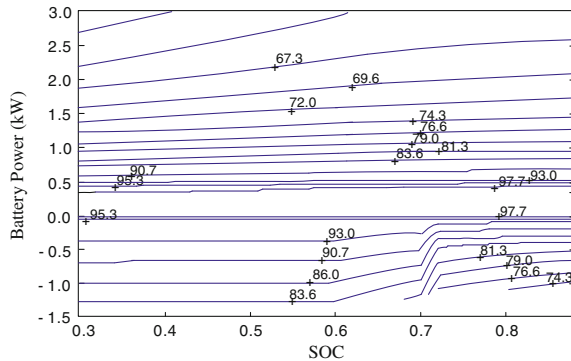
The battery efficiency can be calculated by substituting Eq. 3.69 to Eq. 3.70.

Another definition for the battery efficiency is called a local efficiency, representing the battery power ratio, which yields

$$\eta_B(t) = \frac{P_{\text{dis}}(t)}{P_{\text{chg}}(t)} = \frac{E(t) - R_{\text{int}}(t) \cdot i(t)}{E(t) + R_{\text{int}}(t) \cdot i(t)} \quad (3.71)$$

This expression is almost the same as Eq. 3.66 except that the open voltage and internal resistance depend on the SOC and charge/discharge current $i(t)$. Test data

Fig. 3.17 Battery efficiency map



prove that the local efficiency of the battery relies on the power (or charge/discharge rate) much more strongly than on the SOC. An efficiency map with the vertical axis, power, and the horizontal axis, battery SOC, (see Fig. 3.17) clearly delineates the local efficiency of a battery.

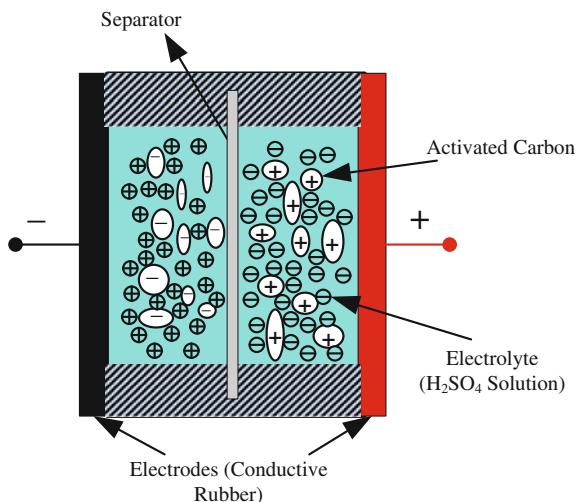
3.4 Ultracapacitor

The term “ultracapacitor” (or “supercapacitor”) is used to describe any electric double-layer or redox capacitor with specific energy and specific power intermediate to batteries and traditional capacitors.

Generally, a capacitor’s energy capacity is dependent on its amount of stored charges and the potential for charging between its plates. The quality of the dielectric through which the electric field can be sustained has a great impact on the charge potential. However, in an ultracapacitor, the term “dielectric” might be replaced by “electrolyte” (electrically active chemical) since an ultracapacitor is more like a battery than a conventional capacitor at this point [21]. The electrolyte separates plates that are in fact two layers of the same substrate. The charged plates polarize the electrolyte, which makes positive ions move one way and negative ions the other and causes a second set of charges to form. Therefore the so-called “electric double layer” gives a high surface area for storing charges. The use of the high surface area material such as a porous powdery activated carbon in place of the conventional insulating barrier results in very high charge potential or capacitance. Nevertheless, unlike in a battery, no chemical reactions are involved in an ultracapacitor and the positive and negative charges are created entirely by static electricity. The structure of an ultracapacitor is depicted in Fig. 3.18.

Compared to traditional capacitors, an ultracapacitor is capable of charging and storing energy at an exponentially higher density. Theoretically, a capacitance of one Farad could be provided by a few milligrams of material with an area of about 1 cm^2 for an ultracapacitor. So far commercial ultracapacitors have capacitance as high as 5,000 F. The specific energy of ultracapacitors ranges from 0.5 to 30 Wh/kg [22, 23].

Fig. 3.18 Structure of an ultracapacitor



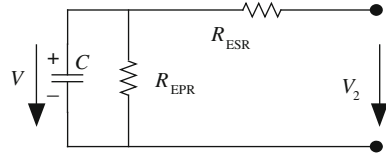
In addition, ultracapacitors have much higher specific power (up to 6000 W/kg) than batteries [24]. In other words, ultracapacitors can release energy more quickly. This is because batteries work based on the movement of charge carriers in a liquid electrolyte while the discharge/charge rate of ultracapacitors is typically limited by current heating of the electrodes. Generally, an ultracapacitor that has as 1/10th energy density as a conventional battery has power density ten to a hundred times as great. As a result, ultracapacitors are particularly suitable for charging and releasing large amounts of power quickly while batteries do better in storing large amounts of energy over long periods of time.

The application of ultracapacitors as energy storage devices for the complete solution of energy requirements of an electric vehicle does not seem to be realistic right now due to their unsatisfactory characteristics on energy density. However, their high power density makes them advantageous as a load-leveling device for a battery-powered electric vehicle or a hybrid electric vehicle. Additionally, ultracapacitors are highly suitable for applications involving regenerative braking power since they can be recharged very quickly. The cost of ultracapacitors has dropped quickly to US \$2.85/kJ or US \$0.01/F and is expected to fall further [25]. Thus the large-scale applications of ultracapacitors in the future will be realistic. Complementary descriptions for ultracapacitors can be found in Chap. 6.

3.4.1 Equivalent Circuit

As depicted in Fig. 3.19, the series resistance R_{ESR} is the charge/discharge resistance. The parallel resistance R_{EPR} represents the self-discharge losses. The ultracapacitor has the capacitance C . However, R_{EPR} only has impact on the long-term energy storage performance.

Fig. 3.19 Equivalent circuit of an ultracapacitor



The instantaneous voltage $V(t)$ for the ultracapacitor during discharge, with a time constant τ that depends on C , R_{ESR} and the external load, can be calculated as

$$V(t) = V_0 \exp\left(-\frac{t}{\tau}\right) \quad (3.72)$$

where V_0 is the initial voltage.

The total charge Q is obtained by

$$Q = V \cdot C \quad (3.73)$$

or

$$Q = Q_0 - \int_0^t i dt \quad (3.74)$$

where i denotes discharge current.

The relation between the discharge current and the terminal voltage of the ultracapacitor is:

$$V_2 = V - i \cdot R_{ESR} \quad (3.75)$$

Since the output power determines the current as

$$i = \frac{P_2}{V_2} \quad (3.76)$$

substituting Eqs. 3.73 and 3.76 to 3.75 yields

$$V_2^2 = \frac{Q}{C} V_2 - P_2 \cdot R_{ESR} \quad (3.77)$$

Therefore the final expression for the terminal voltage of the ultracapacitor is obtained as:

$$V_2 = \frac{1}{2} \cdot \frac{Q}{C} + \sqrt{\frac{1}{4} \cdot \left(\frac{Q}{C}\right)^2 - P_2 \cdot R_{ESR}} \quad (3.78)$$

The state of charge (SOC) of the ultracapacitor can be described as the percentage of the rated energy capacity, which depends on the terminal output voltage,

$$SOC = \frac{E_0 - E_1}{E_0} \quad (3.79)$$

where E_1 denotes the amount of energy flow from the ultracapacitor and E_0 represents the rated energy capacity.

The energy flow from the ultracapacitor is directly determined by the capacitance and the voltage change as expressed in the following equation

$$E_1 = \frac{1}{2} C \cdot (V_0^2 - V^2) \quad (3.80)$$

The real ultracapacitor bank can be modeled by using multiple ultracapacitor cells in parallel and series. The total resistance and capacitance of the ultracapacitor bank are delineated as

$$R_{UCbank} = n_1 \cdot \frac{R_{ESR}}{n_2} \quad (3.81)$$

$$C_{UCbank} = n_2 \cdot \frac{C}{n_1} \quad (3.82)$$

where n_1 is the number of capacitors in series; n_2 is the number of ultracapacitor branches in parallel.

3.4.2 Ultracapacitor Efficiency

Similar to the efficiency analysis of a battery, the global efficiency of the ultracapacitor is defined as the ratio of the energy delivered to the energy required to fully charge the ultracapacitor. The test where the ultracapacitor is charged or discharged at a constant current is called a Peukert test, while in a Ragone test, the ultracapacitor is charged or discharged at a constant power. Next we discuss the global efficiency of the ultracapacitor for both tests.

In the Peukert discharge test, the discharge current i is a constant, so according to Eqs. 3.73–3.75, the terminal voltage of the ultracapacitor is

$$V_{2dis} = V - i \cdot R_{ESR} = \frac{Q_0 - i \cdot t}{C} - i \cdot R_{ESR} \quad (3.83)$$

Similarly, the terminal voltage for the constant-current-charge case is expressed as

$$V_{2chg} = V + i \cdot R_{ESR} = \frac{i \cdot t}{C} + i \cdot R_{ESR} \quad (3.84)$$

The total energy delivered and the total energy to charge up the ultracapacitor are defined as

$$E_{\text{dis}} = \int_0^{t_d} V_{2\text{dis}} \cdot i dt, \quad (3.85)$$

and

$$E_{\text{chg}} = \int_0^{t_d} V_{2\text{chg}} \cdot i dt, \quad (3.86)$$

respectively, where $t_d = Q_0/i$ is the total charge/discharge time.

Therefore, the global efficiency for the ultracapacitor is obtained as

$$\eta = \frac{E_{\text{dis}}}{E_{\text{chg}}} = \frac{\int_0^{Q_0/i} \left(\frac{Q_0 - i \cdot t}{C} - i \cdot R_{\text{ESR}} \right) dt}{\int_0^{Q_0/i} \left(\frac{i \cdot t}{C} + i \cdot R_{\text{ESR}} \right) dt} = \frac{Q_0 - 2C \cdot R_{\text{ESR}} \cdot i}{Q_0 + 2C \cdot R_{\text{ESR}} \cdot i} \quad (3.87)$$

The ultracapacitor Ragone case is analyzed next. Differentiate both sides of Eq. 3.77, the following differential equation is derived using the relations in Eqs. 3.74 and 3.76:

$$\left(1 - \frac{R_{\text{ESR}} \cdot P_2}{V_2^2} \right) \cdot \frac{d(V_2^2)}{dt} = -\frac{2P_2}{C} \quad (3.88)$$

Thus the discharge time is expressed in terms of the discharge power as

$$t = \frac{C(P_2 \cdot R_{\text{ESR}} \cdot (\ln(V_2^2) - \ln(V_{20d}^2)) + V_{20d}^2 - V_2^2)}{2P_2} \quad (3.89)$$

where V_{20d} represents the terminal voltage when the electric charge reaches Q_0 (the subscript d means discharge).

Similarly, considering that the direction of power in the charge process is reversed, the charge time is represented by the charge power as:

$$t = \frac{C(P_2 \cdot R_{\text{ESR}} \cdot (\ln(V_2^2) - \ln(V_{2ec}^2)) + V_2^2 - V_{2ec}^2)}{2P_2} \quad (3.90)$$

where V_{2ec} denotes the initial terminal voltage for the charge process (the subscript e means empty and c means charge).

According to the constraint condition existing in Eq. 3.78, we obtain the electric charge for the depletion as

$$Q = 2C \cdot \sqrt{P_2 \cdot R_{\text{ESR}}} \quad (3.91)$$

so the terminal voltage at the end of discharge is

$$V_{2ed} = \sqrt{P_2 \cdot R_{\text{ESR}}} \quad (3.92)$$

At the beginning of the discharge (i.e., the electric charge equals Q_0), the terminal voltage on the basis of Eq. 3.78 is

$$V_{20d} = \frac{Q_0}{2C} + \sqrt{\frac{1}{4} \left(\frac{Q_0}{C} \right)^2 - P_2 \cdot R_{\text{ESR}}} \quad (3.93)$$

Therefore the total discharge time is

$$t_d = \frac{C(P_2 \cdot R_{\text{ESR}} \cdot (\ln(P_2 \cdot R_{\text{ESR}}) - \ln(V_{20d}^2)) + V_{20d}^2 - P_2 \cdot R_{\text{ESR}})}{2P_2} \quad (3.94)$$

Similar to the analysis for the discharge case, the initial terminal voltage for the charge process (the electric charge at the very beginning equals zero) is calculated as

$$V_{2ec} = \sqrt{P_2 \cdot R_{\text{ESR}}} \quad (3.95)$$

When the ultracapacitor is charged up (i.e., the electric charge reaches Q_0), the terminal voltage increases to

$$V_{20c} = \frac{Q_0}{2C} + \sqrt{\frac{1}{4} \left(\frac{Q_0}{C} \right)^2 + P_2 \cdot R_{\text{ESR}}} \quad (3.96)$$

Based on Eq. 3.90, the total charge time is obtained as

$$t_c = \frac{C(-P_2 \cdot R_{\text{ESR}} \cdot (\ln(P_2 \cdot R_{\text{ESR}}) - \ln(V_{20c}^2)) + V_{20c}^2 - P_2 \cdot R_{\text{ESR}})}{2P_2} \quad (3.97)$$

So the global efficiency for the ultracapacitor in the Ragone test is calculated as

$$\eta = \frac{E_{\text{dis}}}{E_{\text{chg}}} = \frac{t_d \cdot P_2}{t_c \cdot P_2} = \frac{P_2 \cdot R_{\text{ESR}} \cdot (\ln(P_2 \cdot R_{\text{ESR}}) - \ln(V_{20d}^2)) + V_{20d}^2 - P_2 \cdot R_{\text{ESR}}}{-P_2 \cdot R_{\text{ESR}} \cdot (\ln(P_2 \cdot R_{\text{ESR}}) - \ln(V_{20d}^2)) + V_{20d}^2 - P_2 \cdot R_{\text{ESR}}} \quad (3.98)$$

Additionally, the local efficiency, representing the ultracapacitor power ratio, is defined as

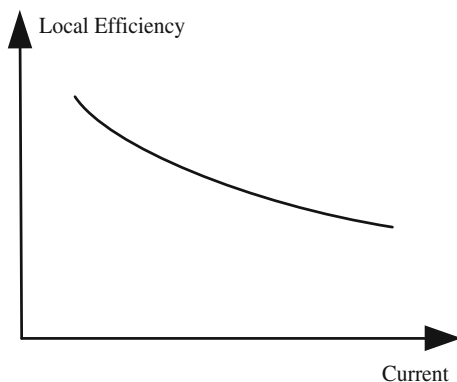
$$\eta_B(t) = \frac{P_{\text{dis}}(t)}{P_{\text{chg}}(t)} = \frac{V(t) - R_{\text{ESR}}(t) \cdot i(t)}{V(t) + R_{\text{ESR}}(t) \cdot i(t)} \quad (3.99)$$

The typical relation between the local efficiency and current of an ultracapacitor is depicted by Fig. 3.20.

3.5 Fuel Cell

Fuel cell, invented in 1854 by the UK physicist William Grove, is a direct converter of chemical energy to electrical energy [26]. The most widely discussed type of fuel cell is the hydrogen fuel cell, where energy is derived from the oxidation of hydrogen.

Fig. 3.20 A typical curve of efficiency versus current of an ultracapacitor



This oxidation process occurs at a much lower temperature than that produced by an active combustion, so a fuel cell does not actually burn its fuel, which might go against readers' intuition. A fuel cell can continuously supply power from a continuously available external fuel supply or by filling up a tank so it is essentially different from a battery which can not be charged at the same time when it is charged.

Several types of fuel cells exist including proton exchange membrane (PEM) fuel cells, solid oxide fuel cells, direct methanol fuel cells, etc. However, till now, only low-operating-temperature (50–100°C) PEM fuel cells are proved to be suitable for automobile applications.

The PEM fuel cell was invented in the early 1960s by Willard Tomas Grubb and Lee Niedrach of General Electric (GE) Corporation [27]. The electrode-bipolar plates in a typical membrane electrode assembly (MEA) are made of metal, nickel or carbon nanotubes. They are usually coated with a catalyst (platinum, nano iron powders or palladium) for higher efficiency. These plates are separated from electrolyte (ceramic or a membrane) by carbon paper.

In a PEM fuel cell, a proton-conducting polymer membrane separates the anode and cathode sides. On the anode side, hydrogen diffuses to the anode catalyst and then dissociates into protons and electrons. Protons react with oxidants, and then oxidants become multi-facilitated proton membranes (MFPM). The protons are conducted through the membrane to the cathode while the electrons travel in an external circuit. On the cathode side, oxygen molecules react with electrons and protons to produce pure water. The acid in the electrolyte provides structure for the electrolyte as well as a barrier to electrons. Thus electrons do not move through the electrolyte. The schematic of a PEM fuel cell is drawn in Fig. 3.21.

The chemical reaction equations for PEM fuel cells are described as

Cathode:



Anode:



Fig. 3.21 Schematic of a PEM fuel cell

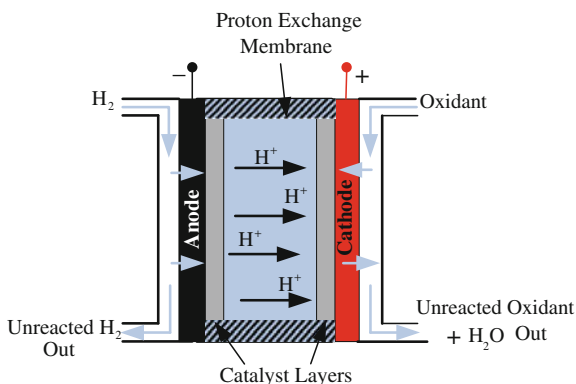


Table 3.2 Some characteristics of fuel cell [28, 29]

Characteristics/type	Fuel cell with hydrogen in 70 MPa CGH ₂ vessel
Energy/weight	1600 Wh/kg (hydrogen)
Energy/size	770 Wh/l (hydrogen)
Energy/consumer-price	50 Wh/US \$ (hydrogen) 73 US \$/kW (stack)
Electrical efficiency	50% (stack) 30% (system)
Durability	7300 h (stack)

Hydrogen fuel cell propulsion systems are an attractive long-term option for vehicles because of zero emission and high efficiency. At low load conditions, a PEM fuel cell can reach its highest efficiency in contrast to internal combustion engines (ICE). However, at high load conditions, no advantage is shown over optimized ICE drive trains. Almost all large automobile manufacturers are making efforts for development and improvements of hydrogen fuel cell vehicles (FCVs).

Most PEM fuel cells produce less than 1.16 V as output, which is far from enough to power a FCV. Thus multiple cells must be assembled to create a fuel cell “stack”. The potential power from a fuel cell stack relies on the number and size of the individual cells inside and the surface area of the PEM. Besides, a fuel cell stack is required to be combined with several other components (including a hydrogen circuit for hydrogen supply, an air circuit for oxidant supply, a coolant circuit for cooling the stack and a humidifier circuit for water emissions and water injection) to form a fuel cell system. The coolant circuit and the humidifier circuit can be integrated into one water circuit due to the fact that most fuel cell stacks employ deionized water as a coolant.

As mentioned above, FCVs combine some best features of electric vehicles and conventional vehicles, namely high efficiency, zero emissions and a reasonable range. Unfortunately the FCVs are not realistic so far due to several significant limitations, i.e., high manufacturing cost, low fuel energy density (see Table 3.2), relatively high cost of operation, difficulties in producing hydrogen, and difficulty in transporting and storing hydrogen. These problems must be carefully considered

for any large-scale FCV production plan. However, with the gradual reduction in fuel cell cost, new progress in increasing fuel cell energy density, and maturation of hydrogen transportation and storage technologies, it is possible that FCVs may dominate the automobile market some day in the future.

3.5.1 Relation Between Pressure and Flows

According to the analysis in [30], the flow of hydrogen (for the anode reaction in a PEM fuel cell) through a valve is proportional to its partial pressure, expressed as follows

$$\frac{q_{H_2}}{P_{H_2}} = \frac{k_{an}}{\sqrt{M_{H_2}}} = K_{H_2} \quad (3.100)$$

where q_{H_2} represents molar flow of hydrogen, P_{H_2} partial pressure of hydrogen, k_{an} anode valve constant, M_{H_2} molar mass of hydrogen, K_{H_2} hydrogen valve molar constant.

At the anode inside a PEM fuel cell, three factors (hydrogen input flow, hydrogen output flow and hydrogen flow that reacts) determine the effective hydrogen partial pressure as follows

$$\frac{d}{dt}P_{H_2} = \frac{RT}{V_{an}} \left(q_{H_2}^{in} - q_{H_2}^{out} - q_{H_2}^r \right) \quad (3.101)$$

where R denotes universal gas constant, T fuel cell stack absolute temperature, V_{an} volume of the anode, $q_{H_2}^{in}$ hydrogen input flow, $q_{H_2}^{out}$ hydrogen output flow, $q_{H_2}^r$ reacted hydrogen flow.

According to Faraday's law, the reacted hydrogen flow for a fuel cell stack is determined by the following equation:

$$q_{H_2}^r = \frac{N_0 I}{2F} = 2K_r I \quad (3.102)$$

where N_0 is the number of fuel cells in series in a stack, I fuel cell stack current, F Faraday's constant, K_r modeling constant.

We can obtain the following expression for the hydrogen partial pressure by substituting Eqs. 3.100 and 3.102 into 3.101 and employing the Laplace transform:

$$P_{H_2} = \frac{1/K_{H_2}}{1 + \tau_{H_2}s} \left(q_{H_2}^{in} - 2K_r I \right) \quad (3.103)$$

where s represents the Laplace operator, and the hydrogen time constant τ_{H_2} is given by

$$\tau_{H_2} = \frac{V_{an}}{K_{H_2}RT} \quad (3.104)$$

The overall reaction in a PEM fuel cell can be written as: $\text{H}_2 + \frac{1}{2}\text{O}_2 \rightarrow \text{H}_2\text{O}$. Therefore the reacted oxygen flow $q_{\text{O}_2}^r$ is obtained according to Faraday's law and relationship in Eq. 3.102

$$q_{\text{O}_2}^r = \frac{N_0 I}{4F} = K_r I \quad (3.105)$$

which is two times as much as the reacted hydrogen flow.

The oxygen partial pressure at the cathode can also be calculated, which is similar to the calculation process of the hydrogen partial pressure.

$$P_{\text{O}_2} = \frac{1/K_{\text{O}_2}}{1 + \tau_{\text{O}_2} s} (q_{\text{O}_2}^{\text{in}} - K_r I) \quad (3.106)$$

where the oxygen time constant τ_{O_2} is expressed as

$$\tau_{\text{O}_2} = \frac{V_{\text{an}}}{K_{\text{O}_2} RT} \quad (3.107)$$

and k_{O_2} is oxygen valve molar constant, $q_{\text{O}_2}^{\text{in}}$ oxygen input flow.

3.5.2 Fuel Cell Voltage Expressions

In a PEM fuel cell stack, the output voltage is usually less than the internal potential under normal operating conditions. The relation of the output voltage V_{out} of a fuel cell stack (N_0 cells), Nernst cell potential E_{cell} , and three voltage drops (i.e., activation loss V_{act} , overall ohmic voltage drop V_{ohm} , and concentration overpotential V_{actc}) is delineated as [31]:

$$V_{\text{out}} = N_0 \cdot (E_{\text{cell}} - V_{\text{act}} - V_{\text{ohm}} - V_{\text{conc}}) \quad (3.108)$$

The activation voltage drop in a fuel cell can be calculated by Tafel equation as follows

$$V_{\text{act}} = \frac{RT}{\alpha z F} \cdot \ln\left(\frac{I}{I_0}\right) = T \cdot [a + b \cdot \ln(I)] \quad (3.109)$$

where α and z represent the electron transfer coefficient and the number of electrons participating in the fuel cell reaction, respectively; I_0 is the exchange current.

The ohmic voltage can be expressed as a multiplication of the current and the ohmic resistance (consisting of the membrane resistance, the conduction resistance between the membrane and electrodes and the electrode resistance) shown below

$$V_{\text{ohm}} = I \cdot R_{\text{ohm}} \quad (3.110)$$

The ohmic resistance is related to the current and temperature. The relation is depicted as

$$R_{ohm} = R_{ohm0} + K_{RI} \cdot I - K_{RI} \cdot T \quad (3.111)$$

where K_{RI} and K_{RT} denote the empirical constants, and R_{ohm0} stands for the standard resistance (at standard state, 298 K and 1-atm pressure).

The concentration gradients derive from the mass diffusions from the flow channels to the catalyst surfaces during the chemical reaction. The concentration voltage is due to the slow transportation of reactants/products to/from the reaction area at high current densities. The following equation defines the concentration voltage drop as

$$V_{conc} = -\frac{RT}{zF} \ln \left(\frac{I_{lim} - I}{I_{lim}} \right) \quad (3.112)$$

where I_{lim} is the limited current.

The acquisition of the Nernst cell potential is introduced in [31]

$$E_{cell} = E_{0,cell} + \frac{RT}{2F} \ln \left[p_{H_2} \cdot (p_{O_2})^{0.5} \right] - E_{d,cell} \quad (3.113)$$

where the reference cell potential $E_{0,cell}$ is decided by the standard reference potential (at standard state, 298 K and 1-atm pressure) and temperature T with the given empirical constant K_E , and expressed as:

$$E_{0,cell} = E_{0,cell}^0 - K_E(T - 298) \quad (3.114)$$

$E_{d,cell}$ that appears in the equation for calculating the cell potential is considered to reflect the effect of the fuel and oxidant delay particularly in the transient state. The expression of $E_{d,cell}$ is:

$$E_{d,cell} = \lambda_e \left[i(t) - i(t) * \exp \left(-\frac{t}{\tau_e} \right) \right] \quad (3.115)$$

where “*” represents the convolution operator.; λ_e is a constant factor; $i(t)$ is the transient current; τ_e is the total flow delay. In steady state, $E_{d,cell}$ equals zero.

Converting Eq. 3.115 using Laplace transform, we obtain expression of $E_{d,cell}$ in Laplace domain as

$$E_{d,cell}(s) = \lambda_e I(s) \frac{\tau_e s}{\tau_e s + 1} \quad (3.116)$$

A feedback from the fuel cell stack current is applied to control the hydrogen and oxygen flow rates according to the power demand. To accomplish the feedback control strategy, the fuel cell current is taken back to the input while converting the hydrogen into molar form.

The amount of hydrogen flow from the hydrogen tank available to meet the load requirement is obtained by

$$q_{H_2}^{req} = \frac{N_0 I}{2FU} \quad (3.117)$$

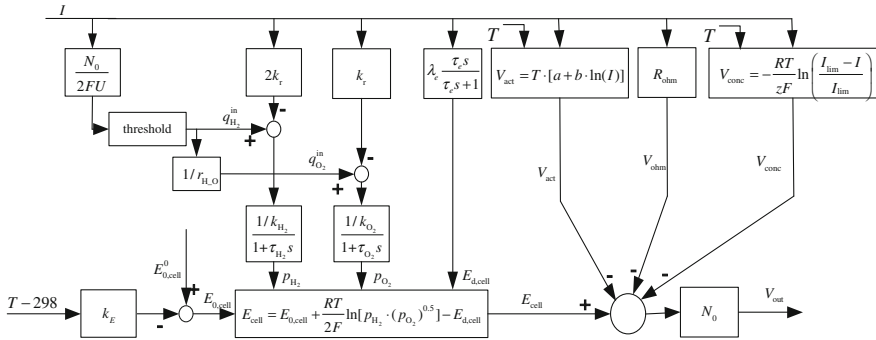


Fig. 3.22 The model of a PEM fuel cell stack

where U is the utilization rate. For a given hydrogen flow requirement, the required oxygen flow is determined by the hydrogen–oxygen flow rate, expressed as:

$$q_{O_2}^{req} = \frac{1}{r_{H-O}} q_{H_2}^{req} = \frac{N_0 I}{2r_{H-O} F U} \quad (3.118)$$

In summary, the block diagram of the model of a PEM fuel cell stack using the above equations is shown in Fig. 3.22.

3.5.3 Fuel Cell Efficiency

There exist several definitions for fuel cell efficiency, e.g., the electrochemical efficiency, voltage efficiency, current efficiency, global efficiency, etc.

Define the electrochemical efficiency (or “electrochemical Carnot efficiency”) of a fuel cell to be the ratio between the maximum work available in the case of a reversible process W_{cell} and the heating value of the single energy carriers, Q_H , so the expression for the electrochemical efficiency is [32].

$$\eta_{ec} = \frac{W_{cell}}{Q_H} \quad (3.119)$$

W_{cell} can be obtained by the decrease of the “free energy” G , namely

$$W_{cell} = -\Delta G \quad (3.120)$$

The “free energy” G can be expressed by the following relation as

$$G = H - Q_S \quad (3.121)$$

where H represents the enthalpy; Q_S is the heat dissipated to the ambient environment that equals the entropy variation.

The heating value of the single energy carriers, Q_H equals the decrease of enthalpy, expressed as

$$Q_H = -\Delta H \quad (3.122)$$

Using the maximum work available in the case of a reversible process, potential E_{cell} can be solved as

$$E_{\text{cell}} = \frac{W_{\text{cell}}}{n_e \cdot F} = \frac{-\Delta G}{n_e \cdot F} \quad (3.123)$$

where n_e denotes the number of free electrons for every kmol of hydrogen.

The “caloric voltage” V_{ec} which measures the voltage (impossible to reach) provided by a total conversion of enthalpy into electrical energy is defined by

$$V_{\text{ec}} = \frac{-\Delta H}{n_e \cdot F} \quad (3.124)$$

Consequently, the electrochemical efficiency can be rewritten as

$$\eta_{\text{ec}} = \frac{E_{\text{cell}}}{V_{\text{ec}}} \quad (3.125)$$

The voltage efficiency of a fuel cell is defined by

$$\eta_v = \frac{V_{\text{out}}/N_0}{E_{\text{cell}}} \quad (3.126)$$

As the fuel cell current I increases, the voltage efficiency decreases accordingly. Therefore at low loads, the voltage efficiency is high.

The current or Faradic efficiency is the ratio between the actual fuel cell current and the theoretical current I_t , given by

$$\eta_I = \frac{I}{I_t} = \frac{I}{\lambda_h} \quad (3.127)$$

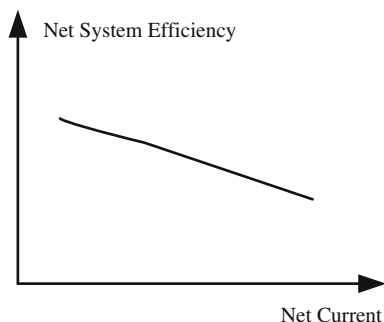
The global efficiency of a fuel cell is defined as

$$\eta_{\text{cell}} = \frac{(V_{\text{out}}/N_0) \cdot I}{E_{\text{cell}} \cdot I_t} = \frac{V_{\text{out}}/N_0}{E_{\text{cell}}} \cdot \frac{I}{I_t} = \eta_v \cdot \eta_I \quad (3.128)$$

The system efficiency of a fuel cell stack has to consider the power delivered to the auxiliary devices e.g., the compressor motor, hydrogen circulation pump, coolant fan motor, etc. It can be calculated by the ratio between the load demand and the theoretically deliverable power related to the enthalpy as:

$$\eta_{\text{stack}} = \frac{P_{\text{load}}}{N_0 \cdot V_{\text{ec}} \cdot I} = \frac{P_{\text{out}} - P_{\text{aux}}}{N_0 \cdot V_{\text{ec}} \cdot I} = \frac{V_{\text{out}} \cdot I - P_{\text{aux}}}{N_0 \cdot V_{\text{ec}} \cdot I} = \eta_{\text{ec}} \cdot \eta_v - \frac{P_{\text{aux}}}{N_0 \cdot V_{\text{ec}} \cdot I} \quad (3.129)$$

Fig. 3.23 System efficiency versus current of a fuel cell stack



where P_{load} , P_{out} and P_{aux} represent the load demand, total output power and the auxiliary power, respectively. Figure 3.23 shows a typical curve of system efficiency versus current of a fuel cell stack.

3.6 Flywheel

A flywheel is a mechanical device with a large moment of inertia, used for storing energy in the form of kinetic energy. The rotational kinetic energy is released when the flywheel slows down. In conventional vehicles, an internal combustion engine (ICE) uses a flywheel to steady the rotation of the shaft against the fluctuating torque exerted on it due to linear piston motion.

In electric or hybrid electric vehicles, the delivered energy of the flywheel can be captured by employing an electric generator connected to it. The gearbox is equipped between the flywheel and the electric generator to satisfy the requirements of the generator mechanical input. Gearboxes will be discussed in detail in the next section. The power electronics circuits convert the energy to match the requirements of the vehicle traction motor. On the other hand, the regenerative braking energy can be stored in the flywheel through accelerating the flywheel. In this case, the electric generator becomes an electric motor to provide the mechanical torque required by the flywheel. At this point, the flywheel looks like a chemical battery. Figure 3.24 gives the basic connection from the flywheel to the traction motor.

The flywheels, unlike chemical batteries, have significant advantages that they are not affected by temperature changes, nor do they suffer from memory effect. Usually flywheels have a longer life than chemical batteries. Another advantage is that due to the simple mechanical structure, it is possible to calculate the exact amount of stored energy as long as the rotation speed is measured. However, flywheels are not capable of completely replacing the chemical batteries or other energy storage systems in vehicles so far because there exists a potential safety problem due to the risk of fatal accident at extremely high rotation speeds. In this event, a flywheel ruptures like a bomb since its tensile strength is exceeded and all of its stored energy is released at once. Another drawback of flywheels is that

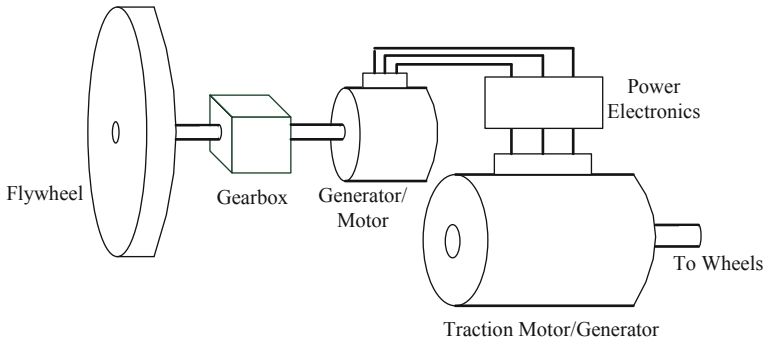


Fig. 3.24 Connection from a flywheel to a traction motor for electric or hybrid electric vehicles

flywheels act like gyroscopes when applied to vehicles [33]. Without external interference, the flywheel tends to stay in one position and does not move to another axis other than the spin axis readily. When an external torque or movement appears on one axis, the flywheel tends to move around another axis. This gyroscopic effect may be detrimental to the vehicle dynamic characteristics. Nevertheless, the effect could be employed to protect the vehicle from rolling over during sharp turns. On the other hand, it is possible to cancel the gyroscopic effect by using the dual flywheel structure with opposite direction of motion of the flywheels. In this case there should be appropriate gear mechanism coupling the two flywheels. The last concern is life time, losses, and heating of the bearing associated with the high speed operation. Magnetic levitated bearing, a popular choice for high speed flywheels, mitigates these problems but adds extra cost.

It is possible that in the near future flywheels will play a very important role in vehicles particularly in electric or hybrid electric vehicles provided the strength and density of materials for flywheels are improved and flywheels are well employed below the rupture point and well guarded.

3.6.1 Expressions for Flywheel Energy Storage and Release

At an angular speed ω , the total stored kinetic energy E in the flywheel is obtained by

$$E = \frac{1}{2} \cdot J \cdot \omega^2 \quad (3.130)$$

with J being the moment of inertia of the flywheel.

The moment of inertia of an arbitrary rotational object is given by the same general equation as

$$J = \int R^2 dM \quad (3.131)$$

where R is the perpendicular distance to the rotation axis and M represents the mass. Various shapes determine different particular calculation expressions. The moment of inertia for a solid-cylinder is expressed as

$$J = \frac{1}{2} \cdot M \cdot r^2 \quad (3.132)$$

where r denotes the radius of the solid-cylinder.

For a thin-walled empty cylinder with radius r , the moment of inertia can be calculated by

$$J = M \cdot r^2 \quad (3.133)$$

The expression of J for a thick-walled empty cylinder turns into

$$J = \frac{1}{2} M \cdot (r_1^2 + r_2^2) \quad (3.134)$$

where r_1 and r_2 are the radius of inner and outer flywheel rings, respectively.

The stored energy when the flywheel speeds up from angular speed ω_2 to ω_1 , and the released energy when the flywheel slows down from ω_1 to ω_2 are equivalent, obtained by

$$\Delta E = \frac{1}{2} \cdot J \cdot (\omega_1^2 - \omega_2^2) \quad (3.135)$$

The load demand is satisfied by the majority of the output mechanical power of the flywheel while the other minor part is lost. The power equation of the flywheel when releasing energy is

$$P = T \cdot \omega = -J \cdot \frac{d\omega}{dt} \cdot \omega = P_{\text{load}} + P_l \quad (3.136)$$

where T represents mechanical torque on the shaft, and P_{load} and P_l denote the load demand and power losses, respectively.

It has to be noted that the amount of energy which can be safely stored in the flywheel depends on the rupture point. The hoop stress on the rim of the cylinder σ_h is a critical factor for the design of a flywheel whose expression is given by

$$\sigma_h = \rho^2 \cdot r^2 \cdot \omega^2 \quad (3.137)$$

where ρ is the material density; r is the radius of the cylinder; ω is the angular speed of the cylinder.

Normally the kinetic energy stored in the flywheel is proportional to the tensile strength (calculated by $\frac{\sigma_h}{\rho}$), expressed as

$$E \propto \frac{\sigma_h}{\rho} \quad (3.138)$$

3.6.2 Flywheel Power Losses

The angular speed is extremely high for storing sufficient kinetic energy in the flywheel, so the air resistance has to be taken into account when calculating the power losses. Meanwhile, the losses on the shaft cannot be neglected since the friction and gyroscopic forces exist. Consequently, the total power losses equal the sum of the air resistance losses $P_{a,l}$ and bearing losses $P_{b,l}$, expressed below

$$P_l = P_{a,l} + P_{b,l} \quad (3.139)$$

The two terms in the above equation as functions of angular speed are given as follows. The losses due to air resistance are determined by the air density ρ_a , dynamic viscosity of air β_a , angular speed ω , radius of the cylinder r , and the geometric ratio α as [34]

$$P_{a,l} = 0.04 \cdot \rho_a^{0.8} \cdot \beta_a^{0.2} \cdot (\omega \cdot r)^{2.8} \cdot (2 \cdot r)^{1.8} \cdot (\alpha + 0.33) \quad (3.140)$$

The geometric ratio is defined as

$$\alpha = \frac{h}{2 \cdot r} \quad (3.141)$$

where h denotes the width of the cylinder.

A frequently-used expression for calculating the bearing losses is depicted below

$$P_{b,l} = \mu \cdot \gamma \cdot r_s \cdot M \cdot g \cdot \omega \quad (3.142)$$

where μ , γ and r_s are the friction coefficient, corrective force factor considering unbalance and gyroscopic forces, and radius of the shaft, respectively, and g represents the gravity acceleration.

3.7 Gearbox

A gearbox converts the speed and torque from a power source to a different speed and torque level required by another device. The most common use of the gearbox is in vehicles. The job of the gearbox is to keep the engine running at its most efficient speed and meanwhile allowing the vehicle to run at a wide range of speeds.

The angular speed of the engine crankshaft is usually higher than that of vehicle wheels, therefore the gearbox that lies ahead of the differential helps reduce the higher engine speed to meet the requirement of the wheel speed while increasing the torque in the meantime. The differential could decrease the engine speed by about four times as the final vehicle speed and the gearbox is responsible for the rest of the speed reduction.

Modern vehicles have a gearbox with multiple gear ratios. In manual-transmission vehicles, gear ratios of the gearbox can be changed when the clutch has disengaged the engine. The clutch is typically operated by a pedal for regulating torque transfer from the engine to the gearbox. In automatic-transmission vehicles, a fluid flywheel or torque converter is equipped between the engine and gearbox. The hydraulics is used in automatic transmission to select gear ratios according to the pressure exerted by fluid within the transmission assembly. The driver is freed from the necessity of shifting gears manually.

3.7.1 Expressions for Gear Ratios

Let ς be the gear ratio, and neglecting all the power losses, the relation between the engine speed ω_E and torque T_E and the speed ω_2 and torque T_2 before the differential are given by

$$\omega_E = \varsigma \cdot \omega_2 \quad (3.143)$$

and

$$T_E = \frac{1}{\varsigma} \cdot T_2 \quad (3.144)$$

respectively. To calculate gradeability (uphill climbing capability), we neglect rolling resistance and aerodynamic resistance, and assume vehicle has no acceleration. These assumptions are used to calculate the lowest gear ratio. According to Eq. 2.4, the vehicle torque on the wheels can be described

$$T_V = F_U \cdot r_w \approx m_v \cdot g \cdot p \cdot r_w \quad (3.145)$$

where r_w represents the wheel radius. Assume that γ is the ratio of the angular speed before the differential to the angular speed of wheels, the largest gear ratio (the 1st gear) chosen to meet the towing requirements can be calculated by the following equation

$$\varsigma_1 = \frac{T_{V \max}}{\gamma \cdot T_{E \max}} = \frac{F_{U \max} \cdot r_w}{\gamma \cdot T_{E \max}} = \frac{m_v \cdot g \cdot p_{\max} \cdot r_w}{\gamma \cdot T_{E \max}} \quad (3.146)$$

Neglecting the power losses, the engine speed in this case (uphill running with the maximum incline gradient) is proportional to the vehicle speed as

$$\omega_E = \varsigma_1 \cdot \gamma \cdot \frac{v_{\min}}{r_w} \quad (3.147)$$

where ς_1 represents the 1st gear ratio, so the maximum engine torque could be determined based on the engine speed. The second smallest gear ratio (the 4th gear) can be selected with respect to the maximum vehicle speed. Thus the

maximum vehicle speed should be solved first by the following relation considering C_r is a constant.

$$P_{\max} = F_{\max} \cdot v_{\max} = \left(\frac{1}{2} \cdot \rho_a \cdot A \cdot c_d \cdot v_{\max}^2 + c_r(v_{\max}) \cdot m_v \cdot g \right) \cdot v_{\max} \quad (3.148)$$

Consequently, if the maximum vehicle speed and the maximum engine speed are known, the 4th gear can be calculated as follows

$$\varsigma_4 = \frac{r_w \cdot \omega_{E\max}}{v_{\max} \cdot \gamma} \quad (3.149)$$

It is possible to choose the fifth gear with which the vehicle runs at the most frequently used city speed meeting the requirements of rough running limits.

In the meantime, another method is often employed to guarantee that the ratio of neighboring gears should lie within a fixed boundary, and gearbox gaps created due to discrete gear ratios cannot be too large [35], described as:

$$\varsigma_k \approx \varsigma_1 \cdot \left(\frac{2}{3} \right)^{k-1}, k = 1, 2, \dots, 5 \quad (3.150)$$

3.7.2 Analysis of Gearbox Losses

The gearbox is considered as highly efficient in transmitting loads, so the previous discussion about the gearbox assumes that its efficiency is 100%. However, it is obviously not realistic. Nowadays the requirements from the customers to decrease gearbox power losses for cost and lubricant reduction are getting more and more stringent. To compensate the shortage of gearbox losses analysis, this section introduces all sorts of power losses existing in the gearbox. The gearbox power losses can be divided into two different losses depending on speed and load, respectively. The speed-dependent losses consist of windage losses and oil churning losses, and the load-dependant losses include sliding friction loss and rolling friction loss. The analysis of these losses is given as follows.

3.7.3 Windage Losses

Windage losses are contributed by the factors such as oil mist created due to the centrifugal force acting on the lubricant, turbulence within the gearbox with respect to the expulsion of the oily atmosphere, and the losses at the side faces of the gears. The amount of windage losses is dependent on the mechanical rotational speed of the gear, the tooth module, the amount of oil mist, and the radius of the gears.

The mathematical model used to calculate the windage losses is expressed as [36]

$$P_w = n^{2.9} \cdot \left(0.16 \cdot (2 \cdot r_f)^{3.9} + (2 \cdot r_f)^{2.9} \cdot b \cdot m_n^{1.15} \right) \cdot 10^{-17} \cdot \phi \cdot \lambda \quad (3.151)$$

where n is the mechanical rotational speed, r_f the root radius, b the face width of the gear, m_n the normal module. The oil mixture function ϕ reflects the percentage of the oil mist in the atmosphere inside the gearbox, and $\phi = 1$ indicates that no oil exists in the atmosphere. For free space, the gearbox space function λ is set to 1, and it reaches to 0.5 for a fitting enclosure.

3.7.4 Oil Churning Loss

The oil churning loss is produced because of the action of the gears moving the lubricant inside the gearbox. Since the gears contact with the lubricant directly, the deeper the gears are submerged, the higher the oil churning loss. In summary, the factors including the viscosity of the oil, rotational speed, element diameter, operating temperature, tooth module and so on could influence the oil churning losses. Nevertheless, the expressions for the churning loss have different forms dependent on different positions [37].

For shafts, the churning loss is expressed as

$$P_{c\_shaft} = 3.685 \cdot k_d \cdot \nu \cdot n^3 \cdot D^{4.7} \cdot L \cdot 10^{-22} \quad (3.152)$$

For both of the gear faces, the churning loss is calculated by

$$P_{c\_gear} = 0.737 \cdot k_d \cdot \nu \cdot n^3 \cdot D^{5.7} \cdot 10^{-22} \quad (3.153)$$

For tooth surfaces, the churning is obtained as

$$P_{c\_tooth} = 3.685 \cdot k_d \cdot \nu \cdot n^3 \cdot D^{4.7} \cdot b \cdot \left(\frac{R_f}{\sqrt{\tan(\beta)}} \right) \cdot 10^{-22} \quad (3.154)$$

In the above three equations, k_d is the gear dip factor and set to 1 for the case that the element is fully submerged, ν the kinematic viscosity at operating temperature, n the rotational speed, D the element diameter, L the contact line length, R_f the roughness factor, and β the helix angle.

3.7.5 Sliding Friction Losses

Similar to other elements using kinematics, the instantaneous sliding friction loss of the gearbox is a multiplication of the sliding velocity V_s and the friction force F_s , expressed as

$$P_s = V_s \cdot F_s \quad (3.155)$$

where the friction force is determined by the friction coefficient μ and the gear load w as

$$F_s = \mu \cdot w \quad (3.156)$$

Anderson et al. [38] proposed an expression of the instantaneous coefficient of sliding friction for spur gears as follows

$$\mu = 0.0127 \cdot \log \left(\frac{29.66 \cdot w}{b \cdot \mu_0 \cdot V_s \cdot V_T^2} \right) \quad (3.157)$$

where μ_0 is the ambient viscosity at ambient temperature, V_T the rolling velocity. It has to be noted that this analysis for the sliding coefficient does not take the gear surface temperature into account due to its minor influence.

3.7.6 Rolling Friction Losses

An elastohydrodynamic lubricant film is produced between the gear teeth in contact when the teeth mesh in the gearbox. The factors that have impact on the rolling friction losses are the thickness of the lubricant film, the rotational speed of gears, the working pressure angle and the contact point along its contact path. In the meantime, during the buildup of the lubricant film, the shear values and thermal behavior of the lubricant, the gear material and the normal tooth load have their respective influences. Similar to the sliding friction power loss, the rolling friction power loss is given by

$$P_r = F_r \cdot V_T \quad (3.158)$$

where P_r and F_r denote the rolling friction power loss and force, respectively.

To calculate the rolling friction force, Anderson et al. presented an expression as [38]

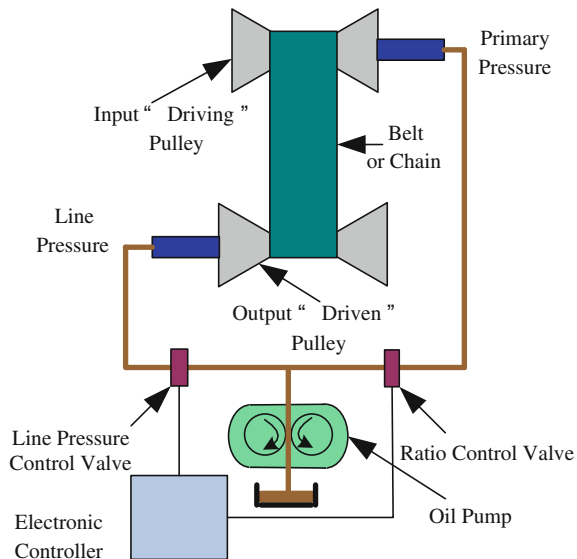
$$F_r = 9.10^7 \cdot h \cdot \phi_t \cdot b \quad (3.159)$$

with the parameters h representing the isothermal central film thickness, ϕ_t the thermal reduction factor related to the decrease in oil film thickness as the pitch-line velocity increases, and b the face width.

Thereby, the total power losses of the gearbox can be obtained as the sum of the above losses:

$$P_{\text{loss}} = P_w + P_c + P_s + P_r \quad (3.160)$$

Fig. 3.25 Structure schematic of a pulley-based CVT



3.8 Continuously Variable Transmission (CVT)

The continuously variable transmission (CVT) for vehicles can produce an infinite number of gear ratios within a fixed interval. Though several other types exist such as the toroidal CVT, ratcheting CVT, hydrostatic CVT, and so on, most vehicles use a pair of variable-diameter pulleys (pulley-based CVT) [39]. Each of the pulleys looks like a pair of opposing cones, with a metal/rubber belt or chain running between them. For the belt made of rubber, the V-belt is preferred. The V-belt bears a V-shaped cross section, which could increase the friction grip of the belt. One pulley as the input “driving” pulley is connected to the engine crankshaft, where the energy from the engine goes into the transmission, and the other pulley as the output “driven” pulley is linked with the driveshaft and transfers energy to the driveshaft. Hence, a metal/rubber belt or chain, an input pulley, and an output pulley act as the three key elements that enable the CVT technology to work. The structure of the pulley-based CVT is shown in Fig. 3.25.

When the halves of the pulleys move closer, the belt has to ride higher on the pulley. In this case, the diameter of the pulley gets larger. Conversely, when the halves of the pulleys are far apart, the belt is forced to ride lower on the pulley, so the diameter of the pulley becomes smaller. The hydraulic pressure, centrifugal force or spring tension may be utilized to produce the required force for adjustment of pulley halves.

The variation of the diameter of the pulleys could change the CVT gear ratio accordingly. For instance, if the diameter of the driving pulley is smaller, and that of the driven pulley is larger, then the rotational speed of the driven pulley gets lower. Thus the gear ratio is consequently lower. In theory, the CVT could create an infinite number of gear ratios at any engine or vehicle speed.

Because the hydraulic part of CVTs contributes higher transmission losses and slip exists in the CVT power transmitter device, the efficiency of CVTs is usually lower than that of the conventional gearboxes in manual-or automatic-transmission structures. However, the CVT permits the selection of any engine speed-torque combination, therefore, the optimization of power flow is possible and the fuel consumption could be small. The efficiency of the engine and the overall propulsion system increases as a result [40].

In summary, since there is no direct relation between a given vehicle speed and a given engine speed, the CVT can change the engine speed as required to achieve maximum power for quicker acceleration as well as maximum efficiency for better fuel economy than a manual-or automatic transmission. Nevertheless, the user acceptance is the biggest problem so far. The noises from the CVT often sound strange to the ears which are used to manual or automatic transmissions because the CVT permits any engine speed. Furthermore, the CVT provides a smooth increase to maximum power while the automatic transmission offers a sudden burst of power, so drivers may feel slower in vehicle acceleration using the CVT. In fact, the mean acceleration of a CVT is generally superior to that of an automatic transmission. The automakers are making efforts to make the CVT feel more like a conventional transmission. Most CVTs are set up to creep forward as the brake pedal is released, which gives the user a similar feeling to a conventional transmission and indicates that the CVT is working. A “manual” mode is employed in other CVTs to simulate the gear changes in manual transmission.

Till now, CVTs have appeared in many types of vehicles from major automobile manufacturers.

3.8.1 CVT Representations

Assume that angular speed and torque on the input pulley are represented by the symbols ω_1 and T_1 , and those on the output pulley are symbolized as ω_2 and T_2 , then the definition of the transmission ratio ς is expressed as

$$\varsigma = \frac{\omega_1}{\omega_2} \quad (3.161)$$

Since the peripheral speeds for the two pulleys are equivalent, the following relation is valid

$$D_2 = \varsigma \cdot D_1 \quad (3.162)$$

where D_1 and D_2 denote the diameters of the input and output pulleys, respectively.

Considering the mechanical torque losses T_{loss} , the definition of the transmission ratio implies that

$$T_{i2} = \varsigma \cdot (T_{i1} - T_{\text{loss}}) \quad (3.163)$$

where T_{t1} and T_{t2} represent the torque transmitted by the belt or chain to the two pulleys.

Based on Newton's second law, the mechanical state equations for the input "driving" pulley and output "driven" pulley are given by

$$J_1 \frac{d\omega_1}{dt} = T_1 - T_{t1} \quad (3.164)$$

and

$$J_2 \frac{d\omega_2}{dt} = T_{t2} - T_2 \quad (3.165)$$

Combination of Eqs. 3.161–3.165 and considering that ς is a variable yield

$$T_1 = \frac{T_2}{\varsigma} + \frac{J_{CVT}}{\varsigma} \cdot \frac{d\omega_2}{dt} + J_1 \cdot \frac{d(\varsigma \cdot \omega_2)}{dt} + T_{\text{loss}} \quad (3.166)$$

where J_1 and J_2 represent moments of inertia of the two pulleys, and the total moment of inertia of the CVT is defined as

$$J_{CVT} = J_1 \cdot \varsigma^2 + J_2 \quad (3.167)$$

The efficiency of the CVT is dependent on the output torque and speed as well as the transmission ratio. It gets higher as the torque increases for a given speed and transmission ratio [40] or as the output pulley rotates faster with a constant torque and transmission ratio. Besides, higher transmission ratio results in higher CVT efficiency when the output speed and torque are fixed.

Assume the efficiency of the CVT is known as $\eta_{CVT}(T_2, \omega_2, \varsigma)$, then during the acceleration and cruise periods when $T_2 > 0$, the relation between the input and output torques is

$$T_1 = \frac{T_2}{\varsigma \cdot \eta_{CVT}(T_2, \omega_2, \varsigma)} \quad (3.168)$$

For the braking period when $T_2 < 0$, the following formula holds

$$T_1 = \frac{T_2 \cdot \eta_{CVT}(T_2, \omega_2, \varsigma)}{\varsigma} \quad (3.169)$$

3.8.2 CVT Power Losses

The power losses of the CVT are divided into two types, i.e., the hydraulic losses and mechanical losses. The hydraulic power losses come from the oil pump while the mechanical power losses are created due to the friction at the mechanical contacts between various components in the CVT.

The CVT shift dynamics can be depicted in the following equation [41]

$$\frac{d\varsigma}{dt} = \beta(\varsigma) \cdot \omega_1 \cdot (P_1 - P_1^*) \quad (3.170)$$

where $\frac{d\varsigma}{dt}$ is the shift speed, $\beta(\varsigma)$ the coefficient dependent on the transmission ratio, P_1 the applied primary pressure on the input pulley provided by the oil pump, P_1^* the steady-state pressure on the input pulley.

The CVT shift dynamics can be described by another expression which is derived from Eq. 3.170

$$\frac{d\varsigma}{dt} = \alpha(\varsigma) \cdot \omega_1 \cdot P_2 \cdot \left(1 - \frac{P_1^*}{P_1}\right) \quad (3.171)$$

where P_2 , called the line pressure, is the applied pressure on the output pulley, and the coefficient $\alpha(\varsigma)$ is

$$\alpha(\varsigma) = \beta(\varsigma) \cdot \frac{F_1 \cdot A_2}{F_2 \cdot A_1} \quad (3.172)$$

In the above expression of $\alpha(\varsigma)$, F and A symbolize the thrust and the actuator area, and the subscript 1 and 2 represent the variables for the input and output pulleys, respectively. The thrust ratio F_1/F_2 is known as a function of the transmission ratio.

To calculate the required line pressure to achieve the desired transmission ratio ς_d , a shift speed target is defined firstly as

$$\left. \frac{d\varsigma}{dt} \right|_{\text{target}} = \frac{\varsigma_d - \varsigma}{\Delta t} \quad (3.173)$$

where ς is the actual transmission and Δt is the sampling time.

As the shift speed target is known, the line pressure requirement for the oil pump can be obtained from Eq. 3.171 as

$$P_{2,\text{target}} = \frac{\left. \frac{d\varsigma}{dt} \right|_{\text{target}}}{\alpha(\varsigma) \cdot \omega_1 \cdot \left(1 - \frac{P_1^*}{P_1}\right)} \quad (3.174)$$

Thereby, a faster shift speed could be implemented by increasing the line pressure from the oil pump with a given pressure on the input “driving” pulley. It is available to improve the engine operation on the optimal operation line for better fuel economy by increasing the shift speed, as expected. Nevertheless, this leads to a boost of the line pressure, which may increase the hydraulic losses. The hydraulic losses due to the use of the oil pump is represented by

$$P_{h,\text{loss}} = P_2 \cdot Q \quad (3.175)$$

where Q represents the oil flow from the oil pump.

The mechanical torque losses on the input and output pulleys $T_{1m,loss}$, $T_{2m,loss}$ can be expressed as a function of the oil pump pressure, angular speed, and the transmitted torque as follows

$$T_{1m,loss} = a_1 \cdot (p_1 + b_1 \cdot \omega_1^2) + c_1 \cdot \omega_1 + d_1 \cdot T_{t1} \quad (3.176)$$

$$T_{2m,loss} = a_2 \cdot (p_2 + b_2 \cdot \omega_2^2) + c_2 \cdot \omega_2 + d_2 \cdot T_{t2} \quad (3.177)$$

The coefficients a_i, b_i, c_i and d_i ($i = 1, 2$) can be acquired from experiments. $b_i \cdot \omega_i^2$ represents the torque losses created by the centrifugal force effect. Thus the total CVT torque losses, T_{loss} that appears in Eq. 3.166 can be obtained as

$$T_{loss} = T_{1m,loss} + \frac{1}{\zeta} \cdot T_{2m,loss} \quad (3.178)$$

Furthermore, the mechanical power losses can be obtained based on the fundamental power-torque relations as follows

$$P_{m,loss} = T_{1m,loss} \cdot \omega_1 + T_{2m,loss} \cdot \omega_2 \quad (3.179)$$

In summary, the total CVT power losses are contributed by the hydraulic power losses and the mechanical power losses together, described as

$$\begin{aligned} P_{loss} &= P_{h,loss} + P_{m,loss} \\ &= P_2 \cdot Q + T_{1m,loss} \cdot \omega_1 + T_{2m,loss} \cdot \omega_2 \end{aligned} \quad (3.180)$$

3.9 Planetary Gears

Planetary gear trains are used widely in today's hybrid and plugin hybrid electric vehicles to realize a function similar to the CVT in conventional vehicles. A planetary gear train has one or more planetary gears orbit around a sun gear or central axis of the train. Therefore, there is a moving axis in planetary gear trains (carrier). Figure 3.26 shows the schematics of a planetary gear train. It can be seen, there are three axes in total: sun axis, planet carrier axis and ring axis. The possible relative motions among these axes make planetary gear train very interesting.

Among the three shafts of a planetary gear train, any shaft can be treated as input shaft or output shaft. Hence, the combination will be either two input shafts and one output shaft, or one input shaft and two output shafts. In some applications, one of the gear set is grounded so that only one input and one output is available. In this case, the planetary acts as a speed reduction gear set.

3.9.1 Speed Relationships

Based on mechanical structure of the planetary gear train, the relationship between the numbers of sun gear teeth and ring gear teeth can be described by the following equation:

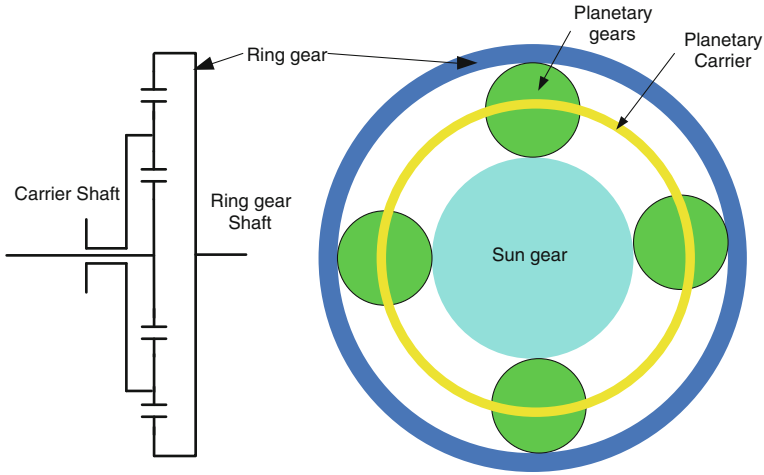


Fig. 3.26 Planetary gear train

$$\frac{N_s}{N_r} = \frac{\omega_c - \omega_r}{\omega_s - \omega_c} \quad (3.181)$$

where N denotes the number of teeth; ω the angular speed. The subscripts s , r and c represent “Sun”, “Ring” and “Carrier”, respectively. Equation 3.181 can be rewritten using the other form as:

$$\frac{N_r}{N_s + N_r} \omega_r + \frac{N_s}{N_s + N_r} \omega_s = \omega_c \quad (3.182)$$

Assume that N_1 and N_2 are the teeth numbers of input and output gears, respectively, and the gear ratio of the planetary gear train can be expressed as

$$\kappa = \frac{N_2}{N_1} \quad (3.183)$$

Let σ denote the standing gear ratio, and its expression is shown as follows

$$\sigma = \frac{N_r}{N_s} \quad (3.184)$$

By substituting Eq. 3.184 into Eq. 3.182, the speed relationships of the various shafts are obtained below

$$\omega_s = \omega_c(1 + \sigma) - \omega_r \sigma \quad (3.185)$$

$$\omega_r = \frac{\omega_c(1 + \sigma) - \omega_s}{\sigma} \quad (3.186)$$

Table 3.3 Planetary gear set combinations

Fixed shaft	Input shaft	Output shaft	Speed ratio	Rotational direction
Sun	Ring	Carrier	<1	Same
	Carrier	Ring	>1	Same
Carrier	Sun	Ring	<1	Reverse
	Ring	Sun	>1	Reverse
Ring	Sun	Carrier	<1	Same
	Carrier	Sun	>1	Same

$$\omega_c = \frac{\omega_s + \omega_r \sigma}{1 + \sigma} \quad (3.187)$$

Six planetary gear set combinations are summarized in Table 3.3. One shaft is fixed, and the other two act as the input and output shafts responsible for driving and driven functions.

3.9.2 Efficiency of Planetary Gear Train

If one shaft is fixed, the power is transmitted via a free shaft to the other free one. The expressions for input power acting on individual shafts, i.e., the sun, ring and carrier shafts, respectively are given by

$$P_s = T_s \omega_s \quad (3.188)$$

$$P_r = T_r \omega_r \quad (3.189)$$

$$P_c = T_c \omega_c \quad (3.190)$$

where T denotes the input torque.

As mentioned at the beginning of this section, the planetary gear trains are placed in the gearbox of hybrid vehicles to implement various gear ratios. They are also utilized as the first stage of the gearbox in a wind turbine for compactness. Therefore, discussion on power losses of the planetary gear train is almost the same as that in Sect. 3.7.2, “Analysis of Gearbox Losses”.

The windage losses and oil churning losses are contributed by three individual shafts. This relationship is described as

$$P_W = P_{sW} + P_{cW} + P_{rW} \quad (3.192)$$

$$P_C = P_{sC} + P_{cC} + P_{rC} \quad (3.193)$$

where the subscripts W and C are shortened forms of the words “windage” and “churning”, respectively.

Unlike the previous two losses, the friction losses (i.e., sliding friction losses and rolling friction losses) depend on combinations of two directly-contacting

shafts. Since only the carrier shaft shares respective physical touches with the other two shafts, two types of friction losses are calculated by

$$P_S = P_{scS} + P_{rcS} \quad (3.194)$$

$$P_R = P_{scR} + P_{rcR} \quad (3.195)$$

where the subscripts S and R represent the sliding and rolling friction losses, respectively.

All the detailed calculation processes of the above four losses can be found in [Sect. 3.7.2](#). Thus the total power loss is derived by the following expression

$$P_{\text{loss}} = P_W + P_C + P_S + P_R \quad (3.196)$$

Suppose T_1 and ω_1 to be the torque and speed of the input shaft, respectively, and the efficiency of the planetary gear train η_p can be computed by

$$\eta_p = \frac{T_1 \omega_1 - P_{\text{loss}}}{T_1 \omega_1} \quad (3.197)$$

Usually the efficiency of the planetary gear train is related to the efficiency of the inverted train denoted by γ . Two different cases are discussed here. First, the sun or ring gear acts as the driving link, and the carrier shaft is the driven one. Second, only the carrier shaft is considered as the input shaft, and the sun or ring gear is free. Both cases use the assumptions that the torque and speed of the input shaft are positive, and one shaft should be fixed.

For the first case, the total power loss is expressed using the definition of the inverted train as:

$$P_{\text{loss}} = (1 - \gamma)T_i(\omega_i - \omega_c), \quad i = s, r \quad (3.198)$$

which indicates the power loss calculation under the framework of the inverted train is determined by the relative speed between the sun/ring gear and the carrier shaft. Thus, the efficiency of the planetary gear is obtained using Eqs. 3.197 and 3.198, shown below

$$\eta_p = \frac{T_i \omega_i - (1 - \gamma)T_i(\omega_i - \omega_c)}{T_i \omega_i} = 1 - (1 - \gamma) \left(1 - \frac{\omega_c}{\omega_i} \right) \quad (3.199)$$

For the second case, since the sun/ring gear is the output opposite to the first case, a different expression form for the efficiency of the planetary gear train is considered as

$$\eta_p = \frac{P_2}{P_2 + P_{\text{loss}}} = \frac{-T_i \omega_i}{-T_i \omega_i + P_{\text{loss}}}, \quad i = s, r \quad (3.200)$$

where P_2 is the output power.

Because the torque and speed of the input shaft is assumed to be positive, the output torque is negative due to the resisting moment, and the speed of the output shaft is positive. This can explain why the sign ahead of $T_i \omega_i$ is minus.

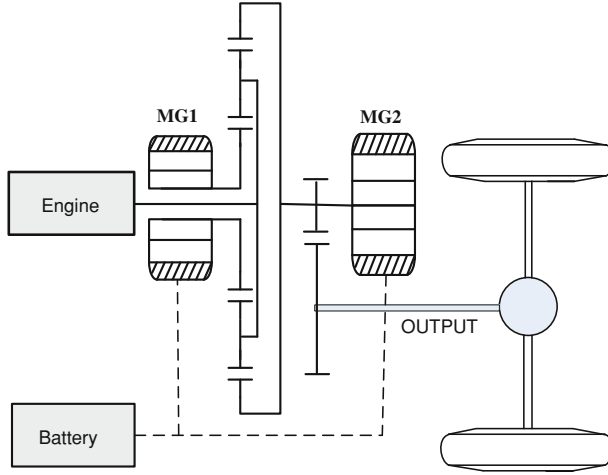


Fig. 3.27 The Toyota Prius hybrid powertrain configuration

The power loss for the second case also can be described by introducing the inverted train as

$$P_{\text{loss}} = \frac{(-T_i)(\omega_i - \omega_c)}{\gamma} - (-T_i)(\omega_i - \omega_c) = \frac{1 - \gamma}{\gamma} (-T_i)(\omega_i - \omega_c) \quad (3.201)$$

Eventually, the efficiency of the planetary gear train in the second case can be obtained by substituting Eq. 3.201 into Eq. 3.200, expressed as

$$\eta_P = \frac{-T_i \omega_i}{-T_i \omega_i + \frac{1 - \gamma}{\gamma} (-T_i)(\omega_i - \omega_c)} = \frac{1}{1 + \frac{1 - \gamma}{\gamma} \left(1 - \frac{\omega_c}{\omega_i}\right)} \quad (3.202)$$

3.9.3 Optimized Control of the Planetary Based HEV

Modern hybrid electric vehicles use planetary gear train to realize continuous variable transmission, referred to as e-CVT [42–49]. For example, in the Toyota Prius, the engine is connected to the carrier, the generator is connected to the sun gear, and the ring gear is connected to the final drive. The second electric motor is also connected to the ring gear Fig. 3.27.

In the Prius, the ring gear has 78 teeth, the sun gear has 30 teeth, hence the speed relation among the three components can be expressed as (e-engine, m-motor and g-generator),

$$\omega_e = \frac{N_r}{N_s + N_r} \omega_m + \frac{N_r}{N_s + N_r} \omega_g = 0.7222 \omega_m + 0.2778 \omega_g \quad (3.203)$$

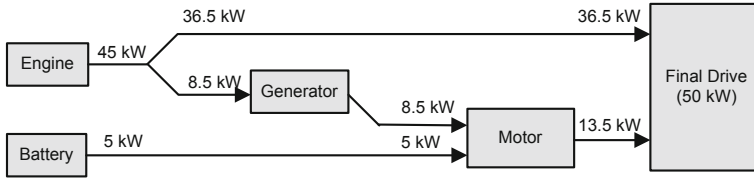


Fig. 3.28 The power flow example in Prius hybrid powertrain

At any given time, the ring gear speed is decided by the vehicle speed. Since the motor and the ring gear are on the same shaft, they have the same speed which is proportional to the vehicle speed. This means the engine speed and generator speed can be adjusted from Eq. 3.203. The control objective is to adjust generator speed so that the engine speed and power can be controlled in its best efficiency region.

For a given vehicle speed, by using the power demand requested from the driver, the desired engine operating point (power and speed) can be determined based on maximum engine efficiency. Hence the generator speed can be determined:

$$\omega_g = \frac{\omega_e - 0.7222 \omega_m}{0.2778} = 3.6 \omega_e - 2.6 \omega_m \quad (3.204)$$

By controlling the generator power, the engine speed can be controlled to match the speed calculated by Eq. 3.204.

Example For the Prius HEV, at vehicle speed corresponding to $\omega_m = 2,250$ rpm and power demand of 50 kW, it is determined that at this power level, the engine is most efficient if it is operated at 2,000 rpm and 45 kW. Neglect losses, calculate the speed of the generator, and power and torque of each powertrain component.

Solution From Eq. 3.204, we can get the generator speed $\omega_g = 1,350$ rpm. The following calculations can then be made: $P_e = 45$ kW, $T_e = P_e / \omega_e = 215$ Nm. Hence

$$T_r = \frac{N_r}{N_r + N_s} T_e = 155 \text{ Nm}$$

$$T_g = \frac{N_s}{N_r + N_s} T_e = 60 \text{ Nm}$$

$$P_r = T_r \omega_r = 36.5 \text{ kW}$$

$$P_g = T_g \omega_g = 8.5 \text{ kW}$$

Since the vehicle power demand is 50 kW, the motor must deliver additional 5 kW to final drive to satisfy the whole vehicle power demand. The power flow is shown in Fig. 3.28.

This above example demonstrates that the overall fuel economy of the Prius HEV can be optimized by controlling the generator power in real time. However,

when the losses of each component are considered, the control problem becomes more complex. Hence, advanced control algorithms based on optimal control theory and intelligent systems approach, such as dynamic programming, quadratic programming, fuzzy logic, and some analytical approaches can be employed to optimize the operation of the vehicle system.

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Chapter 4

Analytical Approach for the Power Management of Blended Mode PHEV

Plug-in Hybrid electric vehicles (PHEVs) use grid electricity to power the vehicle for an initial driving range, referred to as charge depletion (CD) mode. Using electric energy from the utility grid to displace part of fuel is the major feature of PHEVs [1, 2]. There are two basic types of PHEV: extended range electric vehicles (EREVs), and blended mode PHEVs.

EREVs offer pure electric driving capability in the initial driving range, referred to as all-electric range (AER). In order to realize pure electric driving in all driving conditions, EREVs are equipped with a full-sized traction motor powered by the battery pack. One of the disadvantages of EREVs is the increased system cost due to the full-sized traction motor and power requirements for the battery; the other is the high losses in the electric system (battery and electric motor) at high power operations. These constraints have led to the concept of the blended mode PHEV.

A blended mode PHEV usually has less powerful electric drive capability. Therefore, it can typically achieve cruise and moderate acceleration in the electric mode at low to moderate vehicle speeds. For operations requiring either higher power or higher torque, the thermal engine must be used, either with or without electric assistance depending on vehicle control strategies. EREV can adopt the blended operation as well in order to reduce system losses at higher power demands.

Control strategies for a blended mode PHEV can be complex and multi-dimensional, and will have significant impacts on vehicle performance, drivability and fuel consumption [3–5]. One of the PHEV's primary capabilities is fuel displacement by depleting the on-board electric energy storage system (ESS) to a preset low threshold state of charge (SOC). It is generally desirable that the on-board ESS has reached this depleted state (charge sustaining SOC) by the end

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of the “designed” vehicle travel distance. On one hand, aggressive charge depletion may result in higher electric loss incurred in the vehicle systems and affect the overall energy efficiency of the vehicle, i.e., more energy is consumed whether it is from gasoline or electricity. On the other hand, vehicles with less than sufficient charge depleting operations may not achieve fuel displacement function as designed, and the capacity of the on-board ESS is under-utilized. Therefore, how to achieve optimized CD operations in PHEV applications is one of the fundamental problems of PHEV control. It becomes more challenging in real applications because the trip distance and drive scenarios are not precisely known.

4.1 Simplified Analytical Solution

The objective of the PHEV optimization problem is to minimize the vehicle fuel consumption for a given driving range subject to specific constraints, such as component capabilities, available ESS energy and so on.

The problem can be formulated as follows:

$$\text{Objective : minimize } m_f = \int_0^T f(P_{eng}) dt \quad (4.1)$$

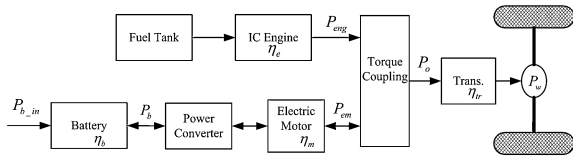
$$\text{Subjected to : } \begin{cases} P_{b,\min}(t) \leq P_b(t) \leq P_{b,\max}(t) \\ P_{em,\min}(t) \leq P_{em}(t) \leq P_{em,\max}(t) \\ 0 \leq P_{eng}(t) \leq P_{eng,\max}(t) \\ SOC_{\min} \leq SOC(t) \leq SOC_{\max} \end{cases} \quad (4.2)$$

where:

- P_b is the output power of the battery
- P_{em} is the output power of the electric motor
- P_{eng} is the engine output power
- SOC is the battery state of charge
- $f(P_{eng})$ is the fuel mass flow rate of the engine as a function of engine power and engine speed
- m_f is the mass of total fuel consumption
- T is the total time of the drive cycle

4.1.1 Vehicle Model

We will use a typical parallel configuration as shown in Fig. 4.1 as the blended mode PHEV for fuel economy optimization. The parallel PHEV allows both the engine and electric motor to deliver power in parallel to drive the wheels. The propulsion power may be supplied by either the engine alone or the motor alone or

Fig. 4.1 Power flow of PHEV**Table 4.1** Vehicle parameters

Curb weight (kg)	1988
Full load mass (kg)	2490
Frontal area (m ²)	2.88
Rolling coefficient	0.015
Wheelbase (m)	2.6
Aerodynamic coefficient	0.41

Table 4.2 HEV main components

Fuel converter	130 kW gasoline engine
Motor	50 kW PM Motor
Battery	360 V, 24 Ah lithium-ion battery

both [6]. If the motor power is sufficient, it can also realize pure electric driving mode. The electric motor can be used as a generator to charge batteries during regenerative braking or absorbing engine power to charge battery when the engine has excessive power.

Although a generic parallel PHEV model is used here, the methodology is also applicable to other types of PHEVs including planetary gear based configurations, such as Prius and GM/Chrysler Two-Mode Hybrid whose main operation can be considered as parallel [7–9]. EREVs may also adopt this control as necessary to avoid massive electric losses at high power demands so as to save total energy consumption (gasoline + electricity) for a given drive cycle. The parameters and main components of the vehicle are listed in Tables 4.1 and 4.2.

Reference [10, 11] analyzed the efficiency of conventional HEVs including series and parallel HEVs. Analysis of the fuel consumption is generally operated on a specific drive cycle based on energy balance and component efficiencies. In this section, the focus is on a PHEV for specific driving cycles based on similar concepts of energy balance and component efficiencies.

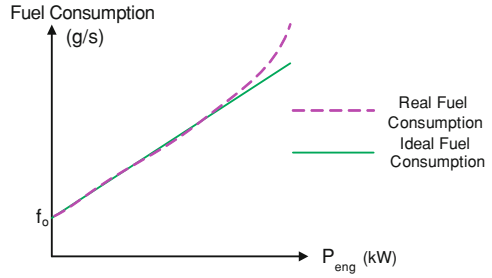
As shown in Fig. 4.1, based on power balance, the power consumed to propel the vehicle, P_o , is equal to the power provided by the engine, P_{eng} and the electric motor, P_{em} , neglecting power losses of the mechanical coupling.

$$P_o = P_{eng} + P_{em} \quad (4.3)$$

$$P_b = P_{em} + P_{em\_loss} \quad (4.4)$$

$$P_{b\_in} = P_b + P_{b\_loss} \quad (4.5)$$

Fig. 4.2 The fuel rate for versus engine speed



where P_{em_loss} is the loss of the electric motor, P_{b_loss} is the loss of the battery during discharging/charging, P_b is battery output power to the electric motor, P_{b_in} is battery power considering battery power loss. P_{em} , P_b , P_{b_in} have signs with positive indicating discharging and negative indicating charging. P_{em_loss} and P_{b_loss} are always positive. P_o can be calculated by the following equation based on vehicle parameters and speed:

$$P_o = \frac{1}{\eta_T} \left(\frac{m_a g f_r}{3600} v + \frac{C_D A}{76140} v^3 + \frac{\delta \cdot m_a \cdot v}{3600} \frac{dv}{dt} + \frac{m_a \cdot g \cdot \sin \alpha \cdot v}{3600} \right) \quad (4.6)$$

where

- P_o , demand power, kW
- η_T , transmission efficiency
- m_a , vehicle mass, kg
- g , acceleration of gravity, m/s^2
- f_r , rolling coefficient
- v , vehicle speed, km/h
- C_D , aerodynamic coefficient
- A , frontal Area, m^2
- δ , rotating mass coefficient
- α , slope angle, rad

In a specific drive cycle, the total energy demand E_a and available battery energy E_b are constant.

$$E_b = \int_0^T P_{b\_in} dt = const. \quad (4.7)$$

$E_b = 0$ is for charge sustaining operations, and $E_b > 0$ is for charge depleting operations.

$$E_a = \int_0^T P_o dt = const. \quad (4.8)$$

The engine efficiency is represented by a nonlinear static map which describes fuel rate as a function of engine speed and engine torque as shown in Fig. 4.2.

It can be seen from Fig. 4.2 that the fuel rate can be approximately represented by a linear function as engine power for each engine speed,

$$f\_rate = f(P_e, \omega) \quad (4.9)$$

For further simplicity, a linear relationship is assumed to obtain an optimized solution as

$$f = f_o + kP_{eng} \quad (4.10)$$

where f_o is caused by mechanical friction and pumping losses in the engine, k reflects the combustion efficiency approximately. f_o varies obviously with different engine power ratings and increases with engine size while k is almost the same for different-size engines. For the specific engine used in this chapter, the value of f_o and k are 1.59×10^{-1} g/s and 7.13×10^{-2} g/(kW $\times$ s), respectively.

The electric losses in the PHEV include the battery loss, electric motor loss and inverter loss. From Chap. 3, it can be seen that electric losses can be divided into three categories. One category is almost constant, such as frictional loss, which is only a function of motor speed. The second category is directly proportional to output power, such as magnetic losses in the motor. The last category is proportional to the square of output power, such as copper losses in a motor, and battery losses due to battery internal resistance. Hence, we can use a 2nd order polynomial to represent the electric system losses,

$$P_{b\_in} = P_{em} + Loss(P_{em}) = P_{em} + L_o + AP_{em} + BP_{em}^2 \quad (4.11)$$

where $Loss(P_{em})$ is the electric loss, L_o , A , B are the index of polynomial coefficients which depend on vehicle powertrain components. These constants can be obtained through theoretical calculations or measurements in an actual system.

4.1.2 Control Strategy

The previous work has demonstrated three different control strategies in CD mode [12, 13]. The control strategies can be summarized as all electric-range (AER) strategy, engine dominant blended strategy, and electric dominant blended strategy. In the electric dominant control strategy, the motor size and battery power rating can be scaled down compared to AER control. If the maximum motor torque and battery power is sufficiently large, the operation is similar to the AER control strategy. The motor supplies the main driving torque, and the engine turns on when the demand torque exceeds the maximum motor torque. In the engine dominant control strategy, the engine provides most of the driving torque, and the motor assists the vehicle operation by using the onboard electric energy. The electric motor is only turned on when the road load demand exceeds the engine optimal torque/efficiency. In references [14, 15], only engine operation is optimized, thus not using the full potential of hybrid technology.

In this section, as shown in Fig. 4.3, the proposed strategy is to use electric power to drive the vehicle until a threshold power demand P_s is reached. Then, the

Fig. 4.3 Energy management strategy

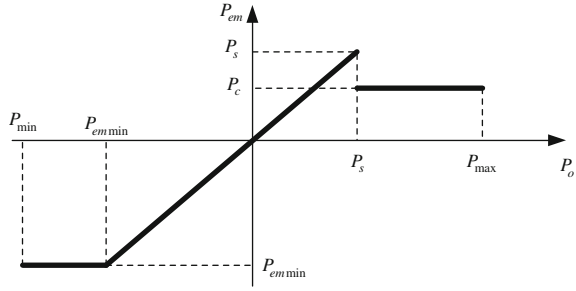
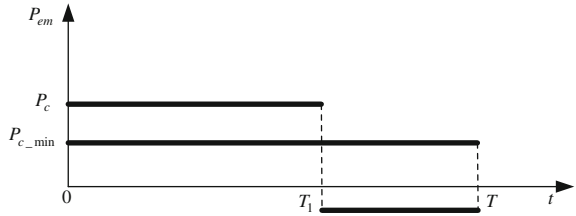


Fig. 4.4 Two segments in the whole trip



engine turns on to meet the desired output power and desired electric system power P_c . A constant motor mechanical power $P_{em} = P_c$ is maintained during engine running until the end of the drive cycle

$$S_{eng} = \begin{cases} on & P_o > P_s \\ off & P_o \leq P_s \end{cases} \quad (4.12)$$

$$P_{em} = \begin{cases} P_{em\ min} & P_o < P_{em\ min} \\ P_o & P_{em\ min} < P_o < P_s \\ P_c & P_s < P_o < P_{em\ max} \end{cases} \quad (4.13)$$

where $P_{em\ min}$ is the maximum regenerative power, P_s is power threshold below which the engine is off. P_c is the constant motor mechanical power used to assist the engine.

As shown in Fig. 4.4, it is assumed that if $P_{em} = P_c$, the battery energy is used up at time T_1 . If $P_{em} = P_{c\_min}$, the battery energy is used up at time T .

A fixed distance and constant speed are first used for the analytical analysis.

$$T = \frac{S}{V_o} \quad (4.14)$$

where S is distance and V_o is the constant speed, T is the time of the whole trip, which depends on S and V_o . P_o is dependent on V_o .

If $P_o > P_s$, the engine will turn on assuming after T_1 the battery energy will be used up. T_1 depends on P_c . During the time interval between T_1 and T , only the engine provides the energy for the vehicle. The total fuel consumption in this drive cycle is:

$$\begin{aligned}
m_f &= \int_0^{T_1} \dot{m}_f(P_{eng})dt + \int_{T_1}^T \dot{m}_f(P_{eng})dt \\
&= \int_0^{T_1} (f_o + k(P_o - P_c))dt + \int_{T_1}^T (f_o + kP_o)dt \\
&= (f_o + k(P_o - P_c))T_1 + (f_o + kP_o)(T - T_1) \\
&= (f_o + kP_o)T - kP_cT_1
\end{aligned} \tag{4.15}$$

T_1 can be obtained from

$$E_b = \int_0^{T_1} P_b dt = \int_0^{T_1} (P_c + Loss(P_c))dt = (L_o + (1 + A)P_c + BP_c^2)T_1 \tag{4.16}$$

Replacing T_1 , Eq. 4.15 can be expressed as:

$$m_f = (f_o + kP_o)T - \frac{kE_bP_c}{L_o + (1 + A)P_c + BP_c^2} \tag{4.17}$$

By calculating the derivative of Eq. 4.17, the following equation can be obtained:

$$\begin{aligned}
\frac{dm_f}{dP_c} &= -kE_b \frac{(L_o + (1 + A)P_c + BP_c^2) - P_c(1 + A + 2BP_c)}{(L_o + (1 + A)P_c + BP_c^2)^2} \\
&= -kE_b \frac{L_o - BP_c^2}{(L_o + (1 + A)P_c + BP_c^2)^2}
\end{aligned} \tag{4.18}$$

Set Eq. 4.18 to zero and solve for P_c , we can obtain,

$$P_{c\_opt} = \sqrt{\frac{L_o}{B}} \tag{4.19}$$

By calculating the second derivative of Eq. 4.15, the following equation can be obtained:

$$\frac{d^2m_f}{dP_c^2} = \frac{2kE_b(-2B^2P_c^4 + B^2P_c^3 + 2L_oBP_c^2 + BL_oP_c + L_o + L_oA)}{(L_o + (1 + A)P_c + BP_c^2)^3} \tag{4.20}$$

replacing $BP_c^2 = L_o$, Eq. 4.20 can be simplified,

$$\frac{d^2m_f}{dP_c^2} = \frac{2kE_bL_o(2\sqrt{BL_o} + 1 + A)}{(L_o + (1 + A)P_c + BP_c^2)^3} > 0 \tag{4.21}$$

Hence, m_f is a minima at $P_{c\_opt} = \sqrt{L_o/B}$. Therefore, if the engine is on, the best fuel economy (or minimum fuel consumption) can be achieved when $P_{c\_opt} = \sqrt{L_o/B}$. This value depends on powertrain components.

If $T_1 = T$, from Eq. 4.16, we can obtain the motor minimum power $P_{\min}$ to ensure the available energy of the battery is just used up, i.e., the battery SOC drops down to a preset low threshold at the end of the trip.

$$P_{c\_min} = \frac{-(1+A) + \sqrt{(1+A)^2 - 4B(L_o - \frac{E_b}{T})}}{2B} \quad (4.22)$$

Consider the ideal condition, if all power losses are zero, i.e., $L_o \rightarrow 0$, $A \rightarrow 0$, $B \rightarrow 0$, then $\lim P_{c\_min} = E_b/T$. This is consistent with the assumption. Based on the relationship among P_o , $\sqrt{L_o/B}$ and P_{c_min} , and considering Eqs. 4.18 and 4.21, the results can be discussed as follows:

1. if $P_o < \sqrt{L_o/B}$, then $\frac{dm_f}{dP_c} < 0$, the fuel consumption decreases with power, so $P_{c\_opt} = P_o$
2. if $P_{c\_min} \leq \sqrt{L_o/B} \leq P_o$. The fuel consumption has the minimum value at $P_{c\_opt} = \sqrt{L_o/B}$
3. if $P_{c\_min} > \sqrt{L_o/B}$, then $\frac{dm_f}{dP_c} > 0$. The fuel consumption increases with power, so $P_{c\_opt} = P_{c\_min}$.

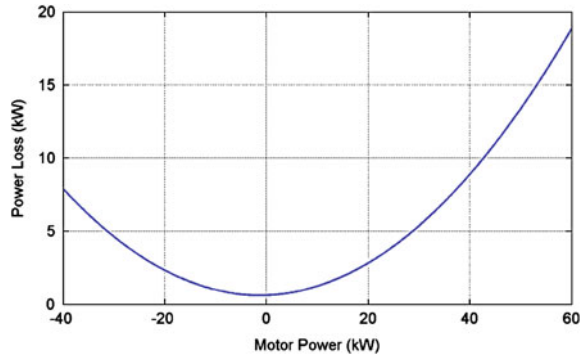
If $P_c = P_o$, from 0 to T_1 , the engine will be turned off, which means the vehicle is in all electric mode. The total fuel consumption becomes,

$$m_f = \int_{T_1}^T \dot{m}_f(P_{eng})dt = \int_{T_1}^T f_o + kP_o dt = (f_o + kP_o)(T - T_1) \quad (4.23)$$

The above set points for P_c can be used for the control of the PHEV to optimize fuel economy (minimize fuel consumption). From the above analysis, it can be seen that since the optimal values of P_c depend on P_o , P_{c_min} and $\sqrt{L_o/B}$, we will need to calculate their values based on drive cycles, then decide the engine turn-on threshold, as well as battery/motor power once the engine is turned on. Hence the control can be described in the following steps:

- Obtain L_o , B , and A for the electric systems. This can be done from simulations of the electric system or through experiments of the actual electric system, including battery, inverter, and electric motor.
- Calculate $\sqrt{L_o/B}$ and P_{c_min} .
- In drive cycle simulations or real world driving, calculate power demand of the vehicle P_o . The power demand is determined by looking at the pedal positions, and the auxiliary electric power demand.

Fig. 4.5 Electric power loss characteristics



- If $P_o \leq \sqrt{L_o/B}$, then run the vehicle in pure electric mode. The engine is off.
- If $P_o > \sqrt{L_o/B}$ but $\sqrt{L_o/B} \geq P_{c\_min}$, then turn engine on. Set the motor to provide constant power of $P_c = \sqrt{L_o/B}$, and the engine provides the difference between power demand and motor power: $P_{engine} = P_o - \sqrt{L_o/B}$.
- If $\sqrt{L_o/B} \leq P_{c\_min}$, then also turn the engine on. Set the motor to provide constant power of $P_c = P_{c\_min}$, and the engine provides the difference between power demand and motor power: $P_{engine} = P_o - P_{c\_min}$.

It can be seen that the engine turn-on threshold and motor power are only determined by the power demand, the electric system loss characteristics, and the total battery energy. The control strategy is based on optimal power of each component as well as vehicle power demand. Hence it is referred to as optimal power strategy in this section. The control can be easily implemented in a vehicle controller.

4.1.3 Determining the Thresholds Using Constant Speed Driving

In this section, we will use constant driving profiles to obtain the control parameter table which can be used for transient drive cycles. First, the electric system loss can be obtained using experimental data. The data was used to fit a second-order curve to obtain L_o , A and B , as shown in Fig. 4.5, $L_o = 0.649$, $A = 1.23 \times 10^{-2}$, $B = 4.85 \times 10^{-3}$. According to Eq. 4.19, $P_{c\_opt} = \sqrt{L_o/B} = 11.5\text{kW}$. In order to calculate the fuel consumption using equations derived in Sect. 4.1.2, a target CD range of 40 miles is selected.

Three different control strategies were studied. As described in Sect. 4.1.2, mode one uses an electric dominant control strategy. Mode two uses an electric assist control strategy, and mode three uses the optimal power strategy. In mode two, P_{c_min} can be calculated from vehicle parameters and the known constant speed, and $P_c = P_{c\_min}$ is ensured. This means the available battery energy is just exhausted at the end of the trip. Because P_{min} needs to be obtained first, it is

Table 4.3 Calculation results

Vehicle speed (mph)	Power demand (kW)	Pmin (kW)	M1 (kg)	M2		M3	
				(kg)	(%)	(kg)	(%)
30	6.15	3.77	1.13	1.69	−49.50	/	/
40	10.53	5.20	1.79	2.13	−19.14	/	/
50	16.77	6.62	2.64	2.83	−7.41	2.81	−6.47
60	25.32	8.01	3.68	3.76	−2.15	3.75	−1.86
67	32.83	8.98	4.51	4.51	0	4.51	0
70	36.58	9.39	4.90	4.87	0.54	4.86	0.61
80	51.00	10.75	6.35	6.17	2.80	6.17	2.80
90	69.00	12.1	7.83	7.65	2.27	7.72	1.39
100	90.95	13.43	9.48	9.30	1.86	9.52	−0.44

M1 electric dominant control strategy

M2 electric assist control strategy

M3 optimal power strategy

difficult to implement in real time simulation unless the trip distance is known. But it can be used as a theoretical calculation to construct the control parameter table. Mode three works only when $P_o > P_{c\_opt}$, and $P_c = P_{c\_opt}$ at this time.

The fuel consumption is calculated based on the above analysis and the results are listed in Table 4.3. As shown in Table 4.3, when the vehicle speeds are at 30 and 40 mph, the total power demand is less than the optimal power P_{c_opt} . So the vehicle operates in pure electric mode, i.e., mode one, $P_c = P_o$. The all-electric mode control strategy has the best fuel economy.

When the vehicle speeds are at 50, 60 and 67 mph, mode two, i.e., $P_c = \sqrt{L_o/B}$ is better to be employed if the engine is on. But the all-electric mode control strategy is still the best for minimum fuel consumption at such speeds.

When the vehicle speeds are at 70 and 80 mph, then mode three has the best fuel-saving performance among all three modes. Through the above results, the engine off-threshold can be obtained.

When vehicle speeds are at 90 and 100 mph, the total power demand is greater than the motor maximum power, and the engine has to be turned on all the time. At this time $P_c = P_{min}$, the use of mode two provides the best fuel economy.

As seen from Table 4.3, the engine on/off threshold is 32 kW. The optimal motor mechanical power with different vehicle power demands is obtained and described as a curve, shown in Fig. 4.6. The table data can be used to implement vehicle control strategies in the simulation model.

4.1.4 Validation of Control Parameter Table Using PSAT

Then, we use software PSAT to simulate the vehicle fuel economy in constant drive cycles to gain confidence of the proposed strategy. Table 4.4 shows the simulated results from PSAT using different constant speed driving profiles for the

Fig. 4.6 Optimal motor mechanical power with different vehicle power demands

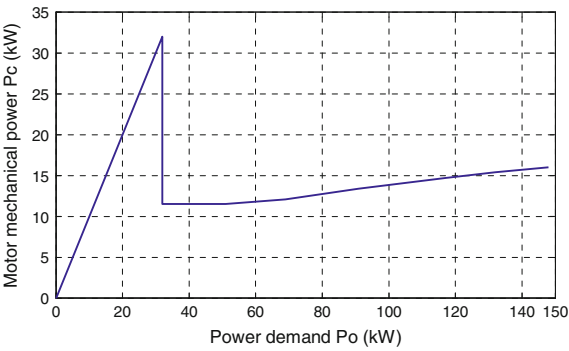


Table 4.4 Constant speed cycle simulation results

Vehicle speed (mph)	Fuel consumption (kg) (AED)		Fuel consumption (kg) (optimal power)	Fuel savings (%) comparison to results from PSAT
	Analytical	PSAT	PSAT	
30	1.13	1.45	1.45	0
40	1.79	1.84	1.84	0
50	2.64	2.66	2.66	0
60	3.68	3.61	3.60	0.28
70	4.90	4.82	4.76	1.25
80	6.35	6.11	6.04	1.15
90	7.83	7.85	7.54	3.95

proposed optimal power strategy and the default all-electric drive (AED) strategy. For ease of comparison, in the same table, we have also listed the fuel economy of the AED strategy calculated using the analytical method from the previous section. It can be seen from Table 4.4 that, (1) the simulated fuel economy is very close to the calculated fuel economy shown in Table 4.3. Hence it validates the equations and parameters derived in the Sect. 4.1.2; (2) there is no improvement at 30, 40, 50 and 60 mph by using the proposed optimal power strategy because the power demand is less than the threshold for the engine to be turned on. As the power demand increases, the proposed optimal power strategy shows fuel savings at 70, 80, and 90 mph.

4.1.5 Implementation of the Control Strategy in Standard Driving Cycles

The above simple simulation shows that the proposed control strategy can help save fuel as the power demand increases. Since power demand in transient drive cycles is much higher, the estimated fuel savings can be more significant. Hence, it is important to see how well the proposed strategy performs in various transient

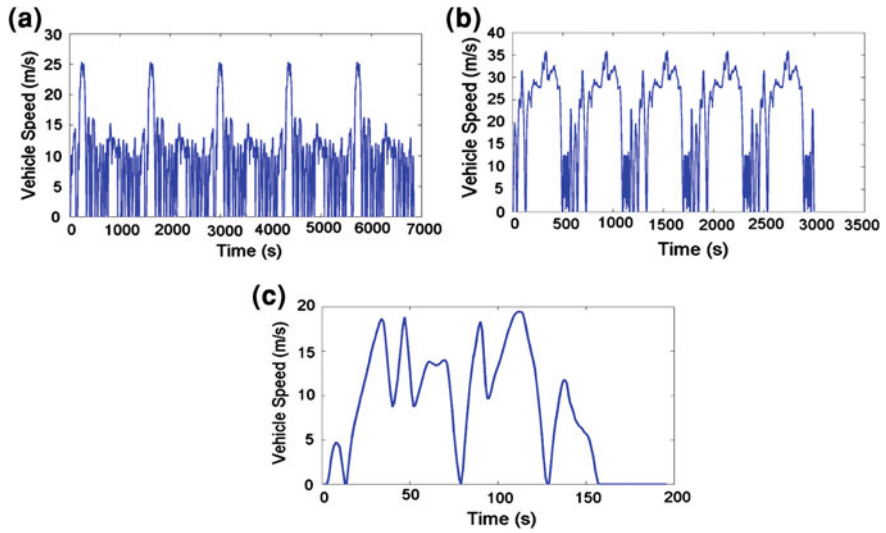


Fig. 4.7 The speed profile of three drive cycles used for the study. **a** Five consecutive UDDS. **b** Five consecutive US 06. **c** CR city cycle

Table 4.5 Comparison among these three cycles

	Maximum speed (mph)	Average speed (mph)	Maximum acceleration (m/s ²)	Maximum deceleration (m/s ²)	Cycle distance (miles)	Total # of cycles
UDDS	56.7	19.6	1.48	−1.48	7.45	5
US06	80.3	50.0	3.76	−3.1	8.01	5
CR City	43.4	18.4	2.6	−3.31	1.00	40

drive cycles. For this purpose, the proposed strategy is applied to UDDS, US06, and CR City Cycle as shown in Fig. 4.7.

Compared to UDDS, US06 and CR-city cycles are more aggressive in terms of acceleration and deceleration, thus better simulate aggressive driving conditions in the real world. A comparison among the three cycles is shown in Table 4.5.

The electric drive range was also tested in the UDDS drive cycle. The SUV can run 23 miles in electric driving until the battery SOC drops to 0.3, as shown in Fig. 4.8. The results indicate the battery parameters selected for the SUV are appropriate.

For fuel economy comparison, the battery final SOC must be at the same level, so SOC correction is necessary. In references [16, 17], the linear regression method was used to ensure that the initial and final SOC are the same. In this chapter’s discussion, the initial SOC is 1.0, the target end SOC value is 0.3, so the difference between the final SOC and target value is considered. The linear fitting was adopted to determine the fuel consumption by setting the difference value to

Fig. 4.8 The electric range in UDDS

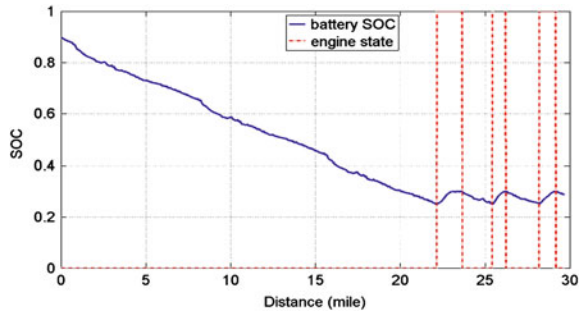
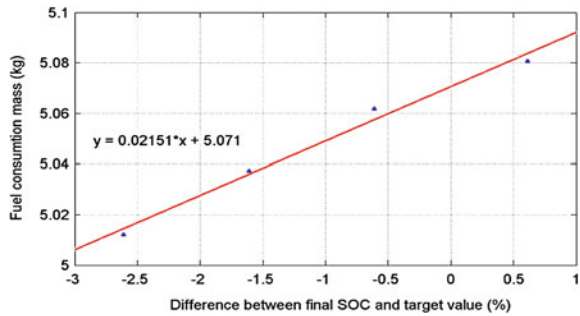


Fig. 4.9 Example of SOC correction in a random driving cycle



zero. Figure 4.9 shows an example of SOC correction for fuel consumption in a random driving cycle. In Fig. 4.9 the negative difference in X-axis means battery was depleted more and vice versa, leading to better or worse fuel economy.

Different drive cycles are simulated in PSAT by incorporating the proposed optimal power control strategies. Figure 4.10 shows the power demand of the different drive cycles. The power distribution between the engine and motor are determined by the proposed optimal power control strategy. Figure 4.11 shows the power distribution between the engine and motor for different drive cycles. It can be seen that the power distribution between the engine and the motor follows the proposed optimal power strategy. When power demand is less than the optimal power threshold, i.e., $P_o > P_{c\_opt}$, the engine remains off. When the power demand exceeds this threshold, the engine is turned on and the motor provides power assistance according to control parameters shown in Fig. 4.6.

Figure 4.11b–e show the power distribution between the engine and motor for the UDDS and US06 drive cycles. It can be seen that since the power demand in the UDDS drive cycle is relatively low, the engine turn-on time is much less than in CR-City and US06 drive cycles. It is observed that only a portion of the negative power is recovered by the motor through regenerative braking. This is consistent with the general practice in HEV control in which frictional brakes are used to ensure vehicle stability and safety. It can also be observed from Fig. 4.11 that summation of motor power and engine power is more than the total power demand. This is due to the fact that the motor and engine power has to overcome

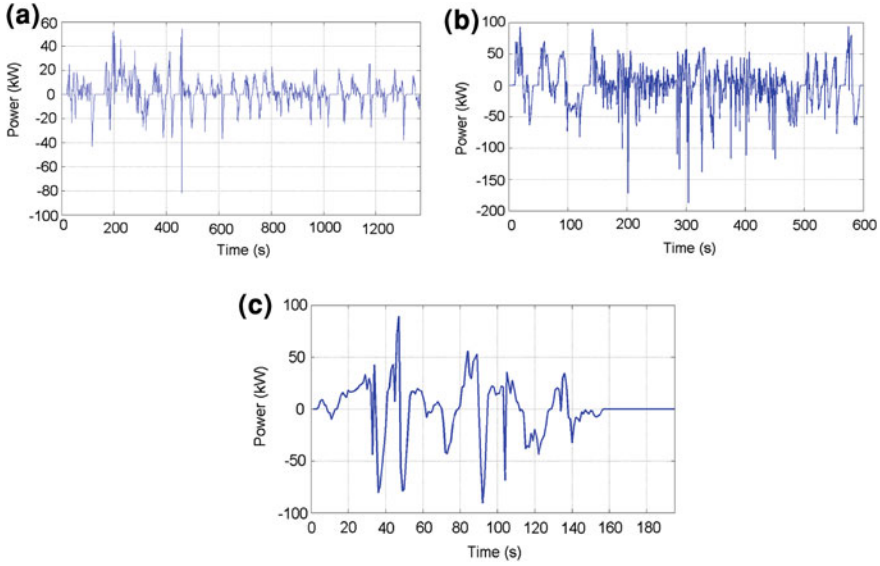


Fig. 4.10 Total power demand of different drive cycles. **a** Power demand in UDDS cycle. **b** Power demand in US06 cycle. **c** Power demand in CR-city cycle

the drive losses and supply power to the auxiliary power demand which is not included in the vehicle power demand shown in Fig. 4.10.

In blended-mode PHEVs, the motor power is not sufficient to realize the AER control strategy in high power demands. The engine provides most of the driving torque in the engine dominant strategy, which is obviously not beneficial for fuel economy. Therefore, only the electric dominant strategy was used for comparison. The simulation results of the PHEV are shown in Tables 4.5 and 4.6 which contain the value of fuel mass after SOC correction in the constant-speed cycle and typical drive cycle scenario. For the purpose of comparing fuel consumption results with various strategies, the fuel consumption obtained with the electric dominant control strategy is taken as the baseline. It can be seen that the optimal power strategy improves by 4.0, 4.2 and 2.56% in 5UDDS, CR city and 5US06, respectively. In the constant-speed profile, there is no improvement at speeds of 30, 40, 50 and 60 mph. The reason is that the power demand is less than the threshold for the engine to be turned on.

The fuel savings shown in Table 4.6 obtained by the proposed optimal power strategy is primarily due to the reduction in electric system losses. As discussed earlier, the electric system losses increase significantly as the power increases. Hence, there is a threshold at which it is beneficial to turn on the engine to provide the main power for propulsion power demand while using the motor to supplement the power demand. However, it is important to make sure the available battery energy is consumed at the end of the drive cycle otherwise the battery is under-utilized.

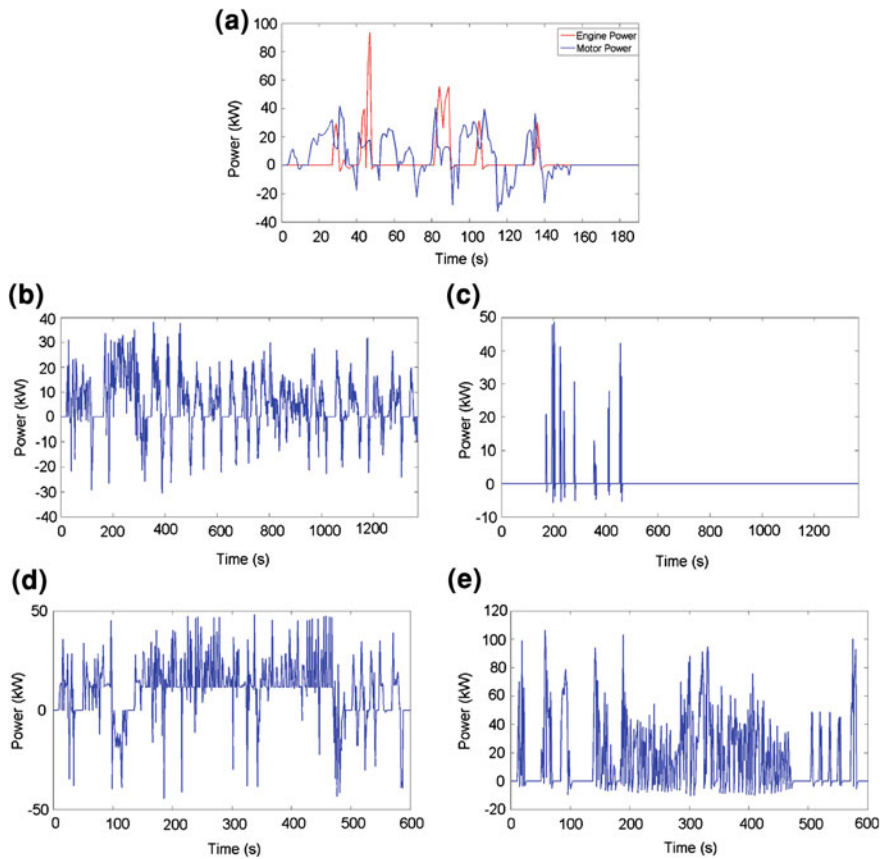


Fig. 4.11 Power distribution between engine and motor for different drive cycles. **a** Power distribution between engine and motor for the CR-city cycle. **b** Motor power in UDDS cycle. **c** Engine power in UDDS cycle. **d** Motor power in US06 cycle. **e** Engine power in US06 cycle

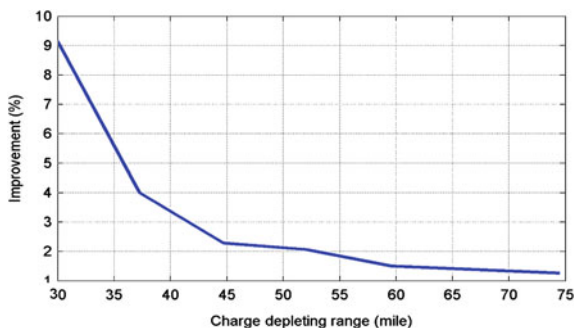
Table 4.6 Typical drive cycle simulation results

Drive cycle	AED fuel consumption (kg)	Optimal power fuel consumption (kg)	Improve (%)
5UDDS	2.25	2.16	4.0
CR city	5.72	5.48	4.2
5US06	5.47	5.33	2.56

In order to evaluate the fuel economy using the same battery parameters with different CD ranges, different consecutive UDDS was adopted. As shown in Fig. 4.12, the proposed control strategy also achieves better fuel economy than the electric dominant control strategy even if the range is greater than 40 miles, but the percentage of improvement reduces.

In real-world driving, the trip distance and energy consumption are not precisely known. Modern vehicular navigation systems may provide trip information

Fig. 4.12 The improvement with different CD ranges in UDDS



to be used by the CD strategies. Since the proposed strategy requires only the trip distance and the all-electric range (or battery energy status) of the vehicle, it should be feasible to implement this control strategy in real vehicle applications using estimated trip information.

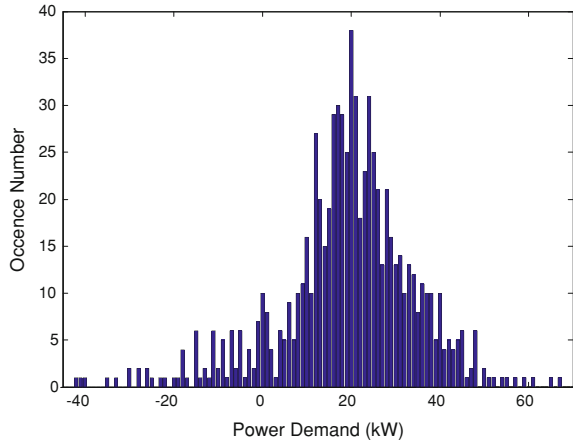
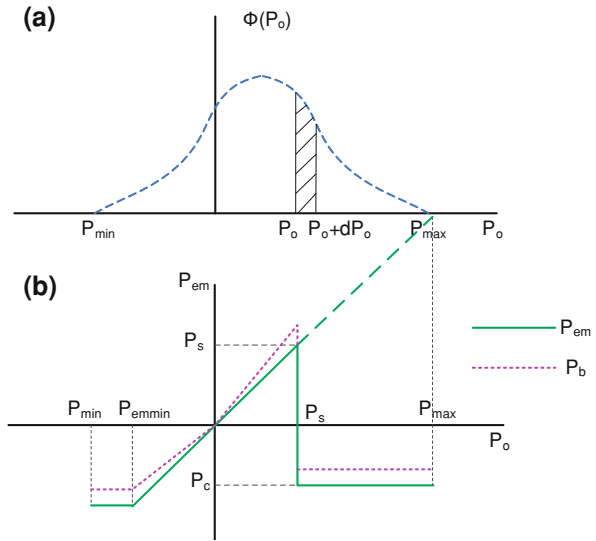
In this section, a control strategy was developed based on optimal power operations of the PHEV analyzed through constant vehicle speed operations. A middle-size plug-in SUV model was built in PSAT, and three typical cycles were used to evaluate the fuel consumption. If the trip distance is shorter than the all-electric range and the power demand is low, the AER control strategy is the best. If the drive cycle is more aggressive, the AER will not meet the requirement of high power demands. If the trip distance exceeds the all-electric range, the optimal power strategy can perform better than the electric dominant control strategy.

We only consider the total fuel consumption during specific drive cycles based on the electric system loss characteristics, vehicle power demand, total battery energy, and trip distance. It does not rely on the detailed trip information other than the total trip distance. Therefore, it is possible to implement the control strategy in real time if the total distance is known before the trip. Since most people commuting to work know their approximate driving distance, this control strategy can potentially provide significant fuel savings.

Only fuel usage is considered as the optimization objective. It is possible to calculate the total energy consumptions which include fuel and electric energy. Hence the proposed analytical approach can also be used to minimize total energy consumptions for given drive cycles.

4.2 Unified Analytical Solution

The above control strategy is developed through the analysis on constant speed driving. The control strategy is then applied to a standard driving cycle to test the effectiveness. In this section, we will look at the more generic control strategy development. In a typical drive cycle, the distribution of vehicle power demand is shown in Fig. 4.13.

Fig. 4.13 Vehicle power distributions**Fig. 4.14** Power management strategy used in this chapter

It can be seen that the distribution follows Cauchy distribution or superposition of Cauchy distributions which is limited by the minimum and maximum power. Hence we can use an idealized curve as shown in Fig. 4.14a to represent the power distribution. Specifically, the shadow area $\Phi(P_o)dP_o$ represents the time that the transmission output power change from P_o to $P_o + dP_o$. Therefore, the total vehicle operation time in one drive cycle is considered as the integration of time over the whole power range. It is defined as

$$T = \int_{P_{min}}^{P_{max}} \Phi(P_o) dP_o \quad (4.24)$$

In this drive cycle, the average output power $\overline{P_o}$ is

$$\overline{P_o} = \frac{\int_0^T P_o dt}{T} = \frac{\int_{P_{\min}}^{P_{\max}} P_o \Phi(P_o) dP_o}{T} \quad (4.25)$$

The control objective is to maximize the use of electric power during driving when the power demand P_o is less than a threshold P_s . Otherwise, the engine will start to run to meet desired output power and desired electric system recharging power P_c . The constant recharging power is maintained during engine running. This strategy in one drive cycle is shown in Fig. 4.14b.

This strategy can be expressed as a linear piecewise function shown below:

$$P_{em} = \begin{cases} P_{em \min} & P_o < P_{em \min} \\ P_o & P_{em \min} < P_o < P_s \\ P_c & P_s < P_o < P_{em \max} \end{cases} \quad (4.26)$$

where $P_{em \min}$ is the maximum regenerative power, P_s is the power point at which the engine will be turned on and P_c is the constant recharging power during engine running.

4.2.1 The Total Fuel Consumption and Total Battery Energy

Since the engine starts after P_o reaches the threshold P_s , the total fuel consumption in this drive cycle can be defined as:

$$\begin{aligned} X(P_s, P_c) &= \int_{t_s}^T f(t) dt = \int_{P_s}^{P_{\max}} f(P_{eng}) \Phi(P_o) dP_o \\ &= \int_{P_s}^{P_{\max}} (f_o + k P_{eng}) \Phi(P_o) dP_o = \int_{P_s}^{P_{\max}} [f_o + k(P_o - P_c)] \Phi(P_o) dP_o \end{aligned} \quad (4.27)$$

It is desirable to use as much battery energy as possible until the vehicle reaches its destination, i.e., battery SOC is expected to drop to the lowest possible level. Therefore, the total net battery energy consumed in this driving cycle can be defined as the integral of battery power P_b over the whole drive cycle $[0, T]$ and is considered as a constant.

$$E_b(P_s, P_c) = \int_0^T P_b dt = \int_{P_{\min}}^{P_{\max}} P_b \Phi(P_o) dP_o = \text{const.} \quad (4.28)$$

The above equation can be expanded as

$$\begin{aligned}
 E_b(P_s, P_c) &= \int_0^T P_b dt = \int_{P_{\min}}^{P_{\max}} P_b \Phi(P_o) dP_o \\
 &= \int_{P_{em \min}}^{P_{\max}} [P_{em} + Loss(P_{em})] \Phi(P_o) dP_o \\
 &= \int_{P_{\min}}^{P_{em \min}} [P_{em \min} + Loss(P_{em \min})] \Phi(P_o) dP_o \\
 &\quad + \int_{P_s}^{P_{\min}} [P_o + Loss(P_o)] \Phi(P_o) dP_o \\
 &\quad + \int_{P_s}^{P_{em \min}} [P_c + Loss(P_c)] \Phi(P_o) dP_o
 \end{aligned} \tag{4.29}$$

In this equation, the loss function is approximated as a 2nd order polynomial.

$$Loss(x) = L_o + Ax + Bx^2, \quad x = P_{em \min} \text{ or } P_o \text{ or } P_c \tag{4.30}$$

The maximum energy needed for the whole drive cycle can be obtained when the desired output power is only provided by the electric motor in the whole cycle.

$$\begin{aligned}
 E_{b \max}(P_s, P_c) &= E_b(P_{\max}, 0) \\
 &= \int_{P_{\min}}^{P_{em \min}} [P_{em \min} + Loss(P_{em \min})] \Phi(P_o) dP_o \\
 &\quad + \int_{P_{em \min}}^{P_{\max}} [P_o + Loss(P_o)] \Phi(P_o) dP_o
 \end{aligned} \tag{4.31}$$

This $E_{b \max}$ is a constant for a given drive cycle. The difference between E_b and $E_{b \max}$ is:

$$\begin{aligned}
 E(P_s, P_c) &= E_{b \max}(P_{\max}, 0) - E_b(P_s, P_c) \\
 &= \int_{P_{em \min}}^{P_{\max}} [P_o + Loss(P_o)] \Phi(P_o) dP_o - \int_{P_{em \min}}^{P_s} [P_o + Loss(P_o)] \Phi(P_o) dP_o \\
 &\quad - \int_{P_s}^{P_{em \min}} [P_c + Loss(P_c)] \Phi(P_o) dP_o \\
 &= \int_{P_s}^{P_{\max}} [P_o + Loss(P_o)] \Phi(P_o) dP_o - \int_{P_s}^{P_{em \min}} [P_c + Loss(P_c)] \Phi(P_o) dP_o
 \end{aligned} \tag{4.32}$$

Since both $E_{b\max}$ and E_b are constant, $E(P_s, P_c)$ is also a constant. In other words, $\frac{dE(P_s, P_c)}{dt} = 0$. This definition will be used in the next section. If we define:

$$\Psi_o(P_s) = \int_{P_s}^{P_{\max}} \Phi(P_o) dP_o, \text{ then } \frac{d\Psi_o(P_s)}{dP_s} = -\Phi(P_s) \quad (4.33)$$

$$\Psi_1(P_s) = \int_{P_s}^{P_{\max}} P_o \Phi(P_o) dP_o, \text{ then } \frac{d\Psi_1(P_s)}{dP_s} = -P_s \Phi(P_s) \quad (4.34)$$

$$\Psi_2(P_s) = \int_{P_s}^{P_{\max}} P_o^2 \Phi(P_o) dP_o, \text{ then } \frac{d\Psi_2(P_s)}{dP_s} = -P_s^2 \Phi(P_s) \quad (4.35)$$

Equations 4.27 and 4.32 can be simplified as follows:

$$X(P_s, P_c) = f_o \Psi_o + k \Psi_1 - k P_c \Psi_o \quad (4.36)$$

$$E(P_s, P_c) = (1 + A) \Psi_1 + B \Psi_2 - (1 + A) P_c \Psi_o - B P_c^2 \Psi_o \quad (4.37)$$

4.2.2 Optimization Strategy

The main objective of the control strategy optimization is to minimize the fuel consumption by coordinating the operations of two power resources: battery and ICE. Therefore, the optimal problem is to minimize the fuel consumption for a given battery energy. Therefore, we can formulate the optimization problem as:

$$\text{Minimize } \{X(P_s, P_c) = f_o \Psi_o + k \Psi_1 - k P_c \Psi_o\} \quad (4.38)$$

Subject to:

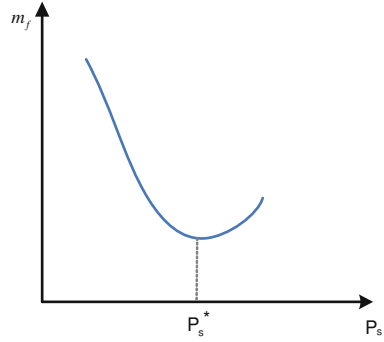
$$\frac{dE(P_s, P_c)}{dP_s} = 0 \quad (4.39)$$

$$E_b(P_s, P_c) = \text{const.} \quad (4.40)$$

Constraint Eq. 4.39, which was written in a derivative form instead of $E(P_s, P_c) = 0$, is for convenience of further analysis. In other words, it is used to find the solutions of the derivative function of Eq. 4.38. Hence, the optimization problem can be expressed as:

$$\frac{dX(P_s, P_c)}{dP_s} = 0 \quad (4.41)$$

Fig. 4.15 The optimization problem



Expressed in a figure, it is to find the optimal solutions P_s^* and P_c^* corresponding to the minimum m_f , where P_s^* is the optimal power threshold to turn on the engine Fig. 4.15.

The derivation of the total fuel consumption is:

$$\frac{dX(P_s, P_c)}{dP_s} = -f_o\Phi(P_s) - kP_s\Phi(P_s) + kP_c\Phi(P_s) - k\Psi_o \frac{dP_c}{dP_s} \quad (4.42)$$

Here k is a constant related to the engine combustion efficiency. By simplifying Eq. 4.39, the following equation can be obtained.

$$\frac{dP_c}{dP_s} = \frac{-(1+A)\Phi(P_s)(P_s - P_c) - B\Phi(P_s)(P_s^2 - P_c^2)}{(1+A+2BP_c)\Psi_o} \quad (4.43)$$

Substituting $\frac{dP_c}{dP_s}$ in Eq. 4.42 by the expression in Eq. 4.43, we can obtain

$$\frac{dX(P_s, P_c)}{dP_s} = -\Phi(P_s) \left[f_o - \frac{kB(P_s - P_c)^2}{1+A+2BP_c} \right] = 0 \quad (4.44)$$

Solutions of Eq. 4.44 are the optimal solutions P_s^* and P_c^* corresponding to the minimum X . Therefore the optimal solutions satisfy:

$$f_o = \frac{kB(P_s^* - P_c^*)^2}{1+A+2BP_c^*} \quad (4.45)$$

or

$$P_s^* - P_c^* \approx \sqrt{\frac{f_o(1+A+2BP_c^*)}{kB}} \quad (4.46)$$

Since $A+2BP_c^*$ is much smaller than 1, Eq. 4.46 can be further simplified as

$$P_s^* - P_c^* \approx \sqrt{\frac{f_o}{kB}} \quad (4.47)$$

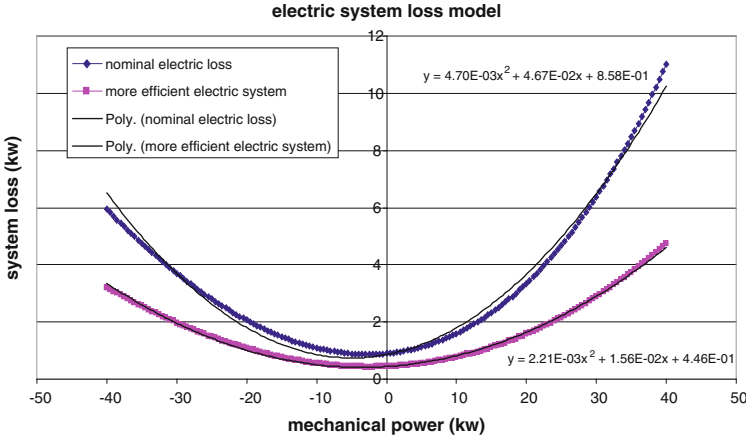


Fig. 4.16 Electric drive system loss models

Combined with Eq. 4.28, the optimal solutions P_s^* and P_c^* can be obtained. It is obvious that Eq. 4.47 does not require particular properties of the distribution function, but the power distribution function affects the optimal solutions P_s^* and P_c^* . This solution is consistent with the results derived in Sect. 4.1.

4.2.3 Model Setup for the Powertrain Components

In the following, all system parameters used to construct the simulation model are obtained from real-word experiments. The model characteristics and parameters are described as follows. For a given set of system characteristics, power distribution characteristics, and net battery energy depletion, a pair of optimal P_s^* and P_c^* that yield minimal fuel consumption can be solved.

A. Electric Drive System Loss Model Characteristics

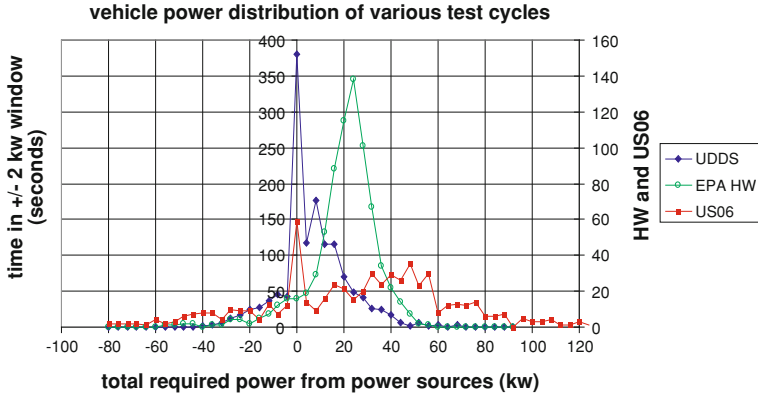
Figure 4.16 shows the losses for a nominal electric loss system and an improved electric loss system, which are determined by the peak efficiency and mechanical power output from the motor and battery. They can be modeled as 2nd polynomials. The loss system parameters are shown in Table 4.7, where V_0 is the battery nominal voltage and R is the nominal DC impedance.

B. Output Power Distribution Model

The propulsion system delivers required power for vehicle operations in any defined cycle tests. The distributions of P_o from the nominal vehicle in three common driving-cycle tests: UDDS, EPA HW and US06, are shown in Fig. 4.17.

Table 4.7 Electric system loss model

	Baseline (ES1)	Improved (ES2)	Improved (ES3)
V_0 (V)	345	345	345
R (ohms)	0.3	0.3	0.15
L_0 (kW)	0.86	0.42	0.45
A	0.0467	0.0297	0.0156
B (1/kW)	0.0047	0.00366	0.00221

**Fig. 4.17** Output power distribution in UDDS, EPA HW and US06

For a given total energy, the distribution of P_o can be modeled as a Cauchy distribution or superposition of Cauchy distribution, limited by the minimum and maximum powers. The distribution function is characterized by the peak power, average power and the power width at half height.

$$\Phi(P_o) = \frac{h}{1 + \left(\frac{P_o - P_{ave}}{P_w} \right)^2} \quad \text{For } P_{\min} \leq P_o \leq P_{\max} \quad (4.48)$$

where h is the peak value of $\Phi(P_o)$, P_{ave} is the average power, and P_w is the half width of the peak (at a half height).

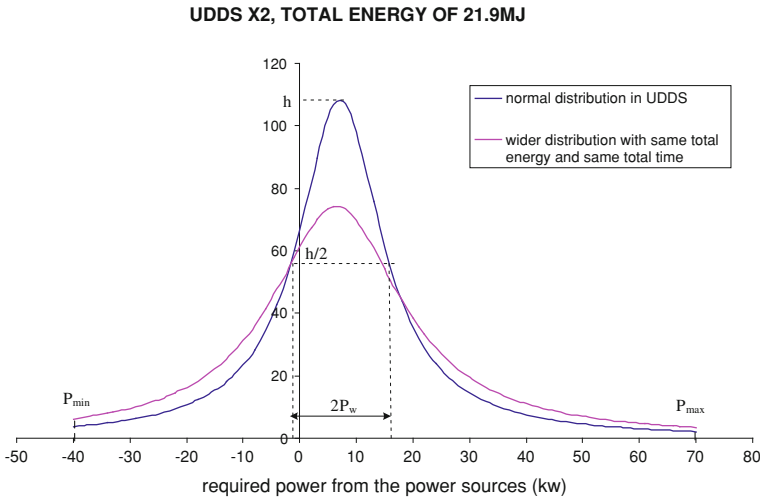
The vehicle operation time and the total energy (Ω) in this drive cycle are given by

$$T = \int_{P_{\min}}^{P_{\max}} \Phi(P_o) dP_o = hP_w \arctan \left(\frac{P_o - P_{ave}}{P_w} \right) \Big|_{P_o=P_{\min}}^{P_o=P_{\max}} \quad (4.49)$$

and

Table 4.8 Drive cycle details

	h (1/kJ)	P_{ave} (kW)	P_w (kW)	P_{min} (kW)	P_{max} (kW)	T (sec)	E (MJ)
UDDS1	108.3	7.1	9	-40	70	2741	21.92
UDDS2	74.3	6.45	14	-40	70	2740	21.93
HW1	30.3	20.5	9	-60	60	765.7	14.00
HW2	20.85	22.2	14	-60	60	765.0	14.02

**Fig. 4.18** Normal and wider distribution in UDDS

$$\begin{aligned}
 e &= \int_{P_{min}}^{P_{max}} P_o \Phi(P_o) dP_o \\
 &= \left\{ \frac{hP_w^2}{2} \ln \left[1 + \left(\frac{P_o - P_{ave}}{P_w} \right)^2 \right] + hP_w P_{ave} \arctan \left(\frac{P_o - P_{ave}}{P_w} \right) \right\} \bigg|_{P_o=P_{min}}^{P_o=P_{max}}
 \end{aligned} \tag{4.50}$$

Parameters in Table 4.8 are used to model normal and wider power distributions with the same total energy and time operation in UDDS and EPA HW drive cycles. “1” means the normal power distributions and “2” means the wider power distributions. The distributions for UDDS and EPA HW are shown in Figs. 4.18 and 4.19, respectively.

C. Engine Model Characteristics

A linear relationship between the fuel consumption rate and the engine output power is considered next. Two different engines, i.e., nominal engine and improved engine, are modeled in Fig. 4.20, and the modeling parameters are listed

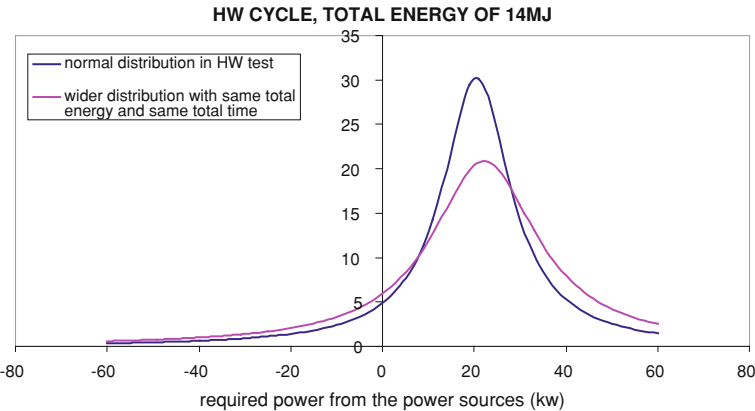


Fig. 4.19 Normal and wider distribution in EPA HW

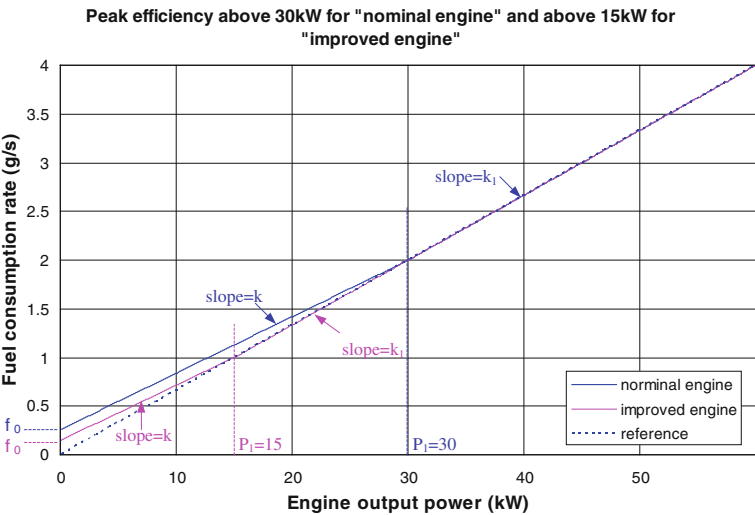


Fig. 4.20 Fuel consumption rate at different engine output powers

Table 4.9 Engine fuel rate parameters

	Nominal engine	Improved engine
f_0 (grams/s)	0.26	0.15
K (grams/s/kW)	0.058	0.05667
P_1 (kW)	30	15
K_1 (g/s/kW)	0.06667	0.06667

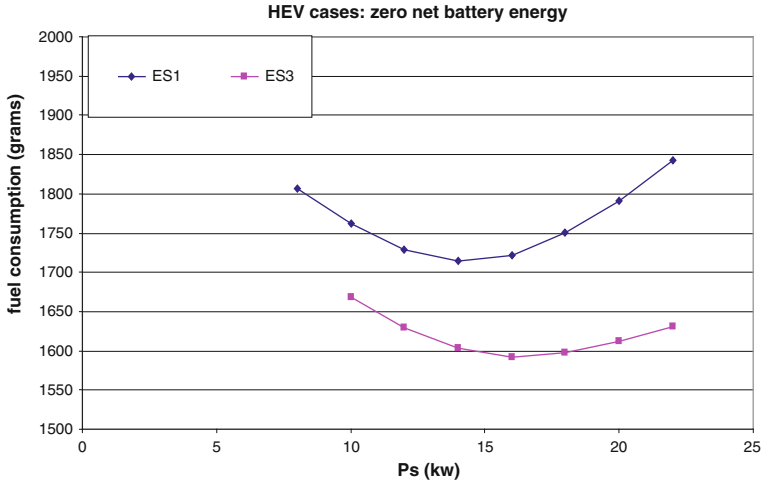


Fig. 4.21 Fuel consumption versus engine output power in UDDS1 with zero battery net energy

in Table 4.9. Because of the close slopes, when the engine output power is higher than 30 kW, the fuel consumption rate for improved engine is very close to that for the nominal engine.

Parameters f_o , k , P_1 , and k_1 are marked in Fig. 4.20 and Table 4.9 will be used for engine piecewise linear model discussion in the next section.

4.2.4 Results and Discussion

Minimizing total fuel consumption in a drive cycle while maintaining a constant battery net energy leads to optimal solutions for a given set of system parameters and output power distribution. This section will discuss the characteristics of the optimal solutions.

4.2.4.1 General Properties of Optimal Solutions (P_s^* , P_c^*)

We first look at the charge-sustaining operation of the PHEV. In other words, the net battery energy consumed in the whole drive cycle is zero. Figure 4.21 shows the dependence of the total fuel consumption on P_s^* in cases of UDDS1 drive cycle, and nominal engine with different electric losses (baseline electric drive ES1 and improved electric drive ES3).

In the following we look at the fuel consumption during charge-depleting mode. Figure 4.22 shows the dependence of the total fuel consumption on P_s^* for the previously indicated cases (ES1 and ES3) during UDDS1 drive cycle in

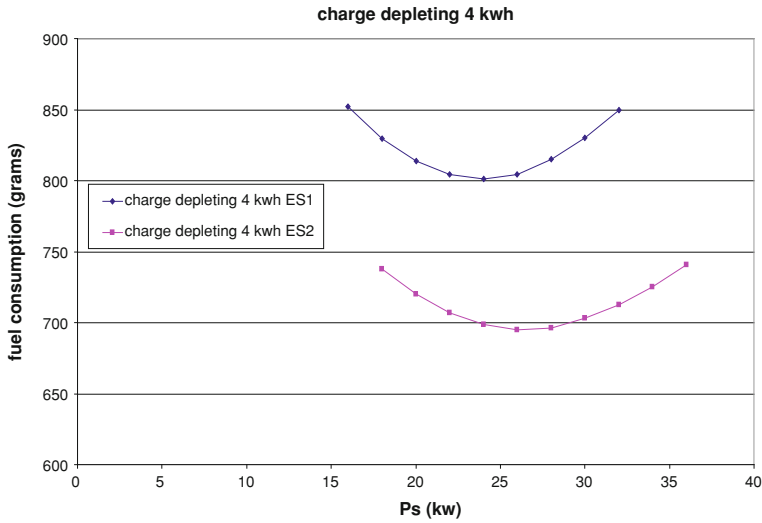


Fig. 4.22 Fuel consumption versus engine output power in UDDS1 with 4 kWh battery net energy

charger-depletion mode with a total of 4 kWh battery energy consumed during the whole drive cycle.

As a result, the total fuel consumption is reduced by using optimal P_s^* and P_c^* . It reduces by around 5% in case of zero net battery energy and 7% in case of charge depleting 4 kWh net battery energy. The higher electric loss model results in the higher fuel consumption. In addition, the higher electric loss model tends to have a higher sensitivity or curvature at the optimal P_s^* . This can be explained by the dependence of the local curvature on electric loss coefficients A and B .

With the UDDS1 drive cycle, nominal engine and baseline electric drive losses, the optimal P_s^* and P_c^* at different net battery energy are shown in Fig. 4.23. Both optimal P_s^* and P_c^* increase with the increase of the net battery energy, yet $P_s^* - P_c^*$ has almost no dependence on the net available battery energy as expected. $P_s^* - P_c^*$ mainly depends on engine characteristics and electric loss coefficient B .

With the same drive cycle UDDS1 and electric driving loss (ES1) parameters, the fuel consumption for the nominal engine and the improved engine are shown in Fig. 4.24. As a result, the improved engine only improves fuel consumption slightly, by about 2% at the low net battery energy. At the higher net battery energy, the improvement is minor since the engine operates at the high output power in this situation, so the fuel consumption for improved engine is very close to that for the nominal engine.

The impacts of vehicle system properties on P_s^* and $P_s^* - P_c^*$ will be discussed next. Here the vehicle system properties include electric driving system losses, power distributions and engine models. Results will be in turn shown for the following cases.

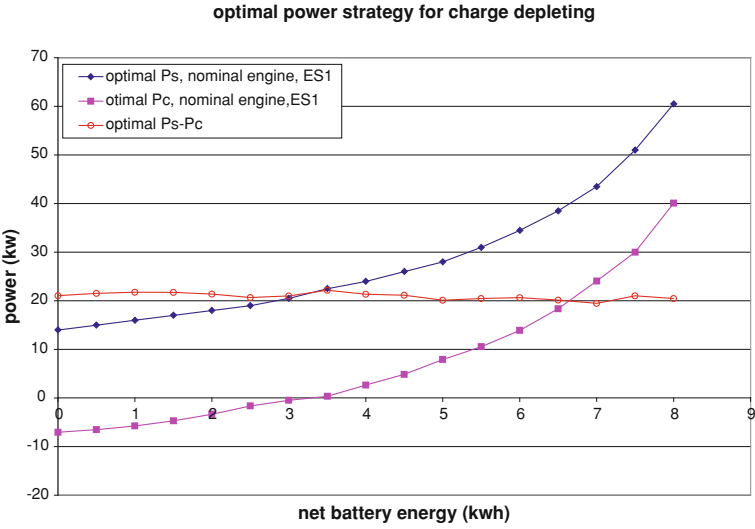


Fig. 4.23 Optimal P_s^* , P_c^* , and $P_s^* - P_c^*$ at different net available battery energy

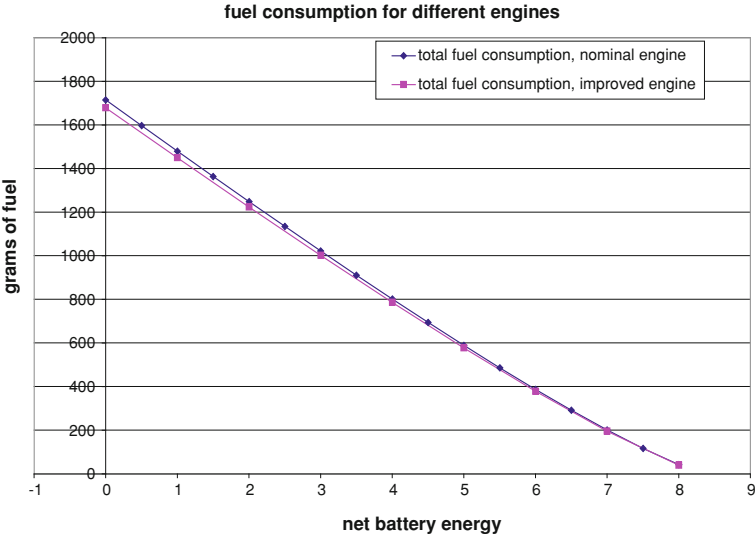


Fig. 4.24 Fuel consumption versus net battery energy for different engines

Figure 4.25 shows the effect of different electric driveline loss models on optimal solutions.

In this case, optimal solutions P_s^* with low electric loss (ES3) are higher than baseline (ES1) solutions because the lower electric loss results in the higher

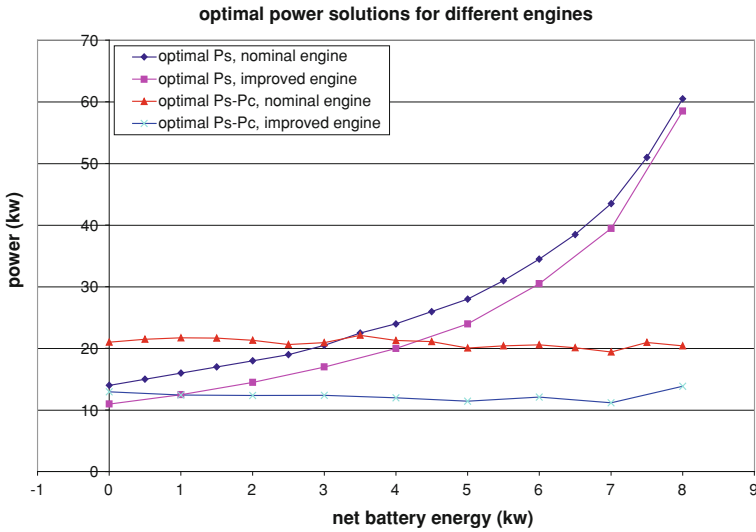


Fig. 4.25 Optimal P_s^* and $P_s^* - P_c^*$ versus net battery energy for different engines

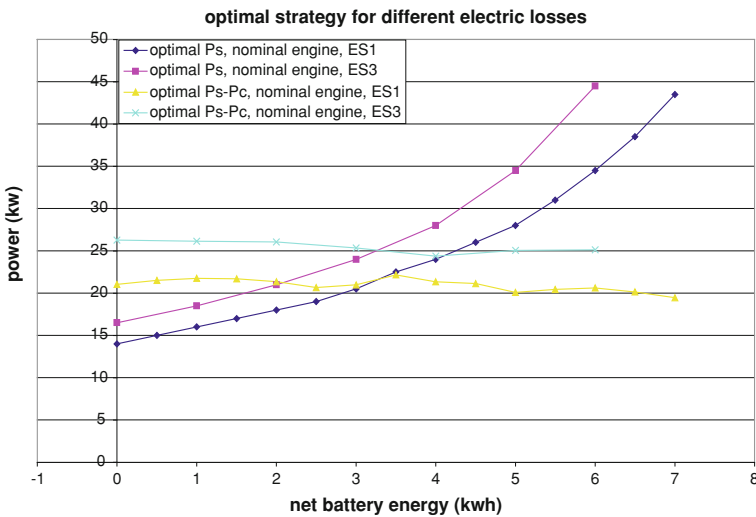


Fig. 4.26 Optimal P_s^* and $P_s^* - P_c^*$ versus net battery energy for the different electric losses

electric output power. In addition, solutions $P_s^* - P_c^*$ with ES3 are higher than ES1 solutions since $P_s^* - P_c^*$ depends inversely on the electric loss coefficient B .

The effect of the different power distribution models on optimal solutions is shown in Fig. 4.26. It can be seen from this figure, in the case of wider power distribution UDDS2, the optimal P_s^* is higher than the values for normal

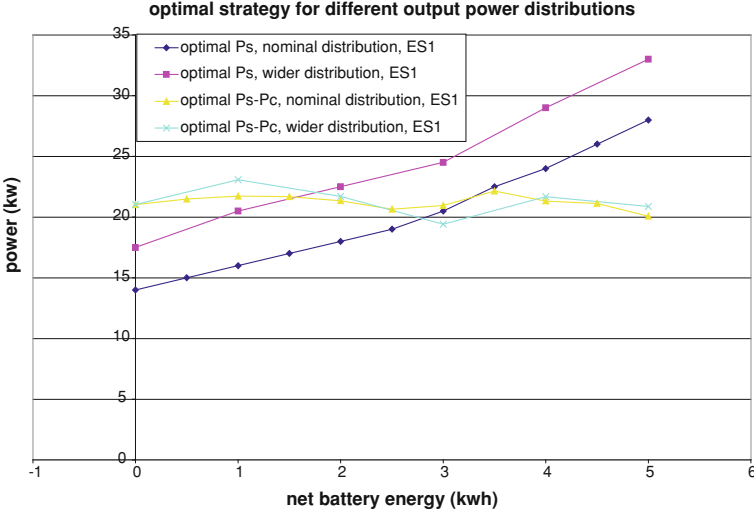


Fig. 4.27 Optimal P_s^* and $P_s^* - P_c^*$ versus net battery energy for the different power distributions

distribution, but optimal $P_s^* - P_c^*$ remains the same. That's because optimal $P_s^* - P_c^*$ is only influenced by engine properties and system electric loss models. The effect of the different engine models on optimal solutions is shown in Fig. 4.27.

In this figure, the optimal power solutions for the improved engine move to low values, and $P_s^* - P_c^*$ for the improved engine is lower than the values for the nominal engine as expected, because the improved engine has the lower engine coefficient f_0/k .

4.2.4.2 Verification of $P_s^* - P_c^*$ approximation

For any power distribution and system properties characterized by this study, the optimal $P_s^* - P_c^*$ that minimizes the total fuel for constant battery energy can be obtained by the piecewise linear engine model in following equation.

$$f = \begin{cases} f_0 + kP_{eng} & P_{eng} \leq P_1 \\ k_1 P_{eng} & P_{eng} > P_1 \end{cases} \quad (4.51)$$

Note that $k_1 \geq k$. Then optimal solutions satisfy

$$\frac{dX(P_s, P_c)}{dP_s} = -\Phi(P_s) \left[f_0 + (k - k_{1eff})(P_s - P_c) - \frac{k_{1eff}B(P_s - P_c)^2}{1 + A + 2BP_c} \right] = 0 \quad (4.52)$$

and $P_s^* - P_c^* \leq P_1$.

Therefore, the following approximation with reasonable accuracy can be utilized to obtain the optimal solutions in the piecewise linear engine model.

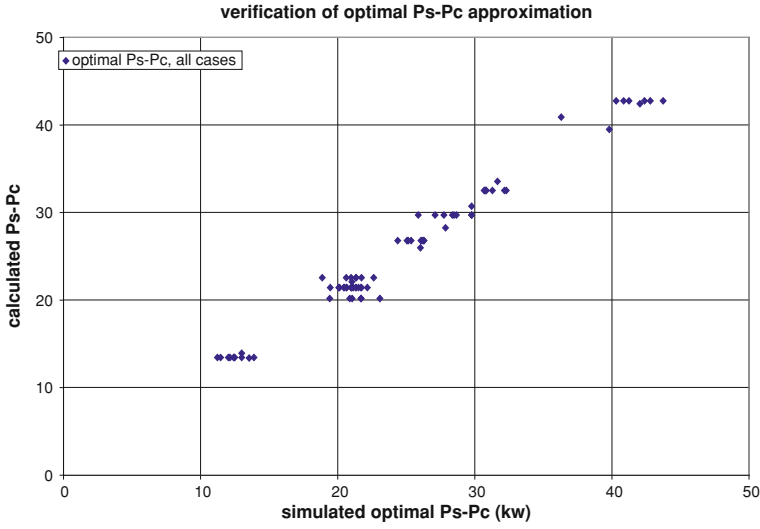


Fig. 4.28 The comparison between simulated $P_s^* - P_c^*$ and calculated $P_s^* - P_c^*$ using the approximation

$$P_s^* - P_c^* \approx (k - k_{1eff} + \frac{\sqrt{(k - k_{1eff})^2 + 4k_{1eff}B'f_o}}{2k_{1eff}B'}) \quad (4.53)$$

where $B' = \frac{B}{1+A}$ and $k < k_{1eff} < k_1$. k_{1eff} is introduced by the non-linearity of the engine model. Since $k - k_{1eff} \leq 0$, $P_s^* - P_c^*$ is reduced from the solution in the linear engine case. Figure 4.28 shows the comparison between simulated $P_s^* - P_c^*$ and calculated $P_s^* - P_c^*$ for all simulation cases, where the horizontal axis is the simulated $P_s^* - P_c^*$ with the optimal solution, and the vertical axis is the calculated $P_s^* - P_c^*$ from the approximation.

4.2.4.3 Case for Constant Engine Power

Using the same equations derived, we can study the fuel economy for other control strategies. In the case for constant engine power, the fuel consumption and battery energy can be expressed by P_s and P_{eng} , and $P_c = P_o - P_{eng}$. So

$$X(P_s, P_c) = f_o \Psi_o + k P_{eng} \Psi_o \quad (4.54)$$

$$E(P_s, P_c) = 2BP_{eng} \Psi_1 + (1 + A)P_{eng} \Psi_o - BP_{eng}^2 \Psi_o \quad (4.55)$$

$$\frac{dX(P_s, P_c)}{dP_s} = -\Phi(P_s) \left[f_o - \frac{kBP_{eng}(2P_s + P_{eng} - 2\Psi_1/\Psi_o)^2}{1 + A + 2B(\Psi_1/\Psi_o - P_{eng})} \right] \quad (4.56)$$

This strategy is less efficient because of higher electric losses due to the non-constant P_c . Therefore, this strategy won't be explored further.

This section analyzed how to minimize the fuel consumption for an idealized parallel ICE-electric powertrain. We have theoretically derived the optimal power solutions based on the specific electric losses, engine and drive cycles. The results show that the fuel economy can be improved definitely for HEVs and PHEVs at the optimal power solutions. This strategy guarantees the optimal solutions for constant battery energy. The model in this chapter can be extended to study other power strategies. But the constant engine power strategy is less efficient because of higher electric losses due to the non-constant P_c . Therefore, only the constant battery energy strategy is explored in this chapter.

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Chapter 5

Wavelet Technology in Vehicle Power Management

5.1 Fundamentals of Wavelets and Filter Banks

A wavelet is a mathematical function utilized to divide a given function or continuous-time signal into different scale components. Wavelet analysis was originated and developed in the middle 1980s. The desire to analyze sensitive seismic signals that the Fourier techniques cannot deal with led to the first appearance of the continuous wavelet transform formula. The wavelet analysis technology has been applied successfully to many signal processing and compression problems including analysis of the electrocardiograms of the heart, sensor signals in robotics, ship vibration signals, etc.

The wavelet transform, as a function by wavelets, on the practical level is usually represented by a filter bank which is an array of band-pass filters that separates the input signal into several components, each one carrying a single frequency subband of the original signal.

We'll start the theoretical concepts with the first appearance of wavelet analysis, i.e., the continuous wavelet transform.

5.1.1 Continuous Wavelet Analysis

The continuous wavelet transform (CWT) was introduced by Morlet and his co-workers [1] to analyze geophysical signals with some kinds of modified windowed Fourier transform (WFT). Thus the Fourier transform is firstly described below.

5.1.1.1 Fourier Transform

The original time-domain signal $f(t)$ is multiplied with a certain “analysis function” and integrated about the time domain for all transforms of $f(t)$ discussed in this section. A transform in a symbolic notation reads

$$f(t) \rightarrow \int_{-\infty}^{+\infty} f(u) \overline{g(u)} du \quad (5.1)$$

where $g(u)$ is the “analysis function” characterizing the transform. This formula is also valid when the “analysis function” is complex-valued. In this case, the overline denotes complex conjugation. Another common aspect of all discussed transforms is invertibility: the original signal $f(t)$ may be reconstructed from the transformed signal [2].

The “analysis function” reads $g_\omega(u) = e^{ju\omega}$ where the angular frequency ω is the parameter relevant for the Fourier transform [2–4]. Substituting the “analysis function”, the transformed signal $\hat{f}(\omega)$ is expressed as

$$\hat{f}(\omega) = \int_{-\infty}^{+\infty} f(u) \overline{g_\omega(u)} du = \int_{-\infty}^{+\infty} f(u) \overline{e^{ju\omega}} du = \int_{-\infty}^{+\infty} f(u) e^{-ju\omega} du \quad (5.2)$$

The original signal may be reconstructed from the transformed signal:

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \hat{f}(\omega) e^{+j\omega t} d\omega \quad (5.3)$$

A notation for the one–one correspondence between a signal and its Fourier transform is to connect both entities to a “correspondence pair”:

$$f(t) \circ - \bullet \hat{f}(\omega) \quad (5.4)$$

5.1.1.2 Windowed Fourier Transform

This WFT is also called “Short Time Fourier Transform” (STFT). The WFT looks for the appearance of the angular frequency ω at a certain time t . The corresponding analysis function is denoted as $g_{(w,t)}(u) = e^{ju\omega} w(u-t)$, where $w(u)$ is a “window function”, usually centered about the origin. Thus the window is shifted from the origin to the desired time t in the expression $w(u-t)$. The transformed signal $\hat{f}_w(\omega, t)$ in the WFT depends on ω and t , expressed as [2, 5]:

$$\hat{f}_w(\omega, t) = \int_{-\infty}^{+\infty} f(u) \overline{g_{(w,t)}(u)} du \quad (5.5)$$

Substituting the expression of $g_{(w,t)}(u)$ into Eq. 5.5, the transformed signal can be rewritten as:

$$\hat{f}_w(\omega, t) = \int_{-\infty}^{+\infty} f(u) \overline{w(u-t)} e^{-ju\omega} du \quad (5.6)$$

The Fourier transform correspondence pair in Eq. 5.4 is used here, so Eq. 5.6 can be replaced as:

$$f(t) \overline{w(t-\tau)} \circ - \bullet \hat{f}_w(\omega, \tau) \quad (5.7)$$

The original continuous-time signal $f(t)$ may be reconstructed from the transformed signal $\hat{f}_w(\omega, \tau)$ [2, 5]:

$$f(t) = \frac{\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \hat{f}_w(\omega, \tau) w(t-\tau) e^{+j\omega t} d\omega d\tau}{2\pi \int_{-\infty}^{+\infty} |w(u)|^2 du} \quad (5.8)$$

This equation is the key for both designing a fast algorithm for computing the WFT and reconstructing the signal from the WFT.

5.1.1.3 Continuous Wavelet Transform

The CWT does not look for angular frequencies but rather for detail sizes a at a certain time t in contrast to the Fourier transform. We also can call the detail sizes “scale factors” equivalently [6]. The high frequencies correspond to small details and vice versa. We have to take into account that the frequencies and detail sizes are inversely proportional to each other when comparing the wavelet transform with the Fourier transforms: there exists a constant β such that:

$$a = \frac{\beta}{\omega} \quad (5.9)$$

Consider a (real or complex) analysis function g , oscillating around the u -axis (mathematically: $\int_{-\infty}^{+\infty} g(u) du = 0$) and decreasing rapidly for $u \rightarrow \pm\infty$. Such a function is called a “wavelet”. In Eq. 5.9, relating scale factors with frequencies, the constant β depends on g .

Starting from g , consider the following family of functions: $g_{(a,t)}(u) = \frac{1}{\sqrt{|a|}} g(\frac{u-t}{a})$. The members of this family are generated from g by shifting the function to t followed by shrinking ($a < 1$) or dilating ($a > 1$) the width of the function. Thus, the CWT reads [2, 7]:

$$L_g f(a, t) = \int_{-\infty}^{+\infty} f(u) \overline{g_{(a,t)}(u)} du = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(u) \overline{g(\frac{u-t}{a})} du \quad (5.10)$$

Choose a finite energy function $\psi(t)$ (oscillating around the t -axis and decreasing rapidly for $t \rightarrow \pm\infty$) which fulfills the “admissibility condition” [8].

$$c_\psi := 2\pi \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega < \infty \quad (5.11)$$

then the CWT is given the precise formulation in accordance with the general use:

$$L_\psi f(a, t) = \frac{1}{\sqrt{c_\psi}} \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(u) \overline{\psi\left(\frac{u-t}{a}\right)} du \quad (a \neq 0), (t \in \mathbb{R}) \quad (5.12)$$

Equation 5.12 can be rewritten as a convolution: With

$$\psi_a(t) := \overline{\psi\left(\frac{-t}{a}\right)} \quad (5.13)$$

we obtain

$$L_\psi f(a, t) = \frac{1}{\sqrt{c_\psi}} \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(u) \psi_a(t-u) du \quad (5.14)$$

Consequently, we may conclude that

$$L_\psi f(a, t) \circ - \bullet \frac{1}{\sqrt{c_\psi}} \frac{1}{\sqrt{|a|}} \hat{\psi}_a(\omega) \hat{f}(\omega) \quad (5.15)$$

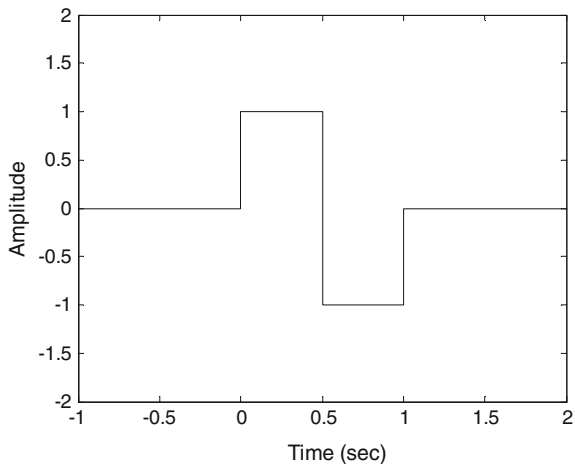
The result in the formal reconstruction formula for the CWT is shown as [2, 7]:

$$f(t) = \frac{2\pi}{\sqrt{c_\psi}} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} L_\psi f(a, t) \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-u}{a}\right) \frac{du da}{a^2} \quad (5.16)$$

The first wavelet we discuss is the Haar wavelet (see Fig. 5.1), defined by

$$\psi(t) = \begin{cases} 1, & t \in [0, 1/2) \\ -1, & t \in [1/2, 1) \\ 0, & \text{otherwise} \end{cases} \quad (5.17)$$

Haar already used this function for constructing an orthonormal basis by means of dilations and integer translations of a so-called mother function [2, 9]. In addition, Haar’s concept coincides with the wavelet transform and its inversion formula. We can also show that the Haar wavelet is an admissible wavelet by computing

Fig. 5.1 The Haar wavelet

$$\hat{\psi}(\omega) = \frac{1}{\sqrt{2\pi}} \left(\int_0^{1/2} e^{-i\omega t} dt - \int_{1/2}^1 e^{-i\omega t} dt \right) = \frac{1}{\sqrt{2\pi}} \left(\frac{1 + e^{-i\omega} - 2e^{-i\omega/2}}{i\omega} \right) \quad (5.18)$$

And so

$$c_\psi = 2\pi \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega = \ln 2 \quad (5.19)$$

The Mexican wavelet (see Fig. 5.2) is defined by

$$\psi(t) = -\frac{d^2}{dt^2} e^{-t^2/2} = (1 - t^2)e^{-t^2/2} \quad (5.20)$$

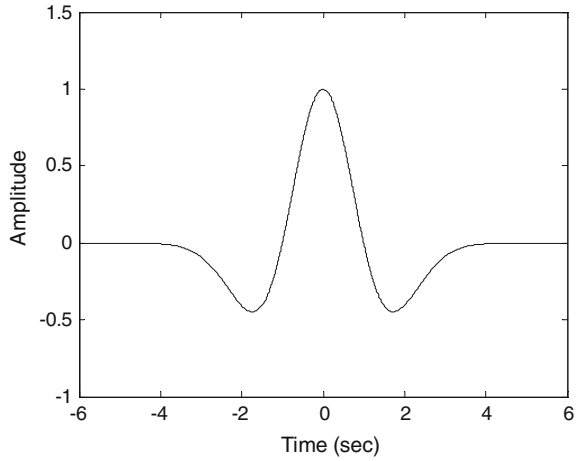
i.e., the second derivative of the Gaussian function, which also appears in the normal distribution in statistics. We observe that although this function is not compactly supported, it satisfies the admissibility condition [2, 9]. The Fourier transform of $\psi(t)$ is expressed as:

$$\hat{\psi}(\omega) = \frac{1}{\sqrt{2\pi}} \omega^2 e^{-\omega^2/2} \quad (5.21)$$

and so

$$c_\psi = 2\pi \int_{-\infty}^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega = \frac{1}{2} \quad (5.22)$$

Fig. 5.2 The Mexican hat wavelet



5.1.2 Discrete Wavelet Transform

5.1.2.1 Discrete Fourier Transform

When numerical algorithms and applications enter the picture, we will not deal with the continuous-time signals any more. Instead, we have to consider sequences obtained by sampling the continuous-time signal $f(t)$ for $t = 0, T_S, 2T_S, \dots, (N-1)T_S$, where T_S is the “sampling distance” and the sequence elements are denoted with $f_k := f(kT_S)$ ($k = 0, \dots, N-1$). Thus the sampled signal reads

$$f = \{f_k\}_{k=0}^{N-1} = \{f(kT_S)\}_{k=0}^{N-1} \quad (5.23)$$

It can be considered as a row vector of N real numbers. The discrete Fourier Transform (DFT) reads [2, 10]:

$$F_k = \sum_{l=0}^{N-1} f_l e^{-\frac{j2\pi lk}{N}} \quad (k = 0, 1, \dots, N-1) \quad (5.24)$$

The original data $\{f_k\}_{k=0}^{N-1}$ may be recovered from the DFT sequence $\{F_k\}_{k=0}^{N-1}$ by the inverse discrete Fourier Transform (IDFT) [2, 10]:

$$f_k = \frac{1}{N} \sum_{l=0}^{N-1} F_l e^{\frac{j2\pi lk}{N}} \quad (k = 0, 1, \dots, N-1) \quad (5.25)$$

5.1.2.2 Fast CWT Algorithm

If the Shannon’s condition [11, 12] is valid for both $f(t)$ and $\psi_a(t)$ (see Eq. 5.13), the spectra of $f(t)$, $\psi_a(t)$ and $L_\psi f(a, t)$ can be computed with the DFT. This leads to the fast CWT algorithm as [2, 13]:

1. Define the sequence $\{\psi_a(kT_S)\}_{k=0}^{N-1}$.
2. Compute the DFT of this sequence resulting in a sequence $\{A_k\}_{k=0}^{N-1}$. Moreover, compute the DFT $\{F_k\}_{k=0}^{N-1}$ of $\{f(kT_S)\}_{k=0}^{N-1}$.
3. Apply the IDFT to the sequence $\frac{1}{\sqrt{c_\psi|a|}}\{F_k A_k\}_{k=0}^{N-1}$ to obtain $\{L_\psi f(a, kT_S)\}_{k=0}^{N-1}$.

5.1.2.3 Discretizing the CWT

Applying the fast CWT algorithm for the scale factors $a_1, \dots, a_M$, we obtain the CWT values

$$L_\psi f(a_i, kT_S) \quad (k = 0, \dots, N-1; i = 1, \dots, M) \quad (5.26)$$

They may be arranged as an $M \times N$ matrix with i numbering rows and k numbering columns. In fact, only N transform values are needed to recover the original signal f , which is a strong indication for the fact that the information of the CWT matrix is redundant. Two CWT values in Eq. 5.26, $L_\psi f(a_1, t_1)$ and $L_\psi f(a_2, t_2)$ are related with each other by the “reproducing kernel condition” [14, 15]. It’s necessary to select a proper discrete subset of the $t - a$ plane for the CWT so that f can be completely reconstructed from the respective transform values on the subsets only. Thus it leads to the notion of the discrete wavelet transform (DWT). The DWT is given by means on transforming a signal $f(t)$ using a basis $\{\psi(2^j t - k) | j, k \in \mathbb{Z}\}$.

So the DWT for $f(t)$ is defined as [2, 15]:

$$L_\psi f(a, t) = \frac{1}{\sqrt{c_\psi a}} \int_{-\infty}^{+\infty} f(u) \psi\left(\frac{u-t}{a}\right) du, a = 2^{-j}, t = k2^{-j}, j, k \in \mathbb{Z} \quad (5.27)$$

The reconstruction of the transformed signal is expressed as:

$$f(t) = \frac{2\pi}{\sqrt{c_\psi}} \sum_{j=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} 2^{j/2} L_\psi f(a, t) \psi(2^j t - k) \quad (5.28)$$

Let $\alpha_{j,k} = \frac{2\pi}{\sqrt{c_\psi}} L_\psi f(a, t)$, $\alpha = \{\alpha_{j,k} | j \in \mathbb{Z}, k \in \mathbb{Z}\}$ and $\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k)$. If a basis of functions $\psi_{j,k}$ with constants $m, M > 0$ satisfies

$$m \|\alpha\|_2^2 \leq \|f\|_2^2 \leq M \|\alpha\|_2^2 \quad (5.29)$$

it is called a Riesz basis with Riesz constants m, M . Sometimes the Riesz basis is also called an exact frame [16]. An orthonormal basis is a special case of a Riesz basis. Any Riesz basis can also be turned into an orthonormal basis by a Gram-Schmidt procedure [17].

5.1.2.4 Multiresolution Analysis

A way to build a wavelet basis and to compute the basis coefficient of a signal efficiently is given by the concept of a multiresolution analysis (MRA) introduced by Mallat [18] and Meyer [19]. Let us define the MRA from an increasing sequence of closed subspaces $V_j, j \in \mathbb{Z}$, in $L_2(\mathbb{R})$, $\dots \subset V_{-2} \subset V_{-1} \subset V_0 \subset V_1 \subset V_2 \subset \dots$ [20]

such that

1. $\bigcup_{j \in \mathbb{Z}} V_j$ is dense in $L_2(\mathbb{R})$,
2. $\bigcap_{j \in \mathbb{Z}} V_j = \{0\}$,
3. $f \in V_j \Leftrightarrow Df = f(2 \cdot) \in V_{j+1}, \forall j \in \mathbb{Z}$,
4. $f \in V_0 \Leftrightarrow Tf = f(\cdot - 1) \in V_0, \forall j \in \mathbb{Z}$
5. $\exists \varphi \in L_2(\mathbb{R}) : \{T^k \varphi | k \in \mathbb{Z}\}$ is a Riesz basis for V_0

with $D := D_{1/2}$ and $T := T_1$, following $T_b f(t) = f(t - b)$ and $D_a f(t) = f(\frac{t}{a})$, and φ a real-valued function in $L_2(\mathbb{R})$, referred to as a scaling function.

From the conditions above, we can obtain that there exists a scaling function φ such that $\{D^j T^k \varphi | k \in \mathbb{Z}\}$ is a Riesz basis for $V_j, \forall j \in \mathbb{Z}$. This scaling function is called a father function.

We define a subspace $W_0 \simeq V_1/V_0$ and take W_0 perpendicular to V_0 by $W_0 = V_1 \cap V_0^\perp$. Furthermore, we define the closed subspaces W_j by $W_j = V_{j+1} \cap V_j^\perp$. Thus the definitions and conditions described above yield

$$V_j = V_{j-1} \oplus W_{j-1} = W_{j-1} \oplus W_{j-2} \oplus W_{j-3} \oplus \dots \quad (5.30)$$

and

$$\bigoplus_{j \in \mathbb{Z}} W_j = L_2(\mathbb{R}) \quad (5.31)$$

Assume a real-valued function ψ such that $\{T^k \psi | k \in \mathbb{Z}\}$ is a Riesz basis for W_0 . This function ψ is called a mother function or wavelet function. Then $\{D^j T^k \varphi | k \in \mathbb{Z}\}$ is a Riesz basis for $W_j, \forall j \in \mathbb{Z}$. So we have a Riesz basis in $L_2(\mathbb{R})$ given by the normalized functions $\{D^j T^k \varphi | j, k \in \mathbb{Z}\}$.

5.1.3 Filter Banks

An MRA can be related to filter banks by regarding a one-level decomposition and reconstruction. At the same time, this relation yields a scheme to calculate the wavelet transform of a function in $L_2(\mathbb{R})$ and to construct it from its transform in a fast way.

5.1.3.1 Discrete Time Case

Assume the discrete time sequences $f(n), n \in \mathbb{Z}$ are square summable. We can derive a coarse half-resolution approximation to the original sequence. This can be done by filtering with a halfband low-pass filter, followed by subsampling by 2 (discarding every odd-indexed sample). Assuming for the sake of simplicity that this filter is FIR, the convolution with a filter having impulse response $[h_0(0), h_0(1), \dots, h_0(L-1)]$ followed by subsampling by 2 corresponds to matrix multiplication of the infinite signal vector $f: [\dots, f(-1), f(0), f(1), \dots]$ by [21]

$$\mathbf{H}_0 = \begin{bmatrix} & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \ddots & h_0(L-1) & h_0(L-2) & \dots & \dots & h_0(0) & 0 & 0 & \ddots \\ & 0 & 0 & h_0(L-1) & \dots & h_0(2) & h_0(1) & h_0(0) & \\ & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \end{bmatrix} \quad (5.32)$$

Assume further that the impulse response and its shifted versions by even shifts (i.e., the rows of the above matrix) form an orthonormal set that is:

$$\langle h_0(n-2k), h_0(n-2l) \rangle = \delta_{lk} \quad k, l \in \mathbb{Z} \quad (5.33)$$

Equation 5.33 can be written in the matrix notation as:

$$\mathbf{H}_0 \mathbf{H}_0^* = \mathbf{I} \quad (5.34)$$

The projection of the original sequence $f(n)$ onto the subspace spanned by the rows of $\mathbf{H}_0$ is expressed as $\mathbf{H}_0^* \mathbf{H}_0 \cdot \mathbf{f}$. Note that multiplication by $\mathbf{H}_0^*$ corresponds to upsampling by 2 followed by convolution with a filter having impulse response $\tilde{h}_0(n) = [h_0(L-1), h_0(L-2), \dots, h_0(1), h_0(0)]$, where L has to be even for the set $\{h_0(n-2l), l \in \mathbb{Z}\}$ to form an orthonormal basis [21, 22].

From the previous analysis, we can know $V_1 = V_0 \oplus W_0$ where V_0 is called the space $L_2(\mathbb{Z})$ and W_0 is called the orthogonal complement of V_0 in V_1 . The filter with impulse response $h_1(n) = (-1)^n h_0(L-1-n)$ and its even shifted versions form an orthonormal basis for W_0 . The orthogonality of $h_0(n)$ and $h_1(n)$ with respect to even shifts is easily verified, because:

$$\langle h_1(n-2k), h_0(n-2l) \rangle = 0 \quad k, l \in \mathbb{Z} \quad (5.35)$$

We can express this equation in the matrix notation as:

$$\mathbf{H}_0 \mathbf{H}_1^* = 0 \quad (5.36)$$

thus $V_0 \perp W_0$. From the orthonormality of $h_0(n-2k)$ it follows [23]

$$\langle h_1(n-2k), h_1(n-2l) \rangle = \delta_{lk} \quad k, l \in \mathbb{Z} \quad (5.37)$$

or

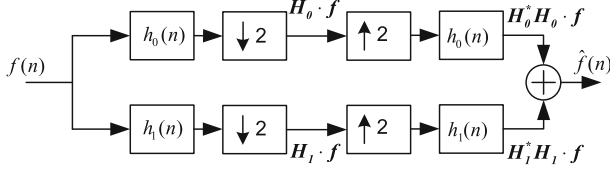


Fig. 5.3 Decomposition of V_1 into V_0 and W_0 , and Reconstruction. $\downarrow 2$ means subsampling by 2 and $\uparrow 2$ means upsampling by 2

$$\mathbf{H}_1 \mathbf{H}_1^* = \mathbf{I} \quad (5.38)$$

The projection of the original sequence onto W_0 is given by $\mathbf{H}_1 \mathbf{H}_1^* \cdot \mathbf{f}$. Since we have projections onto orthonormal and complete subspaces:

$$\mathbf{H}_0^* \mathbf{H}_0 + \mathbf{H}_1^* \mathbf{H}_1 = \mathbf{I} \quad (5.39)$$

By interleaving $\mathbf{H}_0$ and $\mathbf{H}_1$, we obtain a block Toeplitz orthonormal matrix $\mathbf{T}$ [21]:

$$\mathbf{T} = \begin{bmatrix} \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ & h_0(L-1) & h_0(L-2) & \dots & \dots & h_0(0) & 0 & 0 \\ \ddots & h_1(L-1) & h_1(L-2) & \dots & \dots & h_1(0) & 0 & 0 \\ & 0 & 0 & h_0(L-1) & \dots & h_0(2) & h_0(1) & h_0(0) \\ & 0 & 0 & h_1(L-1) & \dots & h_1(2) & h_1(1) & h_1(0) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \quad (5.40)$$

Consequently, $\mathbf{T}$ satisfies

$$\mathbf{T} \mathbf{T}^* = \mathbf{T}^* \mathbf{T} = \mathbf{I} \quad (5.41)$$

which means the two filter impulse responses $h_0(n)$ and $h_1(n)$, together with their even translates, form an orthonormal basis for $L_2(\mathbb{Z})$. We can use filters and sampling rate changes to denote the operators used so far [24] in Fig. 5.3.

Similarly, we can also decompose V_0 into V_{-1} and W_{-1} and so on. We find that $V_{-j} \subset V_{1-j}$, $j = 0, 1, 2, \dots$ and $V_{1-j} = V_{-j} \oplus W_{-j}$, $j = 0, 1, 2, \dots$. Thus we have $\dots V_{-2} \subset V_{-1} \subset V_0 \subset V_1$ and $V_1 = W_0 \oplus W_{-1} \oplus W_{-2} \dots$. The direct sum of W_i is the space of square summable functions $L_2(\mathbb{Z})$.

The decomposition of V_1 into W_0 , W_{-1} , W_{-2} , etc. is a wavelet transform on discrete sequences which is shown in Fig. 5.4 using filters and subsamplers.

With the new definitions, the notion of the resolution of a signal refers to its bandwidth and the notion of the scale of a signal refers to its size. Thus an oversampled version will not have more resolution than a critically sampled version of the same signal. The small scale represents a dilated signal while the large scale stands for a contracted signal.

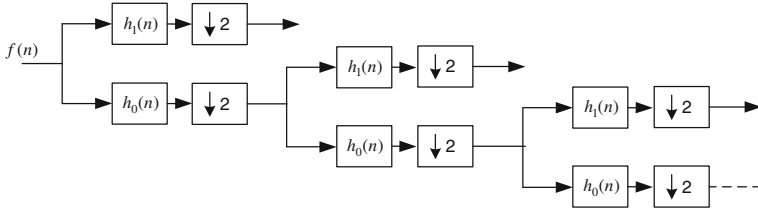


Fig. 5.4 Discrete wavelet transform on sequences

5.1.3.2 FIR Filter Banks

The relation between wavelets with finite length and filter banks is described. Assume there exists an orthonormal basis of the functions $\varphi(t)$ and $\psi(t)$ defined as the father function and mother function in the previous sub-chapter “Multiresolution Analysis”. We can obtain that there exists such coefficients $c_n, n \in \mathbb{Z}$ that the following equations are valid [25]:

$$\varphi(t) = \sum_{n=-\infty}^{+\infty} c_n \varphi(2t - n) \quad (5.42)$$

$$\psi(t) = \sum_{n=-\infty}^{+\infty} (-1)^n c_{-n+1} \varphi(2t - n) \quad (5.43)$$

$$\langle \varphi(t+k), \varphi(t+l) \rangle = \delta_{lk}, \quad k, l \in \mathbb{Z} \quad (5.44)$$

$$\langle \psi(t+k), \psi(t+l) \rangle = \delta_{lk}, \quad k, l \in \mathbb{Z} \quad (5.45)$$

$$\langle \varphi(t+k), \psi(t+l) \rangle = 0, \quad k, l \in \mathbb{Z} \quad (5.46)$$

The finite support of $\varphi(t)$ means that it can be written as a finite linear combination of the terms $\varphi(2t - n)$. From Eq. 5.44, we obtain

$$\langle \varphi(2t - k), \varphi(2t - l) \rangle = \frac{1}{2} \delta_{lk} \quad (5.47)$$

Using $n' = n - 2k$ and $m' = m - 2l$, Eq. 5.47 can be rewritten as:

$$\begin{aligned} \langle \varphi(t+k), \varphi(t+l) \rangle &= \left\langle \sum_{n'} c_{n'+2k} \varphi(2t - n'), \sum_{m'} c_{m'+2l} \varphi(2t - m') \right\rangle \\ &= \frac{1}{2} \sum_{n'} c_{n'+2k} c_{n'+2l} = \delta_{lk} \end{aligned} \quad (5.48)$$

So $\|c_n\| = \sqrt{2}$. The discrete filter with impulse response $h_0(n) = c_n/\sqrt{2}$ is orthogonal to its even translates, and with $h_1(n) = (-1)^n h_0(L - n - 1)$, we obtain an orthogonal perfect reconstruction FIR filter bank with orthogonal impulse

responses [21]. Considering the discrete wavelet transform in Fig. 5.4, we notice that the lower branch is an infinite cascade of filters $h_0(n)$ followed by subsampling by 2. It can be seen that subsampling the signal with z transform $Y(z)$ as follows:

$$Y(z) = \frac{1}{2} \left[F(z^{1/2}) + F(z^{-1/2}) \right] \quad (5.49)$$

It can be verified that subsampling by 2 followed by filtering with $H(z)$ is equivalent to filtering with $H(z^2)$ followed by subsampling by 2. Therefore the cascade of i blocks of filtering operations followed by subsampling by 2 is equivalent to a filter $H^{(i)}(z)$ with z transform:

$$\mathbf{H}^{(i)}(z) = \prod_{k=0}^{i-1} \mathbf{H}(z^{2^k}), \quad i = 1, 2, \dots \quad (5.50)$$

followed by subsampling by 2^i . We define $H^{(0)}(z) = 1$. Assuming that the filter $H(z)$ has an impulse response of length L , the length of the filter $\mathbf{H}^{(i)}(z)$ is $L^{(i)} = (2^i - 1)(L - 1) + 1$ as can be checked from Eq. 5.50.

Instead of considering the discrete time filter, we consider the function $f^{(i)}(t)$ which is piecewise constant on intervals of length $1/2^i$, and equal to

$$f^{(i)}(t) = 2^{i/2} \cdot h^{(i)}(n) \quad n/2^i \leq t < (n+1)/2^i \quad (5.51)$$

$f^{(i)}(t)$ is supported on the interval $[0, L - 1]$. Note that the normalization by $2^{i/2}$ ensures that if $\sum (h^i(n))^2 = 1$ then $\int (f^i(t))^2 dx = 1$ as well. Also it can be obtained that $\|h^{(i)}\|_2 = 1$ when $\|h^{(i-1)}\|_2 = 1$. Using Eq. 5.50 and 5.51, we obtain

$$f^{(i)}(t) = 2^{i/2} \cdot \sum_{m=0}^{L-1} h_0(m) \cdot h_0^{(i-1)}(n - 2^{i-1}m) \quad n/2^i \leq t < (n+1)/2^i \quad (5.52)$$

To write $h_0^{(i-1)}(n - 2^{i-1}m)$ in terms of $f^{(i-1)}(t)$, we observe that

$$f^{(i-1)}(2t - m) = 2^{(i-1)/2} \cdot h_0^{(i-1)}(n) \quad n/2^{i-1} \leq 2t - m < (n+1)/2^{i-1} \quad (5.53)$$

Let $n' = n + 2^{i-1}m$, it can be obtained that:

$$f^{(i)}(t) = 2^{1/2} \cdot \sum_{m=0}^{L-1} h_0(m) \cdot f^{(i-1)}(2t - m) \quad (5.54)$$

Recall that when the filter is regular, $f^{(i)}(t)$ tends to a continuous limit function $\varphi(t)$ as $i \rightarrow \infty$. $\varphi(t)$ satisfies a two-scale difference equation:

$$\varphi(t) = 2^{1/2} \cdot \sum_{n=0}^{L-1} h_0(n) \cdot \varphi(2t - n) \quad (5.55)$$

We also define the bandpass function as:

$$\psi(t) = 2^{1/2} \cdot \sum_{n=0}^{L-1} h_1(n) \cdot \varphi(2t - n) \quad (5.56)$$

Any function $f(t) \in L_2(\mathbb{R})$ can be written as [25]

$$f(t) = \sum_{j=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} \langle 2^{-j/2} \psi(2^j t - k), f(t) \rangle 2^{-j/2} \psi(2^j t - k) \quad (5.57)$$

We assume there exists a filter bank as in Fig. 5.3, with analysis filters $H_0(z)$ and $H_1(z)$, but with general synthesis filters $G_0(z)$ and $G_1(z)$ instead of $\tilde{H}_0(z)$ and $\tilde{H}_1(z)$. Upsampling by 2 corresponds to simply replacing z by z^2 in the z transform [26]. Consequently the output can be expressed in the z transform as:

$$\begin{aligned} \hat{X}(z) &= \frac{1}{2} [G_0(z) \ G_1(z)] \cdot \begin{bmatrix} H_0(z) & H_0(-z) \\ H_1(z) & H_1(-z) \end{bmatrix} \cdot \begin{bmatrix} X(z) \\ X(-z) \end{bmatrix} \\ &= \frac{1}{2} [G_0(z) \ G_1(z)] \cdot \mathbf{H}_m(z) \cdot \begin{bmatrix} X(z) \\ X(-z) \end{bmatrix} \end{aligned} \quad (5.58)$$

Let $P(z) = H_0(z)H_1(-z)$, we can obtain that

$$\det[\mathbf{H}_m(z)] = H_0(z)H_1(-z) - H_0(-z)H_1(z) = P(z) - P(-z) \quad (5.59)$$

The polyphase notation is introduced for the filters as $H_i(z) = H_{i0}(z^2) + z^{-1}H_{i1}(z^2)$, so

$$\begin{aligned} \mathbf{H}_p(z^2) &= \begin{bmatrix} H_{00}(z^2) & H_{01}(z^2) \\ H_{10}(z^2) & H_{11}(z^2) \end{bmatrix} \\ &= \frac{1}{2} \begin{bmatrix} H_0(z) & H_0(-z) \\ H_1(z) & H_1(-z) \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z \end{bmatrix} \\ &= \frac{1}{2} \mathbf{H}_m(z) \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & z \end{bmatrix} \end{aligned} \quad (5.60)$$

where $\mathbf{H}_p(z)$ is called the polyphase matrix [27, 28]. We also obtain

$$\det[\mathbf{H}_m(z)] = -2z^{-1} \det[\mathbf{H}_p(z^2)] \quad (5.61)$$

and

$$\det[\mathbf{H}_p(z)] = \frac{1}{2} z^{1/2} [P(z^{1/2}) - P(-z^{1/2})] \quad (5.62)$$

The autocorrelation of a filter $H_i(z)$ is $H_i(z)H_i(z^{-1})$. The condition Eq. 5.33 becomes

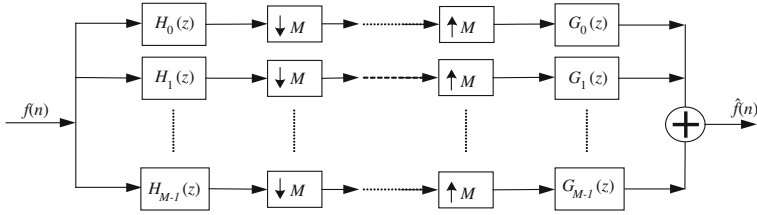


Fig. 5.5 M -channel filter bank

$$H_i(z)H_i(z^{-1}) + H_i(-z)H_i(-z^{-1}) = 2, \quad i \in \{0, 1\} \quad (5.63)$$

The two filters $H_0(z)$ and $H_1(z)$ are orthogonal to each other at even translates Eq. 5.35, so

$$H_0(z)H_1(z^{-1}) + H_0(-z)H_1(-z^{-1}) = 0 \quad (5.64)$$

If $H_0(z)$ and $H_1(z)$ satisfy Eq. 5.63 and 5.64, it can be obtained that [21]

$$H_1(z) = z^{-2k-1}H_0(-z^{-1}) \quad (5.65)$$

Consequently,

$$H_1(z) = -z^{-2k}H_{01}(z^{-2}) + z^{-2k-1}H_{01}(z^{-2}) \quad (5.66)$$

Let $k = 0$, and we obtain

$$\mathbf{H}_p(z) = \begin{bmatrix} H_{00}(z) & H_{01}(z) \\ -H_{01}(z^{-1}) & H_{00}(z^{-1}) \end{bmatrix} \quad (5.67)$$

Finally, since it is a perfect reconstruction system [28–30], we derive $\det[\mathbf{H}_p(z)] = 1$ and

$$\begin{aligned} & [\mathbf{H}_p(z^{-1})]^T \cdot \mathbf{H}_p(z) \\ &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{aligned} \quad (5.68)$$

Here the matrix $\mathbf{H}_p(z)$ is called an orthogonal matrix [31]. This is the extension of the allpass filter concept to matrices with polynomial entries. In summary, there are two possible design approaches for orthogonal filter banks. The first is to find an autocorrelation function that has only a single even-indexed coefficient different from zero. The second is to use lattice structures to synthesize paraunitary matrices, for which complete factorizations have been given by Vaidyanathan and Hoang [32].

Extending from the discrete two-channel filter bank in Fig. 5.3 and Eq. 5.53, a discrete M -channel filter bank is described in Fig. 5.5, where the original signal

$f(n)$ is decomposed by a low-pass filter $H_0(z)$ and high-pass filters $H_k(z)$, $k = 0, 1, \dots, M-1$, into the reference signal and the detail signals, each of which is decimated by a factor of M . For reconstruction, interpolation by a factor of M is performed, followed by reconstruction filters, $G_k(z)$, $k = 0, 1, \dots, M-1$ [33].

The M -channel orthogonal filter bank was constructed by Vadiyanathan [34] and Nguyen [35] for a number of communication applications such as sub-band coders for speech signals. Detailed design process for a Haar-wavelet-based M -channel filter bank (HMF) in vehicle power management will be given in Sect. 5.3.2.

5.2 Feasibility Analysis of Wavelets Applied to Vehicle Power Management

We will discuss whether the wavelet transform can be used for the vehicle power management in this section. Considering the adverse effects of some transient extreme power demands on the power sources, this section analyzes the possible power source combinations available for wavelet application for the purpose of reducing or even eliminating the negative influence.

5.2.1 Adverse Effects of Certain Transient Power Demand on Power Sources

The power demands during vehicle operations include some chaotic and rapid transient parts. The fuel cells and batteries in the fuel cell vehicles and hybrid electric vehicles can hardly handle these power demand components due to their own limitations of characteristics. Adverse effects on the durability and reliability of these power sources will occur accordingly. Details will be explained as follows.

5.2.1.1 Fuel Cell

During the rapid dynamic loading, the oxidant starvation often occurs in the PEM fuel cell due to the gas response rate lagging the loading rate. We can explain it as follows. The local current and temperature rise when the load increases rapidly. The extent of the temperature fluctuation during dynamic loading is dramatically influenced by the loading rates. The quicker the loading rate is, the larger the extent of temperature fluctuation is. On the other hand, the hotter air needs to absorb more water vapor to become saturated, and the oxygen fraction at the inlet is reduced. The oxygen concentration in the cathode catalyst layer is caused to be lower at the higher temperature. If the liquid water presence in the electrodes is not

taken into account, this reduction can result in the performance degradation at the higher temperature. When the rate of transient loading is unacceptably large, the undershoot degree of the fuel cell voltage is very large. The cathode potential drops due to the oxidant starvation, and the fuel cell voltage drops to even negative. So the stability and lifetime of the fuel cell stack are affected by the dynamic rapid loading.

In order to specifically explain the adverse effects of transient rapid loads on the stability and durability of a fuel cell, a 36 kW Fuel Cell Test Station (FCATS-H36000, Hydrogenics, Canada) is utilized as an example as described in reference [36]. The following analysis is based on this example.

The currents at different positions inside the fuel cell stack are different. Also the air stoichiometry influences the current distribution. The cause to that the current near the cathode inlet is larger than those of other positions at the low air stoichiometry of 1.2 is the oxidant starvation which occurs near the cathode outlet resulting in the increase of the reaction resistance. The current near the cathode outlet reduces dramatically. When the air stoichiometry increases to 3, the oxidant starvation is not likely to occur since the oxygen amount is enough for the reaction. The current distribution in the fuel cell stack is almost uniform.

The temperature fluctuations at different positions during transient loading from 0 to 135 A (500 mA cm^{-2}) with the air stoichiometry = 1.2 are discussed here. When the air stoichiometry is low, the current near the cathode inlet increases quickly leading to the dramatic increase of temperature. With the increased temperature, the oxidant starvation becomes severe because the gas response rate lags the loading rate.

The steady-state temperature changes at different positions in the fuel cell stack are related to the loading rates. The times of the loading (from 0 to 500 mA cm^{-2}) are set to <0.1 s, 1 s, 3 s, 5 s and 10 s respectively. The temperature of the cathode inlet reduces along with the decrease of the loading rate. In contrary, the temperature of the cathode outlet increase. The temperature of the cathode inlet is even higher than that of the cathode outlet because of the oxidant starvation when loading from 0 to 500 mA cm^{-2} in only 0.1 s. When the loading speed is low ($10 \text{ s}/500 \text{ mA cm}^{-2}$), the outlet temperature is higher than that of the inlet without any oxidant starvation.

The dynamic temperature responses of the load changes are also included in discussion. The overshoot of the dynamic temperature response becomes more severe when the loading is quicker. In such a case the provided air rate cannot catch up with the loading rate, resulting in the oxidant starvation.

The voltage of the cell shows the undershoot during dynamic loading. The degree of the cathode potential drop is severe when the loading rate is very high. In some extreme situation, the cell voltage even drops to negative. Not only the performance will be degraded, but the stability and the lifetime of the fuel cell stack itself will be dramatically affected.

The steady-state and transient temperature increases at the cathode inlet are both related to the loading degrees. The transient temperature rises obviously with

respect to the quick increase of the loading degree. It is because the high loading degrees lead to severe oxidant starvation.

Summarizing the above conditions, Yan et al. obtained that the oxidant starvation occurs with the transient rapid load due to the gas response lagging the loading rate. As a result, the dynamic performance, and even the stability and lifetime of the fuel cell are affected by the transient rapid load.

5.2.1.2 Battery

The double-layer effect resulting from high-frequency current will be introduced here. Between the electrode and electrolyte inside the battery, there exists a layer where a charge zone is formed. Due to the short distance and the large surface in the porous electrodes, the charge amount cannot be neglected. The charge amount is stored in this layer depending on the electrode voltage. The effect is called double-layer capacitor effect [37, 38]. The double-layer capacitor can be considered to lie in parallel to the electrochemical charge transfer reaction since it's on the electrode surface. As expressed by the Butler-Vollmer equation, the electrochemical charge transfer reaction is decided by the electrochemical potential and charge transfer over-potential. The electrochemical potential can be neglected as it has a zero resistance. The charge transfer over-potential is expressed by the charge transfer resistance R_T and the double-layer capacitance C_D . These two elements are influenced by the state of charge (SOC), temperature, battery aging and current.

The current flowing through the battery can be divided into one part that flows in the charge transfer reaction and the other part that flows into the double-layer capacitor. When the charge current pulse finishes, and the battery enters a rest phase or phase with a smaller charge current, the double-layer capacitor is discharged and the charge amount flows into the charge transfer reaction. It can be considered from the other aspect that the elements R_T and C_D form a low-pass filter for the charge transfer reaction. The double-layer capacitor can carry alternative currents with a high frequency.

For lead-acid batteries, the typical double-layer capacitance of the positive electrode is in the range of 7–70 F/Ah and that of the negative electrode is 0.4–1.0 F/Ah. In reference [38], the cut-off frequencies for the positive and negative electrodes of an automotive lead-acid battery are 10 Hz and 100 Hz, respectively. That means the currents with high frequency cannot flow through the charge transfer reaction. In other words, the high-frequency load is provided by the double-layer capacitor. If the frequency and amount of the load is very high, the battery voltage will be affected dramatically, and more severely, the double-layer capacitor may “breakdown” resulting in confusions or damages to the battery since the energy capacity and the power density of the double-layer capacitor are limited.

The temperature characteristics related to the load frequency and amount are described as follows. During cycling, the battery heats up by the internal heat

sources. The heat generated is impacted by the discharge current profile. Assume that the heat source is a resistance, the heat generation is proportional to the square of the current. The temperature changes of a NiMH cell at various transient loading rates (with the same average current of 1.8A) are different. The period of the current pulses is 10 ms. The duty cycles in four cases are 100%, 50%, 25% and 18%, respectively. So the pulse currents are 1.8 A, 3.6 A, 7.2 A and 10 A, respectively. It can be concluded that the transient surge current through the battery results in the dramatic temperature increase even if the average current is not high. On the other hand, the dramatic temperature increase leads to severe diffusion increase and uncontrollable ion concentration. In extreme cases, the gasification or liquefaction may happen inside the battery.

5.2.2 Applications and Advantages of Wavelets on Analyzing Transient Processes in Electrical Power Systems

The wavelet transform decomposes an original signal into components at different positions and scales. It can be applied to extract signal information in both time and frequency domains. Wavelets with the property of localization are suitable for the analysis of non-stationary and transient signals. Therefore the wavelet transform can be employed as a very effective tool for the decomposition and detection of the transient features in 1-D seismic data, and similar data.

Wavelet technology has been successfully employed in electrical power systems for transient process analysis. Wavelets were first applied precisely to analyze transients under the assumption that they could help detect the transient wave structure [39–41]. By using discrete wavelet transforms, Robertson studied the propagation of transients through switch capacitors [40].

Generally, identification of transients in power systems can be implemented via decomposition of current, voltage or power profiles into fundamental components and their representation by the sum of base wavelet functions. Quadratic waves with five wavelets are sufficient for identification. However, when using the Fourier transform, no less than thirty components are required.

The advantage of the wavelet transform, applied to study the development of transients in power systems, is determined by the degree of similitude between existing transients and base wavelets. A specific example was given to explain how to solve differential equations describing transients in complicated power systems using the multi-resolution wavelet analysis [42]. Daubechies wavelets were utilized for analysis of power transients [43]. This design concept aims at replacement of components in a power system, such as equivalent circuit elements of electrical equipments (transformers, generators, transmission lines with concentrated and distributed parameters, etc.). Wavelet transforms of integral-differential equations expressed as models of complicated elements of power systems (synchronous and induction electric machines, high-voltage converters, etc.)

were also described. Applications of wavelet transforms for power systems provide algebraic equations expressing the complete network. In addition, actual voltage can be estimated through the inverse wavelet transformation. The above iterative, but rapidly converge methods can be combined with classification procedures.

The wavelet transform technology is employed to analyze power signals, using the filtration method for real quantities and subsequent classification for detection of network failures or other events. However, to authors' best knowledge, as the writing of this book, wavelets have not ever been employed in vehicle power management systems for recognition of load transients and the power split. Since the adverse effects of certain transient power demands on the durability and reliability of these power sources will occur in the vehicle operation, it's necessary to apply wavelets in vehicle power management systems due to the advantages of wavelets on analyzing transient processes in electrical power systems.

5.2.3 Power Source Combinations Available for Wavelet Applications in Vehicles

First of all, the advantages of ultracapacitors on transient loading will be introduced. Different from traditional capacitors, ultracapacitors do not have a conventional dielectric. Rather than two separate plates separated by an intervening substance in traditional capacitors, ultracapacitors use two layers of the same substrate, and their electrical properties, the so-called "electrical double layer", resulting in the effective separation of charge despite the vanishingly thin (on the order of nanometers) physical separation of the layers. The lack of need for a bulky layer of dielectric permits the packing of layers with much larger surface area into a given size, leading to their extraordinarily high capacitances in practical sized packages [44]. Consequently ultracapacitors have an unusually high energy density compared to common capacitors. An ultracapacitor with the same size as a typical D-cell sized electrolytic capacitor has a capacitance of several farads while an electrolytic capacitor has a capacitance of only tens of millifarads. The highest energy density in the ultracapacitor production is 30 Wh/kg [45].

In addition, ultracapacitors offer much higher power density than other power sources (i.e., battery and fuel cell). Power density combines the energy density with the rate that the energy can be drawn out of the device. Ultracapacitors can be charged or discharged at a rate that is typically limited by current heating of the electrodes. While existing ultracapacitors have energy densities that are perhaps 1/10th that of a conventional battery or fuel cell, their power density is generally ten to one-hundred times as great. The charge or discharge times of an ultracapacitor varies from several milliseconds to minutes providing maintenance-free operation, which guarantee the advantages of ultracapacitors on transient rapid loading.

In summary, advantages of ultracapacitors compared with batteries and fuel cells include extremely low internal resistance or equivalent series resistance (ESR), high efficiency (up to 97–98%), high output/input power, extremely low heating levels, and improved safety. The specific power of ultracapacitors can exceed 6 kW/kg at 95% efficiency.

Ultracapacitors can act as a charge conditioner, storing energy from other sources (i.e., batteries and fuel cells) for load leveling purposes and then using any excess energy to charge other power sources only at proper times.

As mentioned above, wavelets with the property of localization are suitable for the analysis of non-stationary and transient signals, and it's easy for ultracapacitors to handle transient rapid power demands. Power transients can be extracted from the total power demands during vehicle operation by the wavelet transform and delivered to the ultracapacitors existing in vehicles.

Due to the necessity of the existence of ultracapacitors dealing with the power transients obtained from the wavelet transform, the fuel cell/ultracapacitor combination in fuel cell vehicles, the battery/ultracapacitor combination in series hybrid electric vehicles (SHEV) and battery-powered electric vehicles, and the battery/fuel cell/ultracapacitor combination in battery/fuel cell-powered electric vehicles are available for the wavelet applications in vehicle power management.

5.3 Wavelet-Based Power Split Strategy¹

The wavelet transform applied to the power split strategy in vehicles can extract the high-frequency components from the total power demands. These transients are distributed to the ultracapacitor because of the advantages of the ultracapacitor on power transients. Then the low-frequency components of the power demands are allocated to an individual power source or shared by power sources (i.e., the battery and the fuel cell) with respect to their characteristics, depending on the type of the vehicle.

5.3.1 Wavelet-Based Power Split Structure

To be simple and specific for description of the wavelet application in vehicle power management, the Haar wavelet is employed for the power split strategy. As the most popular mother wavelet, the Haar wavelet has the shortest filter length in the time domain compared to other wavelets. Also, the Haar wavelet is the

¹ Portion of the material in this section are from Xi Zhang, Chunting Mi, Abul Masrur, and David Daniszewski, "Wavelet based power management of hybrid electric vehicles with multiple onboard power sources," *Journal of Power Sources*, vol. 185, no. 2, pp. 1533–1543, 2008. © [2009], with permission, from *Journal of Power Sources*.

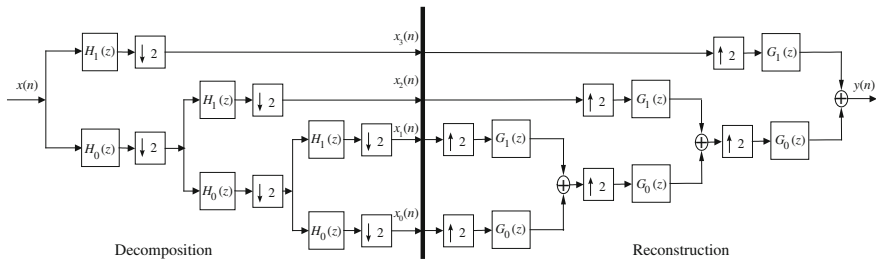


Fig. 5.6 Three-level Haar decomposition and reconstruction diagram

simplest possible wavelet with a nice feature that the WT is equal to its inverse [47]. With these features, the Haar wavelet makes the decomposition calculation much simpler than other wavelets for realization of the wavelet-transform strategy in a realistic system. This can simplify the program composition and further improve the code execution efficiency. Meanwhile, the function of extracting transients can still be implemented well without degradation.

Based on the expression for the Haar wavelet in Eq. 5.17, an M -channel filter bank can be designed [48]. Detailed mathematical expressions of the filter bank design can be found in Sect. 5.3.2. As mentioned in Sect. 5.1.3, by using the Haar wavelet transform, the original power demand signal $x(n)$ is decomposed by a low-pass filter $H_0(z)$ and high-pass filters $H_k(z)$, $k = 0, 1, \dots, M - 1$, into the reference signal and the detail signals, each of which is decimated by a factor of M . For reconstruction, interpolation by a factor of M is performed, followed by reconstruction filters, $G_k(z)$, $k = 0, 1, \dots, M - 1$.

When $M > 2$, the Haar-wavelet-based M bank filter is non-orthogonal [49]. So consider $M = 2$ to guarantee the orthogonality, then the decomposition and reconstruction filters become $[H_1(z) H_0(z)]^T$ and $[G_1(z) G_0(z)]^T$, respectively. The number of wavelet decomposition levels has to be considered properly complying with calculation simplicity and frequency restrictions as well in a realistic system. The optimal value for the level number is three [50]. The three-level Haar wavelet decomposition and reconstruction are used for input power demand signal $x(t)$ during the vehicle operation. As shown in Fig. 5.6, the subsampling and upsampling methods are employed in the decomposition and reconstruction processes respectively. The data size reduces by half in subsampling operations while it doubles in upsampling operation. By using this structure, the respective components from the total power demands can be extracted for power distribution to the power sources in vehicles with the consideration of their own characteristics.

5.3.1.1 Fuel Cell Vehicle

In a fuel cell vehicle, the ultracapacitor is employed as a power buffer as shown in Fig. 5.7. By using the Haar wavelet transform, the bidirectional DC/DC converter

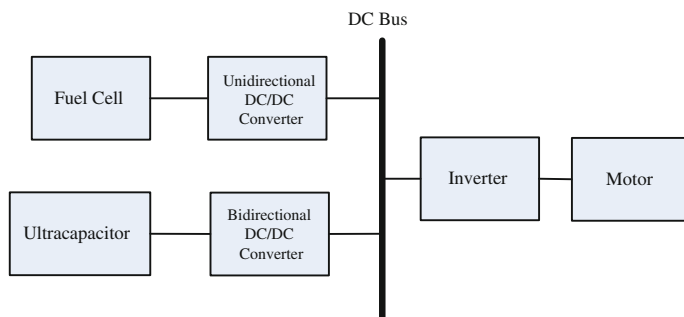


Fig. 5.7 Powertrain structure in a fuel cell vehicle

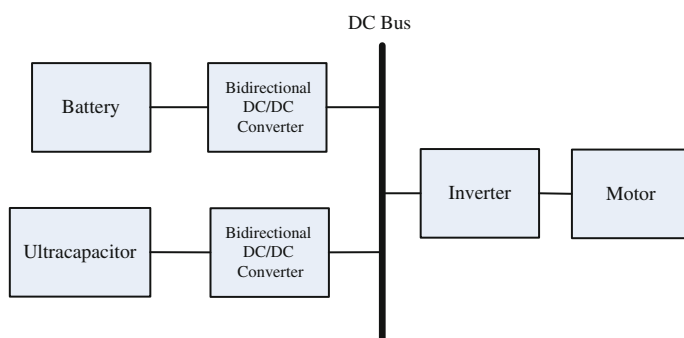


Fig. 5.8 Powertrain structure in a battery-powered electric vehicle

is controlled to assign the high-frequency components to the ultracapacitor. The unidirectional DC/DC converter is placed for voltage regulation of the DC bus. It has to be noticed that because of the regeneration process or calculation of the Haar wavelet transform, the low-frequency components include a negative part which the fuel cell can not afford. So it is designed that the ultracapacitor is responsible for all the high-frequency transients and absorbs the negative part in the low-frequency components, and the fuel cell deals with the other positive slow-variation power demands. The lifetime of the fuel cell is extended consequently based on the analysis in [Sect. 5.2.1](#), which is a major advantage for utilization of the Haar wavelet transform in the fuel cell vehicle power management.

5.3.1.2 Battery-Powered Electric Vehicle

In a battery-powered electric vehicle (see [Fig. 5.8](#)), similar to that in the fuel cell vehicle, the ultracapacitor is considered as a power buffer. The rapid-variation power demands derived from the Haar wavelet transform are delivered to the ultracapacitor. Different from the fuel cell, the battery can deal with the negative

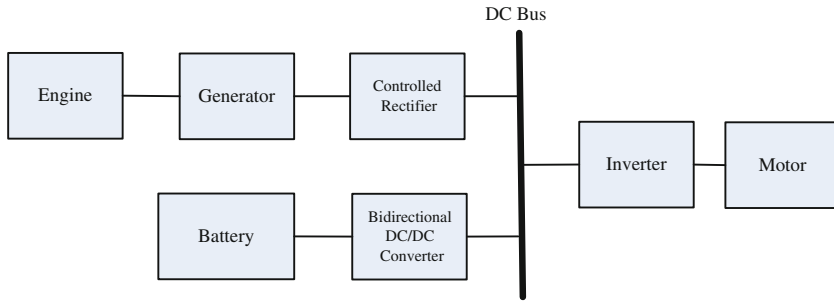


Fig. 5.9 Powertrain structure in a series hybrid electric vehicle without an ultracapacitor

power demands. The bidirectional DC/DC converter connected to the ultracapacitor controls the amount of power from/to the ultracapacitor with the power-oriented control loop. The bidirectional DC/DC converter linked with the battery is in charge of the voltage regulation for the DC bus. In this case, all the high-frequency components obtained by the Haar wavelet transform are occupied by the ultracapacitor, while all the low-frequency power demands are met by the battery, without any constraints of the power flow direction that the fuel cell has. According to the description in [Sect. 5.2.2](#), the rapid-variation and surge load does harm to the battery performance and lifetime, so the utilization of the Haar wavelet transform helps to delay the battery degradation, which is essential to this energy storage system (ESS).

5.3.1.3 Series Hybrid Electric Vehicle (SHEV)

The power train structure of a series hybrid electric vehicle (SHEV) is depicted in [Fig. 5.9](#). Our discussion is based on the engine on/off status alternation. When the engine is turned on, it supplies the requested power to the load. In the meantime, the battery pack is charged by the engine power and possible regenerative power. So the battery SOC increases as expected. This is called the normal operation mode. Once the battery SOC reaches the predetermined maximum level, the engine controller receives a signal to turn off the engine. The operation changes to the electric vehicle (EV) mode, in which only the battery pack serves as the power source generating power for the load and also receives the regenerative braking power. As soon as the battery SOC drops to the given minimum level, the engine starts again preventing the battery from further depletion.

There is no ultracapacitor in the description above. When an ultracapacitor exists (see [Fig. 5.10](#)), the original charging power to the battery in the normal operation mode is divided into a high-frequency portion and a low-frequency portion using the Haar wavelet transform. These two parts are allocated to the ultracapacitor and battery, respectively. In this mode, the controlled rectifier connected to the engine/generator set is responsible for the voltage regulation of

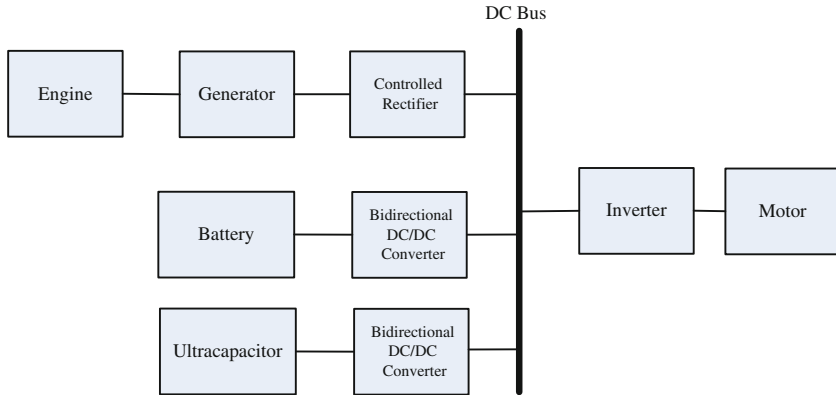


Fig. 5.10 Powertrain structure in a series hybrid electric vehicle with an ultracapacitor

the DC bus. The two bidirectional DC/DC converters are in the operation of power-oriented control. As soon as the battery SOC goes up to the given maximum level, the engine stops, and the battery and ultracapacitor operate in the pure-electric vehicle (EV) mode. The analysis in the battery-powered vehicle is also very suitable for this mode of the SHEV. Not only in the normal operation mode, but in the EV mode, the incorporation of the ultracapacitor and application of the Haar wavelet transform help the battery lifetime extension and performance enhancement.

5.3.1.4 Fuel Cell/Battery-Powered Electric Vehicle

In a fuel cell/battery-powered electric vehicle, three power sources (i.e., the battery, ultracapacitor and fuel cell) are connected through the DC/DC converters to the DC bus as shown in Fig. 5.11. The high-frequency transient power demands derived from the Haar wavelet transform are distributed to the ultracapacitor, and the low-frequency power demands are satisfied by the battery and fuel cell. Considering the unidirectional power characteristics of the fuel cell, the battery absorbs the negative part of the low-frequency components and assists to share the positive part of the low-frequency components with the fuel cell. In this case, both the fuel cell and battery do not have to provide the high peak power occasionally demanded by the load. Consequently the performance and lifetime of the two power sources can be improved due to the discussion in Sect. 5.2.2. The unidirectional DC/DC converter after the fuel cell regulates the DC bus voltage while the two bidirectional DC/DC converters connected to the battery and ultracapacitor respectively are placed for the power-oriented control.

In summary, with the Haar-wavelet-transform-based power management algorithm, the decomposed components of the total power demands can be distributed to the fuel cell, battery and ultracapacitor, compatible with their respective characteristics in order to obtain satisfactory performance in some types

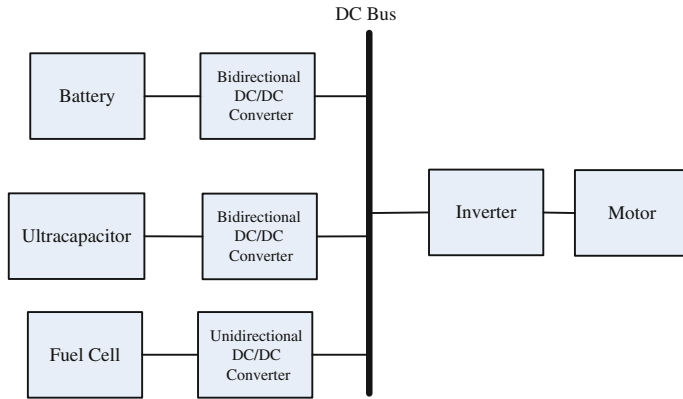


Fig. 5.11 Powertrain structure in a fuel cell/battery-powered electric vehicle

of vehicles. The lifetime of the fuel cell stack and battery pack can be significantly increased, and the long-term cost can be dramatically reduced in spite of one more power converter for the ultracapacitor.

5.3.2 Mathematical Expressions for Wavelet-Based Power Split Algorithm

While the Haar wavelet transform is employed, the high-pass and low-pass filters in Fig. 5.5 are defined as

$$H_k(z) = \frac{1}{M}(z^{-k+1} - z^{-k}), \quad k = 1, 2, \dots, M-1 \quad (5.69)$$

and

$$H_0(z) = \frac{1}{M}(1 + z^{-1} + \dots + z^{-M+1}) \quad (5.70)$$

respectively. The decomposition transfer function matrix is expressed as

$$\begin{aligned}
 H(z) &= \begin{bmatrix} H_1(z) \\ H_2(z) \\ \vdots \\ H_{M-1}(z) \\ H_0(z) \end{bmatrix} = \frac{1}{M} \begin{bmatrix} 1 & -1 & 0 & \dots & 0 & 0 \\ 0 & 1 & -1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 1 & -1 \\ 1 & 1 & 1 & \dots & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ z^{-1} \\ \vdots \\ z^{-M+2} \\ z^{-M+1} \end{bmatrix} \\
 &= H \cdot \begin{bmatrix} 1 & z^{-1} & \dots & z^{-M+2} & z^{-M+1} \end{bmatrix}^T
 \end{aligned} \quad (5.71)$$

where

$$H = \frac{1}{M} \begin{bmatrix} 1 & -1 & 0 & \dots & 0 & 0 \\ 0 & 1 & -1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 1 & -1 \\ 1 & 1 & 1 & \dots & 1 & 1 \end{bmatrix} \quad (5.72)$$

The inverse matrix of $\mathbf{H}$ is calculated as

$$H^{-1} = \begin{bmatrix} M-1 & M-2 & \dots & 1 & 1 \\ -1 & M-2 & \dots & 1 & 1 \\ \vdots & \vdots & \dots & \vdots & \vdots \\ -1 & -1 & \dots & -M+2 & 1 \\ -1 & -2 & \dots & -M+1 & 1 \end{bmatrix} \quad (5.73)$$

Thus the reconstruction transfer function matrix is described as [51]

$$\begin{aligned} \mathbf{G}(z) &= \begin{bmatrix} G_1(z) \\ G_2(z) \\ \vdots \\ G_{M-1}(z) \\ G_0(z) \end{bmatrix} = (H^{-1})^T \cdot [z^{-M+1} \ z^{-M+2} \ \dots \ z^{-1} \ 1]^T \\ &= \begin{bmatrix} M-1 & M-2 & \dots & 1 & 1 \\ -1 & M-2 & \dots & 1 & 1 \\ \vdots & \vdots & \dots & \vdots & \vdots \\ -1 & -1 & \dots & -M+2 & 1 \\ -1 & -2 & \dots & -M+1 & 1 \end{bmatrix}^T \begin{bmatrix} z^{-M+1} \\ z^{-M+2} \\ \vdots \\ z^{-1} \\ 1 \end{bmatrix} \end{aligned} \quad (5.74)$$

Based on the forementioned analysis, the channel number of the filter bank is two. The decomposition and reconstruction filters are

$$[H_1(z) \ H_0(z)]^T = \frac{1}{2} [1 - z^{-1} \ 1 + z^{-1}]^T \quad (5.75)$$

and

$$[G_1(z) \ G_0(z)]^T = [1 + z^{-1} \ 1 - z^{-1}]^T, \quad (5.76)$$

respectively.

5.3.2.1 Drive Cycle Selection

To explain more specifically how the Haar-wavelet-transform-based power split strategy is applied for some types of vehicles, the orange county cycle (OCC) is taken into account as a desired example drive cycle for discussion. The speed curve during the OCC is drawn in Fig. 5.12. The load profile of the OCC drive cycle is shown in Fig. 5.13. For the convenience of design, the load profile is considered as the power demand. It can be seen from Fig. 5.13 that the load profile consists of many transients derived from the speed variations. The specifications and characteristics for the OCC are depicted in Table 5.1. Although the OCC may not be the most typical drive cycle for a commercial vehicle, it does a good job in showing advantages on the application of the wavelet transform for vehicle power management. Moreover, the OCC, as a well-known drive cycle, offers a common standard for analysis.

5.3.2.2 Fuel Cell Vehicle

In a fuel cell vehicle, as analyzed in Sect. 5.3.1, the ultracapacitor deals with all the high-frequency transients and absorbs the negative part of the low-frequency components. Meanwhile, the fuel cell outputs the positive slow-variation power to loads. As shown in Fig. 5.6, after three-level lowpass processing, the smooth slow-variation signal $x_0(n)$ is obtained. The positive part of $x_0(n)$ acts as the power demand for the fuel cell. Other transients $[x_1(n), x_2(n) \text{ and } x_3(n)]$ and the negative part of $x_0(n)$ are distributed to the ultracapacitor as mentioned above. So the power split expressions for the fuel cell and ultracapacitor are given respectively as:

$$P_{\text{FC}}^* = \begin{cases} x_0(n) & \text{if } x_0(n) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (5.77)$$

$$P_{\text{UC}}^* = \begin{cases} x_1(n) + x_2(n) + x_3(n) & \text{if } x_0(n) > 0 \\ x_0(n) + x_1(n) + x_2(n) + x_3(n) & \text{otherwise} \end{cases} \quad (5.78)$$

The power split results are drawn in Fig. 5.14. We can see from this figure that the power demand curve for the fuel cell has global low frequency using the Haar wavelet decomposition, while at some time instants, fast power demands for the fuel cell still exist. The fuel cell connected to a unidirectional DC/DC converter with appropriate capacity and fast response can handle this power demand. The lifetime of the fuel cell is extended since most of the rapid power demands are shifted from the fuel cell to the power buffer, the ultracapacitor.

Fig. 5.12 Speed profile of OCC

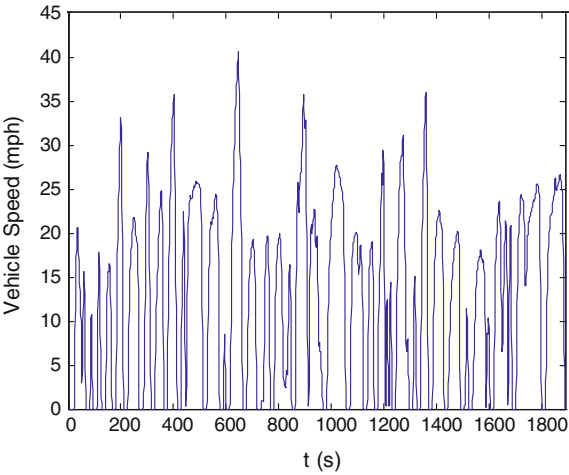


Fig. 5.13 Load profile of OCC

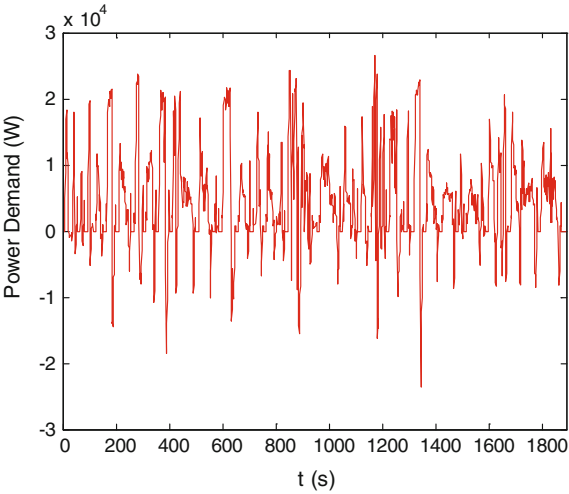


Table 5.1 Specifications of OCC

Time	1,909 s
Distance	6.54 miles
Max speed	40.63 mph
Avg speed	12.33 mph
Max accel	5.95 ft/s ²
Max decel.	-7.52 ft/s ²
Avg accel	1.49 ft/s ²
Avg decel	-2.09 ft/s ²
Idle time	407 s
No. of stops	31

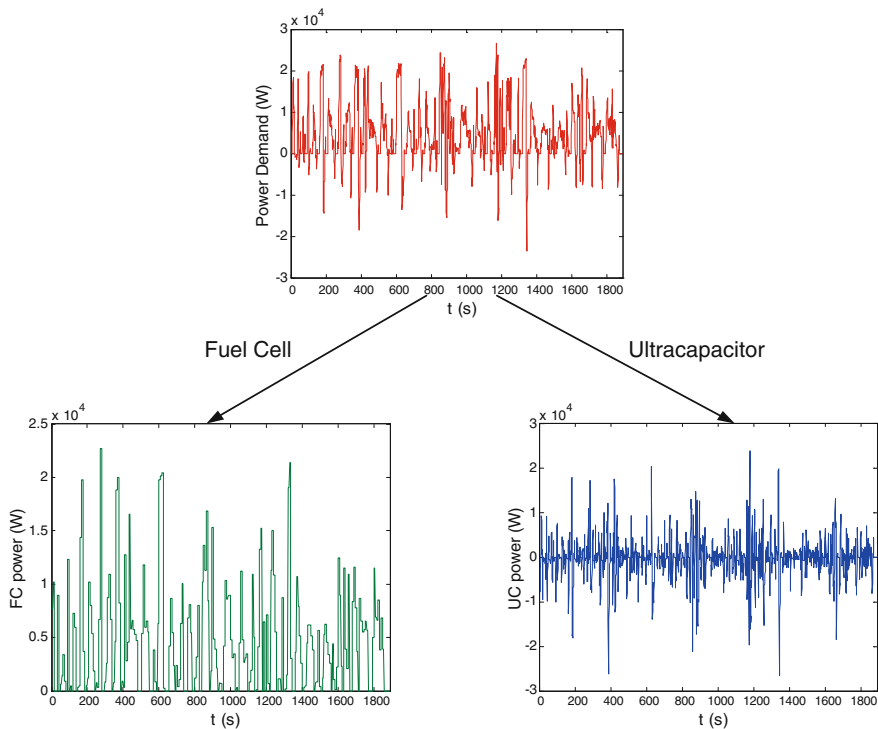


Fig. 5.14 Power split results for a fuel cell vehicle using the Haar wavelet transform

5.3.2.3 Battery-Powered Electric Vehicle

In a battery-powered electric vehicle, the ultracapacitor is responsible for all the high-frequency transients, and meanwhile the battery supplies and absorbs the slow-variation power to/from loads. Different from the unidirectional characteristics of fuel cells, a battery allows bidirectional power flow. So after three-level lowpass processing shown in Fig. 5.6, the low-frequency signal $x_0(n)$ is extracted from the total power demand $x(n)$ as the power demand for the battery. Other transients $[x_1(n), x_2(n)$ and $x_3(n)]$ are distributed to the ultracapacitor. So the power split expressions for the battery and ultracapacitor are shown respectively as:

$$P_{\text{Battery}}^* = x_0(n) \quad (5.79)$$

$$P_{\text{UC}}^* = x_1(n) + x_2(n) + x_3(n) \quad (5.80)$$

The power split results for the battery-powered vehicle are depicted in Fig. 5.15. It is observed from this figure that the power demand curve for the battery has global low frequency using the Haar wavelet decomposition, while at

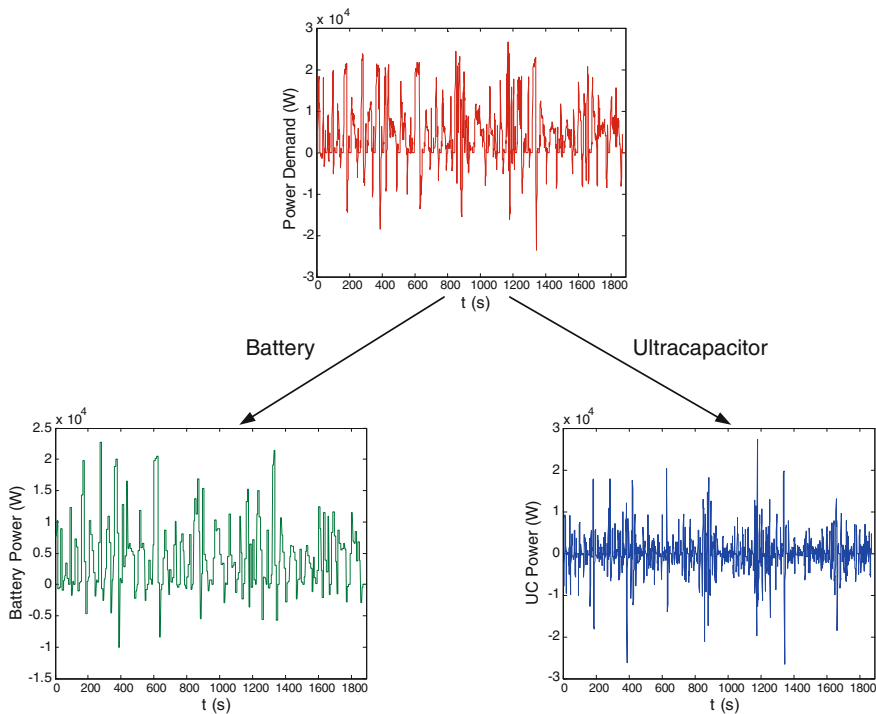


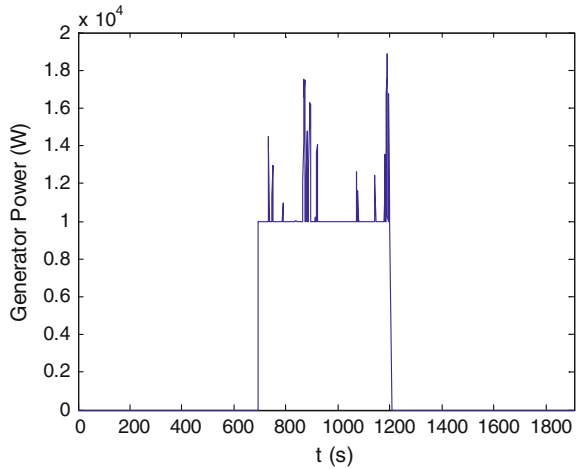
Fig. 5.15 Power split results for a battery-powered electric vehicle using the Haar wavelet transform

some time instants, fast power demands for the battery still exist. Similar to the analysis of the fuel cell vehicle, the fast-response bidirectional DC/DC converter (see Fig. 5.8) of the battery-powered vehicle can deal with this power demand well. Based on discussion in Sect. 5.2.1, the lifetime of the battery is extended since the majority of the rapid and transient power demands is satisfied by the ultracapacitor.

5.3.2.4 SHEV

In a SHEV, as mentioned above, there exist two different operation modes, the EV mode and the normal operation mode. In the EV mode, the SHEV becomes a pure-electric vehicle powered by the battery. So the expressions for power distributed to the battery and ultracapacitor are the same as those in the battery-powered electric vehicle. To separate the EV mode from the normal operation mode, we use different subscripts. In the EV mode, we define $x_{i1}(n) = x_i(n)$, $i = 0, 1, 2, 3$, where $x_i(n)$, $i = 0, 1, 2, 3$, are given in Fig. 5.6. The power split expressions in the EV mode are:

Fig. 5.16 Output power of the engine/generator set



$$P_{\text{Battery}}^* = x_{01}(n) \quad (5.81)$$

$$P_{\text{UC}}^* = x_{11}(n) + x_{21}(n) + x_{31}(n) \quad (5.82)$$

When the engine is turned on, the power from the engine supplies loads and charges the battery/ultracapacitor set. In the meantime, the regenerative braking power charges this set. Let $x_e(n)$ represent the engine/generator power and $x_l(n)$ represent the power demand from loads, so the total power for the battery/ultracapacitor set is, $x(n) = x_l(n) - x_e(n)$. For the description of this mode, different from the EV mode, we define $x_{i2}(n) = x_i(n)$, $i = 0, 1, 2, 3$, where $x_i(n)$, $i = 0, 1, 2, 3$, are originated from Fig. 5.6. The power split expressions in the normal operation mode are listed as

$$P_{\text{Battery}}^* = x_{02}(n) \quad (5.83)$$

$$P_{\text{UC}}^* = x_{12}(n) + x_{22}(n) + x_{32}(n) \quad (5.84)$$

In order to explain the power split strategy in the SHEV to readers visually, the Advanced Vehicle Simulator (ADVISOR) is employed as an effective simulation tool to recognize the different modes in the time category during the OCC drive cycle. We perform the simulation considering the optimal area of the engine efficiency map for high engine efficiency when the engine is on. Also, we give an assumption that the SOC of the ultracapacitor does not change a lot during either the EV mode or the normal operation mode, which is reasonable based on the reality. The SOC of the battery during the vehicle operation is in a fixed range, and the drive cycle starts with the maximum battery SOC, so the EV mode begins followed by the normal operation mode. The output power of the engine/generator set is shown in Fig. 5.16, from which we can recognize the EV mode (0–690 s and

Fig. 5.17 Output power of the battery/ultracapacitor set

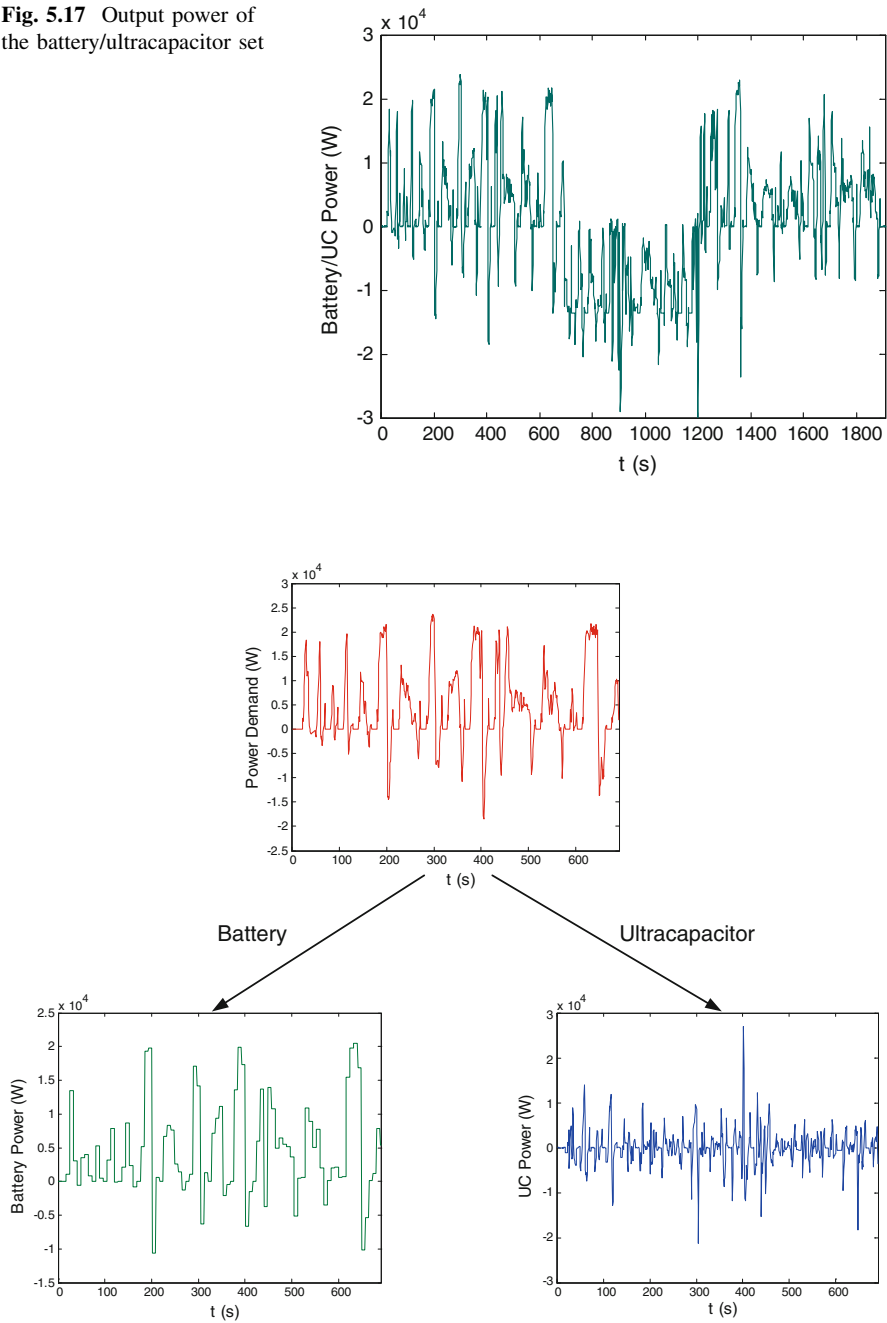


Fig. 5.18 Power split results for a SHEV in the EV mode using the Haar wavelet transform

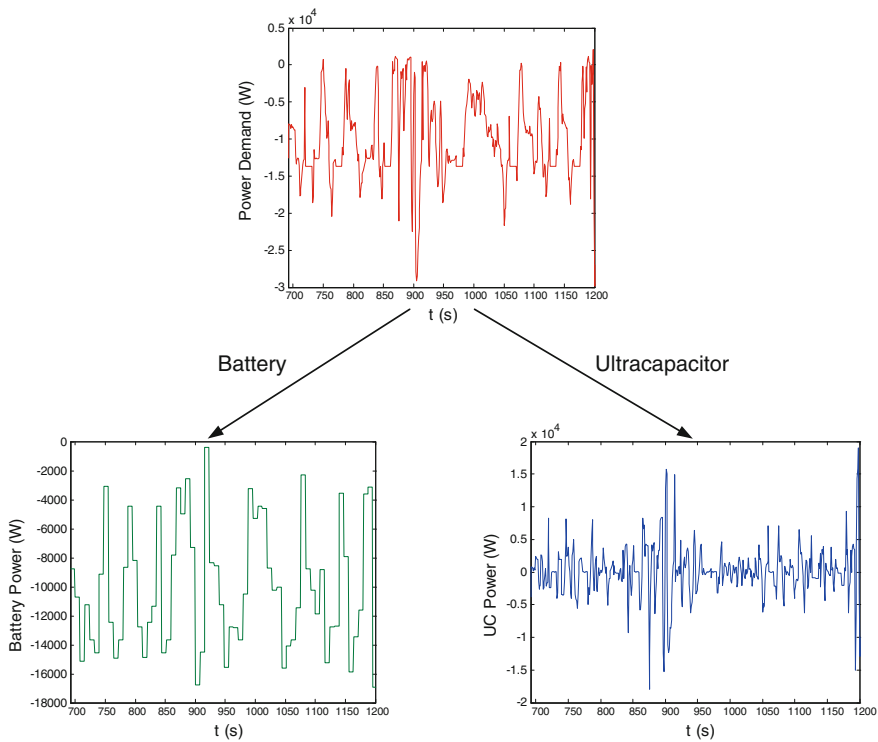


Fig. 5.19 Power split results for a SHEV in the normal operation mode using the Haar wavelet transform

1,202–1,909 s) and the normal operation mode (691–1,201 s). The output power of the battery/ultracapacitor set is derived as a difference between the power from the engine/generator set and the power demand from loads, shown in Fig. 5.17. It is visually found that the battery/ultracapacitor set supplies all the power demand in the EV mode and absorbs power to avoid depletion when the engine starts.

The power split results for the EV mode (0–690 s) and the normal operation mode (691–1,201 s) are shown in Figs. 5.18 and 5.19, respectively. It is observed that the battery still plays a major role for both satisfying the power demand and absorbing power from the engine or loads. The ultracapacitor, as a power buffer, deals with the high-frequency power transients. In addition, it has to be noticed that the power demand curve for the battery has global low frequency using the Haar wavelet decomposition, while at some time instants, fast power demands for the battery still exist. However, the fast-response bidirectional DC/DC converter in the SHEV can handle this power demand. As a result, the lifetime of the battery is extended, thanks to the incorporation of the ultracapacitor.

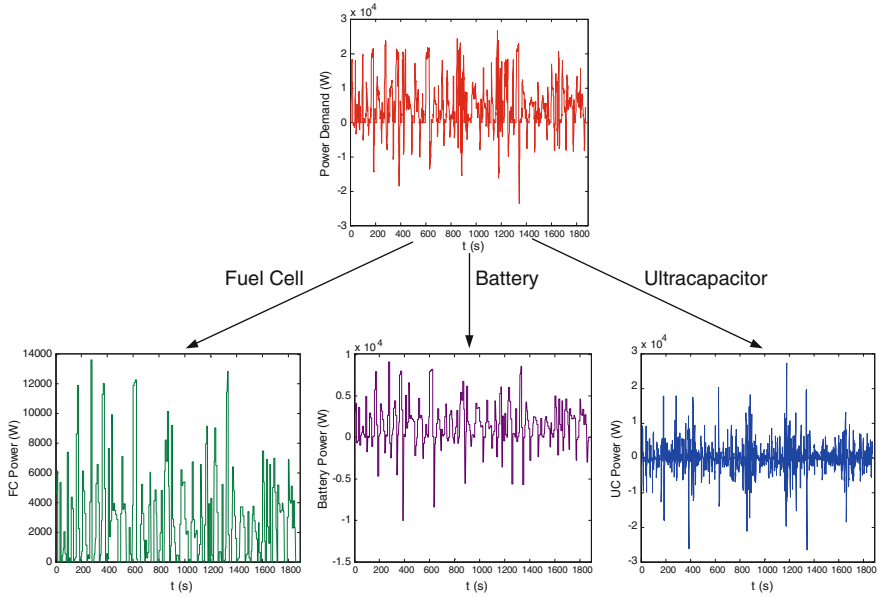


Fig. 5.20 Power split results for a fuel cell/battery powered electric vehicle using the Haar wavelet transform

5.3.2.5 Fuel Cell/Battery-Powered Electric Vehicle

In a fuel cell/battery-powered electric vehicle, as discussed in Sect. 5.3.1, the smooth slow-variation signal $x_0(n)$ is obtained as the power demand for the fuel cell and battery. Other transients $[(x_1(n) + x_2(n) + x_3(n))]$ are distributed to the ultracapacitor. However, $x_0(n)$ contains a negative part, which the fuel cell cannot accept. Thus, the battery absorbs the slow-variation power with the direction from the loads to power sources. The battery also helps absorb a portion of the positive low-frequency components, while the fuel cell deals with the significant portion. So the power sharing method is expressed as follows:

$$P_{\text{FC}}^* = \begin{cases} 0.6x_0(n) & \text{if } x_0(n) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (5.85)$$

$$P_{\text{Battery}}^* = \begin{cases} 0.4x_0(n) & \text{if } x_0(n) > 0 \\ x_0(n) & \text{otherwise} \end{cases} \quad (5.86)$$

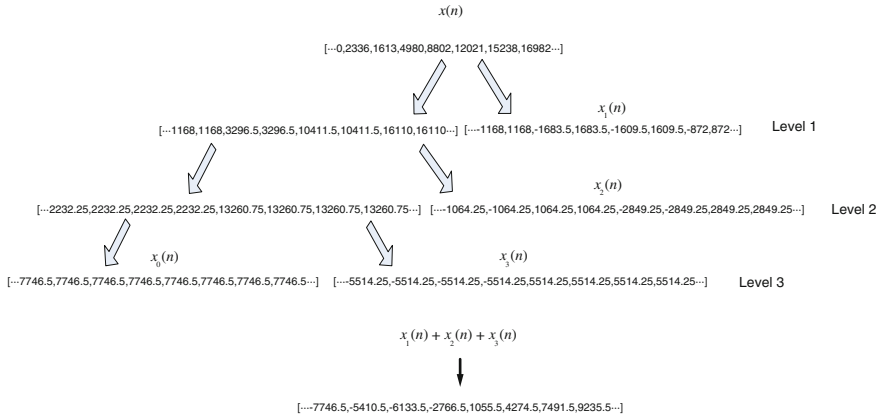


Fig. 5.21 Numerical Haar wavelet decomposition process

$$P_{UC}^* = x_1(n) + x_2(n) + x_3(n) \quad (5.87)$$

Based on this sharing strategy, the power demands for the fuel cell, battery and ultracapacitor are obtained and shown in Fig. 5.20, respectively. It can be observed that the power demand curves for the fuel cell and battery have global low frequencies using the Haar wavelet decomposition, while at some time instants, fast power demands for the fuel cell and battery still exist. However, the number of large and fast power variations reduces dramatically, and the required surge power for the fuel cell and battery also decreases largely because of the assistance of each other. Additionally, the two power converters for the fuel cell and battery respectively with appropriate capacity and fast response can handle the power demands. The lifetime of the fuel cell and battery is extended consequently, which is a major advantage for utilization of the Haar wavelet transform in the fuel cell/battery-powered electric vehicle.

The power split results in different types of vehicles are graphically shown in this section based on the mathematical expressions. It's obvious that the incorporation of the ultracapacitor can reduce the transient burdens on either the fuel cell or battery, which is beneficial to their lifetime extension and performance improvement, related to the discussion in Sect. 5.2.1.

5.4 Demonstration of Wavelet Application for Vehicle Real-Time Environment

In the above analysis, the power demands are already known due to the predefined drive cycle of the OCC. However, in the real-time environment, the exact power demands at some time instant are unable to know ahead of this instant. Consequently,

the question of how wavelet transform is used in vehicle real-time environment arises. We will explain it starting from describing the numerical Haar wavelet decomposition process.

Since the beginning period of OCC (0–20 s) is silent without any power demand, we extract the interval of 20–27 s for description of the specific Haar wavelet decomposition as shown in Fig. 5.21. The data size reduces by half in subsampling operations during the three-level decomposition in Fig. 5.6. We use the low-pass filter $H_0(z)$ and high-pass filter $H_1(z)$ expressed in Eq. 5.75 at each level.

As observed from Fig. 5.21, the frequency of the low-frequency components $[(x_0(n))]$ is only 1/8 of that of the high-frequency components $[x_1(n) + x_2(n) + x_3(n)]$ based on the three-level wavelet transform. So only seven sampling power demand points except the present starting point need to be fore-known for every calculation in power demand decomposition to obtain eight same power points distributed to the battery/fuel cell, and eight various power points assigned to the ultracapacitor. For example, assume the power sampling time is 0.5 s, and the needed power prediction time is 3.5 s. Another prediction time of 3.5 s is independently needed after this calculation operation. At a certain sampling instant, the low-frequency signal x_0 is obtained using the information of some time interval (this instant and another seven sampling instants are included), and the low-frequency signal $x_1 + x_2 + x_3$ is calculated as the difference between x_0 and the present total power demand x . Meanwhile the response time of the power converters is at the stage of milliseconds, so the time delay to the execution of commands will not influence the power distribution performance.

By using the power prediction algorithms in Chap. 4 considering the vehicle speed and motor operation period, we can easily implement the Haar-wavelet-based real-time power management for a running vehicle. Even though the prediction algorithm is not precise enough, the reality of separating the high-and low-frequency components using the wavelet transform will not change at all. The only change is the specific amount of power distributed to different power sources. Also the prediction error can be relatively reduced during the average calculation process using the Haar wavelet transform. Moreover, the calculation size is not large enough so that even a single-chip-machine can handle it. As a result, the availability of wavelet application for real-time vehicle power management is feasible.

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Chapter 6

Dynamic Programming and Quadratic Programming for Vehicle Power Management

In this chapter, following the theoretical fundamentals, the applications of dynamic programming (DP) on several HEV types including series, parallel and series-parallel are specifically given. ADVISOR-based simulation results prove that the DP algorithm is capable of finding optimal power which is from the battery to the electric motor and then the power ratio between them. Quadratic programming (QP) is also contained in discussion of this chapter due to its advantages of saving computational time in real-time realization. The power management strategy on basis of QP algorithm for fuel optimization of PHEV is depicted in details.

Dynamic Programming (DP) is a mathematical method for optimization. It has been used in many different fields by engineers and mathematicians to solve engineering and other optimization problems. Bellman is the first person who realized in the early 1950s that DP could be developed into a systematic tool for optimization [1].

The term dynamic programming was originally cited in the 1940s by Richard Bellman to describe the process of solving problems where one needs to find the best decision. In 1950s, based on this, Bellman solved the complex problems by breaking them into simpler sub-problems [2]. The field was thereafter recognized by the IEEE as a system's analysis and engineering subject.

The word “programming” in “dynamic programming” has no relationship with computer programming, although the dynamic programming optimization process is realized today with an actual “computer program” [3, 4].

The DP method has played an important role in industry applications such as communication, vehicle control, computer science, etc. Bellman utilized the dynamic programming in statistical communication theory [5]. It is shown that under certain conditions, the rate of transmission can be obtained from DP process. Sakoe applied the dynamic programming optimization for spoken word recognition [6]. Fallahi utilized a dynamic programming approach for Quality of Service (QoS-aware) power management in wireless video sensor networks [7]. Carrano built power distribution network expansion scheduling using dynamic programming genetic algorithm [8]. In the vehicular power management field, some researchers have conducted research based on DP. Koot successfully applied DP

on conventional vehicle power management, which showed 2–3% fuel economy improvement [9, 10]. Scordia proposed an optimization method based on dynamic programming, concerning the elaboration of energy management laws for Hybrid Electric Vehicles (HEV) [11]. Jinming Liu developed a dynamic model of the Toyota hybrid powertrain and applied stochastic dynamic programming [12]. Sciarretta summarized the global optimal control strategy for HEVs' energy management [13].

6.1 Principle of Dynamic Programming

Given a discrete-time system [1]

$$x_{k+1} = f_k(x_k, u_k) \quad k = 0, 1, \dots, N-1 \quad (6.1)$$

where the state x_k is an element of a space S_k ; $k = 0, 1, \dots, N$, u_k is an input variable which belongs to a space A_k , $k = 0, 1, \dots, N-1$. The control variable u_k is limited to a given subset $U_k(x_k)$ of B_k , which depends on the current state x_k for all $x_k \in S_k$ and $k = 0, 1, \dots, N-1$.

Given an initial state x_0 , the problem is to find a control law $\psi = \{u_0, u_1, \dots, u_{N-1}\}$ that minimizes the cost function.

$$J_\pi(x_0) = \underset{k=0,1,N-1}{E} \left\{ g_N(x_N) + \sum_{k=0}^{N-1} g_k[x_k, u_k(x_k)] \right\} \quad (6.2)$$

Subject to the system equation constraint

$$x_{k+1} = F_k(x_k, u_k), \quad k = 0, 1, \dots, N-1 \quad (6.3)$$

The problem appears impossible to be solved since the cost function must be minimized over a class of functions of the current state. This issue makes variation optimization techniques impossible in almost each case due to the complexity of the cost function. The dynamic programming technique disassembles the problem into a sequence of simpler minimization problems that are carried out over the control space rather than over a space of functions of the current state.

$u_0^*, u_1^*, \dots, u_{N-1}^*$ are supposed to be serial optimal control elements for the basic problem. Consider the sub-problem whereby we are at state x_i at time i and wish to minimize the cost-to-go value from time i to time N .

$$\underset{k=i, \dots, N-1}{E} \left\{ g_N(x_N) + \sum_{k=0}^{N-1} g_k[x_k, u_k(x_k)] \right\} \quad (6.4)$$

Then the control law is also optimal for this sub-problem. This is the key principle of DP [14, 15]. In the DP algorithm of the above proposition, ideally, we would like to be able to determine closed-form expressions for the “cost-to-go”

function U_k . This is possible in a number of important special cases. In any case, even if a closed-form expression for J_k or the optimal control law u_k^* cannot be obtained, one hopes to obtain characteristics of J_k or u_k^* that are of interest.

Dynamic programming is to split the optimization problem into sub-problems and use the optimal solutions of the sub-problems in order to compute the global optimal solution of the initial problem. The general DP process can be described in the following steps [16, 17]:

1. A cost-to-go function is defined, which usually starts from the terminal state and moves towards the previous states, because it expresses the cost needed to move from N state to state $N - 1$. The “cost-to-go” function for the terminal state is fixed. It also makes sense in the forward way from the terminal state to the previous states.
2. The problem could be divided into sub-problems. Every sub-problem could be considered as a sub-optimal problem, whose solution could construct a feasible global solution sequentially. The total cost of solution will be the sum of each sub-optimal solution. For vehicle power management, the whole drive cycle could be separated into parts based on the time interval according to the precision demand.
3. Possible state transitions from stage to stage are determined, which depends on the limitation of control variable and the limitation of cost function variables.

Consider the optimization problem in Eq. 6.1, and cost-to-go function in 6.4, according to the idea of Dynamic Programming, we can consider N subsystems based on the N stages. Then the optimal solutions of the sub-problems will be used sequentially in order to compute the optimal vector u .

$x_{n+1} = h(x_n, u_n)$ means the state of stage $n + 1$ which summarizes all the already taken decisions (past decisions) in stages $n + 1, n + 2, \dots, N, u_n \in N$ the control variable, namely the decision that should be taken at stage n, f is a function that gives us the state of stage $n + 1$ if we know the state x_n of the previous stage n and the decision u_n taken there. The sum of all the costs $E(k), k = 1, 2, \dots, N$ is the value of the objective function f as shown in Fig. 6.1.

The recursion of the cost-to-go equation is called Bellman algorithm. The optimal cost $E^*(x_n)$ of every sub-problem and every stage n is computed by minimizing overall the sums of the optimal cost-to-go function $E^*(x_{n+1})$ at state $n + 1$, for all possible decisions u_n that can be taken at stage n . It's clear that the optimal solution u of the primary problem, will be the sequence of the decisions $u_n, n = 1, 2, \dots, N$ leading to the value $E^*(x_1)$.

In case that the feasible set is continuous, its quantization is necessary in order to make the state-space finite and tractable.

From Fig. 6.2, a simple DP principle according to Bellman algorithm can be explained. In Fig. 6.2a, the route A31–E is selected due to smaller value compared with A32–E route. Based on DP principle, A31–E is a partial route in the optimal route, and only the ways from A21, A22 and A23 to A31 are considered in the next step. A22–A31 is the shortest route in the three routes. Sequentially, A11–A22

Fig. 6.1 The optimal path for dynamic programming

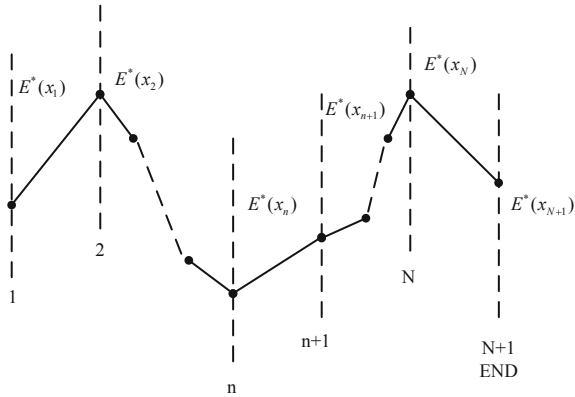
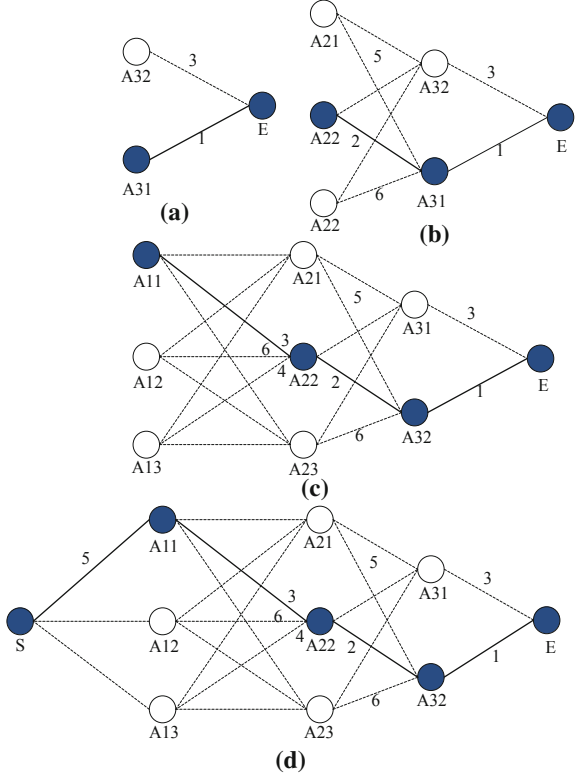


Fig. 6.2 The principle of DP



route is selected according to the value. Through this way, an optimal route could be chosen.

However, it must be recognized that DP cannot provide an optimal solution to every problem. Nonetheless, it is the only general approach for attacking sequential optimization problems under uncertainties.

6.2 Hybrid Electric Vehicle Powertrain Analysis and DP Realization

The drive train of a vehicle consists of engine, clutch, wheels, and vehicle body. To analyze the overall performance of a vehicle, each part is not modeled in detail, and only the relationship between vehicle speed, motor speed, engine speed, and drive train torque is of interest. For a given vehicle, the corresponding engine speed and torque needed for propulsion can be calculated as follows [9, 10].

The force $F_d(t)$ propelling the vehicle consists of inertia, air drag, road slope and rolling resistance (Readers can also see Chap. 2 for more details):

$$F_d(t) = M\dot{v}(t) + \frac{1}{2}\rho C_d A_d v(t)^2 + Mg \sin(\alpha(t)) + C_r Mg \cos(\alpha(t)) \quad (6.5)$$

where M is the mass of vehicle, ρ represents the air density, C_D is air drag coefficient, A_F is the front area, C_r is the wheel rolling resistance, $\alpha(t)$ is the slope. The torque at the crank shaft is below without considering losses in the transmission:

$$\tau_d(t) = \frac{\omega_r}{f_r} \frac{1}{g_r(t)} F_d(t) \quad (6.6)$$

where $g_r(t)$ is the gear ratio, f_r is the final drive ratio.

The engine speed is given by

$$\omega(t) = \frac{f_r}{\omega_r} g_r(t) v(t) \quad (6.7)$$

The power required for propulsion is given by

$$P_d(t) = \omega(t) \tau_d(t) \quad (6.8)$$

By neglecting the temperature issue, the engine could be described as a nonlinear static map where the fuel rate $\dot{g}$ as a function of engine speed ω and torque T .

$$\dot{g} = f(\omega, T) \quad (6.9)$$

For a given engine speed, the mechanical power delivered by the engine, P_m , can be derived from the engine torque as follows:

$$P_m = \eta T \omega \quad (6.10)$$

where η is the engine efficiency.

Using this relation, the fuel map can also be regarded as a nonlinear function of engine speed and power:

$$\dot{m} = f(P_m, \omega) \quad (6.11)$$

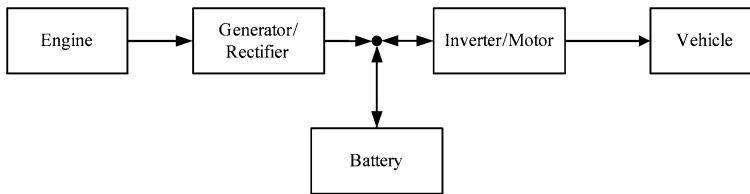


Fig. 6.3 Configuration of series HEV

So it could be easily built as a connection between fuel rate and drive demand power.

6.2.1 Dynamic Programming Realization for Series HEV

HEVs include three basic configurations: series, parallel, and series–parallel type. In a series HEV, only one power converter can provide propulsion power to the wheels. The internal combustion engine (ICE) or fuel cell acts as a prime mover in this configuration to drive an electric generator that delivers power to the battery or energy storage link and the propulsion motor. The simplified component arrangement indicating power flow of a series HEV is shown in Fig. 6.3.

Series and parallel HEVs have obviously different structures and could satisfy different applications. The application of the vehicle and the optimum design for the application determine what the choice of configuration should be. If the HEV is an EV with an engine-assist for achieving acceptable range, then the choice should be a series HEV, whose engine ensures that the batteries remain charged all the time. On the other hand, if the HEV is to be basically a vehicle driven by the engine directly and working with the motor as a supplement, then the choice should be a parallel configuration. Parallel HEVs have been built with acceleration and gradeability performance that is equal to or even better than a conventional car, in all aspects of normal operation. Some series HEVs have also been built that perform nearly as well as or better than conventional vehicles [18].

Series hybrid vehicle offers several advantages:

1. There is no direct mechanical connection between the engine and the driven wheels. Consequently, the engine can be potentially operated at any point on its speed-torque map. This means the engine can always be operated at its maximum efficiency region. The efficiency and emissions of the engine may be further improved by some special design and control technologies, which is much easier to implement than in the whole operating domain due to the decoupling of the wheel from the engine/transmission. So it is easy for a series HEV to use dynamic programming because only adjusting the engine operating point is needed. Furthermore, the mechanical decoupling of the engine from the

driven wheels allows the use of high-speed engines, which could reduce the mass and size of engine.

2. Due to the wide constant torque range and wide speed range of the motor, the traditional continuously variable transmission (CVT) or other types of multi-gear transmission can be eliminated. Therefore, the structure of the drive train can be greatly simplified leading to lower cost. Furthermore, motors may be used in each wheel to drive them directly, thus eliminating the need of mechanical differentials. Such an arrangement also has advantages of decoupling the speeds of two wheels, a similar function of a mechanical differential, and an additional function of anti-slip similar to the conventional traction control. Consequently, the drivability of the vehicle can be significantly enhanced. This is very important for off-road vehicles, which usually operate on difficult terrain, such as ice, snow and soft ground.
3. The control strategy of the drive train may be simple, compared to other configurations, because of the mechanical decoupling between the engine and wheels.

However, series hybrid electric drive trains have some disadvantages as well, such as the following:

1. The mechanical energy developed by the engine changes its form twice to reach its destination—driving wheels (mechanical to electrical in the generator and electrical to mechanical in the traction motor). The inefficiencies of the generator and traction motor may cause significant losses in this process.
2. The generator adds additional weight and cost to the vehicle powertrain.
3. Because the traction motor is the only power plant propelling the vehicle, the whole driving effort to wheels come solely from the motor, and there is no direct mechanical connection between the generator and motor; so the driving ability of motor must be large enough to meet the power demand of vehicle under the maximum acceleration and cruise speed [19]. The redundancy is not as good as that of a parallel hybrid in which both the engine and the motor can still drive the vehicle in a degraded condition if one of the two fails.
4. In case the motors are directly coupled to wheels, all the wheel motors have to be coordinated and controlled properly, to prevent any instability of the vehicle.

The fuel requirement of the engine could be determined by the demanded power. Consequently, for a HEV, due to the existence of two power sources (fuel and battery), the fuel rate could be determined by battery power and driving power, and optimized between the fuel rate and battery power. DP can provide an effective approach in this regard.

For the DP realization, the optimization problem could be treated as a multi-step decision problem, and at each time point one has to decide the ratio between the battery and engine. For the whole trip, the total minimum fuel consumption should be found in this process. In order to compare the fuel consumption, the beginning and ending SOC of the battery for a trip should be the same with default control algorithms. Readers can refer to [Chap. 4](#) in this book for more information.

Several steps are necessary to implement DP algorithm.

1. An optimized variable should be defined. Some papers select the engine torque along with the state of charge (SOC) of the battery. The battery SOC can be easily measured and/or calculated. Charge and discharge rate, power P_s , could be calculated and selected as well [9, 10, 20, 21].
2. Time interval should be defined. However, the computation time will increase exponentially as the time interval decreases.
3. The sample moments are indicated by variable $k = [1, 2, \dots, n]$ with n defined by the length of the drive cycle [9]:

$$n = \left\lceil \frac{t_n}{\Delta t} \right\rceil \quad (6.12)$$

4. Considering the computation time and ensuring the precision, the default time interval $\Delta t = 1$ s.
5. Energy grid ΔE_s and power grid ΔP_s of the battery are defined as the increments between each energy levels required by the vehicle. This is defined as follows:

Battery SOC must be constrained in a certain range. Hence, $E_{s\max}$ and $E_{s\min}$ can be known beforehand for a given battery. This area is mapped onto a fixed grid with distance ΔE_s , such as exactly $m+1$ energy levels are considered, with [9].

$$m = \left\lceil \frac{E_{s\max} - E_{s\min}}{\Delta E_s} \right\rceil \quad (6.13)$$

The relationship between the total power P_s and ΔE_s is proportional, so we can select.

$$P_s = \frac{\Delta E_s}{\Delta t} \quad (6.14)$$

The control input P_s should have a constraint, for the maximum charging and discharging power of battery.

$$P_s(k) = \{u \mid P_{s\min}(k) \leq u(k) \Delta P_s \leq P_{s\max}(k), \quad u \in N\} \quad (6.15)$$

The operating range of the battery could be reduced further by considering only those trajectories which are possible between an initial energy level of the battery $E_s(0)$ and a desired end state $E_s(n)$. And $E_s(0)$ and $E_s(n)$ are restricted to the grid point of E_s .

Both energy levels can be represented by an integer $e \in [0, \dots, m]$, where initial energy level e_0 and final energy level e_n are satisfied. So the feasible area for E_s along the drive cycle is restricted by six individual constraints, the maximum and minimum value of P_s , the maximum and minimum value of E_s , the initial battery energy $E_s(0)$ and the end battery energy $E_s(n)$. These strict boundaries set up a diamond zone, which could be reachable for any $E_s(i)$.

Typically, starting from an initial state $E_s(0)$, it is possible to charge or discharge the battery until one of the boundaries $E_{s\max}$ or $E_{s\min}$ becomes active. It is

possible to define a set L that represents all feasible energy level s and power level k for a given drive cycle according to the boundaries.

$$L = \left\{ (s, k) \left| \begin{array}{l} E_{s\min}^*(k) \leq E_{s\min} + s\Delta E_s \leq E_{s\max}^*(k) \\ 1 \leq k \leq n, \quad 0 \leq s \leq m \end{array} \right. \right\} \quad (6.16)$$

where S_0, S_n are between 0 and m , and usually $S_0 = S_n$, it is possible to charge or discharge.

The DP algorithm creates a cost-to-go matrix U and fills this matrix recursively from $k = n$ down to $k = 1$. It represents the amount of fuel and emissions necessary to reach the end of the drive cycle.

The DP algorithm uses the next expressions to calculate the contents of R .

$$\begin{cases} U_{en,n} = 0 \\ U_{e,k} = \min(U_{e+u,k+1} + \gamma(u\Delta P_s, k)\Delta t) \Big|_{\substack{u \in P_s(k) \\ (e,k) \in R}} \end{cases} \quad (6.17)$$

where γ is the fuel rate according to $u\Delta P_s$ and time step k .

Consider the dynamics of the battery and easy realization of algorithms, each state is selected restrictively to the grid points, then the next state $E_s(k+1)$ will also be an energy level that matches exactly to a grid point, so there is no interpolation needed. Consequently, the calculation time of the DP-algorithm reduces significantly.

The sequence of P_s that achieves minimum fuel consumption is the slope of optimal battery energy curve, which could be calculated afterwards, by starting at $E_s(0)$ and then following the path of minimal cost. Given this sequence for $P_s(k)$, the requested set-points for the alternator are found.

All calculations required for DP can be realized in an acceptable amount of time interval due to the simple dynamics and all the restrictions on E_s and P_s . However, the number of computations increases rapidly with the drive cycle length and the grid density.

The following example of DP realization is modeled based on the software called Advanced Vehicle Simulator (ADVISOR), which consists of models, data, and text files developed under Matlab and Simulink [22, 23]. It is designed for rapid analysis of the performance and fuel economy of all types of vehicles e.g. conventional, electric, fuel cell and hybrid electric vehicles. ADVISOR can be used to estimate the fuel economy of vehicles that have not yet been built, compare relative emissions produced on a drive cycle, evaluate a power management strategy for hybrid vehicles, develop control algorithms for intelligent control of vehicles, and optimize the design of vehicles through changing the size of each component.

The models in ADVISOR are mostly empirical, relying on drivetrain component input/output relationships measured in the laboratory, and quasi-static, using data collected in steady state (e.g. constant torque and speed) tests and correcting them for transient effects such as the rotational inertia of drivetrain components.

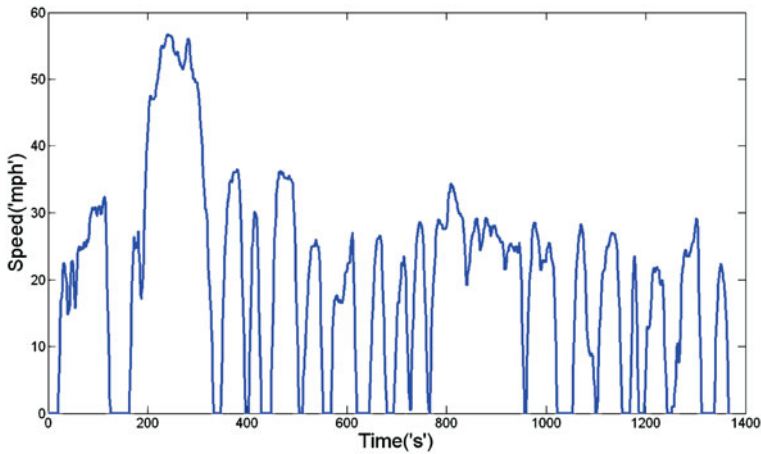


Fig. 6.5 UDDS drive cycle

3. Choose a drive cycle and get the fuel rate table.

In this example, two drive cycles are selected. One is called U.S. FTP-72, which represents urban driving conditions, and the other one is HWFET which represents the highway drive cycle.

The U.S. FTP-72 (Federal Test Procedure) cycle is also called Urban Dynamometer Driving Schedule (UDDS) or LA-4 cycle, which is shown in Fig. 6.5. The same drive cycle is also called A10 or CVS cycle in Europe and the ADR 27 cycle in Australia [24].

The cycle with a whole distance of 7.5 mile simulates a city route with 18 stops. The maximum speed is 56.7 mile/h and the average speed is 19.6 mile/h.

The HWFET cycle, shown in Fig. 6.6, represents highway driving conditions under 60 m/h [25], which is developed by the US EPA for the determination of fuel economy of light duty vehicles. The cycle has a duration of 765 s, a total distance of 10.26 miles and an average speed of 48.3 mile/h.

4. Build the cost-to-go matrix U ;

5. Find the optimal P_s path, and the optimal E_s level.

The whole steps to realize in DP for HEVs are shown in Fig. 6.7.

All the simulation parameters and results about the series HEV calculated from those are as follows:

1. $P_s = 1000 \text{ W}$, $\Delta t = 1 \text{ s}$;
2. P_s boundary: $[P_{s \min}, P_{s \max}] = [-9000 \text{ W}, 10000 \text{ W}]$, SOC boundary $[0.3, 0.9]$;
3. Cost-to-go matrix.

A cost-to-go matrix including 5107 lines and 1370 columns is constructed for UDDS drive cycle and a cost-to-go matrix including 5107 lines and 766 columns is constructed for HWFET drive cycle.

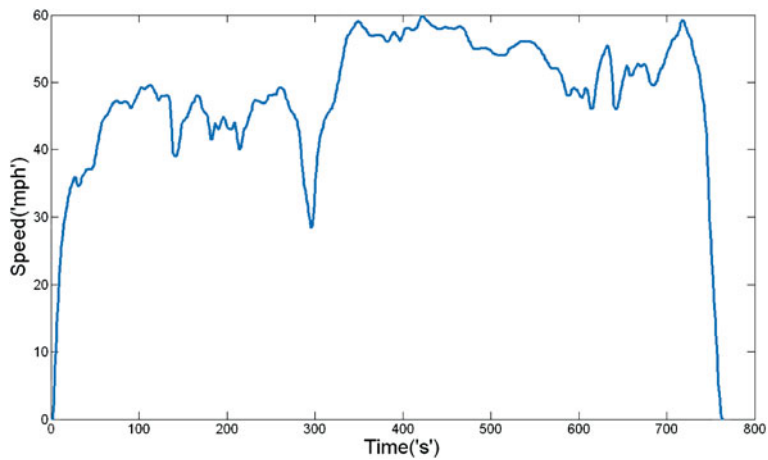
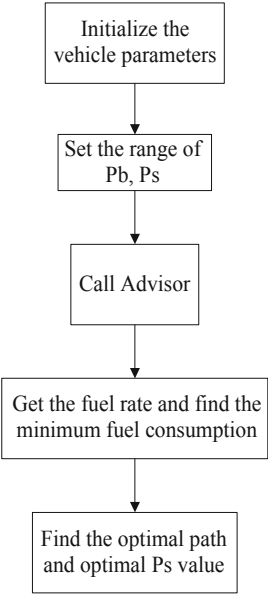


Fig. 6.6 HWFET drive cycle

Fig. 6.7 The steps of realizing DP for HEVs



4. Result

The optimal charging/discharging power to battery under UDDS is shown in Fig. 6.8. The optimal charging/discharging power to battery under HWFET drive cycle is shown in Fig. 6.9. The results are compared in Table 6.2.

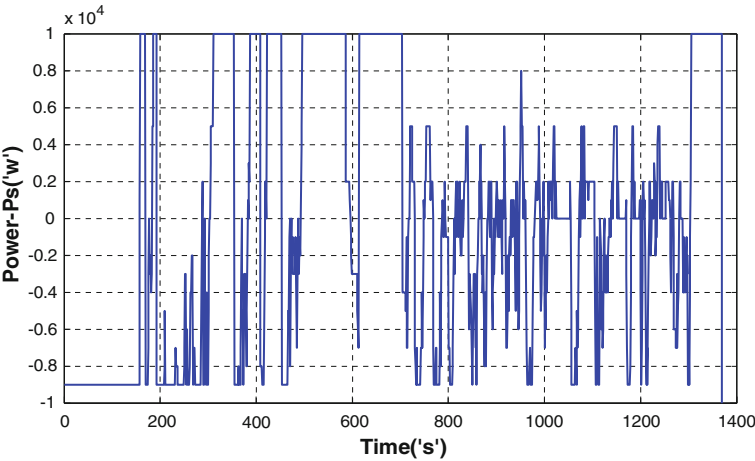


Fig. 6.8 P_s curve through DP training under UDDS drive cycle for SHEV

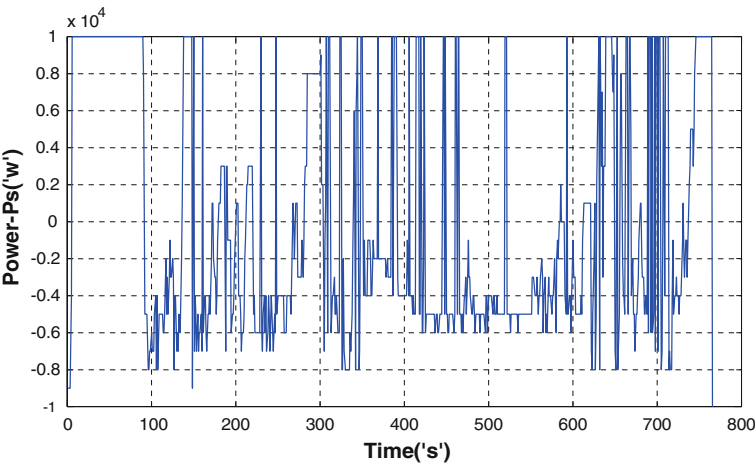


Fig. 6.9 P_s curve through DP training under HWFET drive cycle for SHEV

Table 6.2 Dynamic programming result comparison for series HEV

Drive Cycle	MPG based on default control	MPG based on DP	MPG Improving (%)
UDDS	26.7	27.7	3.75
HWFET	37.75	41.16	9.70

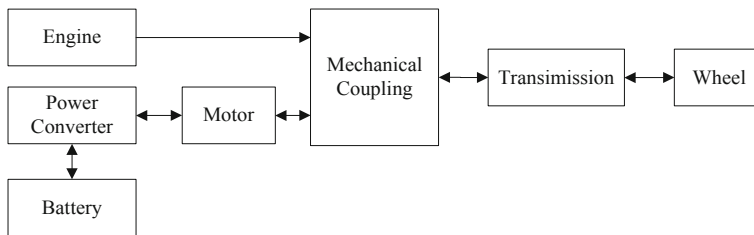


Fig. 6.10 Parallel HEV powertrain configuration

6.2.2 Dynamic Programming Realization for Parallel HEV

In a parallel HEV, as shown in Fig. 6.10 with simplified component arrangement and power flow, the heat engine and the electric motor are connected to the driveshaft through a mechanical coupling device, such as clutches, gears, belts, and in certain cases through a planetary gear system. Power requirements of the electric motor in connection with the parallel hybrid are lower than that of an EV or series HEV, because the heat engine complements the total power requirement of the vehicle. The propulsion power may be supplied by the heat engine, by the battery-motor set, or by the two systems in combination. There are many advantages for parallel HEV as discussed in Chap. 2. But the control of parallel HEV is inherently more complex than series HEV; and the mechanical coupling is also more complex than in a series HEV.

The steps to realize the DP are the same as the series HEV. There is only 1 optimal variable: P_s . The simulation realized in ADVISOR 2002 is shown in Fig. 6.11. The parameters of the example PHEV for DP optimization is shown in Table 6.3.

In this example, the boundary of SOC is 0.9–0.3, the default SOC is 0.6, and using the SOC correction, the beginning and ending SOC are the same. The DP realization is achieved under the UDDS drive cycle and HWFET drive cycle. The optimal P_s curves are shown in Figs. 6.12 and 6.13 respectively. The results from the UDDS drive cycle and the default control algorithm are shown in Table 6.4 for comparison purposes.

6.2.3 Dynamic Programming Realization for Series–Parallel HEV

One of the most popular HEVs nowadays is the Toyota Prius whose powertrain is a typical representative of series–parallel structure. This configuration uses two electrical machines, one is primarily used as a generator, and the other is primarily used as a propulsion motor. Hence they require two inverters, one for each motor/generator. The component arrangement and power flow is shown in Fig. 6.14.

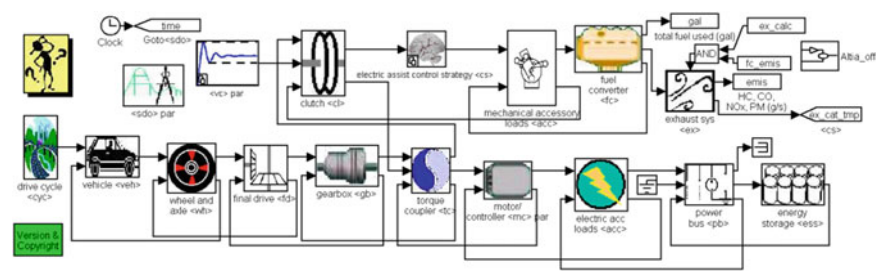


Fig. 6.11 Simulation flowchart in ADVISOR 2002 for Parallel HEV

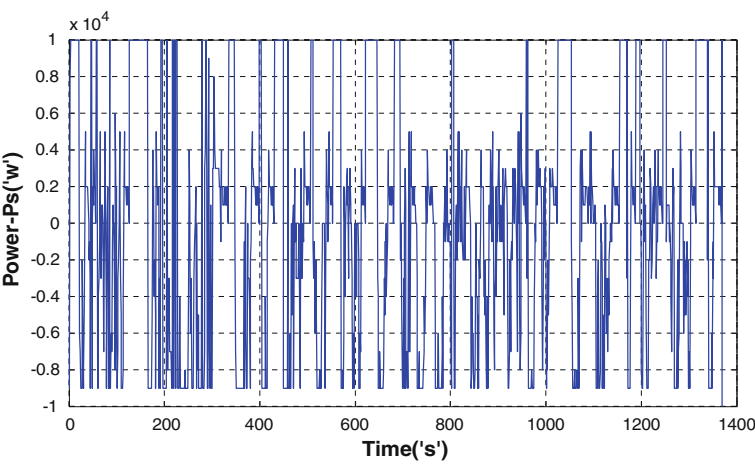


Fig. 6.12 P_s curve through DP training under UDDS drive cycle for PHEV

Table 6.3 Parameters of the parallel HEV

Components	Parameters	Values
Engine	Maximum power	102 kW
	Peak efficiency	0.4
Energy Storage (Battery)	Capacity	12 Ah
	Normal voltage	197 V
Motor	Maximum power	75 kW
	Peak efficiency	0.92
Vehicle	Drive type	Front-wheel drive
	Mass	1972 kg

The Prius drivetrain contains a planetary gear train to split the engine power between the final drive shaft and the generator. Due to the fact that the planetary gears acts as a mechanical coupling as well as a transmission, the speed ratio between the engine and the final drive is continuously variable, which is called

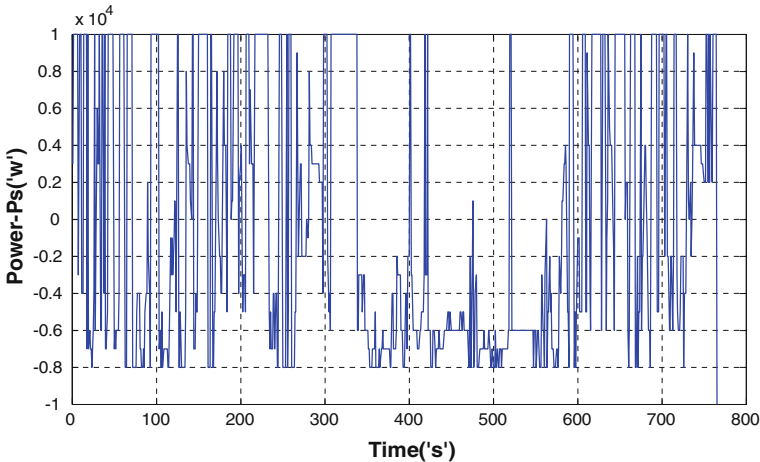


Fig. 6.13 P_s curve through DP training under HWFET drive cycle for SHEV

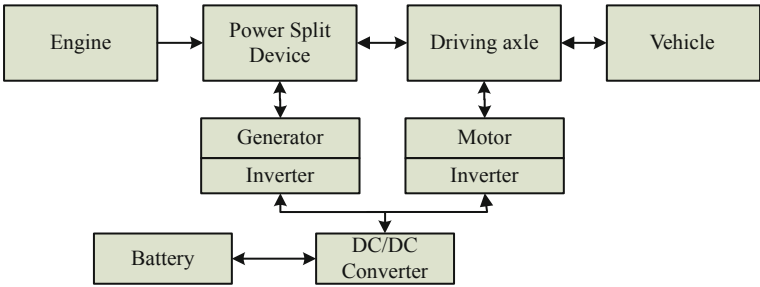


Fig. 6.14 Powertrain of series-parallel hybrid

Table 6.4 Dynamic programming result comparison for SHEV

Drive Cycle	MPG based on default control	MPG based on DP	MPG Improving (%)
UDDS	22.9	23.8	3.93
HWFET	31.1	34.9	12.2

electric continuously variable transmission (e-CVT). More interesting information about the planetary gears can be found in Chap. 3. The generator is connected to the sun gear, the ring gear is connected to the final drive as well as the motor, and the engine is connected to the planet carrier. The motor and generator provide or take power through the power split device, depending on their mode of operation. By controlling the torque and the speed of the generator, the engine speed can be controlled simultaneously to achieve higher operating efficiency and less emissions [9, 26].

Through analyzing the basic power train functions of the Prius vehicle, the following equations can be derived.

$$\begin{cases} (1 + \rho) \cdot w_e = \rho \cdot w_g + w_r \\ \eta \cdot T_e = (1 + 1/\rho) \cdot T_g = (1 + \rho) \cdot T_r \\ w_m = w_r \\ T_w = T_m + T_r = T_m + \eta \cdot T_e / (1 + \rho) \\ w_w = w_r / K = ((1 + \rho) \cdot w_e - \rho \cdot w_g) / K \end{cases} \quad (6.18)$$

where

ρ	The ratio of Sun gear and ring gear;
η	The efficiency of engine;
w_e, w_g, w_r, w_m, w_w	Speed of engine, generator, ring gear, motor and drive axle;
T_e, T_g, T_r, T_m, T_w	Torque of engine, generator, ring gear, motor and drive axle;
K	Final drive train ratio.

The system power is shown below.

$$\begin{aligned} P &= P_w + P_b \\ &= P_w - P_g \cdot \eta_1 + \frac{P_m}{\eta_2} \\ &= \frac{T_e \cdot w_e}{\eta_3} - P_g \cdot \eta_1 + \frac{P_m}{\eta_2} \\ &= \frac{(T_w - T_m) \cdot (1 + \rho) \cdot w_e}{\eta_3 \cdot \eta} - k_1 \cdot T_e \cdot n_g \cdot \eta_1 + \frac{k_2 \cdot T_m \cdot w_m}{\eta_2} \\ &= \frac{(T_w - T_m) \cdot (1 + \rho) \cdot w_e}{\eta_3 \cdot \eta} - k_1 \cdot (T_w - T_m) \cdot w_e \cdot \eta_1 + \frac{k_2 \cdot T_m \cdot w_m}{\eta_2} \end{aligned} \quad (6.19)$$

where η_1, η_2, η_3 are the generator, motor, engine efficiency respectively; k_1, k_2 are the constant coefficients. Therefore, the system power can be determined by two factors, T_m and w_e . Therefore, it has two degrees of freedom, unlike a series HEV or parallel HEV. Although it is difficult to realize DP due to the two-degree of freedom in this system, there are two ways to solve the problem. First, two DOF (degrees of freedom) DP could be constructed, which will require vast computational efforts and will cost much more time than single variant DP. Second, two DOF DP could be converted to one DOF DP through some simplification. Like the Prius model, since there are two factors— T_m and w_e , the engine efficiency map could be known beforehand. So for each T_m and w_e , the efficiency could be calculated and power could be obtained. Because of the known engine efficiency map, for each T_m , the highest efficiency for the engine could be found, so the corresponded w_e could be determined accordingly. Through this way, the highest efficiency operating point could be found and the two-DOF problem could be converted into one DOF problem without losing much precision.

The algorithm is simulated based on the Prius model in Advisor 2004, as shown in Fig. 6.15, the parameters of vehicle are shown in Table 6.5.

Three different drive cycles are simulated including UDDS and HWFET. During the simulation, we define $\Delta t = 1$ s, $\Delta P = 1000$ W, $\Delta E = 1000$ J, and $V = \{-17, \dots, 20\}$. The battery SOC constraint [0.4, 0.9], the initial value of SOC

quadratic programming (discussed in the next section), and driving pattern recognition and GPS-based road condition prediction can help DP realization. Fuzzy logic based controls can benefit from DP because the optimal power distribution for each component can be optimized using DP for given drive cycles which helps to setup the control rule for fuzzy control. Road pattern recognition can then be used for the fuzzy controller to locate the proper control rule that has been developed in DP. More details about DP based fuzzy control setup will be discussed in the [Sect. 7.6](#).

6.3 Efficiency Optimization of PHEV Using Quadratic Programming¹

In this section, we will study the power management of a plug-in hybrid electric vehicle (PHEV) using quadratic programming. Quadratic programming can obtain the global optimal solution of the power distribution between battery/motor and engine while improving vehicle performance. Computation time can be significantly saved compared with dynamic programming. Therefore, it can be used in real-time realization. Two typical drive cycles, namely, UDDS and HWFET drive cycles are used to test the effectiveness of optimization strategy. The simulation results indicate that a significant amount of fuel can be saved with the proposed method.

6.3.1 Architecture of the PHEV

The architecture of the PHEV studied is of a power-split type similar to the Toyota Prius, as shown in Fig. 6.16. However, two clutches are used to configure the operation modes of the powertrain. In this configuration, the vehicle powertrain can be configured as series operation or parallel operation. The detailed operation modes are explained as follows:

Mode 1 motor alone mode. In this mode, C1 is engaged and C2 is open. Motor is the only source of propulsion to drive the vehicle by taking power from the battery.

Mode 2 series mode. In series operation, C1 is engaged to ground the ring gear and C2 is open. So the engine drives the carrier which in turn transfers engine power to the sun gear that drives the generator to produce electricity. The motor is the only source of propulsion but can receive power from the generator and the battery at the same time. The power flow is shown in Fig. 6.17.

Mode 3 parallel mode. In parallel operation, C1 is open and C2 is engaged. So the ring gear is connected to the final drive. The planetary gear train serves as an input split device. The engine power is therefore split between the sun gear and

¹ Portion of the material is from Zhiguang Zhou, and Chris Mi, "Power Management of PHEV Using Quadratic Programming," to appear, International Journal of Electric and Hybrid Vehicles, vol. 3, no. 3, 2011. © Inderscience, [2011].

Fig. 6.16 Architecture of PHEV

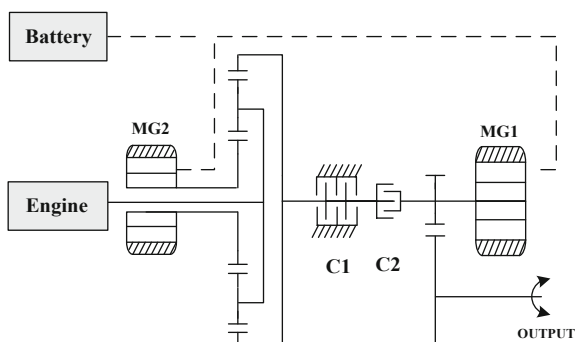


Fig. 6.17 Power flow in series operation of PHEV

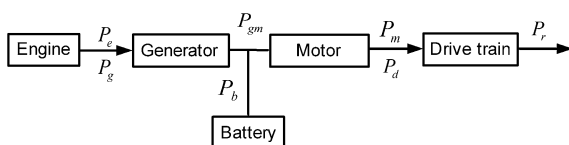
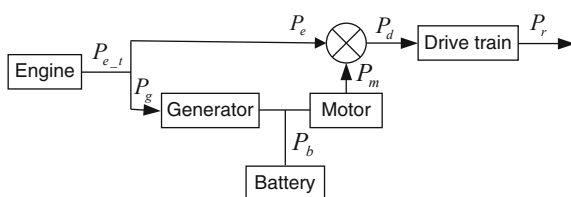


Fig. 6.18 Power flow in parallel operation of PHEV



ring gear. The ring gear power is used to drive the vehicle while the sun gear power is supplied to the generator to generate electricity. The motor provides torque to drive the vehicle by taking energy from the generator or battery. The power flow of the PHEV in parallel operation is shown in Fig. 6.18.

Mode transition is controlled by the transmission controller based on battery SOC and vehicle power demand. To reduce impact of mode transition on vehicle dynamic performance, C1 is always released before C2 engages.

For example, when transitioning from motor alone or series to parallel mode, engine is first started by MG2 with C1 engaged to lock the ring gear. Once the engine is started, C1 can be open and the generator is controlled such that the ring gear speed will increase. When the ring gear speed reaches the motor speed, C2 is engaged.

When transitioning from parallel to series operation, engine power is reduced and C2 is released. At the same time, the generator is controlled such that the ring gear speed will decrease. When the ring gear speed approaches zero, C1 is engaged.

In traditional PHEV control, the vehicle will operate in the CD mode first by using the battery energy until the SOC drops below a preset threshold and at that

Table 6.7 Parameters of PHEV

Component	Contents	Rating
Vehicle	Type	SUV
	Gross weight	3298 kg
Engine	Type	Gasoline 5.7 L
	Peak power	257 kW @5300 RPM
Motor	Type	Permanent Magnet AC
	Peak power	65 kW @ 4200 RPM
Generator	Type	Permanent Magnet AC
	Peak power	65 kW @ 4200 RPM
Battery pack	Type	Lithium-ion battery
	Rated capacity	10 kWh
	Rated voltage	300 V
	Total weight	76 kg

time, the vehicle enters into the CS mode. This is called a CDCS mode. In this paper, the CD mode is defined with slight difference: the engine may be started if vehicle power demand exceeds a certain limit. This is due to the fact that operate the vehicle using the batter/motor only at high power demand will become very inefficient due to large losses associated with the motor and battery impedance as discussed in Chap. 4. The modified CD mode is also called a blended PHEV mode. This paper is to optimize the power distribution between the battery and engine in the blended PHEV mode to minimize energy consumption (fuel + battery energy) for a given driving distance. This is a continuation of the analytical approach explained in Chap. 4. The parameters of the PHEV are shown in Table 6.7.

6.3.2 Power Flow Analysis

From Fig. 6.18, in the parallel mode, the total engine power P_{e_t} is composed of two portions. One portion is P_g that is used to drive the generator to produce electricity, which can be stored in the battery (P_{gb}) or used to drive electric motor (P_{gm}) directly; the other portion is P_e which is directly used to propel the vehicle, either independently, or together with power from electric motor (P_m) [18]. Both power from the battery (P_b) and generator (P_{gm}) can be used to drive the electric motor, depending on control strategy. The total engine output power can be obtained

$$P_{e\_t} = P_e + P_g \quad (6.20)$$

Total Power from engine has the relationship with fuel consumption,

$$P_{e\_t} = f(m_f) \quad (6.21)$$

For the generator, its output power are shared between the motor and the battery, i.e.

$$P_{gb} + P_{gm} = \eta_g \cdot P_g \quad (6.22)$$

where η_g is efficiency of the generator.

For the battery,

$$P_b = \eta_{b\_D} \cdot (\eta_{b\_C} \cdot P_{gb} + P_{bs}) \quad (6.23)$$

where η_{b_D} is discharge efficiency of the battery, η_{b_C} is charge efficiency of battery, P_{bs} is the power consumed from the battery.

For the motor,

$$P_m = \eta_m \cdot (P_b + P_{gm}) \quad (6.24)$$

where η_m is the efficiency of the motor.

Output power to the drive train is

$$P_d = \eta_p \cdot (P_m + P_e) \quad (6.25)$$

where η_p is the efficiency of the gear.

The vehicle power demand is

$$P_r = \eta_d \cdot P_d \quad (6.26)$$

where η_d is the efficiency of the drive train.

From Eq. 6.20 to 6.26, we can obtain

$$P_r = \eta_d \eta_p \cdot (\eta_m \eta_{b\_D} \eta_{b\_C} P_{gb} + \eta_m P_{gm} + P_e) + \eta_d \eta_p \eta_m \eta_{b\_D} \cdot P_{bs} \quad (6.27)$$

In Eq. 6.27, the first item is the power produced by the consumption of fuel, the second item is power stored in battery, so we can rewrite Eq. 6.27 as

$$P_r = g(m_f) + \eta \cdot P_{bs} \quad (6.28)$$

where $\eta = \eta_d \eta_p \eta_m \eta_{b\_D}$.

From Eq. 6.28 we can see that with the previous knowledge of drive cycle, the required power is known at every time moment. So only fuel consumption and power from battery are variables, and we can use the following function to describe the relationship between fuel consumption and power from battery [16, 17], using similar analysis in Chap. 4:

$$\dot{m}_f(P_{bs}) = \alpha_2 P_{bs}^2 + \alpha_1 P_{bs} + \alpha_0 \quad (6.29)$$

where $\alpha_2 > 0$, $\alpha_0 > 0$.

6.3.3 Power Management Using QP

From Sect. 6.3.2, we can see that power management problem can be described with quadratic polynomial, so the optimal solution can be obtained using QP method. Before using QP, the total time of drive cycle is discretized to n time points with the time interval Δt .

$$n = \frac{t}{\Delta t} \quad (6.30)$$

So the relationship between fuel consumption and power from battery can be described in discrete time domain as

$$m_f(k) = \alpha_2(k)P_{bs}^2(k) + \alpha_1(k)P_{bs}(k) + \alpha_0(k) \quad (6.31)$$

where $\alpha_2(k) > 0$, $\alpha_0(k) > 0$, $k = 0, 1, \dots, n$.

At every time point k , let $P_{bs}(k)$ change from

$$\begin{cases} 0 & P_{e\_t}(k) \geq P_r(k) \\ P_r(k) - P_{e\_t \max} & P_{e\_t}(k) < P_r(k) \end{cases} \quad (6.32)$$

to

$$\begin{cases} P_r(k) & P_{bs \max} \geq P_r(k) \\ P_{bs \max} & P_{bs \max} < P_r(k) \end{cases} \quad (6.33)$$

Then the corresponding fuel consumption $m_f(k)$ can be obtained at each time point. Using least square method, coefficients $\alpha_2(k)$, $\alpha_1(k)$ and $\alpha_0(k)$ can be acquired.

The optimization objective of power management is to minimize fuel consumption, so the cost function can be described as

$$\begin{aligned} J &= \sum_{k=1}^n m_f(k) \\ &= \sum_{k=1}^n [\alpha_2(k)P_{bs}^2(k) + \alpha_1(k)P_{bs}(k) + \alpha_0(k)] \end{aligned} \quad (6.34)$$

The target of power management is to minimize the fuel consumption under the precondition of satisfying the requirement from the driver, so it can be described as

$$\begin{aligned} \min J &= \min \left(\sum_{k=1}^n m_f(k) \right) \\ &= \min \left(\sum_{k=1}^n [\alpha_2(k)P_{bs}^2(k) + \alpha_1(k)P_{bs}(k) + \alpha_0(k)] \right) \end{aligned} \quad (6.35)$$

The QP problem can be solved analytically by introducing the Lagrange function

$$L(P_{bs}(k), \lambda) = \sum_{k=1}^n [\alpha_2(k)P_{bs}^2(k) + \alpha_1(k)P_{bs}(k) + \alpha_0(k)] - \lambda \left(\sum_{k=1}^n P_{bs}(k) - E_{bs} \right) \quad (6.36)$$

where E_{bs} is the maximum usable energy supplied by battery alone during the whole trip.

The optimal solution can be obtained by solving

$$\frac{\partial L(P_{bs}(k), \lambda)}{\partial P_{bs}(k)} = 0 \quad (6.37)$$

and

$$\frac{\partial L(P_{bs}(k), \lambda)}{\partial \lambda} = 0 \quad (6.38)$$

The solution is

$$P_{bs\_opt}(k) = \frac{\lambda - \alpha_1(k)}{2\alpha_2(k)} \quad (6.39)$$

where

$$\lambda = \frac{\sum_{k=1}^n \frac{\alpha_1(k)}{2\alpha_2(k)} + E_{bs}}{\sum_{k=1}^n \frac{1}{2\alpha_2(k)}} \quad (6.40)$$

From Eq. 6.40, we can see that λ has the relationship with the whole drive cycle, this means before using QP method, the drive cycle must be known beforehand.

In order to maintain all the components operate in the reasonable range, under the condition of the driving mode, the following constraints are designed,

$$\left. \begin{aligned} \omega_{e\_min} &\leq \omega_e(k) \leq \omega_{e\_max} \\ T_{e\_min} &\leq T_e(k) \leq T_{e\_max} \\ \omega_{m\_min} &\leq \omega_m(k) \leq \omega_{m\_max} \\ T_{m\_min} &\leq T_m(k) \leq T_{m\_max} \\ \omega_{g\_min} &\leq \omega_g(k) \leq \omega_{g\_max} \\ T_{g\_min} &\leq T_g(k) \leq T_{g\_max} \\ P_{bs\_min} &\leq P_{bs}(k) \leq P_{bs\_max} \\ E_{bs\_min} &\leq E_{bs}(k) \leq E_{bs\_max} \\ SOC_{min} &\leq SOC(k) \leq SOC_{max} \end{aligned} \right\} \quad (6.41)$$

where ω_{e_min} , ω_{e_max} , ω_{m_min} , ω_{m_max} , ω_{g_min} , and ω_{g_max} are the minimum and maximum speed of engine, electrical motor and generator respectively; T_{e_min} , T_{e_max} , T_{m_min} , T_{m_max} , T_{g_min} , and T_{g_max} are the minimal and

maximum torque of engine, electrical motor and generator under current speed respectively; P_{bs_min} , P_{bs_max} , E_{bs_min} and E_{bs_max} are the minimal and maximum power and energy from battery at the current time; SOC_{min} and SOC_{max} are minimal and maximum SOC of battery. The energy of battery at the current time can be calculated from

$$E_{bs}(k) = E_{bs}(0) - \sum_{k=1}^n P_{bs}(k). \quad (6.42)$$

6.3.4 Optimization Results and Discussion

In order to verify the optimization results, the QP method is implemented in ADVISOR. Two typical drive cycles UDDS and HWFET is selected to test CDCS control strategy and QP method. The SOC with 8 UDDS drive cycles is shown in Fig. 6.19. It can be seen that using CDCS method the SOC decreases quickly to the specific level 0.3 and at this time the distance is 18.6 km. On the contrary, the SOC changes slowly to the specific level of 0.3 under the control of QP, as the dashed line indicated. The simulation results under the control of CDCS and QP with different cycles of UDDS and HWFET drive cycles are shown in Figs. 6.20 and 6.21 respectively. In both figures, the x-axis is distance and y-axis is MPG. From Fig. 6.20, it can be seen that at different distance the QP method increases MPG from 3.71 to 3.97% compared to CDCS method. Following the increase of distance, MPG under both the QP method and CDCS method are decreasing, but the changing rate is smaller and smaller. From Fig. 6.21, we can see the same changing trend as Fig. 6.20, and the same result can be obtained that using QP method has higher MPG than the CDCS method, and the increase is from 3.42 to 3.69%. It can also be seen that in the HWFET drive cycle the MPG is higher than in UDDS drive cycle for the same distance driven.

The efficiency of motor and engine under the control of the CDCS method and QP method in the UDDS drive cycle is shown in Figs. 6.22, 6.23, 6.24, 6.25 respectively.

From Figs. 6.22 and 6.23, we can see that the CDCS method cannot achieve the global optimization in the whole drive cycle. But using QP method, the global optimization can be implemented and the motor operates in higher efficiency area compared with CDCS method. From Figs. 6.24 and 6.25, it can also be seen that by using QP method the engine operates in higher efficiency area compared with CDCS method. The operation of motor and engine in high efficiency area will lead to the reduction of fuel consumption.

In this section, the QP approach for the optimization of PHEV power management is presented. This optimization problem is formulated based on the QP method. The variables in PHEV power management include the engine, generator, electric motor and energy storage system. The objective function is defined to

Fig. 6.19 SOC over the driving range for DP and CDCS

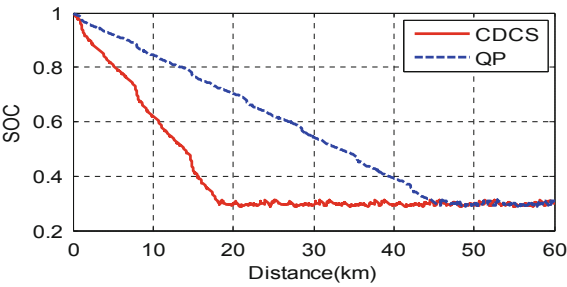


Fig. 6.20 Fuel economy of PHEV with UDDS

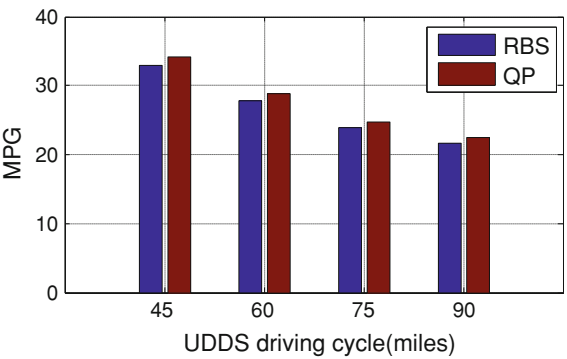
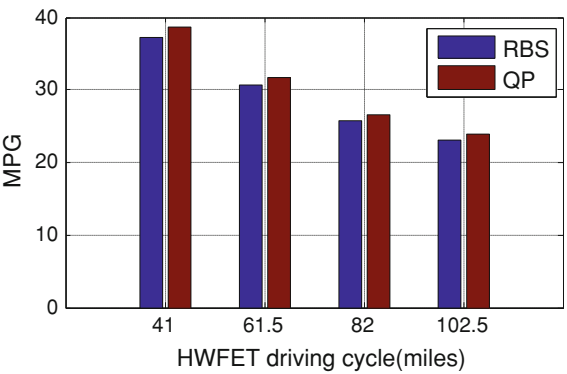


Fig. 6.21 Fuel economy of PHEV with HWFET



minimize the fuel consumption. The satisfaction of vehicle performance requirements is the precondition of the optimization problem and usable power range of engine and battery are selected as the constraints. The optimization is performed in two kinds of drive cycles. The results show that in both UDDS and HWFET drive cycles, the MPG under the control of QP is higher than that under the control of CDCS. It means that the QP method can decrease the fuel consumption while maintaining the vehicle performance. Furthermore, the simulation results reveal

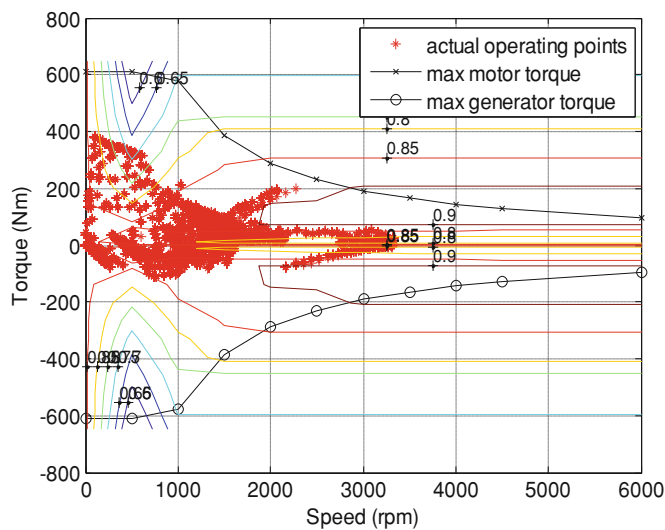


Fig. 6.22 Efficiency of motor with CDCS method

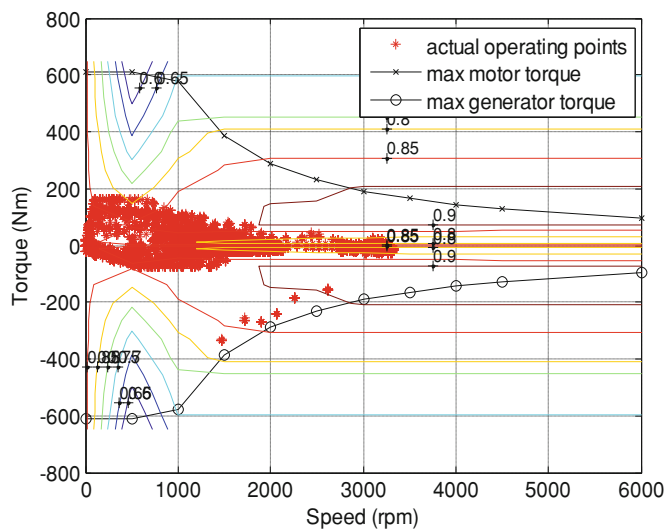


Fig. 6.23 Efficiency of motor with QP method

that the increase of MPG is less with the increase of distance. The conclusion also can be drawn that with the same control method, the vehicle in the HWFET drive cycle has higher MPG than that in the UDDS drive cycle.

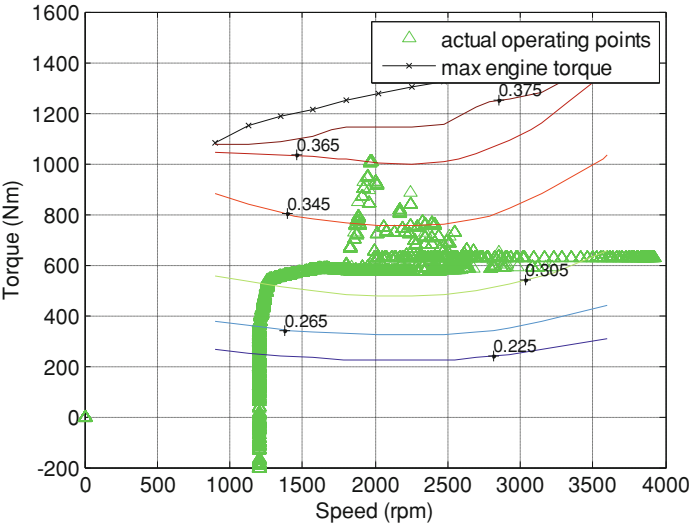


Fig. 6.24 Efficiency of engine with CDCS method

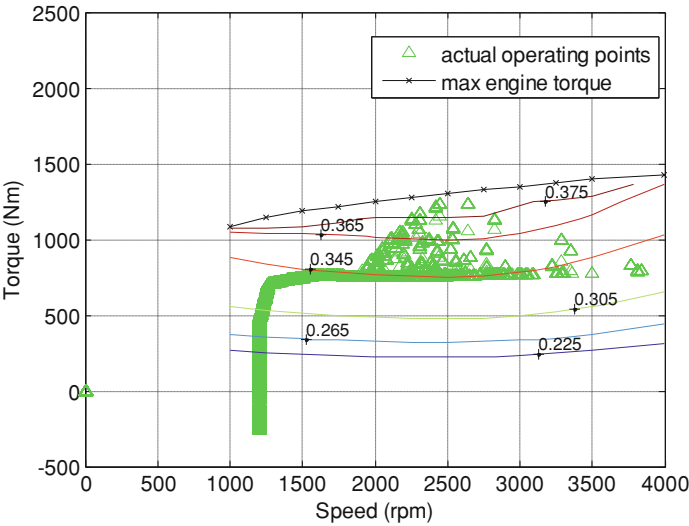


Fig. 6.25 Efficiency of engine with QP method

6.4 Summary

The dynamic programming has been a powerful tool to realize optimal control, from 1950s till now. It has had wide applications due to its effectiveness for the optimization problem. It is mainly based on a simple theory that the whole path is optimal so the sub-trajectory is also optimal.

For a hybrid electric vehicle, in consideration of the importance of energy efficiency, an effective energy management strategy could considerably affect the vehicle's fuel economy. So finding the optimal control strategy for a specific HEV has a great significance. Due to the nonlinearity of HEV models including the vehicle body, engine, motor, and energy storage, the traditional optimization theory, i.e. minimum theory could not be effectively applied to the HEV power management due to high nonlinearity and complexity of the system. Dynamic programming theory could search the optimal trajectory with high efficiency, which does not rely on the precise mathematical model.

This chapter first discusses the power management using dynamic programming on three types of HEVs including series, parallel, and power split series-parallel HEV. Through simulation, the DP algorithm could find the optimal power from the battery to supply the motor which then determine the ratio of power split between batteries and engine accordingly. Through comparison of results, 3–10% improvement on fuel efficiency can be achieved compared to default non-optimized controllers.

DP also has some constraints. It needs to know the whole drive condition in advance to achieve the optimal online control which is difficult to obtain in real-world driving scenarios. Nevertheless, dynamic programming can be used as an effective method and benchmark for improving the fuel economy of HEVs.

Quadratic programming has the advantage of saving computational time. Hence it can be realized in real time by using data from previous trips.

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Chapter 7

Intelligent System Approaches for Vehicle Power Management

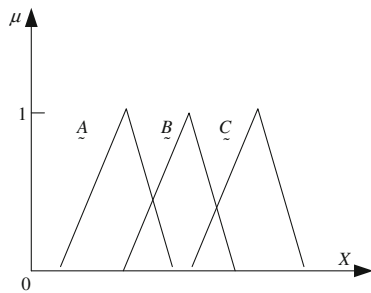
In the past two decades, intelligent system approaches, such as fuzzy logic and neural networks, have been successfully introduced into the field of vehicle control and power management. Applications of intelligent systems in vehicle power management include several aspects, such as power split determination for parallel hybrid electric vehicles, and driving pattern prediction for the improvement of overall vehicle performance and fuel efficiency. Vehicle power management is gradually shifting from rule-based systems with the help of static efficiency maps and driving cycle specific optimization using optimal control to the intelligent approach based on prediction of driving pattern and road conditions.

Both fuzzy logic and neural networks belong to artificial intelligence that provides simple solutions for many difficult problems in computer science, engineering, and some other disciplines. Suppose a multidimensional space has two inputs and one output, and fuzzy logic and neural networks can form this nonlinear input–output relation and realize the complex nonlinearity by combining multiple simple functions. Fuzzy logic separates the space into several rule areas whose partial shapes are determined by membership functions and rule outputs. Neural networks form the shape by combining sigmoidal, radial, or other simple functions that are enlarged, shrunk, upset, and/or shifted by synaptic weights [1]. This chapter gives the basic knowledge of fuzzy logic and neural networks to readers for better understanding of how to use these technologies in the real-world problems, especially when applied to vehicle power management.

7.1 Fundamentals of Fuzzy Logic

Fuzzy logic, introduced by Lotfi Zadeh in 1965 [2], is a form of multi-valued logic derived from fuzzy set theory to deal with imprecision and information granularity. In contrast with binary logic used in classical sets or crisp sets, the fuzzy logic offers a mechanism for representing linguistic constructs such as “many”, “low”, “medium”, “often”, “few”, etc. Generally an inference structure enabling

Fig. 7.1 Membership function of a fuzzy set



appropriate human reasoning capabilities is provided by fuzzy logic. Fuzzy logic is based on the notion of relative graded membership and can be considered as the function of mentation and cognitive processes. Fuzzy sets provide methods to model uncertain or ambiguous data.

7.1.1 Fuzzy Sets

The values assigned to the elements of the universal set fall within a specific range and indicate the membership grade of these elements in the set. The function where smaller values represent lower degrees of set membership is defined as a membership function, and the set is called a fuzzy set. In a fuzzy set, elements have varying degrees of membership. On the contrary, members of a classical or crisp set would not be members unless their membership is assigned a value of 1. If an element x of the universe X is a member of a fuzzy set $\underline{A}$, then the mapping from the fuzzy set to a real numbered value is given by $\mu_{\underline{A}}(x) \in [0, 1]$, as shown in Fig. 7.1.

Let $\underline{A}$, $\underline{B}$ and $\underline{C}$ represent three fuzzy sets on the universe X . Given an element x of the universe, the operations, union, intersection and complement for the fuzzy sets are defined below:

Union:

$$\mu_{\underline{A} \cup \underline{B}}(x) = \max(\mu_{\underline{A}}(x), \mu_{\underline{B}}(x)). \quad (7.1)$$

Intersection:

$$\mu_{\underline{A} \cap \underline{B}}(x) = \min(\mu_{\underline{A}}(x), \mu_{\underline{B}}(x)). \quad (7.2)$$

Complement:

$$\mu_{\underline{\bar{A}}}(x) = 1 - \mu_{\underline{A}}(x). \quad (7.3)$$

De Morgan's laws fit fuzzy sets, expressed as follows:

$$\overline{\underline{A} \cap \underline{B}} = \underline{\bar{A}} \cup \underline{\bar{B}} \quad (7.4)$$

$$\overline{\underline{A} \cup \underline{B}} = \underline{\bar{A}} \cap \underline{\bar{B}} \quad (7.5)$$

The properties of the classical sets also hold for the fuzzy sets as described by the following expressions:

Commutativity

$$\underline{A} \cap \underline{B} = \underline{B} \cap \underline{A} \quad (7.6)$$

$$\underline{A} \cup \underline{B} = \underline{B} \cup \underline{A} \quad (7.7)$$

Associativity

$$\underline{A} \cup (\underline{B} \cup \underline{C}) = (\underline{A} \cup \underline{B}) \cup \underline{C} \quad (7.8)$$

$$\underline{A} \cap (\underline{B} \cap \underline{C}) = (\underline{A} \cap \underline{B}) \cap \underline{C} \quad (7.9)$$

Distributivity

$$\underline{A} \cup (\underline{B} \cap \underline{C}) = (\underline{A} \cup \underline{B}) \cap (\underline{A} \cup \underline{C}) \quad (7.10)$$

$$\underline{A} \cap (\underline{B} \cup \underline{C}) = (\underline{A} \cap \underline{B}) \cup (\underline{A} \cap \underline{C}) \quad (7.11)$$

Idempotency

$$\underline{A} \cup \underline{A} = \underline{A} \quad (7.12)$$

$$\underline{A} \cap \underline{A} = \underline{A} \quad (7.13)$$

Identity

$$\underline{A} \cup \phi = \underline{A} \text{ and } \underline{A} \cap X = \underline{A} \quad (7.14)$$

$$\underline{A} \cap \phi = \phi \text{ and } \underline{A} \cup X = X \quad (7.15)$$

Transitivity

$$\text{If } \underline{A} \subset \underline{B} \subset \underline{C} \text{ then } \underline{A} \subset \underline{C} \quad (7.16)$$

Involution

$$\overline{\underline{\bar{A}}} = \underline{A} \quad (7.17)$$

7.1.2 Fuzzy Relations

The Cartesian product of crisp sets $A_1, A_2, \dots, A_n$, denoted by $A_1 \times A_2 \times \dots \times A_n$, is the set of $a_1, a_2, \dots, a_n$, where $a_1 \in A_1, a_2 \in A_2, \dots, a_n \in A_n$. The Cartesian product of the two universes, (i.e., X and Y) is expressed as:

$$X \times Y = \{(x, y) | x \in X \text{ and } y \in Y\}. \quad (7.18)$$

Fuzzy relations are fuzzy subsets of $X \times Y$. A fuzzy relation $\tilde{R}$ is mapping from the Cartesian space $X \times Y$ to the interval $[0, 1]$ where the degree of the mapping is described by the membership function of the relation for ordered pairs that is written as $\mu_{\tilde{R}}(x, y)$. The expression of the relation $\tilde{R}$ on $X \times Y$ is given by

$$\tilde{R} = \left\{ ((x, y), \mu_{\tilde{R}}(x, y)) \mid (x, y) \in X \times Y \right\}. \quad (7.19)$$

Let $\tilde{R}$ and $\tilde{S}$ be fuzzy relations on $X \times Y$, and the operations for the fuzzy relations are expressed below.

Union

$$\mu_{\tilde{R} \cup \tilde{S}}(x, y) = \max\left(\mu_{\tilde{R}}(x, y), \mu_{\tilde{S}}(x, y)\right). \quad (7.20)$$

Intersection

$$\mu_{\tilde{R} \cap \tilde{S}}(x, y) = \min\left(\mu_{\tilde{R}}(x, y), \mu_{\tilde{S}}(x, y)\right). \quad (7.21)$$

Complement

$$\mu_{\tilde{R}^c}(x, y) = 1 - \mu_{\tilde{R}}(x, y). \quad (7.22)$$

Containment

$$\tilde{R} \subset \tilde{S} \Rightarrow \mu_{\tilde{R}}(x, y) \leq \mu_{\tilde{S}}(x, y). \quad (7.23)$$

The properties such as commutativity, associativity, distributivity, idempotency and involution are also suitable for fuzzy relations described as follows.

Commutativity

$$\mu_{\tilde{R} \cup \tilde{S}}(x, y) = \mu_{\tilde{S} \cup \tilde{R}}(x, y). \quad (7.24)$$

Associativity

$$\mu_{(\tilde{R} \cup \tilde{S}) \cup \tilde{T}}(x, y) = \mu_{\tilde{R} \cup (\tilde{S} \cup \tilde{T})}(x, y). \quad (7.25)$$

where $\tilde{T}$ is another fuzzy relation.

Distributivity

$$\mu_{(\tilde{R} \cup \tilde{S}) \cap \tilde{T}}(x, y) = \mu_{\tilde{R} \cup (\tilde{S} \cap \tilde{T})}(x, y). \quad (7.26)$$

Idempotency

$$\mu_{\tilde{R} \cup \tilde{R}}(x, y) = \mu_{\tilde{R}}(x, y). \quad (7.27)$$

Involution

$$\mu_{\tilde{\tilde{R}}}(x, y) = \mu_{\tilde{R}}(x, y). \quad (7.28)$$

Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy sets on universe X and Y , respectively. The Cartesian product between $\tilde{A}$ and $\tilde{B}$ is a fuzzy relation $\tilde{R}$ contained with the full Cartesian product expressed as

$$\tilde{A} \times \tilde{B} = \tilde{R} \subset X \times Y. \quad (7.29)$$

Every fuzzy set can be considered as a vector of membership values, and each value is related to a particular element in every set.

7.1.3 Membership Functions

The membership functions have three properties, i.e., core, support and boundary whose definitions are shown in Fig. 7.2. The core of the membership function of the fuzzy set $\tilde{A}$ is the region of universe where the membership value is 1 ($\mu_{\tilde{A}}(x) = 1$). The support of the membership function of the fuzzy set $\tilde{A}$ is defined as the region of universe characterized by nonzero membership in the fuzzy set ($\mu_{\tilde{A}}(x) > 0$). The boundary of the membership function for the fuzzy set $\tilde{A}$ is the region of universe where the membership value is between 0 and 1 ($0 < \mu_{\tilde{A}}(x) < 1$).

The fuzzy sets are classified by using two criteria based on the membership functions. Through the first criterion related to membership value 1, two various sets are obtained. They are:

- Normal fuzzy set. A fuzzy set $\tilde{A}$ is called a normal fuzzy set when the membership function has at least one element whose value equals 1.
- Subnormal fuzzy set. If all the membership values are less than 1, the set $\tilde{A}$ is called a subnormal fuzzy set.

The two fuzzy sets are depicted in Fig. 7.3.

Through the second criterion related to the membership function shape, another two different sets are defined. They are:

Fig. 7.2 Properties of membership function

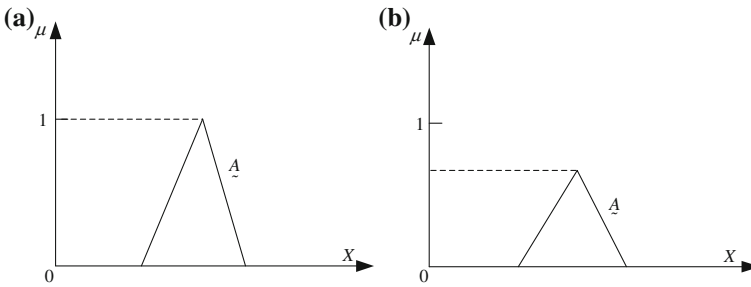
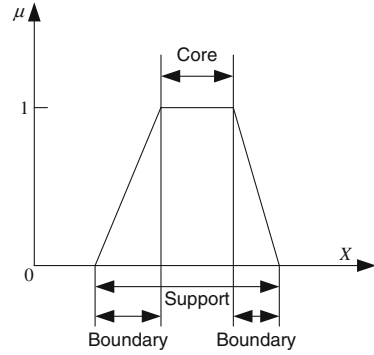


Fig. 7.3 Classification of fuzzy sets using the first criterion **a** Normal fuzzy set **b** Subnormal fuzzy set

- **Convex fuzzy set.** A fuzzy set $\underline{A}$ is called a convex fuzzy set if its membership function is monotonically increasing, or decreasing, or increasing and decreasing with the increasing values for elements in universe.
- **Nonconvex fuzzy set.** A fuzzy set $\underline{A}$ is called a nonconvex fuzzy set if the membership values are not strictly monotonically increasing or decreasing or both monotonically increasing and decreasing with the increasing values for elements in universe.

These two fuzzy sets are shown in Fig. 7.4.

It has to be noted that the intersection of the two convex fuzzy sets is also a convex fuzzy set. The membership functions of a convex fuzzy set can have various shapes, e.g. triangle, trapezoidal, Gaussian, etc.

The fuzzification process involves assigning membership values to crisp quantities for the conversion from crisp to fuzzy. We can use intuition to assign membership values for the fuzzification. The knowledge about the entire problem and linguistic variable should be known in the intuition-based assignment for development of the membership functions, related to human's intelligence and understanding. Figure 7.5 shows an example of assigning membership values

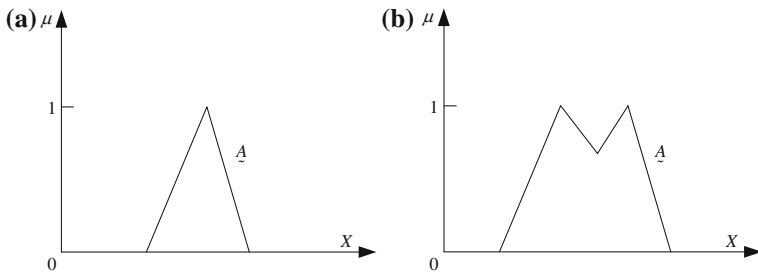
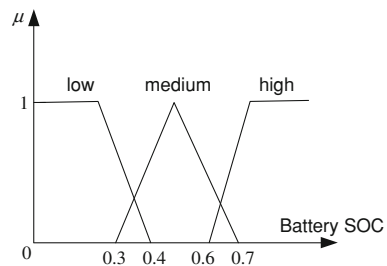


Fig. 7.4 Classification of fuzzy sets using the second criterion **a** Convex fuzzy set **b** Nonconvex fuzzy set

Fig. 7.5 Membership for fuzzy variable “Battery SOC”



using intuition. The range of battery state of charge (SOC) is divided into low, medium and high. When establishing membership functions, one should consider the number of curves and the overlapping of curves which is very important.

Details of other membership value assignment methods such as inference, rank ordering, angular fuzzy sets and inductive reasoning are not given in this section due to the limitation of space. Interested readers can refer to [3] for a better understanding.

7.1.4 Defuzzification

The fuzzy results are unavailable for use in the real world, so the fuzzy quantities are required to be converted into crisp quantities. This process is called defuzzification. Let $\tilde{A}$ be a fuzzy set, the lambda cut set is denoted by A_λ where $0 \leq \lambda \leq 1$.

The lambda cut set is defined as:

$$A_\lambda = \left\{ x / \mu_{\tilde{A}}(x) \geq \lambda \right\} \quad (7.30)$$

The fuzzy set $\tilde{A}$ can be transformed into infinite number of lambda cut sets because λ could be any value in the interval $[0,1]$. The lambda cut sets have four properties described as:

$$(1) \quad \left(\tilde{A} \cup \tilde{B} \right)_{\lambda} = A_{\lambda} \cup B_{\lambda} \quad (7.31)$$

$$(2) \quad \left(\tilde{A} \cap \tilde{B} \right)_{\lambda} = A_{\lambda} \cap B_{\lambda} \quad (7.32)$$

$$(3) \quad \left(\tilde{A} \right)_{\lambda} \neq \left(\overline{A_{\lambda}} \right) \text{ except } \lambda = 0.5 \quad (7.33)$$

$$(4) \quad \text{For any } \lambda \leq \alpha, \text{ where } \lambda, \alpha \in [0, 1], \text{ it holds that } A_{\alpha} \subseteq A_{\lambda} \quad (7.34)$$

A fuzzy relation $\tilde{R}$ can be transformed into a crisp relation using the lambda cut relation expressed as

$$R_{\lambda} = \left\{ (x, y) / \mu_{\tilde{R}}(x, y) \geq \lambda \right\} \quad (7.35)$$

The following properties fit lambda cut relations:

$$(1) \quad \left(\tilde{R} \cup \tilde{S} \right)_{\lambda} = R_{\lambda} \cup S_{\lambda} \quad (7.36)$$

where $\tilde{S}$ is another fuzzy relation and S_{λ} is its lambda cut relation.

$$(2) \quad \left(\tilde{R} \cap \tilde{S} \right)_{\lambda} = R_{\lambda} \cap S_{\lambda} \quad (7.37)$$

$$(3) \quad \left(\tilde{R} \right)_{\lambda} \neq \left(\overline{R_{\lambda}} \right) \quad (7.38)$$

$$(4) \quad \text{For any } \lambda \leq \alpha, \text{ where } \lambda, \alpha \in [0, 1], \text{ it holds that } A_{\alpha} \subseteq A_{\lambda} \quad (7.39)$$

Besides the lambda cut sets and relations capable of converting fuzzy sets and relations into crisp sets and relations, respectively, there exist other seven defuzzification methods that can convert fuzzy quantities into crisp quantities.

They are the max-membership principle, centroid method, weighted average method, mean-max membership, centre of sums, centre of largest area, and first of maxima or last of maxima. Details of these defuzzification methods can be found in [3].

7.1.5 Fuzzy Rules

There are three forms of statements for rule formation. They are assignment statements, conditional statements and unconditional statements.

In assignment statements, the variable is assigned with a value, and the assignment operator “=” is employed. When forming fuzzy rules, the value may be a linguistic term.

In conditional statements, if the conditions are satisfied then it enters the following statements (restrictions). For example, if battery SOC > 0.8 Then shut off the engine. This can be considered as a fuzzy conditional statement (If condition C Then restriction R).

In unconditional statements, there is no specific condition that has to be satisfied. The control may be transferred without any condition. The unconditional restrictions in the fuzzy form can be:

$$\begin{array}{ll} R^1 & \text{Output is } B^1 \\ & \text{AND} \\ R^2 & \text{Output is } B^2 \\ & \text{AND} \\ & \dots, \text{ etc.} \end{array}$$

where B^1 and B^2 are fuzzy consequents.

The linguistic terms such as “AND”, “OR” and “ELSE” connect the conditional, unconditional and restriction statements. The consequent of rules or output is expressed by the restrictions $R^1, R^2, \dots, R^n$.

A compound rule structure can be decomposed to several canonical rules using the aforementioned properties and operations of fuzzy sets. The follows are the methods for decomposition of rules as:

(1) Multiple conjunction antecedents

The fuzzy intersection operation is employed. The rule “IF x is $\tilde{C}^1$ AND $\tilde{C}^2 \dots$ AND $\tilde{C}^n$ THEN y is $\tilde{D}^r$ ” can be written as “IF x is $\tilde{C}^r$ THEN y is $\tilde{D}^r$ ” where $\tilde{C}^r = \tilde{C}^1$ AND $\tilde{C}^2 \dots$ AND $\tilde{C}^n$. The membership function for $\tilde{C}^r$ can be expressed as

$$\mu_{\tilde{C}^r}(x) = \min \left[\mu_{\tilde{C}^1}(x), \mu_{\tilde{C}^2}(x), \dots, \mu_{\tilde{C}^n}(x) \right]. \quad (7.40)$$

(2) Multiple disjunctive antecedents

The fuzzy union operation is used. The rule “IF x is $\underline{C}^1$ OR $\underline{C}^2 \dots$ OR $\underline{C}^n$ THEN y is $\underline{D}^r$ ” can be written as “IF x is $\underline{C}^r$ THEN y is $\underline{D}^r$ ” where $\underline{C}^r = \underline{C}^1 \text{ OR } \underline{C}^2 \dots \text{OR } \underline{C}^n$. The membership function for $\underline{C}^r$ is given by:

$$\mu_{\underline{C}^r}(x) = \max \left[\mu_{\underline{C}^1}(x), \mu_{\underline{C}^2}(x), \dots, \mu_{\underline{C}^n}(x) \right]. \quad (7.41)$$

(3) Conditional statements with ELSE

We can split the rule “IF $\underline{C}^1$ THEN ($\underline{D}^1$ ELSE $\underline{D}^2$)” into two canonical form rules as “IF $\underline{C}^1$ THEN $\underline{D}^1$ OR IF NOT $\underline{C}^1$ THEN $\underline{D}^2$ ”.

We can also transform another rule “IF $\underline{C}^1$ THEN ($\underline{D}^1$ ELSE IF $\underline{C}^2$ THEN $\underline{D}^2$)” into two canonical form rules as “IF $\underline{C}^1$ THEN $\underline{D}^1$ OR IF NOT $\underline{C}^1$ AND $\underline{C}^2$ THEN $\underline{D}^2$ ”.

(4) Nested IF–THEN rules

The rule “IF $\underline{C}^1$ THEN (IF $\underline{C}^2$ THEN $\underline{D}^2$)” can be decomposed into “IF $\underline{C}^1$ AND $\underline{C}^2$ THEN $\underline{D}^2$)”

The process of concluding from the consequents obtained by several fuzzy rules is called aggregation of fuzzy rules. Two methods such as conjunctive system of rules and disjunctive system of rules are responsible for aggregation of fuzzy rules.

(1) Conjunctive system of rules

In the case that “AND” is used to connect all the fuzzy rules, the output of the aggregation may be fuzzy intersection of all rule consequents, described as $y = y^1 \text{ AND } y^2 \text{ AND } \dots \text{AND } y^n$. Thus the membership function is

$$\mu_y(x) = \min [\mu_{y^1}(x), \mu_{y^2}(x), \dots, \mu_{y^n}(x)] \quad (7.42)$$

(2) Disjunctive system of rules

In the case that the fuzzy rules are connected by “OR”, the aggregated output can be expressed by the fuzzy union of all rule consequents as $y = y^1 \text{ OR } y^2 \text{ OR } \dots \text{OR } y^n$. Thus the membership function for y is given by:

$$\mu_y(x) = \max [\mu_{y^1}(x), \mu_{y^2}(x), \dots, \mu_{y^n}(x)]. \quad (7.43)$$

7.1.6 Fuzzy Decision Making

Decision making is very important in every field, whether scientific, social or economic. We consider the information about the outcome and select two or more alternatives for subsequent action in the decision making process. The problem in decision making under uncertainty is that the information is typically vague, ambiguous and otherwise fuzzy. Thus the uncertainty is the prime domain for fuzzy decision making. There are several methods for fuzzy decision making, such as fuzzy ordering, individual decision making, multi-person decision making, multi-objective decision making, and fuzzy Bayesian decision method. They are given in details below.

Fuzzy ordering is expressed by ranks, i.e., the first rank, second rank, etc. If there is uncertainty or ambiguity, the fuzzy ordering is used. Let $\underline{M}$, $\underline{N}$ and $\underline{P}$ be three fuzzy numbers, the truth that $\underline{M}$ is greater than $\underline{N}$ is given by

$$T(\underline{M} \geq \underline{N}) = \max_{x \geq y} \left(\min \left(\mu_{\underline{M}}(x), \mu_{\underline{N}}(y) \right) \right) \quad (7.44)$$

and the truth that $\underline{M}$ is greater than $\underline{N}$ and $\underline{P}$ is expressed as

$$T(\underline{M} \geq \underline{N}, \underline{P}) = \min \left(T(\underline{M} \geq \underline{N}), T(\underline{M} \geq \underline{P}) \right) \quad (7.45)$$

Thus, the fuzzy ordering of the fuzzy numbers is performed as a result. For example, if $T(\underline{M} \geq \underline{N}, \underline{P}) > T(\underline{N} \geq \underline{M}, \underline{P}) > T(\underline{P} \geq \underline{M}, \underline{N})$, then the ordering would be $\underline{M}$ first, $\underline{N}$ second, and $\underline{P}$ third.

Individual decision making is related to the set of possible actions, set of goals P_i ($i \in x_n$) described in terms of fuzzy sets, and set of constraints Q_j ($j \in x_m$) expressed in terms of fuzzy sets. The fuzzy sets impressing goals and constraints in individual decision making are defined not through the set of actions but through the sets characterizing relevant states of nature. For an element $b \in B$ where B is a fuzzy set, the fuzzy decision is given by

$$F(b) = \min \left[\inf_{i \in N_n} P_i(b), \inf_{j \in N_m} Q_j(b) \right] \quad (7.46)$$

In multi-person decision making, the goals of the individual decision maker differ so that each maker places different ordering arrangements. The individual decision maker has access to different information on which their decision is based. Given the individual preference ordering P_k , $k \in N_n$ of a set x , the function "Social Choice" is defined by a fuzzy relation as $S : X \times X \rightarrow [0, 1]$. The function has membership $S(x_i, x_j)$ which represents the preference of alternative x_i over x_j . Let $M(x_i, x_j)$ and N be the number of decision makers preferring x_i over x_j and the

total number of decision makers, respectively. Then the “Social Choice” is expressed as

$$S(x_i, x_j) = \frac{M(x_i, x_j)}{N} \quad (7.47)$$

Multi-objective decision making considers the set of alternatives A and the collection of objectives O , where

$$A = \{a_1, a_2, \dots, a_n\} \quad (7.48)$$

and

$$O = \{o_1, o_2, \dots, o_r\} \quad (7.49)$$

The decision function (DF) can be written as intersection of all objectives

$$DF = o_1 \wedge o_2 \wedge \dots \wedge o_r \quad (7.50)$$

Thus the membership for the alternative is obtained as

$$\mu_{DF}(a^*) = \max_{a \in A}(\mu_{DF}(a)) \quad (7.51)$$

where a^* is the alternative that maximizes DF. Let $\{b_1, b_2, \dots, b_n\}$ be a set of preferences and define $DM(o_n, b_n)$ as decision measure (DM). Thus

$$DF = DM(o_1, b_1) \wedge DM(o_2, b_2) \wedge \dots \wedge DM(o_r, b_r) \quad (7.52)$$

For a particular alternative, the DM is

$$DM(o_i(a), b_i) = b_i \rightarrow o_i(a) = \bar{b}_i \cup o_i(a) \quad (7.53)$$

So DF can be obtained using the following expression as

$$DF = \bigcap_{i=1}^r (\bar{b}_i \cup o_i(a)) \quad (7.54)$$

Suppose $d_i = \bar{b}_i \cup o_i(a)$, then

$$\mu_{d_i}(a) = \max(1 - \mu_{b_i}(a), \mu_{o_i}(a)) \quad (7.55)$$

The membership for the decision function (DF) is given by

$$\mu_{DF}(a^*) = \max_{a \in A}(\min(\mu_{d_1}(a), \mu_{d_2}(a), \dots, \mu_{d_r}(a))) \quad (7.56)$$

In fuzzy Bayesian decision method, the events are vague, ambiguous and uncertain, but this problem can be solved below.

A set of states of nature is given by

$$S = \{S_1, S_2, \dots, S_n\} \quad (7.57)$$

The probabilities that these states occur are expressed accordingly as

$$P = \{P(S_1), P(S_2), \dots, P(S_n)\} \quad (7.58)$$

In the meantime, it is obtained that

$$\sum_{i=1}^n P(S_i) = 1 \quad (7.59)$$

Let A be a set of m alternatives, i.e.,

$$A = \{A_1, A_2, \dots, A_m\} \quad (7.60)$$

If the future state is S_j , the utility value is u_{ji} for an alternative a_j . The expected utility with a_j , i.e., $E(u_j)$ is given by

$$E(u_j) = \sum_{i=1}^n u_{ji} P(S_i) \quad (7.61)$$

The decision made in the fuzzy Bayesian decision method is the maximum expected utility for all alternatives.

$$E(u^*) = \max_j E(u_j) \quad (7.62)$$

7.1.7 Fuzzy Inference System

Fuzzy inference systems (FISs) are associated with a number of names, such as fuzzy-rule-based systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers, and simple (and ambiguously) fuzzy systems [4]. As shown in Fig. 7.6, a fuzzy inference system is composed of a fuzzification interface, a database, a rule base, a decision-making unit and a defuzzification interface. The functions for these units are described here. The fuzzification interface converts the crisp inputs into fuzzy numbers. The database defines the membership functions of the fuzzy sets for establishment of fuzzy rules. The rule base gives fuzzy rules (e.g. IF...THEN...) required where connectors such as “OR” and “AND” are used for connection of several simple rules. The decision-making unit performs the inference operations based on fuzzy rules. The fuzzification interface converts the inference fuzzy results into crisp outputs.

Generally when the FIS is employed as a controller, it always takes the crisp inputs and crisp outputs. The operating principles for the FIS are given below. The fuzzification interface transforms the crisp inputs into fuzzy numbers, in other words, the input variables are compared with the membership functions on the antecedent part to obtain the membership values of each linguistic label. After that, the rule base is established whose firing strength (weight) is obtained by combining the membership values on the premise part. The rule base and the database

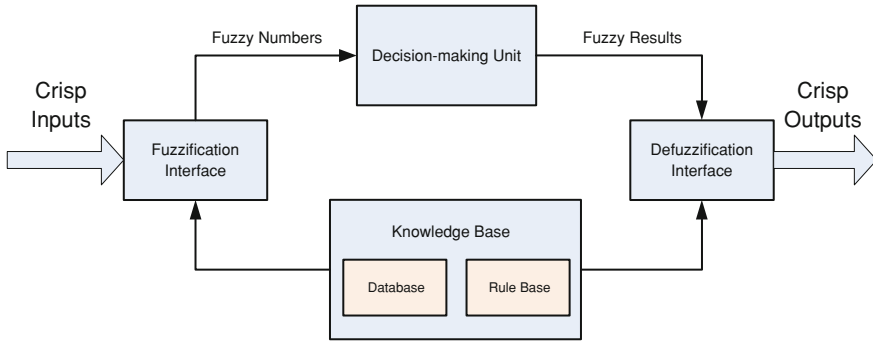


Fig. 7.6 Block diagram of fuzzy inference system

form a knowledge base. Finally, the defuzzification interface works to transform the fuzzy results to the crisp outputs which are used finally in the real world.

Mamdani's fuzzy inference method, introduced by Ebrahim Mamdani in 1975, is the most commonly used fuzzy methodology [5]. This method was first used as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules derived from human operators. The Mamdani-type inference expects the output membership functions to be fuzzy sets. The output using a single spike as the output membership function is sometimes known as a singleton output membership function. It improves the efficiency of the defuzzification process since it greatly simplifies the computation required by the more general Mamdani method.

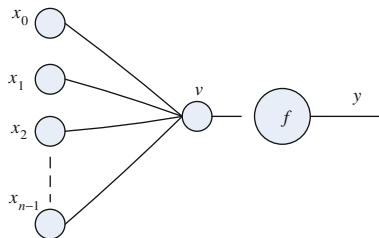
Another important inference is called the Sugeno method. The Sugeno fuzzy model was proposed to formalize a system approach for establishment of fuzzy rules from an input–output data set. The Sugeno method is ideal for acting as an interpolating supervisor of multiple linear controllers to be applied to different operating conditions of a dynamic nonlinear system because each rule linearly depends on the input variable of a system.

The main difference between the Mamdani and Sugeno methods is that the output membership functions are either linear or constant in Sugeno-type systems. Also the difference exists in consequents of fuzzy rules of these two methods. Thus their aggregation and defuzzification procedures differ suitably. In general, the Mamdani method is easier to be implemented than the Sugeno method. Interested readers can find details of these two fuzzy inference methods in Ref. [3].

7.2 Neural Networks

A neural network (NN) is a mathematical model or computational model which intends to simulate the structure and/or functional aspects of biological neural networks [6]. The neural network is comprised of an interconnected group of neurons and processes information by means of a connectionist approach to

Fig. 7.7 Structure of a neuron



computation. Neural networks can be employed for modeling complex relations between inputs and outputs. In a neural network model, simple nodes (or neurons) are connected to form a network of neurons, i.e. a neural network. Thus the neurons introduced below are critical to all neural networks.

7.2.1 Neuron

A neuron is a nonlinear, parameterized and bounded function. The inputs of the neuron are variables of the neuron, and the output is the value of the neuron. The basic structure of the neuron is shown in Fig. 7.7 where f represents a parameterization function. There are two types of parameterization described below.

For a given neuron, assume there are n inputs with signals x_0 through x_{n-1} weighted by the parameters $\{w_i\}$, $i = 0, 1, 2, \dots, n-1$. The potential v is a weighted sum of all the inputs with an additional constant bias. Thus the output of the neuron is expressed as

$$y = f(v) = f\left(w_n + \sum_{i=0}^{n-1} w_i x_i\right) \quad (7.63)$$

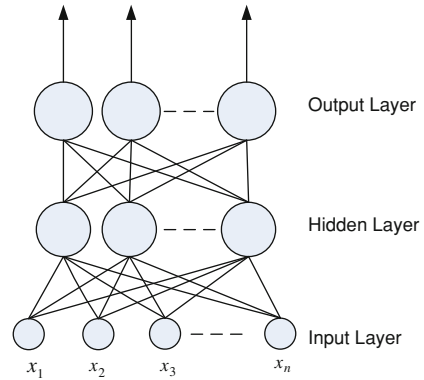
The output is analogous to the axon of a neuron, and its value propagates to inputs of the next layer through a synapse.

The other type is that the parameters are assigned to the neuron nonlinearity when the function f is a radial basis function (RBF) or a wavelet as an activation function. For example, the output of a Gaussian RBF is described as

$$y = \exp \left[-\frac{\sum_{i=0}^{n-1} (x_i - w_i)^2}{2w_{n+1}^2} \right] \quad (7.64)$$

where w_{n+1} and w_i , $i = 0, 1, 2, \dots, n-1$ represent the standard deviation and the position of the center of the Gaussian, respectively.

Fig. 7.8 Structure of a feedforward neural network



The RBFs are local nonlinearities and vanish asymptotically in all directions of the input space, however neurons with a potential and sigmoid nonlinearity have an impact along the direction defined by $v = 0$ in an infinite range.

Since a neuron is a nonlinear parameterized function of its input variables, a network is the composition of the nonlinear functions of several neurons. We will next look at several types of neural networks.

7.2.2 Feedforward Neural Network

A feedforward neural network is a neural network where the connections between units do not form a directed cycle. The information moves from the inputs, through the hidden neurons (if any) and then to the output neurons in only one direction i.e., forward (see Fig. 7.8).

The earliest and simplest kind of feedforward neural network is a single-layer perceptron network. The inputs are fed directly to the outputs through a series of weights. The sum of the products of the weights and the inputs is obtained in each neuron. If the value is above some threshold, the neuron takes the activated value, otherwise it takes the deactivated value. The term “perceptron” refers to networks consisting of only one of these neurons. Perceptrons can be trained using a learning algorithm called the delta rule. The errors between the calculated output and sample output data can be calculated to create an adjustment to the weights and implement a form of gradient descent. The expression for the typical perceptron is shown below:

$$f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0 \\ 0 & \text{otherwise} \end{cases} \quad (7.65)$$

where $\mathbf{x}$ is a real-valued vector as the input; $f(\mathbf{x})$ is the output; $\mathbf{w}$ is a vector of real-valued weights; $\mathbf{w} \cdot \mathbf{x}$ is the dot product; and b is the bias, a constant term that has nothing to do with the input value.

The multi-layer perceptron neural network consists of multiple layers (i.e. an input and output layer and one or more hidden layers) of computational units. Each neuron in one layer connected to the neurons of the subsequent layer directly. A number of learning techniques are employed in multi-layer networks, where back propagation is the most popular one. When back propagation is used, the output values are compared to the expected result to compute the value of some predefined error function. Through the information of the error feedback, the weights of each connection can be adjusted to reduce the error value. The network may converge to some state with a small error after a large number of training cycles. A method called gradient descent for nonlinear optimization is used to adjust weights. The derivative of the error function is therefore obtained and the weights are adjusted to decrease the error.

The two main sigmoid activation functions in the multi-layer perceptron neural network are given by

$$f(v_i) = \tanh(v_i) \quad (7.66)$$

and

$$f(v_i) = (1 + e^{-v_i})^{-1} \quad (7.67)$$

where v_i is the weighted sum of the input synapses of the i th neuron and y_i is its output.

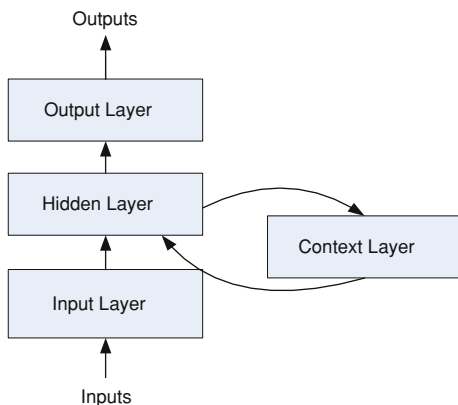
Multi-layer perceptron neural networks using a back propagation algorithm are useful for research in terms of their ability to solve extremely complex problems stochastically like speech recognition, image recognition, machine translation and computer security.

7.2.3 Recurrent (Feedback) Neural Network

A recurrent neural network is a neural network where the connections between units form a directed cycle, i.e., a path that following the connections leads back to the starting neuron. In the architecture of the recurrent neural network, time should be explicitly considered since the output of a neuron cannot be a function of itself at the same instant time, however it can be a function of the past values. Figure 7.9 shows the structure of a recurrent neural network. In this figure, a context layer is added retaining information between observations. New inputs are fed into the recurrent neural network at each time step. The previous information of the hidden layer is transferred to the context layer. The output of the context is then fed back to the hidden layer.

Each connection of a recurrent neural network has a delay because of the discrete-time framework. The sum of the delays of the edges of a cycle in the graph of connections cannot be zero because a quantity cannot be a function of itself at the same time.

Fig. 7.9 Structure of a recurrent neural network



The relations between nonlinear models for recurrent neural networks and the conventional dynamic linear models can be investigated through discrete-time equations. The general linear system is expressed as

$$\mathbf{x}(k) = A\mathbf{x}(k-1) + B\mathbf{u}(k-1) \quad (7.68)$$

$$\mathbf{y}(k) = C\mathbf{x}(k-1) + D\mathbf{u}(k-1) \quad (7.69)$$

where $\mathbf{x}(k)$ is the state vector at time kT ; $\mathbf{y}(k)$ is the output vector at time kT ; and $\mathbf{u}(k)$ is the input vector at time kT . The canonical form of a nonlinear system is given by

$$\mathbf{x}(k) = \Phi[\mathbf{x}(k-1), \mathbf{u}(k-1)] \quad (7.70)$$

$$\mathbf{y}(k) = \Psi[\mathbf{x}(k-1), \mathbf{u}(k-1)] \quad (7.71)$$

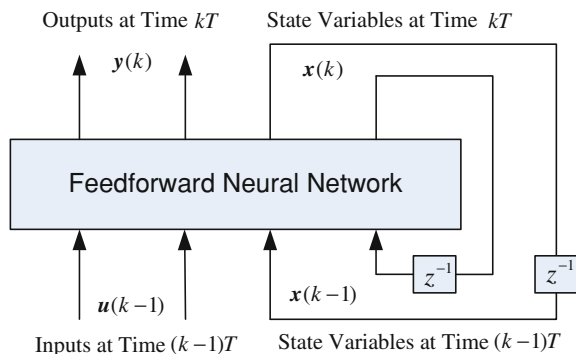
where Φ and Ψ are nonlinear vector functions, e.g., recurrent neural networks. Any recurrent neural network can be cast into a canonical form as shown in Fig. 7.10 where z^{-1} represents a unit time delay.

7.2.4 Radial Basis Function (RBF) Neural Network

A radial basis function (RBF) neural network is a neural network which employs radial basis functions as activation functions. A RBF is a real-valued function whose value depends only on the distance from the origin or alternatively on the distance from some other point called a center. The RBF network is a linear combination of radial basis functions. The general expression for the RBF network is given by

$$y(\mathbf{x}, \mathbf{w}) = \sum_{i=1}^N w_i \phi(\|\mathbf{x} - \mathbf{c}_i\|) \quad (7.72)$$

Fig. 7.10 The canonical form of a recurrent neural network



where $\mathbf{x}$ is the input vector; $y(\mathbf{x}, \mathbf{w})$ is the output of the network; $\mathbf{w}_i$ represents the weight; N is the number of neurons in the hidden layer; $\mathbf{c}_i$ is the center vector; and $\|\mathbf{x} - \mathbf{c}_i\|$ is the distance from the center. It can be shown that any continuous function on a compact interval can be interpolated with arbitrary accuracy by this equation if a large number of RBFs are utilized.

The RBF chosen in applications is usually a Gaussian. Thus the output of the Gaussian RBF network is described as

$$y(\mathbf{x}, \mathbf{w}) = \sum_{i=1}^N \left[w_{N+1,i} \exp \left(-\frac{\sum_{j=1}^n (x_j - w_{ij})^2}{2w_i^2} \right) \right] \quad (7.73)$$

where the number of neurons in the hidden layer is N ; the output neuron is numbered $N + 1$; $\mathbf{x}$ represents the input vector with n inputs; and $\mathbf{w}$ is the vector of $(n + 2)N$ parameters.

The RBF network has two classes of parameters. The first is referred to the parameters of the output layer conveying information from the N hidden neurons. The second is the parameters of the RBFs (centers and standard deviations for Gaussian RBFs). It has to be noted that the RBF network has two layers of processing, i.e., the layer from inputs to RBFs and the layer from hidden neurons to the output. All the connections of the first layer equal 1. The output is a linear function of the parameters of the last layer and meanwhile a nonlinear function of the parameters of the Gaussians.

Interested readers can refer to Ref. [6] to find other types of neural networks (e.g. Kohonen self-organizing networks, Stochastic neural networks, Modular neural networks, etc.) in details.

Learning of neural networks is the algorithm procedure where parameters of neurons are estimated in order to make errors of the neural network as small as possible. Two classes of learning methods (supervised learning and unsupervised learning) are briefly discussed as follows.

7.2.5 Supervised Learning

Supervised learning is a machine learning technique for learning a function from training data. Pairs of input vectors and desired outputs are considered as the training data. The output of the function can be a continuous value or can predict a class label of the input vector.

In supervised learning, given a set of example pairs $(x, y), x \in X, y \in Y$, we want to implement the aim that is to find a function $f : X \rightarrow Y$ in the allowed class of functions matching the examples. In other words, the mapping implied by the data is expected to be inferred and the cost function containing prior knowledge about the problem domain is related to the mismatch between the mapping and the data. In neural networks, a commonly used cost function is the mean-squared error at the aim of minimizing the average squared error between the output of the network and the target value over all the example pairs. The mean-squared error is given by

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n e_i^2 \quad (7.74)$$

where $e_i = y_i - \hat{y}_i$ is the difference between the network output and the target value.

The back propagation algorithm for training neural networks is obtained when gradient descent for multi-layer perceptron neural networks is used. Learning will benefit from the assistance of a “teacher” that provides examples of values of the inputs and of the corresponding values of the neural network output. For instance, given the new $(m + 1)$ th training pattern, the weights could be updated as follows:

$$w_{ij}^{(m+1)} = w_{ij}^{(m)} + \Delta w_{ij}^{(m)} \quad (7.75)$$

where $\Delta w_{ij}^{(m)}$ is related to the supervision of the “teacher”. Given a constant η , one form of $\Delta w_{ij}^{(m)}$ using the gradient descent technique can be expressed as

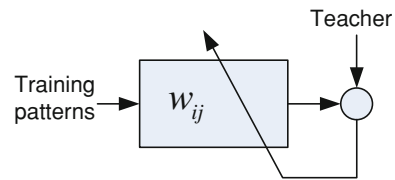
$$\Delta w_{ij}^{(m)} = -\eta \frac{\partial \text{MSE}^{(m)}}{\partial w_{ij}^{(m)}} \quad (7.76)$$

Figure 7.11 shows the supervised learning process expressed in Eq. 7.75.

7.2.6 Unsupervised Learning

Unsupervised learning is a class of problems which determines how the data are organized. The learner is given only unlabeled examples in unsupervised learning, which is different from supervised learning. In other words, the network is provided with inputs but not with desired outputs. Unsupervised learning is closely related to density estimation in statistics. On the other hand, unsupervised learning also encompasses many other techniques which seek to summarize and explain key features of data. No teacher is present in unsupervised learning since the learning

Fig. 7.11 A supervised learning process



should find the similarities between elements of the database and translate them into vicinities in the “map”. The most popular neural networks using unsupervised learning are the self-organizing map (SOM) and adaptive resonance theory (ART).

The SOM is trained to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples called a map. The SOM is very useful for visualization of low-dimensional views of high-dimensional data, akin to multi-dimensional scaling. The weights of neurons are initialized either to small random values or sampled evenly from the subspace spanned by the two largest principle component eigenvectors. With the latter alternative, learning is much faster because the initial weights already give good approximation of SOM weights [7]. Competitive learning is employed in the training. The Euclidean distance of a training example to all weight vectors is calculated. We call the neuron with the weight vector most similar to the input as the best matching unit (BMU). The weights of the BMU and neurons that are close to it are then adjusted towards the input vector. The magnitude of this change decreases with time and with the distance from the BMU.

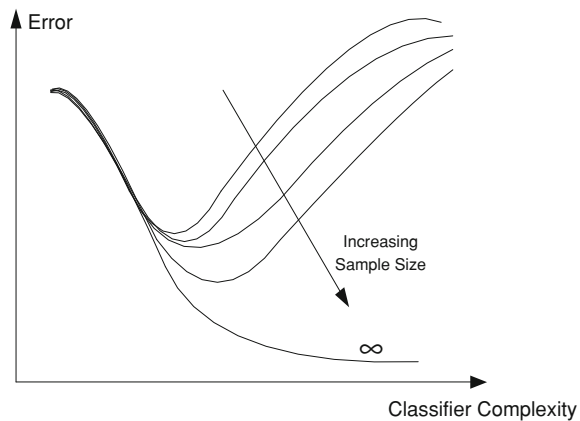
The number of clusters may vary with problem size in the ART model. The degree of similarity between members of the same clusters is controllable by a vigilance parameter. Meanwhile ART networks are applied for considerable pattern recognition tasks, e.g., automatic target recognition and seismic signal processing. The basic ART network consists of a comparison field and a recognition field composed of neurons, a vigilance parameter and a reset module. Two methods, i.e., the slow learning and fast learning methods, exist for training the ART network. Differential and algebraic equations are used for the slow learning and fast learning methods to calculate the degree of weight adjustments, respectively. In the slow learning method, the calculation leads to continuous values and depends on the length of time the input vector is presented, while in the fast learning method, binary values are utilized.

7.2.7 Properties of Neural Networks

If the way neural networks are trained utilizes the specific architecture, it is called a neural network classifier. Several observations can be made on the properties of neural network classifiers as follows [8].

- The back-propagation rule and its derivatives rarely find the global minimum. The computational effort and the large number of local minima in the error landscape are not allowed.

Fig. 7.12 Classification error as a function of the classifier complexity and training effort, i.e., sample size



- Since an unrestricted neural network classifier is too complex for most problems, the global minimum is undesirable for almost all the neural networks with more than one hidden neurons.
- The back-propagation rule makes the computation sufficiently large resulting in dramatic cost of time and computer resources.
- Optimization of neural networks starts with small weights, which is beneficial for normal operation. This corresponds with linear neurons and thereby with an entire linear neural network. At first, an optimal linear solution is approximated. Then the network shows a moderate nonlinearity due to the growing weights. The training stops at one of the nearest local minima.
- A neural network shows the behavior of the classification error as a function of the classifier complexity and training effort, i.e., sample size (see Fig. 7.12).
- Faster neural methods have less built-in regularization and should therefore be more explicitly protected against overtraining, e.g. by the addition of noise or by weight decay.
- Most neural networks have more neurons than required for implementation of the final classifier. Nevertheless this redundancy is useful during the training procedure.
- For a given problem, the solution of the neural network is probably not the best classifier, but this solution is often reasonable and works well. Meanwhile, a unique neural network classifier never exists since the sets of possible neural network solutions are related to specific analysts with different levels of skills.

7.3 Application of Fuzzy Logic and Neural Network in Vehicle Power Management

Reference [9] provided a comprehensive overview of intelligent vehicle power management. Four case studies were provided as examples to explain the different aspects of application of intelligent systems approach in modern vehicle power management.

In Ref. [10], a fuzzy logic controller for a parallel HEV was established in order to optimize the fuel economy based on the analysis of efficiency maps. Through the efficiency map of an internal combustion engine (ICE), the optimal operating points can be determined in the speed-torque plane to improve the efficiency of the ICE. Once the optimal speed and torque are known, the torque can be controlled by varying the engine throttle angle and speed through shifting gears of automated manual transmission. Besides, the efficiency optimization of the other two major components of a parallel HEV, i.e., a battery and an electric motor (EM), has been taken into account in this study. This study shows earlier application of fuzzy logic in vehicle power management.

Figure 7.13 shows the simplified block diagram of the power controller. The driver inputs from the brake and accelerator pedals are converted to a driver power command in the first block “Driver Command Interpreter”. The signals from the pedals are normalized to a value between zero and one (zero: pedal is not pressed, one: pedal is fully pressed). The braking pedal signal is then subtracted from the accelerating pedal signal, so that the driver input takes a value between -1 and $+1$. The negative part of the driver input is sent to a separate brake controller that will compute the regenerative braking and the friction braking power required to decelerate the vehicle. The controller will always maximize the regenerative braking power, but it can never exceed 65% of the total braking power required, because regenerative braking can only be used for the front wheels. The positive part of the driver input is multiplied by the maximum available power at the present vehicle speed. The maximum available power is computed by adding the maximum available ICE and EM power. The maximum available EM and ICE power depends on EM/ICE speed and EM/ICE temperature, and is computed using a two-dimensional look-up table with speed and temperature as inputs. Interested readers can refer to Ref. [10] for further comprehension.

In Refs. [11] and [12], the torque distribution strategy in a parallel HEV was developed using fuzzy logic. An intelligent energy management agent (IEMA) was proposed to incorporate true drive cycle analysis within an overall framework for power management in a parallel HEV. The information of the driving situation knowledge is subsequently integrated in a fuzzy logic-based torque distribution and state of charge (SOC) compensation strategy for the torque distribution (for the engine and electric motor (EM)) and the battery charge sustaining tasks. Therefore we can realize the purposes of meeting the driver’s torque demand while achieving satisfactory fuel consumption and emissions, and maintaining the battery SOC at a satisfactory level to enable effective delivery of torque to the vehicle over a wide range of driving situations. This case study provides an advanced research approach of fuzzy logic applied to vehicle power management with consideration of real-time driving situation and/or the behavior of the driver.

The intelligent energy management agent (IEMA) explicitly incorporates a driving situation identifier whose role is to identify the roadway type, the driving style of the drivers as well as the current driving mode and trend. The primary function of the IEMA is to distribute the required torque between the internal combustion engine (ICE) and the electric motor (EM). Four subsystems, driving

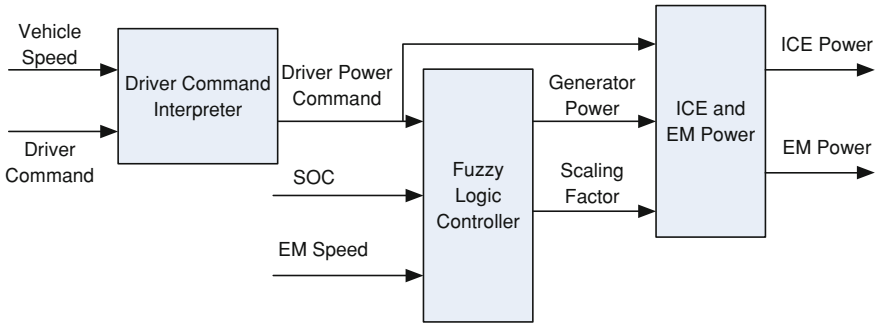


Fig. 7.13 Block diagram of the power controller. Source [10], © (2002) IEEE

information extractor (DIE), driving situation identifier (DSII), fuzzy torque distributor (FTD), and state-of-charge compensator (SCC), are embedded in the IEMA to realize its function. The architecture of IEMA is shown in Fig. 7.14, where T_e is current engine torque; $T_{ec,FTD}$ is the increment of engine torque for propulsion; $T_{ec,TD}$ is the increment engine torque compensating for the effect of driver variability; $T_{ec,SOC}$ is the increment of engine torque for charging; T_{ec} is engine torque command. Interested readers can refer to Refs [11] and [12] for further comprehension.

Driving patterns are the instantaneous decisions of the driver to deal with the environment. It has been shown that driving patterns have a significant impact on fuel economy and emissions [13, 14]. Standard driving cycles, such as the UDDS drive cycle, are useful to determine the fuel economy and emissions of automobiles under a predefined driving pattern. It would not be possible for a drive to follow a fixed driving schedule in real life driving. Hence, driving patterns need to be predicted in real-time driving of the vehicle for better power management of vehicles.

Pattern recognition has been extensively used in other fields in the past few decades [15–18]. It has also been used in the automotive field for fault diagnosis [19, 20]. In the recent years, pattern recognition has been used in helping power management of vehicles by predicting the drive cycle characteristics or drivers behavior [21, 22].

The study in Ref. [22] showed how a neural network is trained for online prediction of roadway types and traffic congestion levels that appeared in Ref. [23]. This type of knowledge is incorporated into vehicle power management since the driving style and environment have strong influence on fuel consumption and emissions. Generally, the driving patterns can be observed in the speed profile of the vehicle in a sequence of different road types such as local, freeway, arterial/collector, etc. augmented with different traffic congestion levels. A set of eleven standard facility-specific (FS) drive cycles was developed in Ref. [22] to represent passenger car and light truck operations over a range of facilities and congestion levels in urban areas. These eleven drive cycles are classified into four categories, i.e., freeway, freeway ramp, arterial, and local. According to a qualitative measure called level of service (LOS), the two categories, freeway and arterial are further divided into subcategories to describe operating conditions within a traffic stream based on speed and travel time, freedom to maneuver, traffic interruptions,

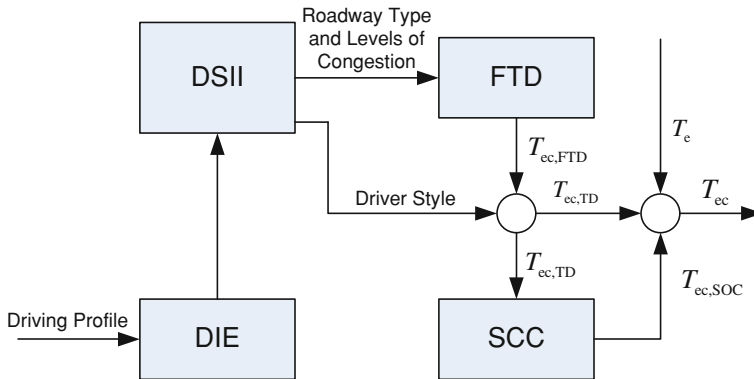
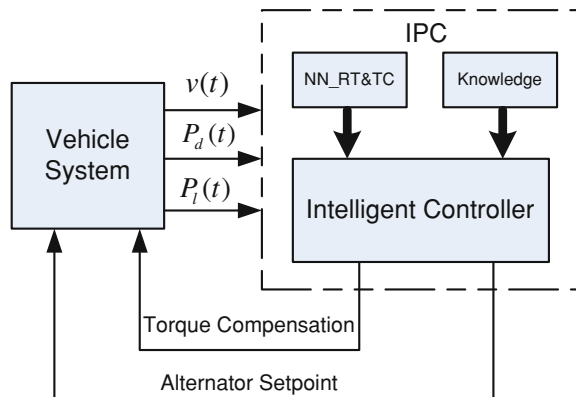


Fig. 7.14 Architecture of IEMA. Source [11, 12], © (2005) IEEE

Fig. 7.15 The block diagram of IPC. Source [22], © (2008) IEEE



comfort, and convenience. Neural network was used to predict the roadway type and traffic congestion levels (NN_RT&TC).

The NN_RT&TC was then embedded into an intelligent vehicle power management system, IPC, as shown in Fig. 7.15. Signals such as the vehicle speed, $v(t)$, the required driveline power $P_d(t)$ and the required electric load power $P_l(t)$ are sent to the IPC. The knowledge base existing in the IPC consists of the knowledge about the optimal alternator set point and torque compensation learnt from the 11 drive cycles described. By using the prediction results (i.e. the roadway type and traffic congestion level), vehicle information, and the knowledge associated with the roadway type, the optimal values of the torque compensation and alternator set point during time interval $[t, t + \Delta t]$ are obtained as outputs of the Intelligent Controller. Interested readers can find more theoretical and test details in Ref. [22] for further comprehension.

7.4 A Fuzzy Logic Controller Based on DP Results for a Parallel HEV

In Chap. 6, we discussed DP and QP algorithms for the power management of HEV. The DP algorithm is based on a fundamental hypothesis. Since it is a global approach to a problem that has a certain extent in time, the problem must be known and well formulated for all its duration. In other words, the drive cycle over which the fuel consumption is minimized must be entirely known at the beginning of the trip. Therefore, it can not be applied to an online controller.

In order to be able to implement an online controller, fuzzy logic control may be used. As we already see from previous sections, fuzzy logic is a powerful tool for describing nonlinear characteristics of power distribution ratio [24–29]. Through analyzing the ratio of engine power to the system power with the variation of vehicle speed, the fuel efficiency can be optimized. The ratio can be influenced by the vehicle speed, vehicle acceleration and deceleration, and battery SOC.

With results obtained from DP or QP, the whole online power management controller can be designed based on a fuzzy rule shown in Fig. 7.16. The membership functions of these parameters (i.e., vehicle speed, SOC, acceleration and power ratio) are described in Fig. 7.17. Vehicle speed, SOC and power ratio belong to $\{NB, NM, NS, PS, PM, PB\}$, and acceleration belongs to $\{NB, NS, ZO, PS, PB\}$. Here, NB—negative big; NM—negative medium; NS—negative small; PS—positive small; PM—positive medium; PB—positive big; ZO—zero.

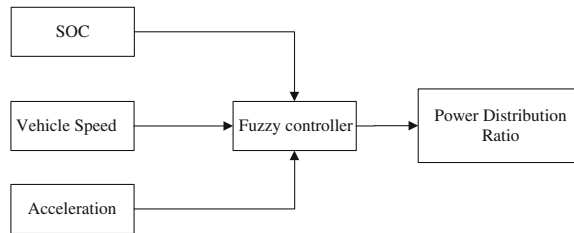
The rule table is complicated in which it includes about 129 rules. The rules listed in Table 7.1 below are a small part of the rule table.

The fuzzy logic distribution are embedded into the block ‘Coordinated Controller’, and three other drive cycles have been tested in the simulation software ADVISOR. The results are shown in Table 7.2. The simulation results in Table 7.2 show that 3.95–4.71% improvement could be realized after the fuzzy logic tables are applied to the controller in the Prius Model.

7.5 Sliding Mode and Fuzzy Logic Based Powertrain Controller for a Series HEV [30]¹

In this section, we will develop control strategies to improve fuel economy, and enhance engine efficiency as well as extend battery cycle life in a series hybrid electric vehicle (SHEV) powertrain, based on fuzzy logic, fixed-boundary-layer sliding mode controllers (FBLSMCs) and an optimized battery charge scenario.

¹ © [2010] Journal of Asia Electric Vehicles. Reprinted, with permission, Zheng Chen, Xi Zhang, and Chunting Mi, “Slide Mode and Fuzzy Logic Based Powertrain Controller for the Energy Management and Battery Lifetime Extension of Series Hybrid Electric Vehicles,” Journal of Asia Electric Vehicles, vol. 8, no. 2, December 2010.

Fig. 7.16 Fuzzy logic controller construction

The fuzzy logic based power management controller is developed to determine the engine power based on two inputs, battery SOC and vehicle power demand. The goal of the fuzzy logic based controller is to enhance the engine and battery operation efficiency and at the mean time, extend battery life. An appropriate battery charge scenario is designed to remove surge charge current, and avoid persistently-high charge power, which are positive factors to the battery lifetime extension. Besides, two robust FBLSMCs against uncertain disturbances are configured in the powertrain control system, responsible for engine speed control and engine torque control, respectively. Simulation results are obtained for comparison between the proposed and default powertrain control schemes. Through these simulations, the effectiveness and superiority of the proposed powertrain control strategy are validated.

7.5.1 Introduction

As we have seen from earlier examples, hybrid electric vehicles offer higher fuel efficiency and lower emissions. Among the four types of HEV configurations, series HEV (SHEV) architecture has recently been used extensively in the development of a new class of plugin HEV (PHEV), extended ranged electric vehicle (EREV), due to its capability of being driven electrically.

In a SHEV, the electric power as the only propulsion power comes from the ESS and the engine/generator unit that converts the energy from fuel into electricity. The simple and decoupled mechanical structure in SHEV brings many advantages although there are some unsatisfactory characteristics, such as the requirement of larger power capacity for the traction motor, an additional generator than a parallel HEV. By using the traction motor for propulsion, the operating noises can be reduced, which provides the stealth function for certain military applications. In addition, high efficiency operation of the engine can be obtained with optimization of engine control [31–36].

Recently, many researchers have been focusing on various control issues of the SHEV powertrain. Reference [37] introduced a modified instantaneous equivalent consumption minimization strategy (ECMS) into a SHEV powertrain control system. A simulated annealing (SA) algorithm was proposed to optimize the operational parameters for SHEV fuel economy and emissions [38]. Reference [39] presented a knowledge-based control strategy for fuel consumption minimization using information of the engine efficiency map, vehicle battery behavior and

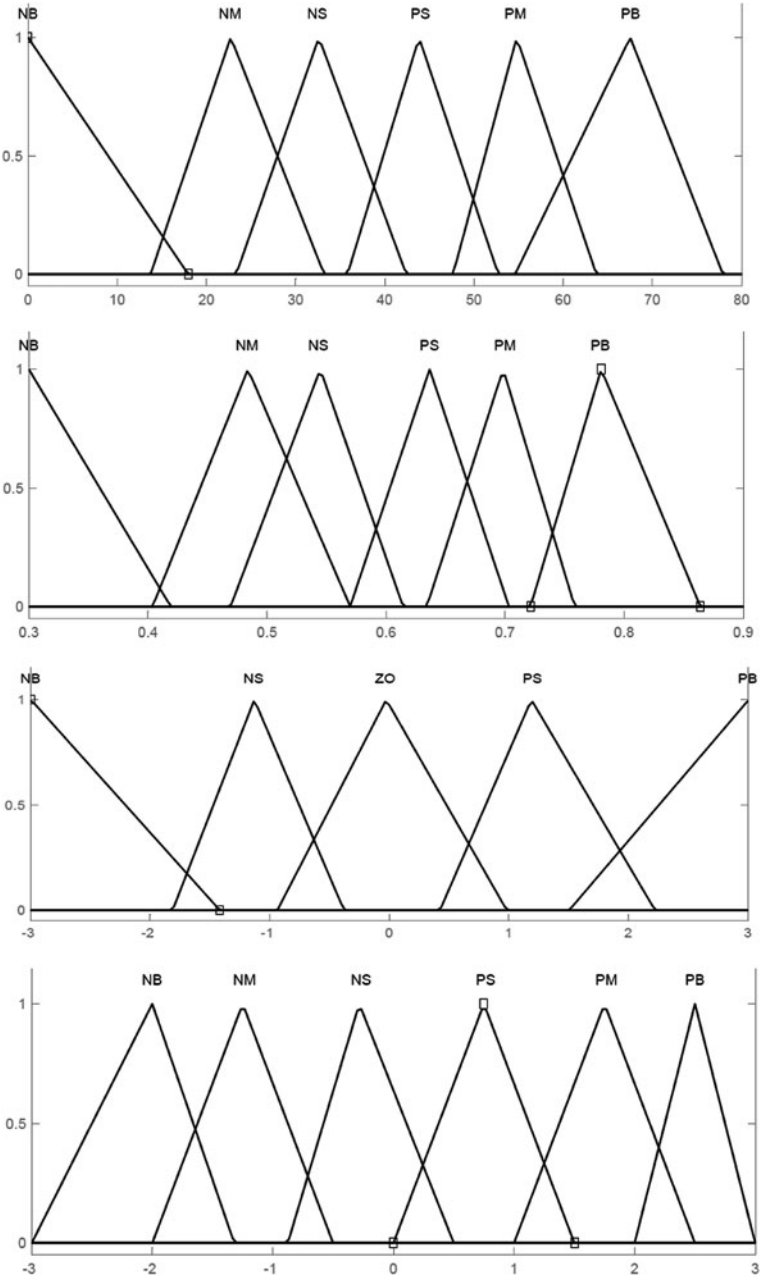


Fig. 7.17 Membership function of Speed, SOC, Acceleration and Ratio

Table 7.1 Part of fuzzy logic rules

Vehicle Speed	Acceleration	SOC	Ratio
PB	PB	PB	NS
PM	PB	PM	NM
PM	PS	PS	NM
PS	NS	NS	PS
PS	NM	NM	PM
PB	NB	NM	PM

Table 7.2 Online controller rules

	Default (mpg)	Fuzzy logic (mpg)	Improvement (%)
ARB02	35.4	36.8	3.95
LA92	36.7	38.3	4.36
NEDC	42.5	44.5	4.71

some overall parameters characterizing the expected trip. A power-flow management algorithm considering a normal operation mode and an electric vehicle (EV) operation mode appeared in [40]. However, these SHEV powertrain control strategies fail to sufficiently address the highly nonlinear parameter variations and sudden external disturbances during the vehicle operation.

There are two typical power management methods for SHEVs: the thermostat control strategy and power follower strategy. The thermostat control strategy works similar to a thermostat device, which uses the fuel converter as follows. To maintain charge in the battery, the fuel converter turns on when the SOC reaches the low limit. The fuel converter turns off when the SOC reaches the high limit. The fuel converter operates at the most efficient speed and torque level. The power follower strategy is much more complicated than the thermostat strategy. It defines the engine-on and engine-off zones, however, it mainly uses the engine, which could work in the optimal area, and the redundant or insufficient energy will charge to or discharge from the battery [40]. The power follower strategy only uses the battery as the supplement energy source and it does not include the energy distribution between two sources: engine and battery. So designing an intelligent power management algorithm becomes necessary which could determine each source’s output based on the vehicle status, such as acceleration, vehicle velocity, battery SOC, and engine speed, etc. The use of fuzzy logic can help circumvent the need for rigorous mathematical modeling. For a series HEV, fuzzy logic could deal with the problem without very complicated tools and the nonlinear equation [41–45]. It will accomplish the whole procedure through several steps. First, it needs to define the membership of each key status: power demand, vehicle velocity and SOC as inputs and power ratio, the power distribution between the engine and the battery, as outputs. Then it defines the rules based on experience or mathematical computing, and at last it finishes the defuzzification based on the output membership function.

Once the power ratio is decided by the fuzzy controller, the engine needs to be controlled to operate in the most efficient area. For this purpose, sliding mode

control (SMC) is introduced in this section to control the operation of the engine. SMC is an efficient tool to control complex high-order dynamic plants operating under uncertain conditions due to the order reduction property and low sensitivity to disturbances and plant parameter variations [41–43]. Consequently, it is very suitable for automotive applications. The chattering-free fixed-boundary-layer sliding mode controller (FBLSC) is utilized with the advantage that the boundary width is kept fixed so that the area where the system trajectories are attracted toward the boundary will not vary unexpectedly at all. To locate the engine operation in the optimal efficiency region, two proposed FBLSCs, responsible for engine speed and torque respectively, work together due to the simultaneous speed and torque magnitude constraints in such an area. As a result, the strong system robustness can be achieved against the nonlinear parameter variations and external disturbances.

A third aspect to be studied in this section is the battery life extension through optimized charge scenarios. The battery technology attracts more and more attention from researchers involved in HEV research since it is the key technology and bottleneck of the future HEVs and PHEVs [44]. Considerable battery manufacturers dedicate themselves into the breakthrough of barriers on the cost, size, life and energy density of batteries [45–47]. Unfortunately, researchers so far have not been able to achieve systematical solutions for battery lifetime extension under the present battery technology. In fact, it is very difficult to predict the battery lifetime by using chemical or electrical variables and to test the batteries for the full range of applications in which batteries are used. However, it's possible to analyze some stress factors which induce aging and influence the rate of aging [48]. Consequently, comparison between two aging processes with a couple of different stress factors (e.g. SOC, charge rate, temperature, etc.) is possible as long as other operating conditions are similar.

The battery charge current is determined by the power management controller, as well as the actual engine output power during the engine operation process. In general, the battery charge/discharge current is chaotic and varies rapidly, and surge current exists, which tend to impact the battery life [49]. In the meantime, the battery SOC usually cannot reach a high level in a short time while the low SOC is unfavorable to the battery durability in a long term. To solve the above problems, a smooth battery charge curve of current vs SOC is needed, and this curve has to be ordinate-large at low SOC so that the SOC can increase as quickly as possible. Additionally, persistently-high power should be relatively avoided because it has potential negative influence to battery life [49]. Considering these aspects, this section presents an ellipse-like-based battery charge scenario. In other words, the curve of the charge current vs battery SOC is like an ellipse. When the engine starts, the battery keeps charging at a high rate from the low SOC level, and its SOC increases fast. The charge current gradually drops to zero when the SOC approaches the predetermined maximum level. In this case, an averagely-high SOC can be guaranteed while the persistently-high power can also be avoided. Most importantly, the chaotic and fast-variable current almost disappears, which is very good for battery lifetime extension. Nevertheless, it has to be noted that in the proposed powertrain control method, the power of the engine during its operation is

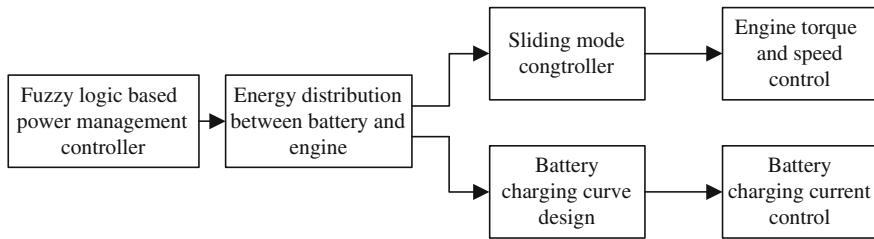


Fig. 7.18 The powertrain controller for SHEV

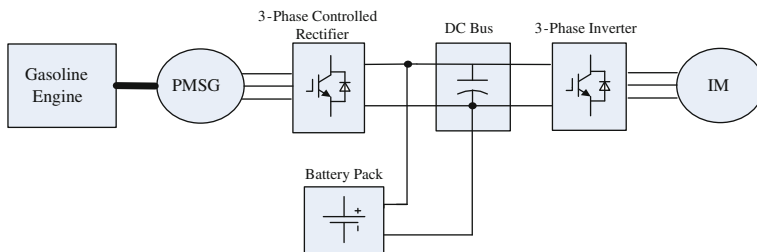


Fig. 7.19 Powertrain structure of the SHEV

determined by power requirements of the battery and traction motor, which is an inverse power derivation process compared to that used in other SHEV powertrain control strategies.

The powertrain controller presented in the section and its specific function for each part is shown in Fig. 7.18.

Integration of the proposed fuzzy logic control algorithms, FBLSCs and ellipse-like-based battery charge scenario is implemented by modifying the original SHEV model in ADVISOR. Simulation results verify that the proposed design strategy of SHEV powertrain controllers is valid and more efficient compared with the conventional methodology.

7.5.2 System Configuration and Drive Cycle Selection

The configuration of the studied SHEV powertrain is shown in Fig. 7.19. The gasoline engine is a Geo Metro 1.0 L SI engine with maximum power of 41 kW at 5,700 rpm. The speed and torque independent permanent magnet synchronous generator (PMSG) generates rated 41 kW output power with approximately highest 95% efficiency. An AC induction motor (IM), output power rated 75 kW power with 92% efficiency, acts as the traction motor for the vehicle propulsion. The ESS consists of 15 Hawker Genesis Lead Acid Battery in series. The capacity and nominal voltage of each cell are 12 Ah and 12 V, respectively.

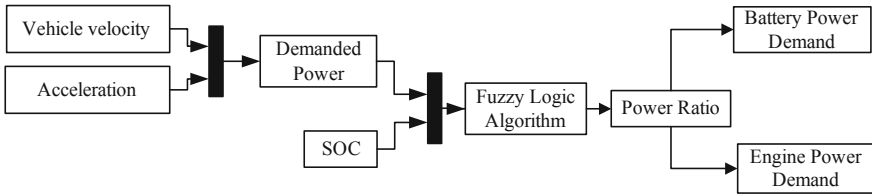


Fig. 7.20 Fuzzy logic power management structure

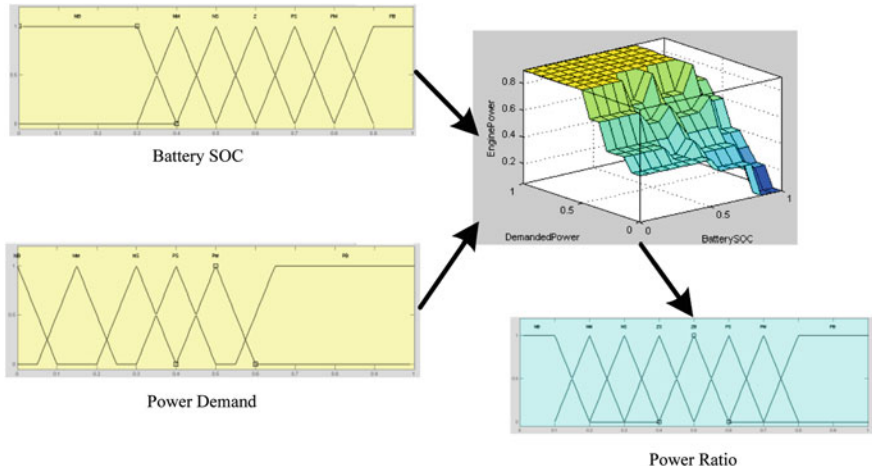


Fig. 7.21 Fuzzy logic rules and each variant membership function

7.5.3 Fuzzy Logic Control Algorithm

The fuzzy logic control algorithm evolves from the aforementioned power follower strategy, since the power follower strategy is only a rule based strategy. The power follower strategy does not consider the optimal issue in the real-world system, and only the SOC is a fixed target. Some engine operating points could be fetched based on the engine efficiency map, whose values are suboptimal. It needs to be further optimized. Fuzzy logic control has been applied as an effective control method in various fields. The advantages of this strategy are its inherent robustness and ability to handle both non-linearity and linguistic knowledge. It also has immunity to imprecise measurements and to component variability. The robust property of fuzzy logic controller enables a HEV to be operated with the improved battery charge balance, regardless of various disturbances. Therefore, the fuzzy logic controller is a suitable method for SHEV power control characterized due to the non-linearity and uncertainties.

In this study, the fuzzy logic controller (FLC) is a Mamdani type fuzzy system as shown in Fig. 7.20. The system demanded power and SOC at each time are considered

the inputs of the FLC; the output is also the membership function which represents the power ratio. The whole structure of fuzzy logic energy system is shown in Fig. 7.20. The demanded power calculated from the vehicle velocity and acceleration is first estimated, and then classified into $\{NB, NM, NS, PS, PM, PB\}$ which represent the vehicle power demand from the minimum value to the maximum value, battery SOC is classified into $\{NB, NM, NS, Z, PS, PM, PB\}$, which could reflect SOC from 0 to 1, and the output ratio is classified into $\{NB, NM, NS, ZS, ZB, PS, PM, PB\}$, as shown in Fig. 7.21.

The whole control rules library consists of 42 If-else rules, shown in the middle of Fig. 7.21.

7.5.4 Establishment of Sliding Mode Control

The vehicle operation process is highly nonlinear, resulting in highly-nonlinear and uncertain engine dynamics. Simple control models cannot handle complicated engine dynamics very well because they need accurate information and lack of robustness that is essential to the control objective. The sliding mode control (SMC) is well known for its advantages in providing a systematic approach to the problem of maintaining stability and consistent performance facing modeling imprecision. In SMC, the system trajectory is maintained to stay on the sliding surface for subsequent time once it is driven onto this surface. The imperfect implementation of the control switching leads to chattering, which is a major drawback of the SMC. The advantages of the fixed-boundary-layer sliding mode controller (FBLSMC) are that, not only chattering phenomenon is removed, but also the boundary width is kept fixed so that the area where the trajectories are attracted toward the boundary is not changed avoiding the instability of normal chattering-free sliding mode controllers. Therefore, the FBLSMC strategy is employed in this study as an effective tool for enhancement of engine efficiency to locate the engine speed and torque into the optimal area.

Besides, an ellipse-like charge current curve (current vs SOC) is chosen considering the aforementioned advantages. Based on the expected engine operation curve and optimum region definition, the desired engine speed and torque can be obtained. As a matter of fact, the engine torque depends on the generator torque which is adjusted by the PWM signals for the controlled rectifier. So the objectives for powertrain control have changed to controlling the engine speed and generator torque to constrain the engine operation in the optimal region. Two FBLSMCs responsible for the engine speed and generator torque respectively are utilized against the parameter variations, external disturbances, and highly-nonlinear system dynamics. The whole control process is shown in Fig. 7.22. The variables in this figure are defined as follows: $\hat{P}_E^r$, original required engine power; P_E^r , required engine power with thresholds; $\hat{\omega}_E^r$, original required engine speed; ω_E^* , required engine speed with thresholds; ω_E , real engine speed; $\hat{T}_E^r$, original required engine torque; T_E^* , required engine torque with thresholds; T_G^* , final required generator torque; T_G , real generator torque.

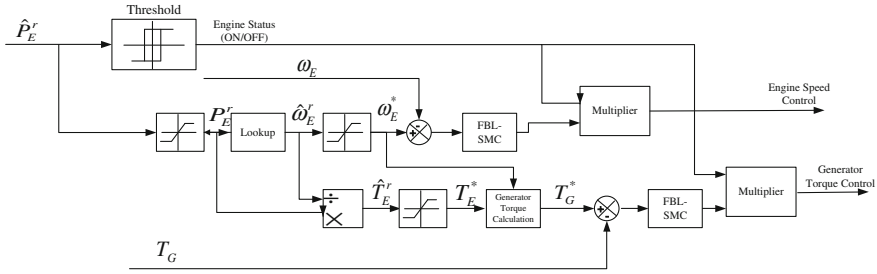


Fig. 7.22 Block schematic of the proposed SHEV powertrain control strategy

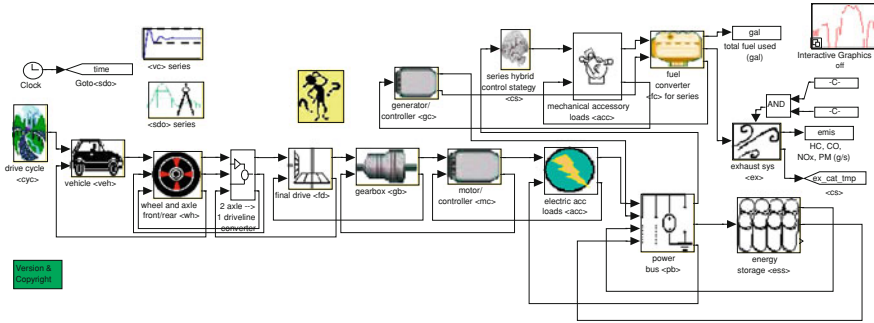


Fig. 7.23 Modified SHEV model for algorithm implementation

The state equation of the engine is expressed as:

$$\frac{d\omega_E}{dt} = \frac{1}{J_s} u f(\omega_E) - \frac{1}{n J_s} T_G \quad (7.77)$$

where $f(\omega_E)$ is the maximum engine torque at a certain ω_E ; n is engine/generator speed ratio ≈ 1 ; J_s is the inertia of the engine/generator set; and u represents the engine throttle angle and acts as a control variable for the engine speed FBLSMC.

The state of the generator employed in the SHEV is described as:

$$\begin{aligned} \frac{di_q}{dt} &= -\frac{R}{L} i_q - \omega_G i_d + \frac{\omega_G}{L} \lambda_m - \frac{u_q}{L} \\ \frac{di_d}{dt} &= -\frac{R}{L} i_d + \omega_G i_q - \frac{u_d}{L} \end{aligned} \quad (7.78)$$

$$T_G = K_{trq} i_q$$

where i_d , i_q are direct- and quadrature-axis stator currents, respectively; L_d , L_q are direct- and quadrature-axis inductances, respectively; λ_m is amplitude of the flux linkages established by the permanent magnet; R is stator resistance; $\omega_G \approx \omega_E$ is generator speed; K_{trq} is a torque constant; and u_d , u_q , as control variables for the generator torque FBLSLC as well as the engine torque control, represent direct- and quadrature-axis stator voltages, respectively.

Fig. 7.24 Engine operation during UDDS (conventional method)

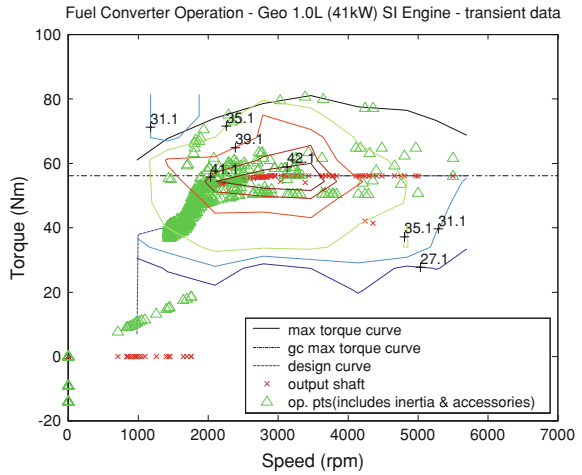
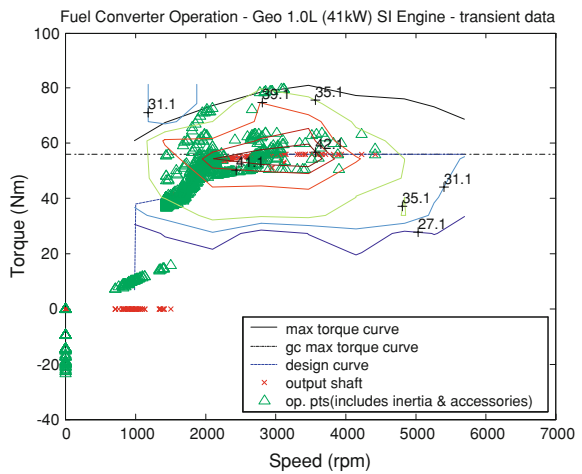


Fig. 7.25 Engine operation during UDDS (proposed method)



7.5.5 Simulation Results

ADVISOR is employed as the simulation tool in this study. The proposed powertrain control strategy is embedded in the modified SHEV model originated from ADVISOR as shown in Fig. 7.23. The engine operation is shown in Figs. 7.24 and 7.25 for the classical “power follower” strategy and the proposed strategy, respectively.

From the comparison between Figs. 7.24 and 7.25, it is clear that most engine operation points using the proposed method concentrate in the optimal area of the engine efficiency map while the majority of the engine operation points using the conventional method are located beyond such an area. In other words, the proposed method can boost the engine efficiency as a result. Some partial battery charging curve is shown in Figs. 7.26 and 7.27 respectively. The charging current looks like partial ellipse in Fig. 7.28 which realizes the charging demand.

Fig. 7.26 Battery charging curve (no current control)

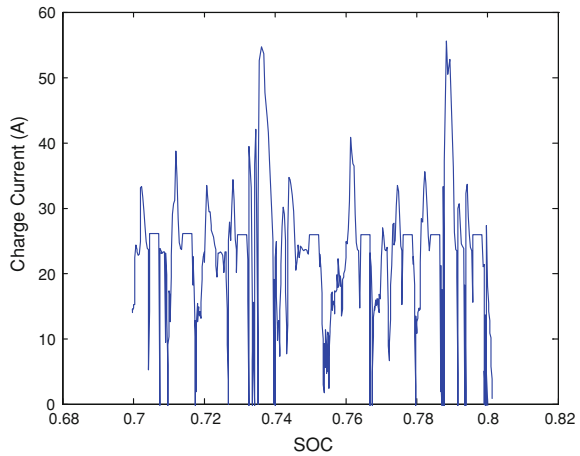
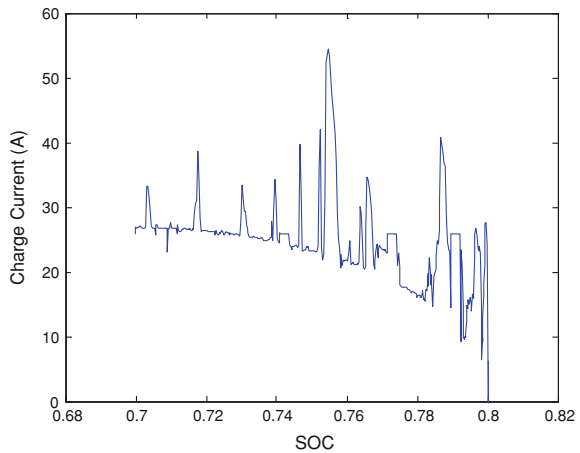


Fig. 7.27 Battery charging curve (charging current control)



The fuel economy based on the proposed control algorithm is 44.5 MPG compared with the original 42.9 MPG, with an improvement of 3.73%.

7.5.6 Discussion

In this section, we demonstrated a fuzzy Logic control algorithm which is used to manage the power distribution between the engine and battery of a SHEV. The fuzzy logic based power management controller can optimize the power distribution between the engine and the battery with respect to the battery SOC and the vehicle power demand. Two fixed-boundary-layer sliding mode controllers (FBLSMCs) are developed for the powertrain controller design in the SHEV for the purpose of efficiency enhancement and battery lifetime extension. The two FBLSMCs are in

charge of the speed control and torque control for the engine, respectively, against the parameter variations and disturbances. A battery charge scenario avoiding the chaotic current is designed for battery life extension with the consideration of some stress factors. The effectiveness and superiority of the proposed SHEV powertrain control strategy are validated through simulation in ADVISOR.

7.6 Fuzzy Logic and Sliding Mode Based Regenerative Braking Control in HEV²

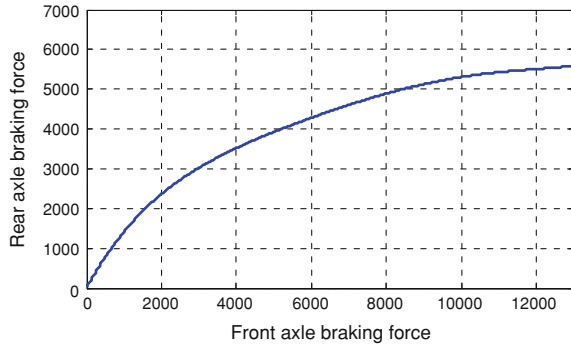
In the HEV and PHEV, the braking action is achieved by combining regenerative braking with the traditional frictional brakes. Regenerative braking force is produced by the electric motor and the mechanical braking force is produced by hydraulic brakes, air pressure brakes, or electromechanical brakes. Regenerative braking is activated during the coasting and deceleration processes to capture a portion of the kinetic energy to charge the on-board energy storage system. This recaptured energy is then used to provide the electric power required by the powertrain, as well as the vehicle accessory power loads during vehicle idle conditions. A good coordination can help recover more kinetic energy hence achieve higher fuel efficiency.

7.6.1 Principle of Braking in PHEV with EMB and Regenerative Braking

Due to the slow response of the traditional frictional brakes, coordination of regenerative braking and frictional braking systems has been proven to be extremely difficult, and the capability of recovering the maximum amount of energy during braking has been a challenge. On the other hand, the electric motor is typically mounted on one axle not on all four wheels. Hence, frictional braking must often be activated to maintain vehicle safety. In order to optimize the regenerative braking control so as to maximize the regenerative braking energy, in this section, we discuss the use of electromechanical braking (EMB) to achieve the distribution of braking force to front and rear axis according to an optimal curve, also known as ideal curve or I-curve. We then use the fuzzy logic control strategy to distribute the braking force between regenerative braking and frictional braking. Figures 7.28 and 7.29 show the architecture of the powertrain and the brake system.

In conventional vehicles and most hybrid vehicles, the braking torque is linearly distributed between front and rear axles. This distribution limits the amount of regenerative braking energy. The reason that the distribution is not according to the I-curve is that the traditional frictional brake (hydraulic or air brakes) are slow

² Portion of the material are from Zhiguang Zhou, Chris Mi, and Guixiang Zhang, "Integrated Control of Electromechanical Braking and Regenerative Braking in Plug-in Hybrid Electric Vehicles," International of Vehicle Design, © Inderscience, [2011].

Fig. 7.31 I-curve

safety of the vehicle and healthy operation of components (motor, inverter, and battery). In order to achieve this goal, this section uses the fuzzy logic control strategy to distribute braking torque to regenerative braking as much as possible under some constraints. The inputs of the fuzzy logic controller are battery state of charge (SOC) and torque change ratio δ , which is defined as

$$\delta(t) = T_{xb_{reg}}(t) / (T_{xb_{reg}}(t-1) + \Delta T_{xb}(t)) \quad (7.79)$$

The output of fuzzy controller is regenerative braking factor β , so the regenerative braking torque T_{xb_freg} and friction braking torque in the front axle can be obtained as

$$T_{xb\_freg} = \beta \cdot T_{xb\_f} \quad (7.80)$$

$$T_{xb\_ffric} = (1 - \beta) \cdot T_{xb\_f} \quad (7.81)$$

The membership functions of the input variables and output variable are shown in Figs. 7.32, 7.33 and 7.34 respectively. In Fig. 7.32, TL means too low, L means low, M means middle, H means high, and TH means too high. In both Figs. 7.33 and 7.34, TS means too small, S means small, M means middle, L means large, and TL means too large. According to engineering expertise and insight, the fuzzy control rules can be constructed as shown in Fig. 7.35.

Under the precondition of distributing braking torque to the front and rear axles, the results of distributing braking torque between regenerative braking and friction braking using look-up table method and using the fuzzy logic control algorithm are shown in Figs. 7.36 and 7.37 respectively. It can be seen that more braking torque is distributed to regenerative braking with fuzzy logic control, which means more regenerative energy can be recovered. The regenerative energy obtained using the two methods are shown in Table 7.3.

7.6.3 Antilock Braking Control

The vehicle braking system is a nonlinear and time variant system, and the vehicle model is uncertain. So it is hard to build the precise mathematical model for the

Fig. 7.32 Membership function of SOC. TL—too low; L—low; M—Medium; H—high; TH—too high

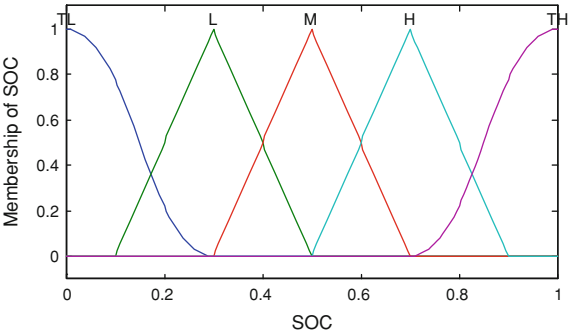


Fig. 7.33 Membership function of δ . TL—too low; L—low; M—Medium; H—high; TH—too high

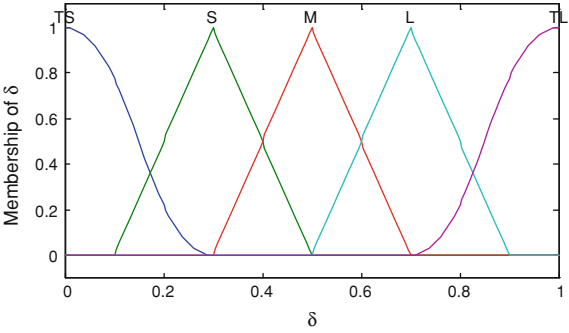
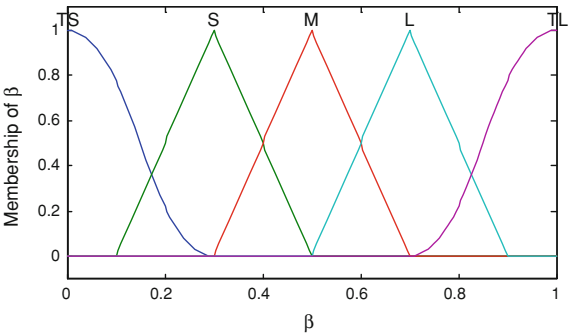


Fig. 7.34 Membership function of β . TL—too low; L—low; M—Medium; H—high; TH—too high



vehicle braking process. Sliding mode control is insensitive to the changing of parameters of the control object. It has good anti-interference ability and good dynamic performance, and can respond quickly. Therefore, it is suitable for both linear and nonlinear systems. But the algorithm of sliding mode control has static error adjustment so it is hard to ensure the static accuracy. It also has high instantaneous switching frequency on sliding mode surface which will affect the control precision of braking torque. In order to solve this problem, this section uses

Fig. 7.35 Rules of fuzzy logic control for braking torque distribution

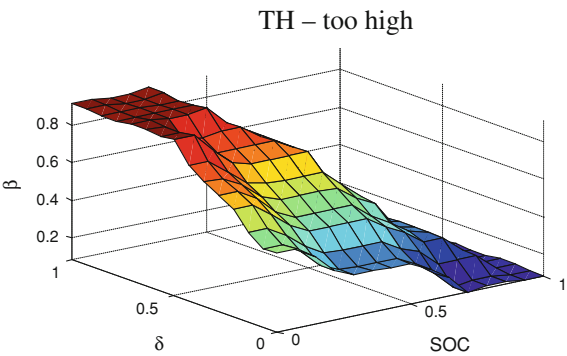


Fig. 7.36 Braking torque distributed between front friction braking and regenerative braking using look-up table method

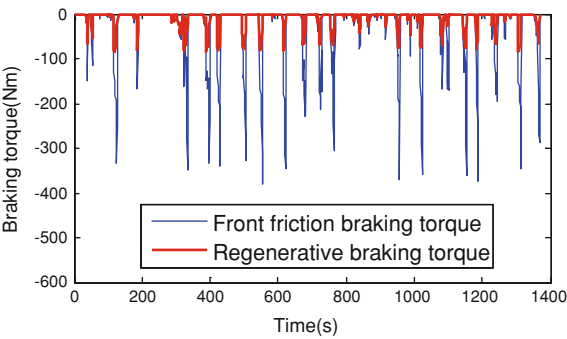
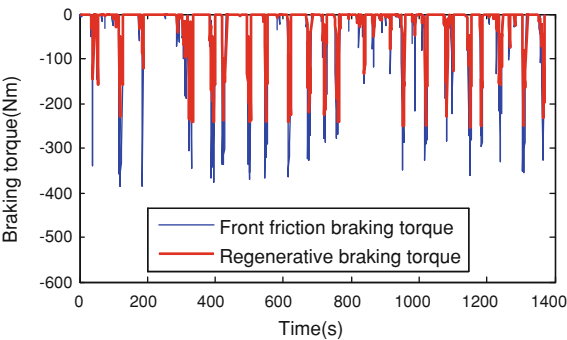


Fig. 7.37 Braking torque distributed between front friction braking and regenerative braking using fuzzy logic control



fuzzy rules to do effective assessment for the switching gain according to sliding mode reaching condition to eliminate the interference, thus to eliminate chattering. The control diagram of the vehicle braking system is shown in Fig. 7.38. In the figure, S_{opt} is the optimal slip ratio; and s is the real slip ratio calculated from the sensor signal of vehicle speed and wheel speed. By using sliding mode control with switching gain fuzzy adjusting, the real slip ratio will track the optimal slip ratio, so as to ensure the vehicle braking system to follow the optimal slip ratio.

Table 7.3 Regenerative energy using lookup table and using fuzzy logic control

Methods	Regenerative energy
Look-up table	971 kJ
Fuzzy logic control	1,136 kJ

In the vehicle EMB system, four wheels are controlled by using the same control method separately. In order to simplify the analysis, aerodynamic drag force and rolling resistance are neglected; and the motion equations are described as follows:

Vehicle motion equation is

$$m \frac{dv}{dt} = -F_x(s) \quad (7.82)$$

Wheel motion equation is

$$J_\omega \frac{d\omega}{dt} = F_x(s)R - T_b(t) \quad (7.83)$$

Wheel longitudinal friction force is

$$F_x(s) = \mu(s)mg \quad (7.84)$$

where m is the one fourth mass of the total vehicle mass; v is the vehicle speed; $F_x(s)$ is the wheel longitudinal friction force; J_ω is the wheel inertia; ω is wheel angle speed; R is wheel radius; $T_b(t)$ is braking torque; $\mu(s)$ is adhesion coefficient between wheel and road surface; and g is gravitational acceleration.

In the condition of braking, the slip ratio can be defined as

$$s = \frac{v - v_\omega}{v} = \frac{v - \omega R}{v} \quad (7.85)$$

where v_ω is the wheel linear speed.

Take derivative of both sides of Eq. 7.85, and we can obtain

$$\dot{s} = \frac{(1-s)\dot{v} - \dot{\omega}R}{v} \quad (7.86)$$

By substituting Eqs. 7.82–7.86, we can obtain

$$\dot{s} = -\frac{\mu(s)mg}{v} \left[\frac{1-s}{m} + \frac{R^2}{J_\omega} \right] + \frac{T_b(t)R}{J_\omega v} \quad (7.87)$$

Select the braking torque as the control object, and the control target is to find out the control rules which can maintain the real slip ratio s oscillating around optimal slip ratio s_{opt} . Define the sliding mode surface as

$$\delta(t) = s_e(t) = s_{opt} - s(t) \quad (7.88)$$

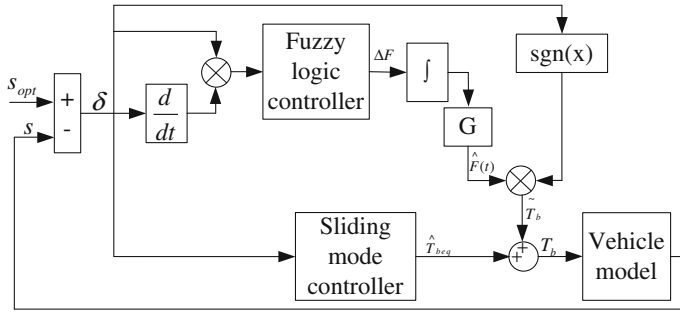
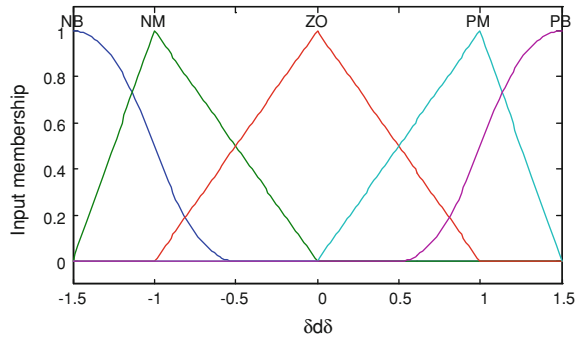


Fig. 7.38 Structure of fuzzy-sliding mode control

Fig. 7.39 Membership function of input $\delta \dot{\delta}$



When the braking system moves along the sliding mode surface, $\dot{\delta}(t) = 0$, so differentiate Eq. 7.88 and combine with Eq. 7.87, and the equal control braking torque can be described as

$$\hat{T}_{beq} = \frac{J_{\omega} N \mu}{mR} (1 - s) + N \mu R \quad (7.89)$$

where $N = mg$, which is the gravity of vehicle.

When the braking system state is outside the sliding mode surface, monitor control braking torque $\tilde{T}_b$ is added to ensure that the system state can arrive at sliding mode surface,

$$\tilde{T}_b = F(t) \cdot \text{sgn}(\delta) \quad (7.90)$$

where $\text{sgn}(\cdot)$ is a sign function; $F(t)$ is used to compensate system interference to make sure the sliding mode existing condition can be satisfied. So the output of control system is

$$T_b = \hat{T}_{beq} + \tilde{T}_b = \frac{J_{\omega} N \mu}{mR} (1 - s) + N \mu R + F(t) \text{sgn}(\delta) \quad (7.91)$$

Fig. 7.40 Membership function of output $\Delta F(t)$

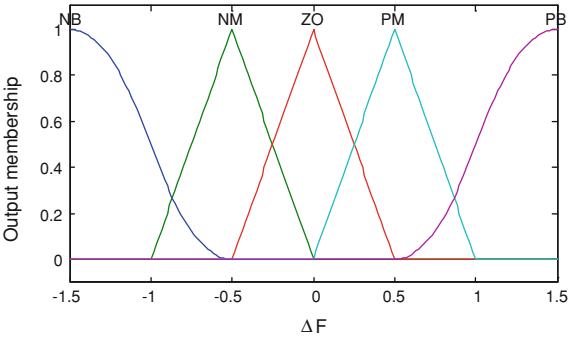


Fig. 7.41 Fuzzy rules

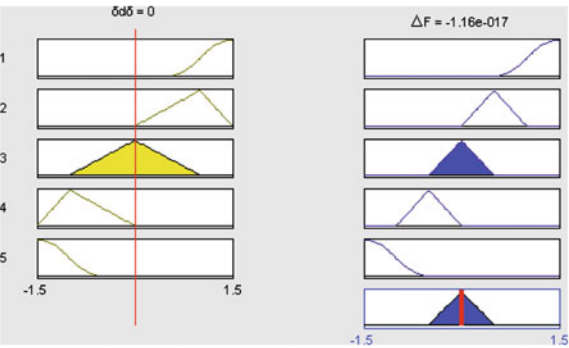
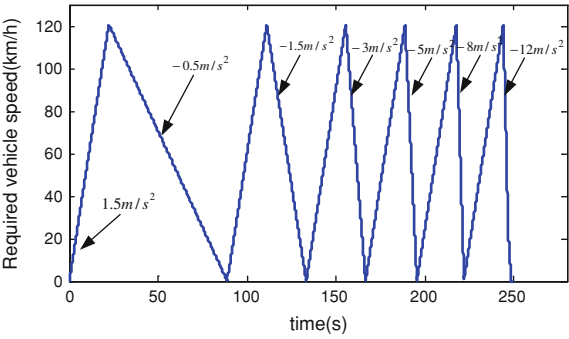
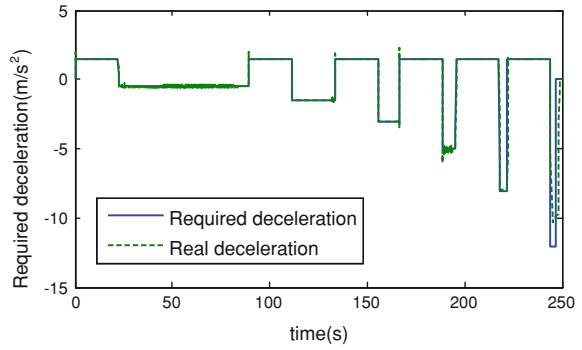
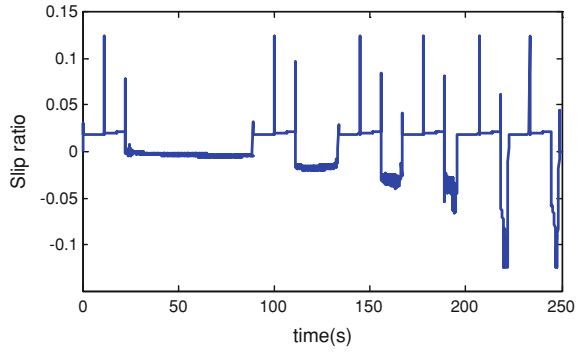
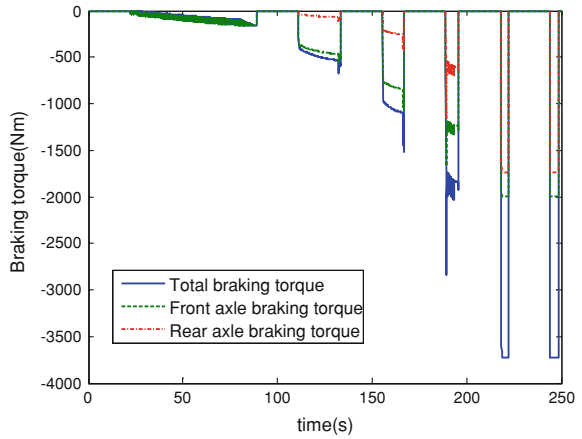


Fig. 7.42 Constructed drive cycle



In the sliding mode control law Eq. 7.91, switching gain $F(t)$ is the reason of causing chattering, because system interference is time variant, and in order to decrease chattering, $F(t)$ is also time variant. In order to eliminate the chattering caused by system interference, this section uses fuzzy rules to estimate switching gain according to sliding mode reaching condition.

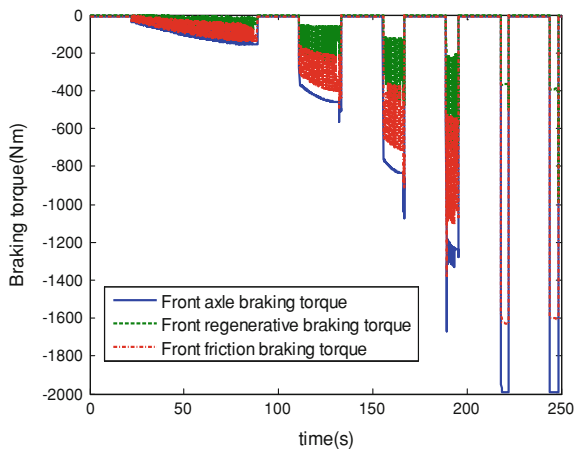
In order to eliminate the high frequency chattering caused by time variable gain $F(t)$, the fuzzy logic rules can be designed as follows:

Fig. 7.43 Required and actual deceleration**Fig. 7.44** Slip ratio**Fig. 7.45** Braking torque between front and rear axle

$$\text{If } \dot{\delta} > 0, \text{ then increase } F(t) \quad (7.92)$$

$$\text{If } \dot{\delta} < 0, \text{ then decrease } F(t) \quad (7.93)$$

Fig. 7.46 Braking torque between regenerative braking and friction braking



With Eqs. 7.92 and 7.93, the fuzzy logic system can be designed about $\delta \dot{\delta}$ and $\Delta F(t)$. In this system, $\delta \dot{\delta}$ is input, and $\Delta F(t)$ is output. The membership function of input and output of fuzzy logic system is shown in Figs. 7.39 and 7.40. In both figures, NB means negative big, NM means negative middle, ZO means zero, PM means positive middle, and PB means positive big. The control rules are shown in Fig. 7.41.

The integration method is used to estimate the upper boundary of $\hat{F}(t)$,

$$\hat{F}(t) = G \int_0^t \Delta F dt \quad (7.94)$$

where G is scale coefficient, $G > 0$.

7.6.4 Simulation Results

In order to test the braking performance under different braking conditions, a special drive cycle is constructed as shown in Fig. 7.42. In the six phases, the acceleration is always 1.5 m/s^2 , but the deceleration is varied, from -0.5 m/s^2 to -12 m/s^2 . The required and actual deceleration is shown in Fig. 7.43. It can be seen that when the deceleration is below -8 m/s^2 , the braking system can supply required braking torque according to the road adhesive force. But when the deceleration is greater than -8 m/s^2 , because of the limit of the road adhesive force, the actual deceleration can not arrive at the required one. During the whole braking process, the slip ratio is shown in Fig. 7.44. From Fig. 7.44 we can see that the slip ratio is always smaller than 1, which means that the wheels are never

locked during the whole cycle. It also proves that the anti-lock braking control strategy used in this section is feasible.

Braking torque distributed between the front and rear axles, and between regenerative braking and friction braking are shown in Figs. 7.45 and 7.46 respectively. The results show that the braking distribution method used in this section is feasible and reasonable.

7.6.5 Discussion

This section discussed the coordination of regenerative braking and EMB with the goal of maximizing the total regenerative braking energy while maintaining the vehicle safety and stability. From the aspect of control method, firstly, an I-curve is used to distribute the total braking torque between front and rear axles so more braking torque is distributed to the front axle. It therefore offers more possibility to capture more regenerative energy. Secondly, fuzzy logic control is used to distribute braking torque between regenerative braking and friction braking on the front axle. Comparing with the look-up table based method, the fuzzy logic control strategy will distribute more braking torque to regenerative braking than to friction braking, which means more regenerative energy can be captured. In order to keep safety and stability of the vehicle, the fuzzy-sliding mode control strategy is used to achieve the function of anti-lock braking. Standard driving cycles are used to test the performance of the control strategy. Simulation results indicate that fuzzy-sliding mode control can keep the real slip ratio following the optimal slip ratio closely and quickly, so that the braking distance can be shortened, and safety and stability of vehicle maintained.

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Chapter 8

Management of Energy Storage Systems in EV, HEV and PHEV

8.1 Introduction

Energy storage systems (ESS) play an important role in EV, HEV and PHEV. The performance of these vehicles is highly dependent on the ESS. According to DOE PHEV Meeting Summary Report (2006), battery warranty cost is believed to be one of the show-stoppers for the mass market penetration of PHEV [1]. Tesla Motors provides only 3 years of warranty on their EV battery [2]. Others charge \$300/year for battery warranty beyond 3 years [3]. It is estimated that the replacement cost of the Chevy Volt battery pack is more than \$10,000 [4].

The EV and PHEV battery will have a warranty of 10/150 (10 years or 150 K miles, whichever happens earlier) in the “green states” in the United States, which is due to CARB regulations allowing a \$3000 incentive if a PHEV battery has the 10/150 warranty. Equally, if not more, important than warranty cost is the customer perception of battery life and the impact on resale value (and residual value) of the car.

There are a few types of energy storage options available for different vehicle applications [5–8]. Nickel Metal Hydride batteries have been widely used in HEVs in the past ten years [9]. Lithium ion batteries are considered as the only viable solution for EV and PHEV at the present time [5–8]. Ultracapacitors have also been investigated for use in PHEV due to their very high power density and long cycle life [10–13]. Flywheel based HEVs have also been investigated [14–17]. Integrated hybrid energy storage systems that contain high energy lithium ion batteries and high power ultracapacitors could potentially provide the best solutions for EV and PHEV [18–26].

Proper management of the ESS in EV, HEV, and PHEV can not only extend the life of the battery ESS, but also help improve overall fuel efficiency of the vehicle. This chapter looks at a few aspects of ESS management. We will start with the basic design and sizing of ESS, followed by battery cell balancing, battery management, and management and control of hybrid energy storage systems.

8.2 Design and Sizing of ESS

The onboard ESS is sized to fulfill towing purposes: to provide sufficient power and energy requested by the powertrain motor; and to store captured energy during regenerative braking. Hence the rating of the ESS will contain two aspects: energy and power. We will use three examples to illustrate the sizing of battery in a PHEV.

Example 1 Size the battery for a HEV that weighs 1500 kg. The goal is to store 40% of the total kinetic energy during the worst scenario braking that the vehicle must be brought to a halt from 70 mph in 10 s. Neglect energy losses due to aerodynamic drag and rolling resistance, and neglect drive line losses, motor losses, and battery losses, during braking.

Solution Vehicle initial speed is $V = 70 \text{ mph} \times 1.609 \times 1000/3600 = 31.3 \text{ m/s}$.

The total kinetic energy is $E = 0.5 mV^2 = 734,768 \text{ J}$. Since 40% of braking energy needs to be stored in the battery, the total energy to be stored is 293,907 J, or 0.08 kWh. The total braking time is 10 s. However, it is generally difficult to achieve regenerative braking at low vehicle speed due to the relatively low voltage generated by the motor/generator. Hence, we will assume that this amount of energy will be recovered during the first 8 s. Hence the average regenerative braking power during braking is 36.7 kW.

Although the average regenerative braking power is only 36.7 kW, if we consider the instantaneous power, the above calculation needs to be modified accordingly. Suppose we apply constant deceleration during braking, then the deceleration is $a = 31.3 \text{ m/s} \div 10 \text{ s} = 3.13 \text{ m/s}^2$. The force due to braking is $F = ma = 1500 \text{ kg} \times 3.31 \text{ m/s}^2 = 4965 \text{ N}$. The total braking power (including regenerative braking and frictional braking) during braking is $P = FV$ which has been plotted in Fig. 8.1.

For nickel metal hydride (NiMH) batteries and lithium ion (Li-ion) batteries, the maximum charge/discharge rate is typically less than 10C, where C is the nominal capacity (C-rate is normally defined to be the amount of current in amps which will charge the battery to its nominal rated amp-hrs in 1 h). Hence, for 36.7 kW of charging power, the energy rating of the battery needs to be at least 1.83 kWh. If the battery voltage is 300 V, then the rated capacity is 6 Ah.

The total energy that is charged to the battery during this braking process is 0.082 kWh which is 4.5% of the nominal energy rating.

In this example, we kept the regenerative braking power to be constant. From Fig. 8.1, it can be seen that there is more power available at higher vehicle speed. Hence, it is desirable to recover more regenerative braking energy at high vehicle speed.

The fact that only 40% energy can be recovered is that during heavy braking, the front axle and the rear axle both are applied for braking action with the front axle realized by regenerative braking and the rear axle realized by frictional braking (see Chap. 7, Sect. 7.5, for more details).

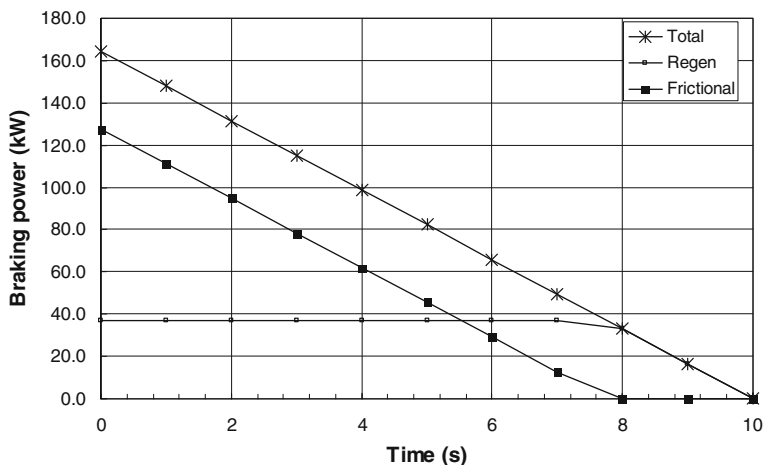


Fig. 8.1 Braking power distribution between regenerative braking and frictional braking. The regenerative braking power is kept constant at 29.4 kW

If we choose to distribute the total braking power between regenerative braking and frictional braking to be 40 and 60%, then the power required for the ESS is much higher, as shown in Fig. 8.2. The maximum regenerative braking power required is 65 kW.

Example 2 Size the battery for a PHEV that weighs 1500 kg. The goal is to have the vehicle capable of electric driving at 50 mph with gentle acceleration (0.1 g). Assume the total resistive force is 450 N. Neglect the driveline loss and the motor/battery losses. Assume no acceleration and the total required electric range is 50 miles at 50 mph with a fully charged battery pack. The allowed battery SOC range is from 100 to 30%.

Solution At vehicle speed 50 mph, or $V = 22.3$ m/s, the acceleration is $0.1\text{ g} = 0.98\text{ m/s}^2$. The force needed for acceleration is $F = ma = 1350$ N. The total force is 1800 N. The power required is $P = FV = 40\text{ kW}$. Therefore, the minimum power requirement for the battery is 40 kW.

Next, we will calculate the energy requirement. Without acceleration, the total power at 50 mph is $P = FV = 10\text{ kW}$. At 50 mph, it takes 1 h to reach 50 miles. Hence, the total energy consumed is 10 kWh during the whole cycle. Since the battery SOC is allowed to drop from 100 to 30% in this process, this 10 kWh represents 70% of the battery nominal energy rating. Therefore, the battery energy rating should be $10\text{ kWh}/0.7 = 14.3\text{ kWh}$. If we choose battery cells rated at 40 Ah, 3.2 V each, the rated energy of each cell is 128 Wh. We will need 112 cells. If we connect all cells in series, then the nominal voltage of the pack will be 358.4 V.

The current is $10\text{ kW}/358.4\text{ V} = 27.9\text{ A}$. The “C rate” of this battery pack is $27.9\text{ A}/40\text{ Ah} = 0.7$. The “C rate” during acceleration at 50 mph is $40\text{ kW}/14.3\text{ kWh} = 2.8$.

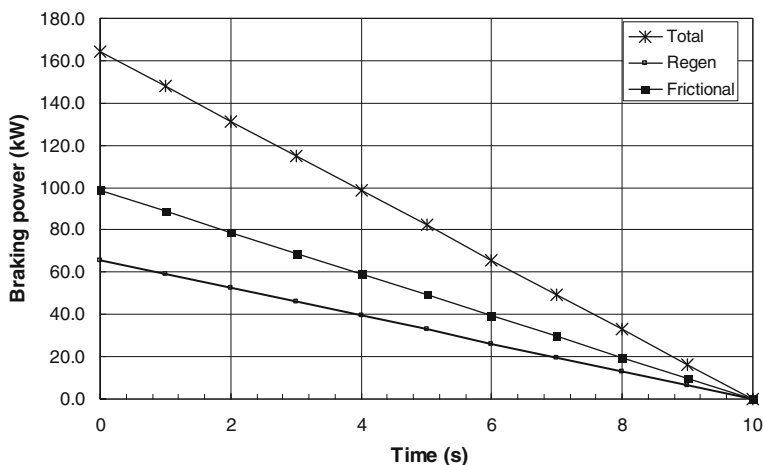
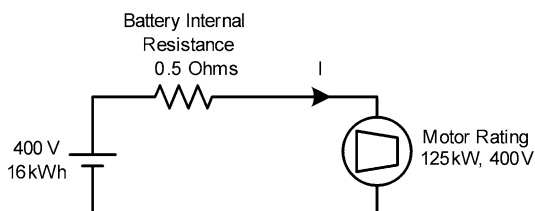


Fig. 8.2 Braking power with linear distribution between regenerative braking and frictional braking

Fig. 8.3 Equivalent circuit of the PHEV battery



Example 3 A PHEV battery pack is rated 40 Ah, nominal voltage 400 V, and the voltage is relatively constant. The battery has internal impedance of 0.5 Ω . Let's look at a few extreme conditions for the battery operation. In all electric mode, the maximum power demand is 125 kW (motor input). What is the maximum discharge current, and how much is the total loss inside the battery pack? How long can the battery last (depleted below some predefined SOC) at the maximum power output?

Solution Due to the internal impedance, the actual battery terminal voltage is 400 V minus the internal voltage drop. Figure 8.3 shows the equivalent circuit of the battery. From the equivalent circuit, the output power of the battery is

$$P_B = (400 - 0.5I) \times I \quad (8.1)$$

If we assume the internal resistance is constant, and also assume the open circuit voltage is constant, then we can plot the output power, loss and efficiency of the battery as a function of current, as shown in Fig. 8.4.

It can be clearly seen that battery loss increases with increasing battery current. For the battery pack, the maximum output power appears when current reaches

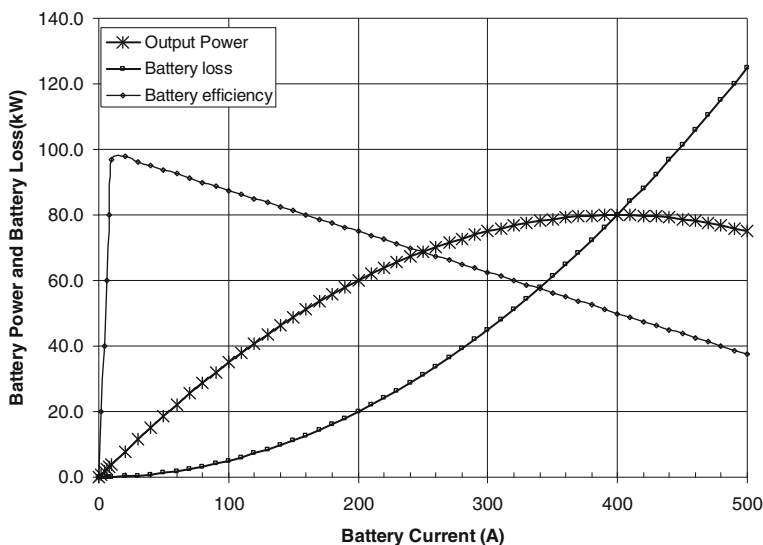


Fig. 8.4 Battery output power and battery loss as a function of battery current. This plot is for an idealized battery whose internal impedance and open circuit voltage are assumed to be constant. For real batteries, the above curve will be slightly different considering that both open circuit voltage and internal impedance are not constants

400 A. At this operating point, the battery loss is the same as the output power, both at 80 kW. The efficiency of the battery is 50%.

Two observations can be made from this example.

- The maximum output power is 80 kW for this battery pack. Hence, it will not be able to satisfy the maximum power demand of 125 kW of the vehicle in electric alone mode.
- The battery internal impedance generates a large amount of losses inside the battery. At the peak power of 80 kW, the battery has an internal loss of 80 kW. This high loss prevents the battery from operating in this kind of condition over an extended period of time.

Hence, it is desirable to operate the vehicle in a blended mode for higher power demands, as discussed in [Chap. 4](#).

Next, almost all batteries have internal leakage (self discharge) in the idle condition. Typically the leakage current increases with temperature. For this battery pack, if the leakage current is 20 mA (which includes battery leak as well as consumption of peripheral circuits associated with the battery, such as BMS, cell monitoring circuits, and cell balancing circuits), we can find out how many days for the battery to self-discharge from 100 SOC to 30% SOC.

$$\frac{40 \text{ Ah}}{0.02} = 2000 \text{ h} = 83 \text{ days} \quad (8.2)$$

It means the battery will last 83 days when stored in idle condition. It is worth to note that battery leakage tends to increase when stored at a higher temperature or extremely low temperatures.

8.3 Battery Cell Balancing

Battery cells are connected in parallel or series to form the battery pack in a HEV, EV, or PHEV. When battery cells are connected in series to form a string, the available energy of the string is determined by the cell that has the least energy. Similarly, when charging the battery, the amount of energy which can be transferred to the string is determined by the cell that has the most energy.

There will be small differences in capacity and internal impedance for hundreds or thousands of cells that are used to form the string. Over time, these differences can be enlarged due to the usage patterns, especially due to the different operating temperatures.

Example A PHEV battery pack is comprised of 125 cells in series. Each cell is rated at 3.2 V, 40 Ah. In testing the vehicle, the cooling system has an inlet temperature of 25°C and outlet temperature of 40°C. The average impedance is 4 mH. The impedance tends to increase with the drop of temperature. Hence the cell impedance at the cooling inlet is measured to be 3.9 milliohms and that at the outlet to be 4.1 milliohms (5% inconsistency). Calculate the difference in capacity of the cells over a period of 100 cycles of usage at 50 A discharge rate with 70% SOC in each cycle. Neglect the differences due to charging of the battery.

Solution Assume the battery cells are starting new and are charged to the same level at the beginning. At 50 A discharge rate, it takes 0.56 h to discharge the battery from 100 to 30%. The total capacity loss for each cell during each cycle due to internal impedance is:

$$\begin{aligned} 0.0039 \text{ m}\Omega \times (50 \text{ A})^2 \times 0.56 \text{ h} &= 5.46 \text{ Wh} = 1.71 \text{ Ah} \\ 0.0041 \text{ m}\Omega \times (50 \text{ A})^2 \times 0.56 \text{ h} &= 5.74 \text{ Wh} = 1.79 \text{ Ah} \end{aligned} \quad (8.3)$$

Assume the cells receive the same amount of energy during each charge, then the total capacity difference after 100 cycles will be

$$(1.79 \text{ Ah} - 1.71 \text{ Ah}) \times 100 \text{ cycles} = 8 \text{ Ah} = 20\% \quad (8.4)$$

The difference in capacity for the two cells after 100 cycles will be 20% or 8 Ah. The process can be illustrated in Fig. 8.5. Hence it is important to balance the cells during operation of the battery pack. There are two categories of balancing methods available: passive balancing and active balancing [27].

For passive balancing, the energy of the high energy cells are discharged to a resistor or transistor and dissipated as heat. For active balancing, the energy from the high energy cells are discharged to charge the lower energy cells.

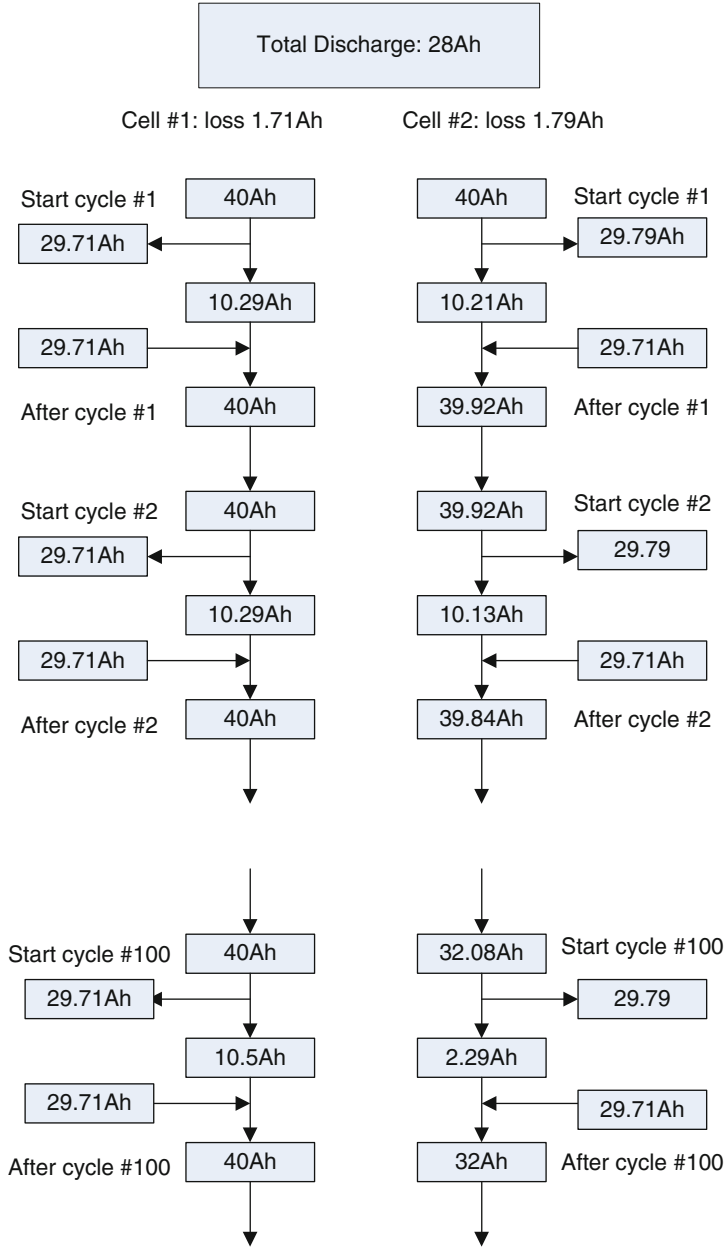


Fig. 8.5 The process of imbalance in battery cells due to inconsistency in cell impedance

For passive balancing, there are typically resistor based and transistor or IC based balancing circuits. Both methods can be used during charge or in idle condition.

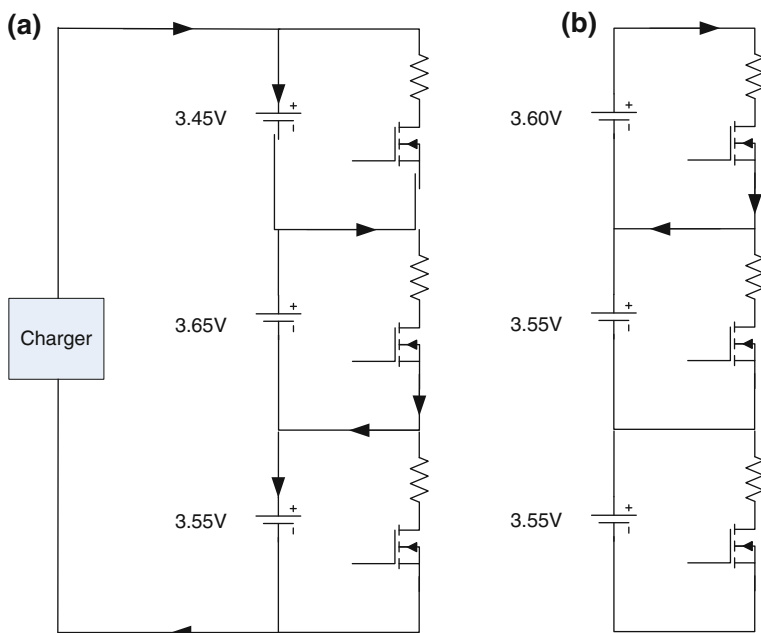


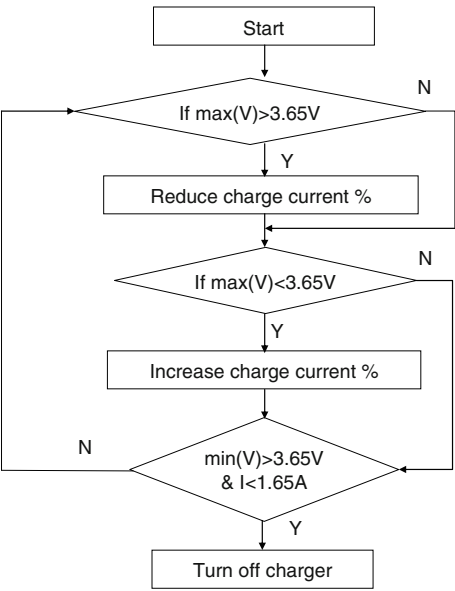
Fig. 8.6 Resistive charge balancing method. **a** Balancing during charge. **b** Balancing during idle

Figure 8.6 shows resistor based passive balancing of a three-cell string [28]. The resistor/transistors are in parallel with each battery cell. When the voltage across any cell is less than the designed voltage (in this case, 3.65 V), the transistor is off hence no current goes through the bypass circuit. All charging current goes through the battery to charge the battery. Once the cell voltage reaches 3.65 V, the transistor is turned on and current flowing through the resistor/transistor starts to increase. In this case, the cells that are below 3.65 V are still charged but the cell that reaches 3.65 V or above is bypassed and stopped charging. Once all cells in the string reach 3.65 V, the charge process will stop.

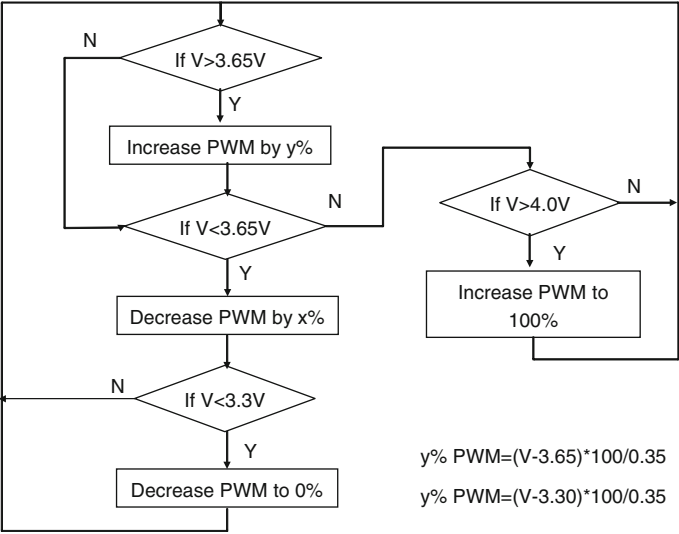
The advantage of this balancing method is that the circuit can be simple and small hence the packaging can be easy. The voltage can be very accurate, up to a few millivolts. The disadvantages are: (1) The balancing is essentially a voltage based balancing method and the energy contents in each cell may still be different even if the cells have the same open circuit voltage; and (2) The energy that flows through the resistor/transistor is wasted as heat. Not only does this decrease the charge efficiency, but also create difficulties for the thermal management of the battery pack. The typical bypass current is designed to be no more than a few amperes.

In order to limit the heat generated in the process of balancing, the charge current needs to be reduced at the time the cell balancing circuit is activated. Therefore the process of balancing control can be illustrated in Figs. 8.7 and 8.8 for the charge controller and balancer controller, respectively. In this example, the

Fig. 8.7 Charger control algorithm designed for cell balancing



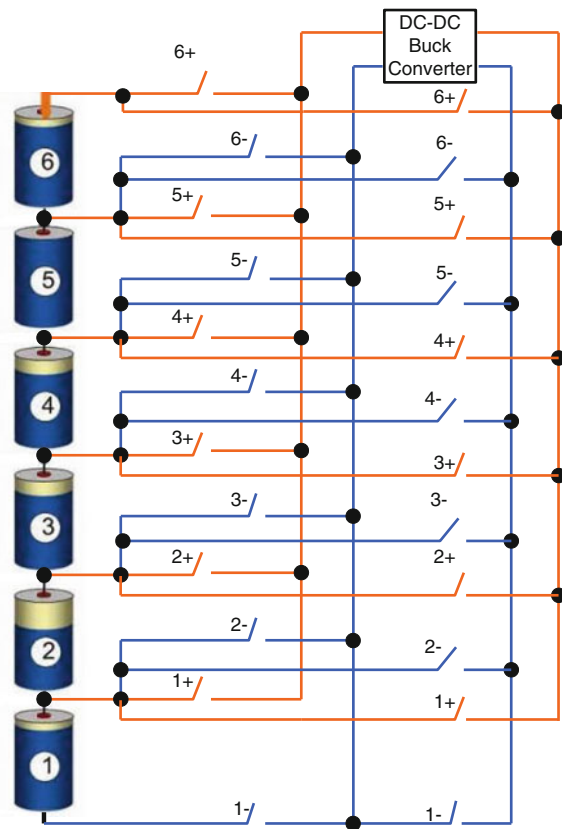
$\% \text{ current decrease} = (V - 3.65) \times 100 / 0.35$; minimum 1.65A
 $\% \text{ current increase} = (3.65 - V) \times 100 / 0.35$; maximum 100%



$y\% \text{ PWM} = (V - 3.65) \times 100 / 0.35$
 $y\% \text{ PWM} = (V - 3.30) \times 100 / 0.35$

Fig. 8.8 Balancer control algorithm designed for cell balancing

Fig. 8.9 DC-DC converter based balancing method



battery is charged full at 3.65 V (open circuit voltage) and 100% at 4.0 V (floating voltage). The balancing starts at cell voltage 3.65 V. The charge current during the balancing phase is reduced by a percentage when $\max(V) = 3.65$, and reduced to 1.65 A at $\max(V) = 4.2$ V.

The charger algorithm will activate the balancing circuit when a cell voltage reaches 3.65 V, and at the same time, it reduces the charging current to 1.65 A. However, if the maximum cell voltage drops below 3.65 V, the balancing circuit is deactivated and the charging current restored. The hysteresis of 3.3 V to 3.65, and 3.65 and 4.0 V, is to prevent the circuit from being in an unstable condition.

The balancing control algorithm will increase the turn-on time for the transistor so more current will go through the bypass circuit.

Active balancing, on the other hand, can be very efficient [29]. There are two types of active balancing circuits. One is the traditional capacitor or inductor based cell balancing, and the other is DC-DC converter based cell balancing. Active balancing provides high efficiency but increases the complexity for the wiring and control algorithm development, and can be expensive if it is built into a battery pack.

A DC-DC converter based cell balancing combines the advantages of a DC-DC converter and the inductive balancing scheme as shown in Fig. 8.9. In this circuit,

the input of DC-DC converter can be switched to any cell and the output can be switched to any other cell through the selective switches. During charge, discharge, or idle time, when the DC-DC converter is activated, the control algorithm will search for the lowest voltage and the highest voltage among all cells. Once the highest and lowest voltage cells are found, the DC-DC converter is controlled to charge the lowest cell using the energy from the highest cell, until the cell reaches the average voltage. This process will continue until all cells have the same voltage.

8.4 Battery Management

Battery management systems (BMS) are widely used in systems where a group of battery cells are connected in series and/or parallel to deliver large power. In an EV, HEV, or PHEV, there are hundreds or even thousands of battery cells in a pack depending on the type of battery cells used. It is critical to monitor and control the batteries so that optimum performance of the system can be achieved and at the same time, the vehicle safety is maintained and the ESS life is extended.

A BMS can have a few levels of functionality. At the simplest level, a BMS should be able to monitor the battery parameters, such as voltage, current, temperature, state of charge (SOC), and state of health (SOH). At the next level, the BMS needs to control the charge and discharge, balance the cells, and maintain health of the battery. The other functions of the BMS include thermal management and safety protections, i.e., capability of isolation faulty battery cells in a fault condition.

8.4.1 *Parameter Monitoring*

The parameters to be monitored include battery voltage, current and temperature. We will first explore voltage monitoring.

There are two types of battery voltage measurements in a battery pack: cell voltage measurement and pack voltage measurement. For pack voltage measurement, due to the high voltage associated with the pack, it is not possible to directly use voltage division. An isolated voltage transducer is appropriate in this case. Figure 8.10 shows an isolated high voltage sensor for pack voltage measurement purposes, made by LEM.

It is important to monitor cell voltages as well. When cells are put in parallel, it is only necessary to measure one voltage for all cells that are in parallel. However, since there are hundreds of cells in series, it would not be practical to measure all cell voltages using a single microcontroller. There are two approaches in practice. One is to divide batteries into groups (modules). Then voltages of cells inside a module are measured locally using a module monitoring circuit and then sent to the central BMS. Another approach is to use “banking technology”.

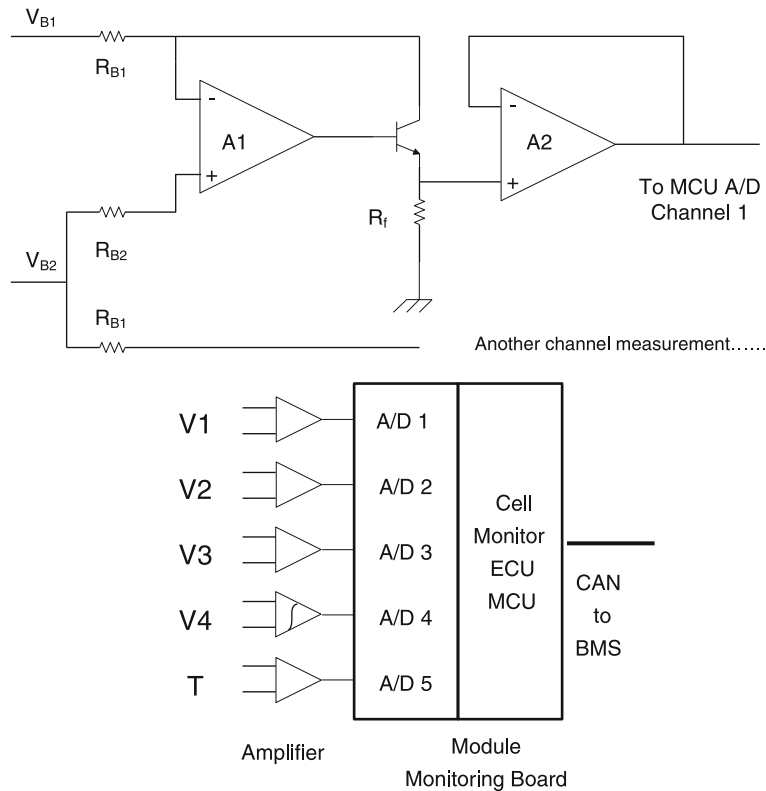


Fig. 8.11 Voltage monitoring for battery cells

A RTD consists of a thin film of platinum on a plastic film. Its resistance varies with temperature and it can typically measure temperatures up to 850°C. It offers the very high linearity between resistance and temperature. The typical resistance is 100 Ω at 0°C. RTDs are expensive so they are used mostly on precision temperature measurements. They are rarely used for temperature monitoring in battery packs.

Thermistors are made of semiconductor material or metal oxides. The resistance of thermistors decreases with increasing temperature. Therefore they are referred to as negative temperature coefficient (NTC) sensors. Thermistors are popular in battery temperature measurement. Figure 8.13 shows the thermistor resistance as a function of temperature, in logarithmic plot.

Thermocouples are based on the effect that the junction between two different metals produces a voltage which increases with temperature. Since they are made of metals, they can measure temperatures up to several thousand degrees Celsius. But their stability and measurement accuracy is not as good as resistor based temperature sensors.

Thermistors can be directly connected to the A/D channels of a microcontroller (MCU), but a buffer circuit is preferred between the thermistor and the MCU,

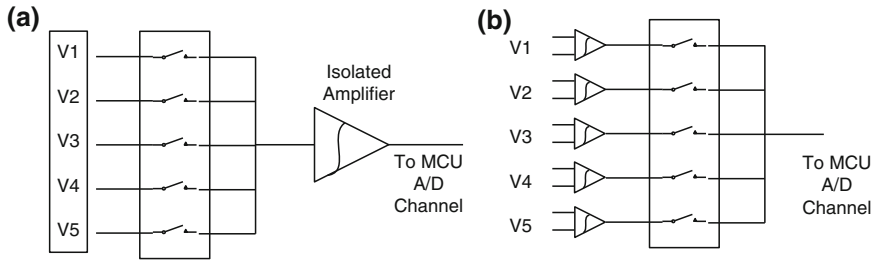


Fig. 8.12 Banking technology. **a** Single isolated amplifier. **b** Multiple isolated amplifiers

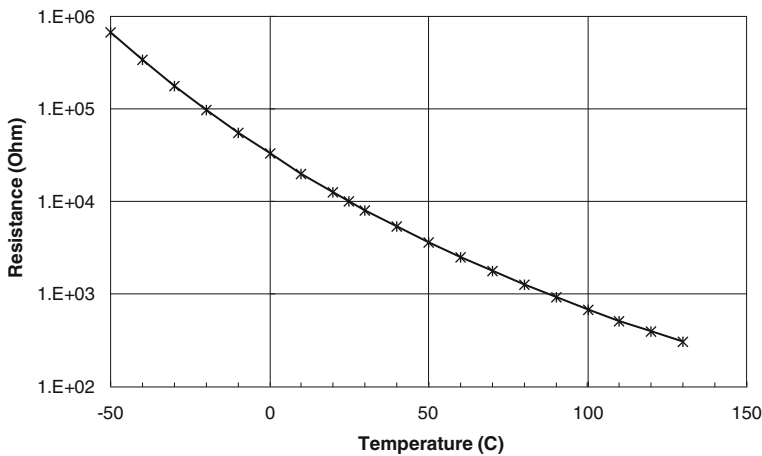


Fig. 8.13 Thermistor resistance value

as shown in Fig. 8.14. A numerical table or liberalized equation is needed inside the MCU to look up the temperature for a given measurement (Table 8.1). In Fig. 8.14,

$$V_T = \frac{V_{cc}}{R_B + R_T} \quad (8.6)$$

Typical resistance of thermistors is 5 k Ω at 25°C with a temperature constant at 4%/°C. Because of the large resistance value, the resistance of connection leads has minimal effect on the measurement accuracy.

Using Eq. 8.6 and the resistance values given in Fig. 8.13, one can easily construct a lookup table for temperatures corresponding to measurement voltage.

Lastly, we will look at current monitoring. Current measurement is realized through the use of current sensors, or current transducers. There are many types of current sensors available for use in battery pack current measurement. LEM DHAB S/25 Dual Channel current sensor and its circuit configuration are shown in Fig. 8.15.

Fig. 8.14 Temperature measurement circuits

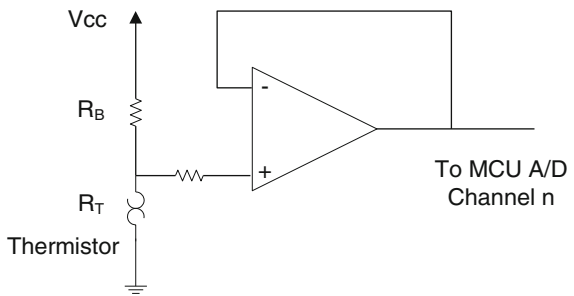


Table 8.1 Lookup table used to find battery temperature

Voltage (V)	4.963	4.927	4.863	4.755	4.586	4.336	3.996	3.571	3.333	3.085
Temperature (°C)	−50	−40	−30	−20	−10	0	10	20	25	30
Voltage (V)	2.579	2.094	1.662	1.298	1.005	0.775	0.598	0.464	0.361	0.284
Temperature (°C)	40	50	60	70	80	90	100	110	120	130

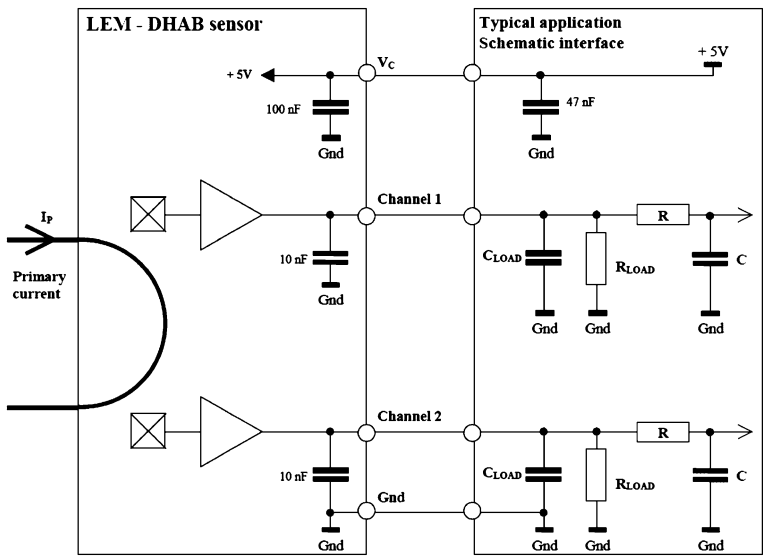
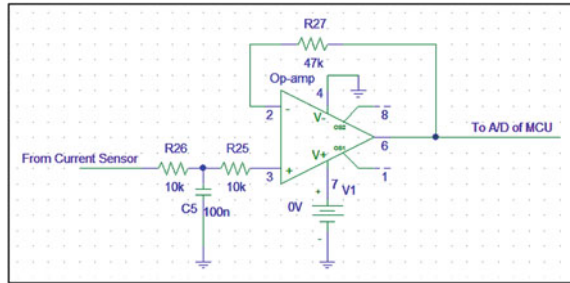


Fig. 8.15 LEM DHAB S/25 Dual Channel current sensor and its circuit configuration Courtesy, LEM USA Inc

This current sensor has two channels of amplifier: one rated at 200 A, and the other at 25 A. The current sensor output for Channel 1 is scaled at 10 mV/A, and for channel 2 is scaled at 80 mV/A. With a single 5 V power supply, the output is 2.5 V at zero current. For channel 1, 0.5 V corresponds to −200 A, and 4.5 V corresponds to 200 A. For channel 2, 0.5 V corresponds to −25 A, and 4.5 V corresponds to 25 A. The amplifier circuit for the current sensor is shown in Fig. 8.16.

Fig. 8.16 Current measurement circuit



8.4.2 Calculation of SOC

State of charge (SOC) calculation is one of the most important functions of a BMS. Traditionally, SOC is calculated by counting how much current (or electrons) has moved in or out of the battery:

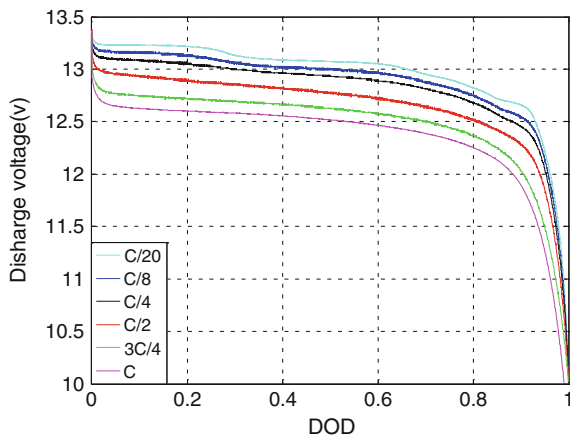
$$SoC(new) = SoC(old) - \frac{I \times T_s}{(Ah)_{nominal}} \quad (8.7)$$

However, this calculation is subject to many uncertainties:

- Measurement accuracy: current sensors have measurement accuracy and resolution. Over time, the error could be cumulated in SOC.
- The amplifier circuit also has accuracy associated with the precision of resistors and power supplies.
- MCU calculation rounding errors
- MCU A/D resolution
- Battery initial SOC which may not be known to the MCU
- Battery loss that cannot be counted for the calculation of SOC using the above equation
- Self-discharge cannot be counted for by the SOC algorithm
- Current has harmonics which could cause measurement error due to discrete sampling by the MCU
- Noises in the measurement loop and in the amplification circuits
- Battery aging could impact how much energy can be charged to the battery. Hence a percentage of SOC may not truly represent how much energy is available.

Therefore, other approaches must be developed to supplement the traditional SOC calculations. One of the most popular approaches is to use battery terminal voltage to calibrate the battery SOC. In this method, the battery is tested to develop a relationship between terminal voltage and SOC for different charge/discharge current and temperature. A lookup table is then built to find SOC based on measurement of battery voltage, current, and temperature. This SOC is then compared with the calculated SOC from the Coulomb counting method. If the discrepancy exceeds a certain threshold, then attention needs to be given and

Fig. 8.17 Battery SOC versus terminal voltage



some further diagnostics needs to happen. A typical SOC and voltage relationship is shown in Fig. 8.17. This method cannot take into account the influence of battery aging.

The second approach is to reset SOC when the battery is fully charged. Some batteries are not allowed to be fully charged but modern lithium ion batteries can be charged full every time without affecting the battery life.

Lastly, advanced mathematical models can be used to predict battery SOC, such as Kalman Filtering, etc. The Kalman filter makes an optimum trade-off between believing the sensor reading and believing the model to achieve the best possible state estimate. The key is to filter the noise and combine with a good mathematic model. Kalman Filtering treats the measurement noise as a random variable and removes measurement noise from the system. In Kalman Filtering, we estimate signal X for each k (state) using

$$X_k = K_k Z_k + (1 - K_k) Z_{k-1} \quad (8.8)$$

where Z_k is the measurement value that has error, and K_k is the Kalman Gain which needs to be determined for different system.

A good mathematic model is a critical part of the Kalman Filter based SOC estimation.

8.4.3 Fault and Safety Protection

The proposed circuit in Fig. 8.18a can be used to balance the battery cells during charging and to isolate faulty cells during charging or discharging. There are two transistors associated with each battery cell. These transistors are typical low on-state resistance MOSFETs, with typical resistance at the milliohms range.

During normal operation, the parallel-connected transistors are turned off and the series-connected resistors are turned on, as shown in Fig. 8.18b. During fault

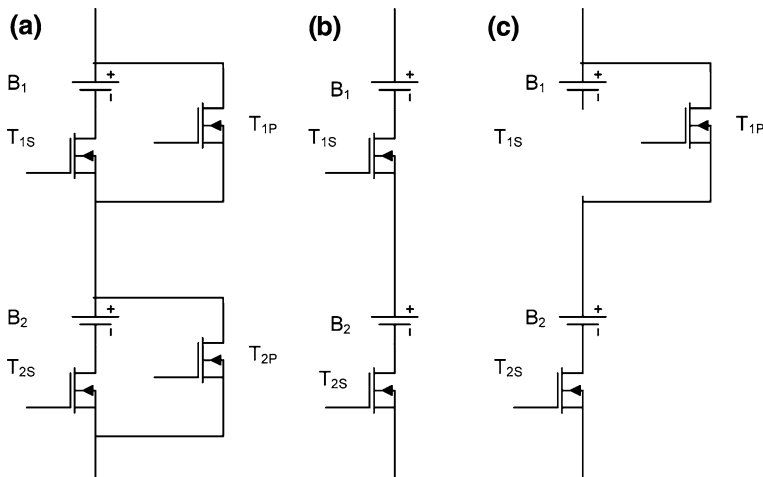


Fig. 8.18 A balance and isolation circuit to manage battery pack in a PHEV. **a** Configuration. **b** Normal operation. **c** B_1 fault or bypass

conditions, assume B_1 has a fault, transistor T_{1P} which is parallel-connected to the faulty cell (B_1 as shown in Fig. 8.18c) is turned on while the series connected transistor T_{1S} for the same cell is turned off.

During charging, the balancing can be performed using the same circuit. When B_1 is full, T_{1P} is turned on and T_{1S} is turned off, so all charging current goes through the bypass transistor T_{1P} . This is more suitable for constant current charging because when one cell is discounted from the battery string, the whole pack voltage is reduced by one cell. Therefore, the charger voltage has to be adjusted accordingly.

The advantage of this circuit is that it does not consume any power (other than the transistor loss) during balancing, and it can isolate any faulty cell during usage of the battery pack. The disadvantage is that the loss on the series connected transistors can be very large during high current operations. Hence, this design is not suitable for large power applications. For example, if the MOSFET voltage drop at 200 A is 0.2 V; ($R_{DS\_ON} = 0.001 \Omega$ which costs \$2), the loss on the single MOSFET will be $200^2 \times 0.001 = 40$ W. For a pack that is composed of 100 cells in series, the loss will be 4 kW at peak. However, when the current is reduced to 60 A, the pack loss due to the transistors will be only 360 W. However, the pack will only be able to supply 24 kW assuming each cell is rated at 4 V.

8.4.4 Charge Management

Proper charge and discharge of batteries can maintain healthy condition of the battery system. Consequently, improper charge and discharge can impact the battery life and capacity.

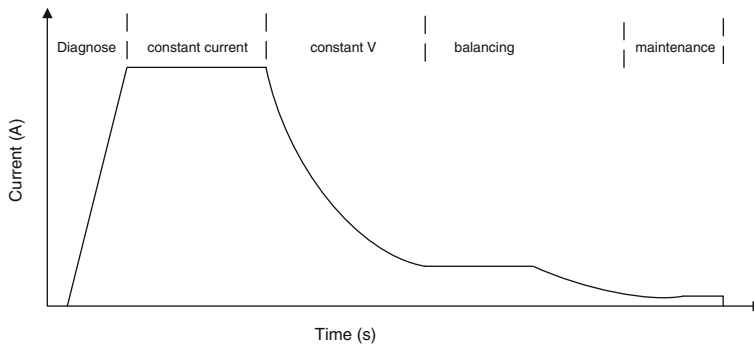


Fig. 8.19 Plug-in charge management

Batteries in the EV, HEV, and PHEV are charged in three scenarios: during plugin charge, during regenerative braking, and opportunity charge using engine power. The plugin charge is usually over an extended period of time at lower charge rate. But the regenerative braking can happen at much higher current level over very short time duration.

Plugin charge usually goes through five phases

- **Diagnosis phase.** When the car is plugged in, the BMS and charger will perform a series of testing to make sure the battery is capable of receiving charge. A small current, typically $C/20$ is injected to the battery. This phase can last a few minutes with the charging current gradually ramped up to the second phase.
- **Constant current charging phase.** Once the battery passes the diagnosis, the battery is charged with constant current, usually at $C/5$ for regular charging, and $C/2-2C$ for fast charging.
- **Constant voltage or reduced current charging phase.** During the constant current charging phase, once one of the cells reaches the maximum voltage, the charging current is reduced. At this point, the battery can either be charged at a reduced current, or enter the constant voltage charging phase.
- **Balancing phase.** However, depending on the imbalance of the battery cells, the constant voltage phase can take a long time. During this phase, the balancing circuit is activated for the cells that have reached the threshold. Once all battery cells reach the preset voltage threshold, the charge is stopped and the charger can be turned off.
- **Maintenance phase.** Some batteries need a maintenance phase in which a very small amount of current is being injected to the battery to make up the leakage loss. Some battery packs have been designed to use this small current to keep the battery warm in cold-weather (Fig. 8.19).

While the management of plugin charge is relatively straight forward, management of the charging of battery during regenerative braking can be very difficult. This is due to the fact that a large current is being injected to the battery to generate the desired braking torque, as well as the heat generated inside the battery

due to battery internal resistance. From the example earlier in this chapter, we could see that the loss can be as large as 10 kW which makes it very difficult to manage the heat inside the battery pack.

8.5 Integrated ESS

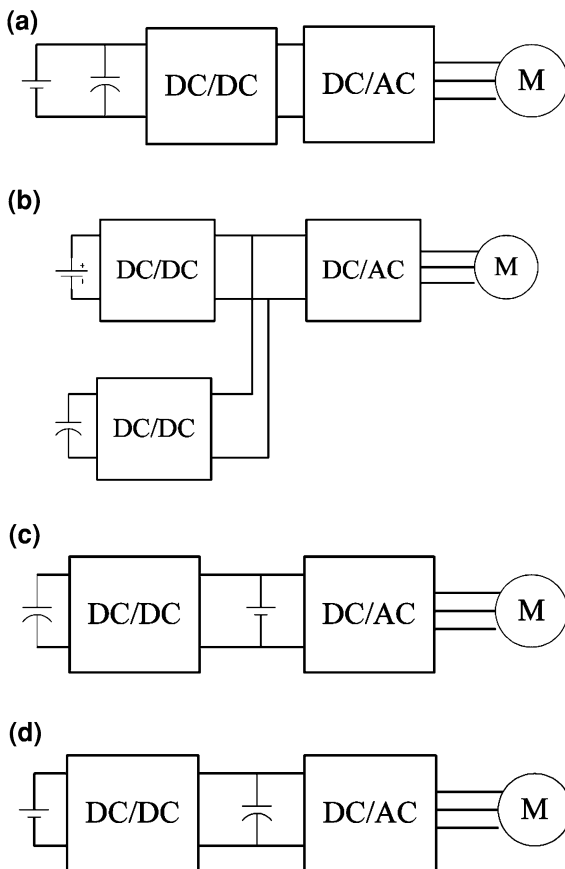
The current EV/PHEV faces many challenges in the energy storage systems area, such as limited power density, poor cycle life, high cost, and poor cold-weather performance. Integrated energy pack with ultracapacitors and lithium-ion batteries can potentially improve EV/PHEV performance by taking advantages of both components while mitigating their limitations [18–26].

Lithium ion batteries are currently considered to be the only viable solution to EV and PHEV energy storage. While they can provide better energy density than other batteries, the power density is still below the expectations for PHEV where a high degree of transient and dynamics requires rapid response from the batteries. For example, the Ford Escape PHEV is equipped with a 10 kWh battery pack which can provide 20 miles electric drive range. But the peak power of the pack can hardly satisfy the acceleration and regenerative braking requirement which may exceed 75 kW. In addition, frequent high rate charge/discharge and irregular charge/discharge current could impact battery cycle life, and degrade the system performance, such as significant drop of battery efficiency at high currents. Other limitations of lithium ion batteries include high internal impedance and poor cycle life in comparison with ultracapacitors, high cost, and poor cold-weather performance. These challenges pose key barriers to the mass market penetration of PHEVs. On the other hand, ultracapacitors have very low impedance, long cycle life, and high power density that can handle fast and large transients in a vehicle. However, ultracapacitors have low energy density and high cost which prevents them from being used alone in PHEVs.

An integrated energy storage system (IESS) integrates ultracapacitors with lithium ion batteries to take advantage of the two and mitigate their limitations. Such system could provide desirable capabilities of high current transients and extend cycle life of the battery through dynamic load leveling. Specifically, the IESS can potentially

- Improve driving performance due to the ultracapacitor's superior cold-weather response, faster and efficient charging and discharging, and longer service life compared to batteries.
- Boost fuel economy and increase electric driving range thanks to improved regenerative braking capability, improved engine-off operation and improved power assist during acceleration.
- Attain similar cost to that of lithium ion battery packs by using thicker electrodes, less supporting material, and smaller current collecting plates for the lithium ion battery cells.

Fig. 8.20 Connection between battery and ultra-cap. **a** Passive connection. **b** Active connection. **c** Ultracapacitor-active connection. **d** Battery-active connection

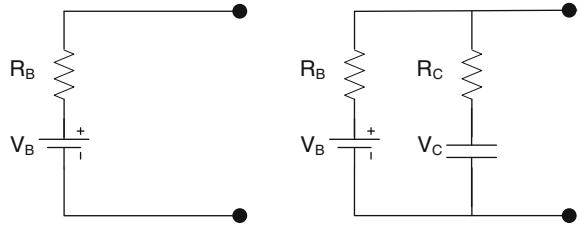


IESS has been investigated for use in EVs and PHEVs to improve vehicle fuel economy, enhance driveability, and extend battery life [18–26]. The Argonne National Laboratory (ANL) and Maxwell Technologies studied the active combination of ultracapacitors and batteries for a PHEV in a DOE funded project [30–32]. Significant advantages were demonstrated through laboratory bench testing. Power electronic converters have been used by ANL [33] and others [34–37] to actively manage the power sharing between the two energy storage components. Wu et al. developed an algorithm to optimize each energy storage component in an IESS [38]. Borhan and Vahidi used model predictive control to manage the IESS to achieve better fuel efficiency [39]. IESS has also been applied to other applications such as consumer electronics [40].

There are four different approaches to connect the ultracapacitor and the battery: passive, semi-active, and active, as shown in Fig. 8.20.

For the passive connection, the ultracapacitor and the battery will share the same voltage. Since the SOC of the ultracapacitor is proportional to the terminal voltage, and the SOC of the battery is nonlinear to its terminal voltage, the exact

Fig. 8.21 Equivalent circuit for the two ESS



power sharing is determined by the system voltage and the internal impedance of the two. Since ultracapacitors have relatively smaller internal impedance, higher current tends to go into or come out from the ultracapacitor.

For actively connected systems, the exact power and energy from the active component can be precisely controlled. However, one or two bidirectional DC-DC converters are necessary, which have to handle the large amount of power of each component.

With proper control algorithms, the system can be designed to have the ultracapacitor handle the large transients and the battery handle the average power. Therefore, the pressure on power requirement can be significantly reduced. Battery life can be extended. More regenerative braking energy can be stored in the ultracapacitor which otherwise is not available.

Example Compare the performance of a PHEV equipped with battery only and with IEES. The maximum braking power is 150 kW of which 40% can be recovered through regenerative braking. The vehicle is required to have pure electric drive capability up to 60 kW power demand. Continuous power is 20 kW (Fig. 8.21).

Pack #1: The 40 Ah, 400 V, 16 kWh battery pack has an internal DC resistance of 0.5 Ω . Assume the battery is initially charged to 400 V.

$$(400 - 0.5I_B) \times I_B = 60,000 \text{ hence, } I_B = 200\text{A} \quad (8.9)$$

At 200 A output current, the DC bus voltage is 300 V and the total power delivered is 60 kW. The internal loss is $I_B^2 R_B = 20\text{kW}$

The maximum energy to be sent in the battery is also 60 kW.

$$(400 + 0.5I_B) \times I_B = 60,000 \quad \text{hence, } I_B = 129\text{ A} \quad (8.10)$$

Hence $I = 129\text{ A}$ i.e., in order to achieve 60 kW braking, the battery needs to have a current of 129 A. Of the 60 kW sent to the battery, 51.7 kW is stored in the battery and 8.3 kW is consumed by the battery internal impedance.

In continuous operation, the power demand is 20 kW. Assume 400 V battery open circuit voltage, then the current is 53.6 A, and the battery loss is 1.44 kW.

Pack #2: The IEES has a 15 kWh lithium ion battery and a 300 Wh ultracapacitor in parallel. The ultracapacitor has internal impedance of 0.1 Ω and the

battery has an internal impedance of 0.5Ω . Assume that the ultracapacitor and the battery are both initially charged to 400 V. Since the two are in parallel, to deliver 60 kW output, the following equation exists:

$$\begin{aligned} V_{bus} &= 400 - 0.5I_B = 400 - 0.1I_C \\ I_{bus} &= I_B + I_C \\ V_{bus} \times I_{bus} &= 60,000 \end{aligned} \quad (8.11)$$

Hence the DC bus voltage will be $V_{bus} = 387$ V with battery delivering 25.8 A (10.3 kW) and ultracapacitor delivering 129 A (51.7 kW). The total loss is $I_B^2 R_B + I_C^2 R_C = 2.0$ kW.

During braking, the total power from the DC bus is 60 kW, therefore, the following equations will hold

$$\begin{aligned} V_{bus} &= 400 + 0.5I_B = 400 + 0.1I_C \\ I_{bus} &= I_B + I_C \\ V_{bus} \times I_{bus} &= 60,000 \end{aligned} \quad (8.12)$$

Hence, the DC bus voltage will be $V_{bus} = 412.15$ V with battery receiving 24.3 A and ultracapacitor delivering 121.3 A. The total loss is $I_B^2 R_B + I_C^2 R_C = 1.8$ kW, battery power is 9.7 kW, and ultracapacitor power is 48.5 kW

During normal operation, the ultracapacitor will no longer be able to provide power. Hence the battery is the only source for propulsion. The total current will be 53.6 A and the total ESS loss is 1.44 kW.

We can see from this example, that by using the ultracapacitor, the power loss can be significantly decreased for very high transient power demand.

For better performance, active connection of ultracapacitor and battery is necessary and advanced control algorithms are necessary. Readers can refer to [Chap. 5](#), Wavelet Transform.

8.6 Management of Vehicle to Grid (V2G)

PHEVs need to be charged from the electric power grid. During charging of PHEVs, the charger will generate inrush current and harmonics, and could cause the interface between the vehicle and the grid not to be coordinated properly. In a broad sense and in the foreseeable future, hundreds of thousands of PHEV will be connected into the power grid as the electric transportation will prevail as our ultimate solution to become independent of fossil fuels. It is imperative to manage the Grid-to-Vehicle (G2V) impact on power system operation considering various factors such as battery size, charging, PHEV distribution, and efficiency [41].

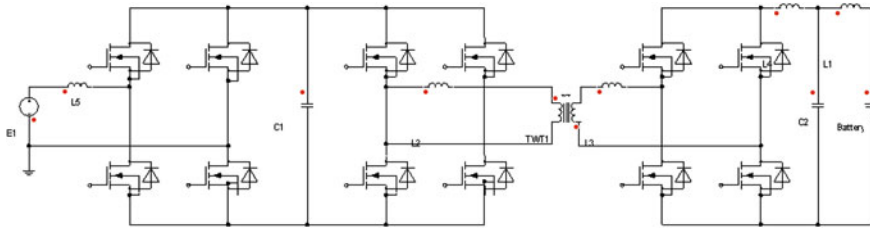


Fig. 8.22 Bidirectional charger used for G2V and V2G functions

In order to optimize G2V it is important to educate the consumers in the context of smart grid. They should be made aware of the fact that battery charging during night-time would improve the utility generation efficiency, as during night-time the electricity is supplied by the base-load generation units. Studies show that with even 50% penetration of PHEVs into the power system, no additional generating capacity or no new power plants are required [41]. Although there are concerns of PHEVs straining the grid, but plug-in HEVs, if properly managed, actually could help prevent brownouts, reduce the cost of electricity and accommodate integration of more renewable energy resources.

There are three levels of charging for PHEVs depending on the voltage level: single-phase AC 120 V, single-phase AC 240 V, and three-phase AC 480 V. The different charging algorithms require corresponding controller designs for the power electronic circuits.

Vehicle-to-Grid, or V2G, is a concept referred to the capability of bidirectional power and energy exchange between the power grid and the vehicle battery [42–46]. With the bidirectional charger, the vehicle can be used as a power back up for the home or office. It is also possible to use the PHEVs battery to control the stability, and regulate the frequency and voltage of the power grid, such as distributed power grid and renewable generation. A bidirectional charger, as shown in Fig. 8.22, is a critical part of the V2G function.

For EVs and PHEVs, the energy that can be used for V2G is limited by the onboard battery size. The unique aspect of power flow in PHEVs is that it is bidirectional, meaning that the vehicle can take power (during charging) and provide power (during discharge) to the grid. Apart from the concept of vehicle-to-grid (V2G) there is the concept of vehicle-to-home. The advantage of V2G is that it is parallel, which means within a grid any car can be used to power any house by feeding its power back to the grid. On the other hand, vehicle-to-home is limited in the sense that a single vehicle can supply only a single house.

PHEVs can be treated as distributed energy resources via V2G and can provide voltage and frequency regulation, spinning reserves, and electrical demand side management [41, 46]. The V2G functions can be classified into two categories: local services and broad area services. Local services include supplying back up power for local house or business, peak shaving, and voltage stabilization or power quality improvement. Broad area services include ancillary services for the grid.

Ancillary services are power services by which the grid operators maintain a reliable operation of grid.

Example Assume there are 20 million passenger cars to be plugged in at the same time to charge. Each car has an average battery pack capacity of 16 kWh and is charged with $C/5$ rate. Calculate the total power demand to the grid.

Solution Assume all cars are charged with level 2 charging, i.e., from 220 V, the charger has efficiency of 90%, battery charging efficiency is 95%, and power factor is 1.0. The power and current needed for each battery pack are

$$P = \frac{16 \text{ kWh}}{5 \text{ h}} \frac{1}{95\%} \frac{1}{90\%} = 3.74 \text{ kW}$$

$$I = \frac{P}{220} = 17 \text{ A} \quad (8.13)$$

Since there are 20 million cars, the total power from the grid is 74,800 MW. Comparing to the total power capacity of the US electric grid (average demand 438,000 MW), this is about 17%.

8.7 Thermal Management

All powertrain components, including the ESS, generate heat. The loss of the ESS can be significant during peak power demands and during heavy regenerative braking as illustrated in the previous examples.

One of the important factors with regard to thermal management is that temperature gradient inside a battery pack can cause inconsistency in the cell capacity and internal impedance. Hence, the available capacity of the pack may be limited by cells that are at the highest or lowest temperatures.

Figure 8.23 shows the temperature distribution inside an air-cooled battery pack. It can be seen that the difference between the maximum (340 K) and minimum temperature (314 K) is 26°C.

In order to reduce the impact of heat on the batteries, liquid cooling can be used. The maximum and minimum temperature can be reduced to be within a few degrees inside a battery pack with liquid cooling.

It is well known that battery internal impedance will increase very quickly with the drop of temperature below zero degree centigrade. Experiments have shown that lithium ion batteries can hardly deliver any power below -20°C . Figure 8.24 shows the discharge curve of a lithium ion battery at 20 A, -15°C . It shows that the battery voltage drops very quickly within the first few seconds from 13.2 to 12 V. It then continues to drop slowly to 11.4 V, which lasts 400 s. After that the voltage starts to increase. This phenomenon is caused by the temperature rise inside the battery due to internal loss of the battery. Hence it has been proposed that internal heating elements are included in battery pack designs so that the battery can be warmed up during cold-weather.

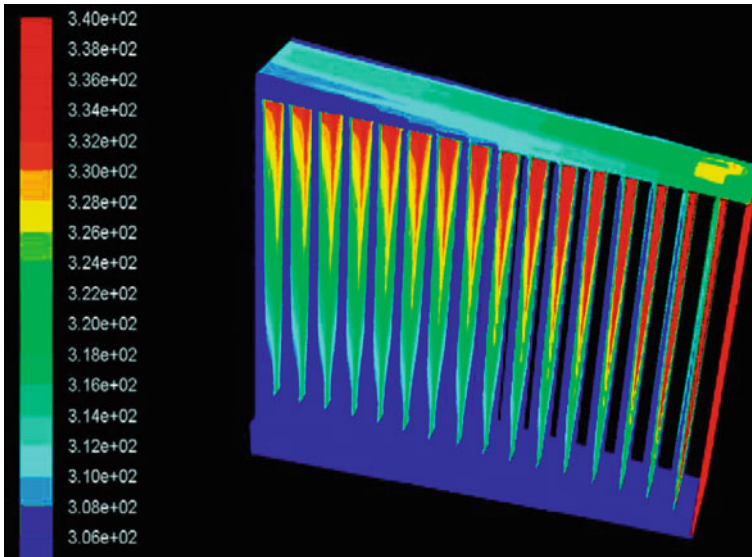


Fig. 8.23 Temperature distribution inside an air-cooled battery pack. The temperature is in Kelvin

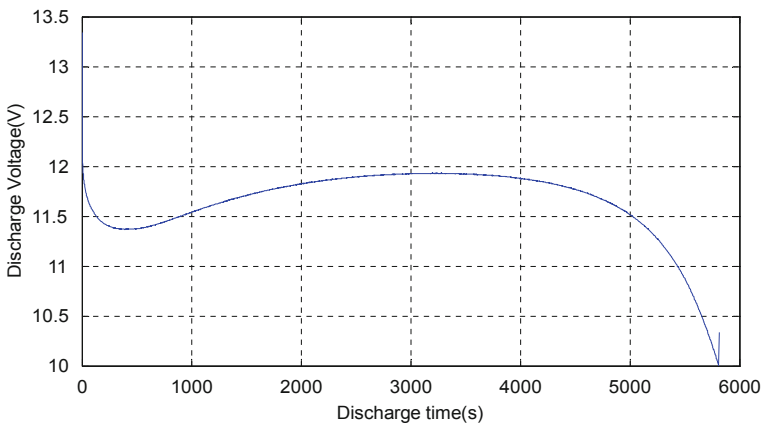


Fig. 8.24 The discharge of a lithium ion battery module (nominal voltage 13.2 V) at -15°C

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Chapter 9

HEV Component Design and Optimization for Fuel Economy

Configurations of HEV and PHEV are more complicated than conventional vehicles. In addition to powertrain control strategies that can help optimize fuel economy, improve vehicle performance, and reduce emissions, the sizes of components in a HEV and PHEV also play an important role in the overall vehicle performance, fuel economy, and emissions. Recent research activities in this field show that component sizing and the control strategy are quite intertwined in such a way that concurrent optimization of component sizing and control strategy is warranted [1, 2].

There exist a number of different optimization algorithms which can be used for HEV design. They can be categorized in different ways, e.g., local optimization algorithm versus global optimization algorithm, deterministic optimization algorithm versus stochastic optimization algorithm, or gradient-based algorithm versus derivative-free algorithm. It is often not obvious to select some optimization algorithms for the application to hybrid powertrain design.

In HEV optimization, most research work attempts to consider the fuel consumption as a single optimization objective [3–6]. A good survey of intelligent vehicle power management can be found in [7]. In this chapter, we intend to improve the vehicle's fuel economy as well as to reduce its emissions such as Hydrocarbons (HC), Carbon Monoxide (CO) and Nitrous Oxide (NO_x) simultaneously. Four objectives may conflict with each other in some situations, and optimal solutions are often not unique. Since it is difficult to prefer one solution over the others without any further information about the problem, in view of multi-objective optimization, good trade-off solutions are considered optimal [8].

The classical methods for handling multi-objective optimization usually map multiple objectives into a single objective, such as the weighted sum method, ϵ -constrain method, weighted metric method etc [9–11]. This chapter introduces the non-dominated sorting genetic algorithm (NSGA-II), one of the most efficient evolutionary algorithms, for the optimization of HEV parameters. A parallel and a series HEV configuration are used as the base vehicle model to study the optimization problem. The algorithm attempts to find a set of trade-off optimal

solutions, namely Pareto optimal solutions that minimize the fuel consumption and three emissions, HC, CO and NO_x simultaneously. In addition, three component sizing parameters and five control strategy parameters are treated as design and control variables to be optimized. The dynamic performances of the original vehicle requirements are considered as constraints.

In this chapter, we first study the total optimization problem in a HEV using evolutionary algorithms to the multi-objective optimization problem of a series HEV. Then, we compare the different optimization algorithms for a parallel HEV. Since the analytical expression of the objective function does not exist, a vehicle simulation model is used for function evaluations. The optimization algorithm is implemented in the simulation software, PSAT and ADVISOR, with simulated experiments on a test drive cycle, which is a combination of city cycle UDDS and highway cycle HWFET. The simulation results obtained in this study show that the proposed optimization approach is effective and important for vehicle designers and vehicle control optimization: the proposed optimization algorithm has the capability of generating a set of trade-off optimal solutions among the fuel economy and the three emissions, and all these solutions have better performances in all four objectives: fuel economy, HC, CO and NO_x . Vehicle designers can use their own criteria to select optimal solutions from this population of trade-off optimal solutions.

9.1 Multi-Objective Evolutionary Algorithm for the Optimization of a Series HEV¹

A multi-objective optimization problem (MOOP) has a number of objective functions that need to be minimized or maximized simultaneously [12]. The problem usually also has a number of constraints that all feasible solutions must satisfy. The MOOP problem can be formally described as follows.

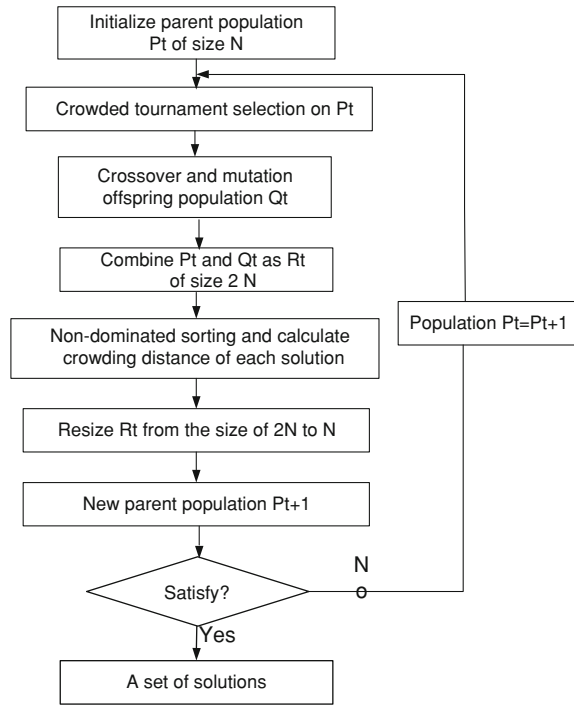
$$\left. \begin{array}{lll} \text{Min/Max} & f_m(x), & m = 1, 2, \dots, M; \\ \text{satisfy} & g_j(x) \geq 0, & j = 1, 2, \dots, J; \\ & h_k(x) = 0, & k = 1, 2, \dots, L; \\ & x_i^{(l)} \leq x_i \leq x_i^{(U)}, & i = 1, 2, \dots, n. \end{array} \right\} \quad (9.1)$$

where $f(x)$ is a multi-objective function, $g_j(x) \geq 0$, $h_k(x) = 0$ is a group of constraints and the decision variables x_i to take a value within a lower $x_i^{(L)}$ and a upper $x_i^{(U)}$ bound.

Evolutionary algorithms mimic natural evolutionary principles to constitute search and optimization. The non-dominated sorting genetic algorithm (NSGA-II) developed by Deb et al. [14], is one of the most efficient evolutionary algorithms.

¹ © [2009] IEEE. Reprinted, with permission, from IEEE VPPC Conference [12].

Fig. 9.1 Computational steps in NSGA-II



Three different operators (crowded tournament selection, simulated binary crossover, polynomial mutation), are applied to the population to create a better population at each iteration. The main task of a selection operator is to emphasize good solutions of population by making multiple copies of them to replace bad solutions of the population. The task of a crossover operator is to exchange partial information between two and more reproduced solutions and to create new offspring solutions. The task of a mutation operator is to locally perturb the offspring solutions. Successive applications of such iterations have been demonstrated to converge close to the true optimal solution of the problem both theoretically and computationally [15, 16].

Figure 9.1 illustrates the major computational steps in NSGA-II. The parent population P_t is first initialized based on the range and constraints of the design variables. Through the crowded tournament selection, simulated binary crossover and polynomial mutation, the offspring population Q_t is generated. Then the parent population P_t and the offspring population Q_t are combined together to form R_t of the size $2N$. After that, a non-dominated sorting procedure is applied to classify the entire population R_t into a number of hierarchical non-dominated fronts. Once the non-dominated sorting is completed, the crowding distance of each solution is also calculated. The new parent population P_{t+1} of size N is derived from R_t of size $2N$ through the following calculation [11, 14]. The calculation starts with the best non-dominated front and continues with the solutions of the

Fig. 9.2 Powertrain configurations of SHEV

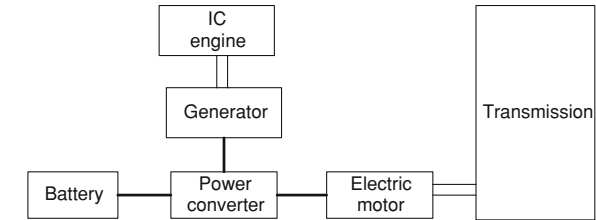


Table 9.1 Vehicle parameters

Gross mass (kg)	Full load mass (kg)	Wheelbase (m)
1373	1659	2.6
Windward area (m ²)	Rolling coefficient	Aerodynamic coefficient
2.0	0.015	0.335

second non-dominated front and so on. When the last allowed front is being considered and there are more solutions in the last front than the remaining slots in the new population, the crowding distance has to be considered to choose the members of the last front which reside in the least crowded region in the front. The iteration of generating new populations repeats until some terminating conditions are met. As the generation progresses, the solutions in the new populations are optimized.

9.1.1 Control Framework of a SHEV Powertrain

A typical powertrain configuration of a series HEV is shown in Fig. 9.2. The vehicle is propelled by a traction motor. The traction motor is powered by a battery pack and/or an engine/generator unit. The engine/generator unit either helps the batteries to power the traction motor when load power demand is high or charges the batteries when the load demand is low. The electric motor can also be used as a generator to charge batteries by regenerative braking. The motor controller is to control the traction motor to produce the power required by the vehicle.

The series thermostat control strategy uses the generator and engine to generate electric energy for use by the vehicle. The powertrain control strategy is described as follows [17].

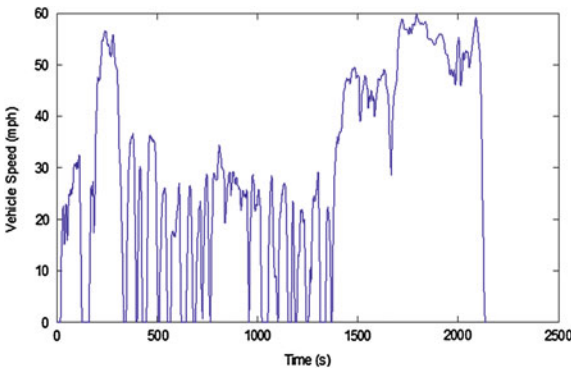
- To maintain charge in the battery, the engine turns on when the state of charge (SOC) reaches the low limit;
- The engine turns off when the SOC reaches the high limit;
- The engine operates at the most efficient speed and torque level.

The major vehicle parameters and main components in a series HEV are listed in Tables 9.1 and 9.2.

Table 9.2 Series HEV main components

Component	Description
Fuel converter	Geo 1.0 liter SI 41 kW
Motor	75 kW Westinghouse AC induction motor
Battery	Hawker Genesis 12V26Ah10EP sealed valve-regulated lead-acid (VRLA) battery

Fig. 9.3 Combined UDDS and HWFET drive cycle



9.1.2
SHEV Parameter Optimization

The proposed optimization algorithm evaluates the vehicle performances based on the simulation results generated by ADVISOR. ADVISOR is a vehicle simulation software developed on the Matlab/Simulink software platform, that adopts forward and backward simulation methods. Figure 9.3 shows the test drive cycle used in our simulation. The test drive cycle is composed of city driving represented by UDDS and highway driving represented by HWFET. Table 9.3 shows that the optimization problem is initially limited to decisions of eight design variables, three component parameters, and five control strategy parameters. The default values and the boundaries of design parameters are also shown in this table.

Before optimization, the vehicle model is assumed to adhere to the following dynamic performance requirement criteria:

- 0 – 60 mph: 10.5 s
- 40 – 60 mph: 5.6 s
- 0 – 85 mph: 24.6 s
- Gradeability 6.8% grade at 55 mph

Since the dynamic performance criteria must be observed during optimization, the above performances are imposed constraints in the optimization process. In the meantime, in order to eliminate the influence of initial battery energy on the fuel consumption and emissions, the SOC correction has to be selected, so the initial and final SOC can be set at almost the same level with the Δ SOC tolerance within

Table 9.3 Design variables

Design variable	Description	Default value	Lower bound	Upper bound
eng_pwr	engine power	41 kW	25 kW	53 kW
mc_pwr	motor power	75 kW	38 kW	112 kW
ess_cap	capacity of batteries	26 Ah	13 Ah	39 Ah
cs_high_soc	highest SOC allowed	0.8	0.7	0.85
cs_low_soc	lowest SOC allowed	0.6	0.3	0.5
cs_max_pwr	maximum power commanded of fuel converter	30 kW	25 kW	40 kW
cs_low_pwr	minimum power commanded of fuel converter	20 kW	5 kW	20 kW
cs_off_time	the shortest allowed duration of a FC-off period	Inf	10 s	1000 s

$[-0.5\%, +0.5\%]$. We can consider that the entire output energy for the cycle is from the engine alone.

For each solution in a population, which contains eight design variables, the algorithm calls ADVISOR to run a simulation using these parameters specified for the test drive cycle to obtain the fuel consumption and emission data. The optimization algorithm calculates the fitness value for each solution, and then generates a new set of solutions by the crossover and mutation operations. The non-dominated sorting algorithm is applied to the newly generated solutions to select the next population. This iteration process repeats until the terminating condition is satisfied, e.g., the maximum number of generations.

9.1.3 Optimization Results

The NSGA-II algorithm shown in Fig. 9.1 is implemented in ADVISOR. The initial population is 40 randomly selected individuals of the design parameters shown in Table 9.3 from the solution space. The terminating condition is set to 80 generations. For each individual, the drive cycle simulation for the evaluation including the objective function and constraints takes an average of about 1 min, on a 3.4 GHz Pentium computer, and takes about 4 days for the whole program to run. Figure 9.4 shows the fuel consumption and emission data generated by the 40 solutions after the 80 generations of optimization, along with the results generated by the default controller in ADVISOR. All 40 solutions consumed less fuel than the default controller, and all 40 solutions generated less emission in CO, NO_x, and HC than the default controller.

In order to illustrate the progress through the generations during the optimization, we use Eq. 9.2 below,

$$F = 0.7 \cdot \text{fuel} + 0.1 \cdot \text{HC} + 0.1 \cdot \text{CO} + 0.1 \cdot \text{NO}_x \quad (9.2)$$

Fig. 9.4 The fuel consumption and emission data generated by the trade-off solutions generated by the optimization algorithm

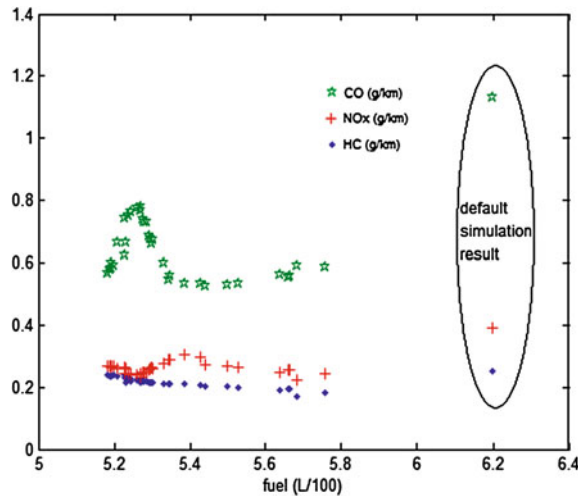
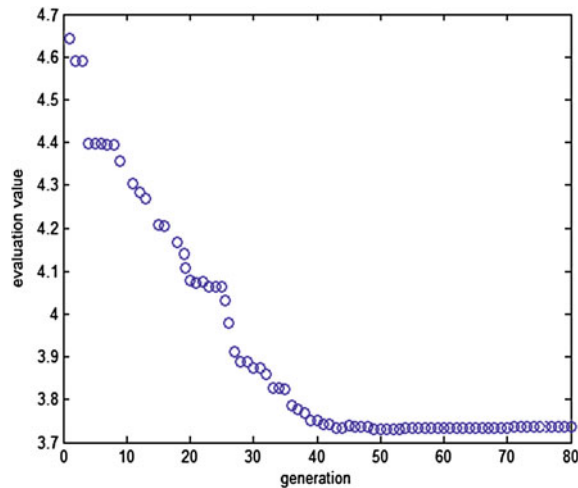


Fig. 9.5 Evaluation of generation progress during optimization



as an evaluation function to select the best one from the 40 solutions at each generation, and the results are illustrated in Fig. 9.5. The data in Fig. 9.5 show that the algorithm converges to the evaluation value of 3.72 after 50 generations.

Table 9.4 shows the optimization results generated by the top ranked five solutions in the final population based on the non-dominated sorting method. Consider solution no. 1 for example: the fuel consumption and the three emissions are reduced by 15%, 14%, 31%, 40%, respectively in comparison to the performances generated by the default controller. This indicates that if the design parameters suggested by this solution are used in the series HEV design, an online controller can be optimized to reach the same or better performances than those generated by this optimal solution.

Table 9.4 The optimization results generated by the top 5 solutions selected by the non-dominated sorting

No.	Fuel (L/100 km)	HC (g/km)	CO (g/km)	NO _x (g/km)
1	5.268	0.213	0.779	0.231
2	5.681	0.170	0.593	0.223
3	5.439	0.201	0.526	0.272
4	5.183	0.238	0.568	0.270
5	5.758	0.184	0.589	0.242

Table 9.5 The values of design variables and performance after optimization

No.	1	2	3	4	5
eng_pwr	25 kW	25.1 kW	25 kW	25.1 kW	25 kW
mc_pwr	82.8 kW	81.4 kW	86.7 kW	80.9 kW	82.9 kW
ess_cap	39 Ah	38.2 Ah	38.9 Ah	38.3 Ah	38 Ah
cs_high_soc	0.73	0.75	0.75	0.74	0.74
cs_low_soc	0.49	0.48	0.50	0.48	0.49
cs_max_pwr	33.1 kW	33.5 kW	32.2 kW	33 kW	31.9 kW
cs_low_pwr	13.2 kW	6.7 kW	9.8 kW	5.6 kW	12.4 kW
cs_off_time	750 s	538 s	598 s	519 s	711 s
0–60 mph	10.2 s	10 s	10 s	10.3 s	9.9 s
40–60 mph	5.4 s	5.3 s	5.3 s	5.5 s	5.2 s
0–85 mph	23.8 s	23.4 s	23.4 s	24 s	22.8 s
Gradeability at 55 mph	8.1%	7.9%	7.9%	8.0%	7.2%
Delta SOC	0.21%	0.26%	0.31%	−0.17%	−0.24%

Table 9.6 The optimization results generated by the top 5 solutions selected by the evaluation function

No.	Fuel (L/100 km)	HC (g/km)	CO (g/km)	NO _x (g/km)	Evaluation value
1	5.183	0.238	0.568	0.270	3.7357
2	5.188	0.234	0.578	0.268	3.7396
3	5.193	0.238	0.582	0.268	3.7439
4	5.194	0.237	0.601	0.266	3.7462
5	5.199	0.238	0.592	0.267	3.7490

Corresponding to the five solutions in Table 9.4, Table 9.5 shows the values of design variables and performance after optimization. Although the engine power is scaled down, through increasing the motor power and battery capacity, the acceleration ability and gradeability of vehicle performance are still improved.

Table 9.6 shows the optimization results generated by the top five solutions selected by the evaluation function from the final population. We can see that the solutions in Table 9.6 are different from those shown in Table 9.4. We use this example to show the importance of the proposed optimization algorithm: it generates a population of multiple trade-off optimal solutions. Vehicle designers and

control engineers can use their own evaluation criteria to select optimal solutions from this population of trade-off solutions.

9.1.4 Discussion

This section presented a study of applying an evolutionary algorithm, NSGA-II, to the multi-objective optimization problem in a series HEV. We showed through simulations that the algorithm has the capability of simultaneously optimizing fuel economy as well as minimizing three emissions: CO, NO_x and HC. At the end of the optimization process, the algorithm generates 40 optimal trade-off solutions and performances. All of these solutions are better, in all four categories, than those generated by the default controller in ADVISOR. We also demonstrated that vehicle designers and control engineers can derive their own trade-off criteria to select the solutions that best suit their specific needs.

9.2 Parallel HEV Design Optimization Example²

As another application example, PSAT is used to optimize a parallel HEV for maximum fuel economy on a composite driving cycle [12]. Four global algorithms, Divided RECTangle (DIRECT), Simulated Annealing (SA), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) are used in the model-based design optimization. The main focus of the example is to show the comparison of different optimization algorithms for optimal vehicle design rather than the result. The vehicle model “gui_par_midsize_cavalier_ISG_in” (available in the PSAT model library) has been chosen for this optimization study. This vehicle is a two-wheel-drive parallel configuration with manual transmission. The basic configuration of the parallel HEV used for simulation study is illustrated in Fig. 9.6 and main components of the HEV are listed in Table 9.7.

The objective is to maximize the composite fuel economy, which is computed based on city fuel economy and highway fuel economy. For example, composite fuel economy can be computed as the weighted average of the SOC-balanced fuel economy values during city drive cycle and highway drive cycle, as given below [19]:

$$\text{Composite Fuel Economy} = \frac{1}{\frac{0.55}{\text{City\_FE}} + \frac{0.45}{\text{Hwy\_FE}}} \quad (9.3)$$

² © [2007] Inderscience. Reprinted, with permission, from the International Journal of Electric and Hybrid Vehicles [13].

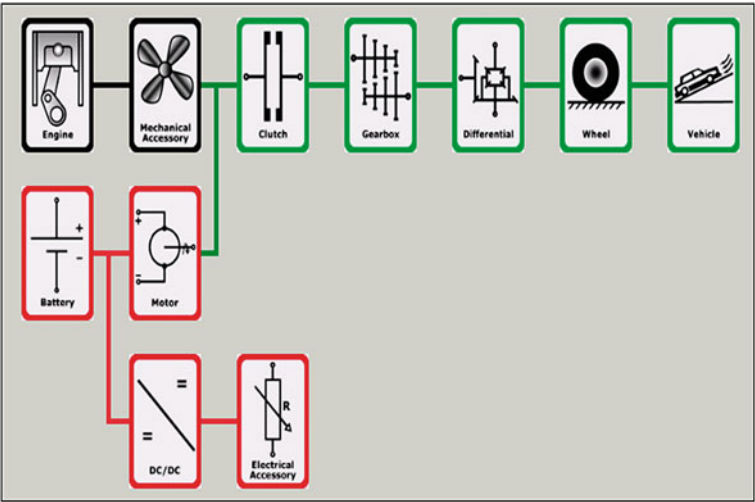


Fig. 9.6 Configuration of the selected parallel HEV in PSAT [18]

Table 9.7 Parallel HEV components

Component	Description
Fuel converter	84 kW and 2.2L Cavalier Gasoline Engine
Motor	ECOSTAR motor model with continuous power of 33 kW and peak power of 66 kW
Battery	Panasonic NiMH Battery with capacity 6.5 Ah and 240 cells
Transmission	4 speed manual gearbox with final drive ratio 3.63
Control strategy	Default Propelling, Shifting and Braking strategies

Fig. 9.7 The FTP-75 drive cycles

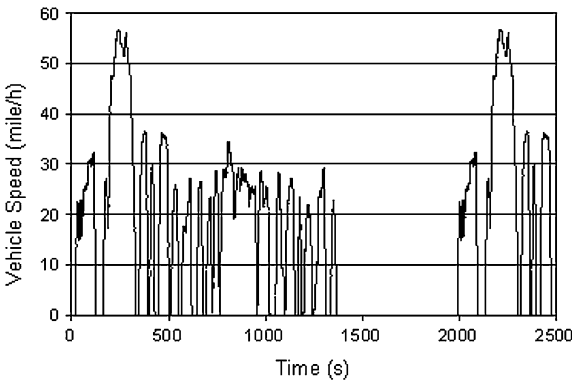
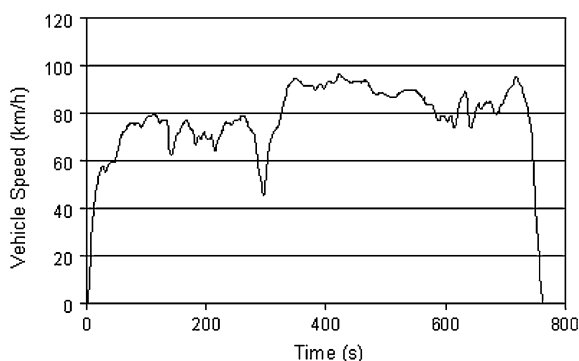


Fig. 9.8 The HWFET drive cycles



where *City_FE* and *Hwy_FE* denotes the city and highway fuel economy values respectively.

The drive cycles selected are Federal Test Procedure city driving cycle (FTP-75) and Highway Fuel Economy Test drive cycle (HWFET). The characteristics of two drive cycles are shown in Figs. 9.7 and 9.8, respectively.

The design problem's constraints come from the following required vehicle performance:

Acceleration time 0–60 mph ≤ 18.1 s

Acceleration time 40–60 mph ≤ 7 s

Acceleration time 0–85 mph ≤ 35.1 s

Maximum Acceleration ≥ 3.583 m/s²

Table 9.8 shows the six design variables used in this study. The first two define the power ratings of the fuel converter (the engine) and motor controller. The third, fourth and fifth variables define the number of battery modules, minimum battery SOC allowed and maximum battery SOC allowed. Note that the SOC values are part of the control strategy parameters. Although they are not related to component sizing, they have direct impact on fuel economy of a HEV design. The sixth design variable defines final drive ratio. Each design variable is also restricted within a lower and an upper bound.

The problem now becomes quite challenging since this is a constrained multi-variable optimization problem.

First, the default vehicle is simulated in PSAT. The design variables and their initial values are listed in Table 9.9. The fuel economy was observed to be 35.1 mpg as given in Table 9.10 under the first column.

Second, the optimization algorithms, DIRECT, Simulated Annealing, Genetic Algorithms, and PSO, are looped with the PSAT Vehicle Simulator and the optimization is carried on. For this step, the same default vehicle configuration given in Fig. 9.6 and Table 9.7 is selected and the bounds for the design variables are taken as given in Table 9.8. The four algorithms are allowed to run for 400 function evaluations. Using the same number of function evaluations will allow us

Table 9.8 Upper and lower bounds of design variables

Design variable	Description	Lower bound	Upper bound
eng.scale.pwr_max_des	Fuel converter power rating	40 kW	100 kW
mc.scale.pwr_max_des	Motor Controller power rating	10 kW	80 kW
ess.init.num_module	Battery number of cells	150	350
ess.init.soc_min	Minimum SOC allowed	0.2	0.4
ess.init.soc_max	Maximum SOC allowed	0.6	0.9
fd.init.ratio	Final drive ratio	2	4

Table 9.9 Initial design variable values

Design variable	Initial value
eng.pwr_max_des	86 kW
mc.pwr_max_des	65.9 kW
ess.init.num_module	240
ess.init.soc_min	0
ess.init.soc_max	1
fd.init.ratio	3.63

to compare the performance of the different algorithms. A comparison of the fuel economy before and after the optimization is given in Table 9.10. A significant improvement in the fuel economy is seen due to optimization (to a less extent in the case of PSO and GA, though). Of all the four algorithms SA performs well with an approximate improvement of 5 mpg.

Table 9.11 shows the final values of the six design variables after optimization. We can notice that the rating of the electric motor is greatly reduced, implying that down-sizing of electric motor has been achieved. On the other hand, the engine is down-sized to a less extent in DIRECT and SA cases, while up-sized in GA and PSO cases. Given the vehicle performance constraints, the trade-off of engine down-sizing and motor down-sizing can be realized by adjusting the lower and upper bounds of the design variables.

Table 9.12 shows the performance results of the hybrid powertrain after optimization. Essentially, all the optimization algorithms resulted in improved vehicle performance.

The vehicle mass changes as the design variables change because the mass of the vehicle depends directly on some design variables. In particular, of the chosen six design variables, three design variables (power ratings of engine and motor, and energy modules) affect the vehicle mass. The vehicle mass before and after the optimization is given in Table 9.13. The vehicle mass decreased in DIRECT and SA cases while the vehicle weight increased slightly in the case of GA and PSO.

Figure 9.9 shows how the objective function (fuel economy) value improves against the design iteration number. The curve with cross (+) symbol is for the SA

Table 9.10 Comparison of fuel economy

Fuel economy				
Before optimization	After optimization			
	DIRECT	SA	GA	PSO
35.1 mpg	39.64 mpg	40.37 mpg	37.6 mpg	37.1 mpg

Table 9.11 Final design variable values

Design variable	Initial value	Final value			
		DIRECT	SA	GA	PSO
eng.pwr_max_des	86 kW	83.1 kW	82.4 kW	95.5 kW	87.1 kW
mc.pwr_max_des	65.9 kW	20.2 kW	21.9 kW	24.2 kW	14.8 kW
ess.init.num_module	240	245	311	300	238
ess.init.soc_min	0	0.25	0.22	0.34	0.26
ess.init.soc_max	1	0.84	0.78	0.89	0.78
fd.init.ratio	3.63	3.9	4.0	3.49	3.42

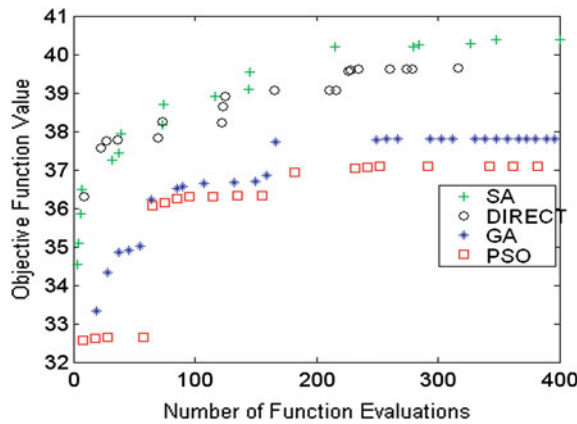
Table 9.12 Comparison of the HEV performance

Constraint	Constr. value	Before opt.	After opt.			
			DIRECT	SA	GA	PSO
0–60 mph (s)	< = 18.1	18.1	15.5	10.8	11.9	11.1
40–60 mph (s)	< = 7	7	6.8	5	4.4	4.9
0–85 mph (s)	< = 35.1	35.1	30.6	20.7	21.2	20
Max. Accel. (m/s ²)	> = 3.583	3.583	3.97	4.07	3.94	3.99

Table 9.13 Mass of HEV before and after optimization

Mass of the vehicle (kg)					
Before optimization	After optimization				
	DIRECT	SA	GA	PSO	
1683	1635	1656	1694	1690	

Fig. 9.9 Performance comparison of DIRECT, SA, GA, and PSO



case; the curve with circle symbols is for the DIRECT case; the curve with star symbols is for the GA case; and the curve using square symbols is for the PSO case. We can see that fuel economy improvement with the SA and DIRECT algorithms is very close until about 125 function evaluations, after which SA leaped ahead of DIRECT. GA is slow to catch with SA and DIRECT initially because it needs to perform a number of function evaluations to generate the initial populations. After about 50 function evaluations, GA did not find any good design point to get further improvement in the fuel economy. The performance of PSO is similar to that of GA. Overall, SA performed the best for this particular design optimization problem.

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Chapter 10

Hardware-in-the-loop and Software-in-the-loop Testing for Vehicle Power Management

10.1 Fundamentals of HIL and SIL

Hardware-in-the-loop (HIL) simulation is a technique where parts of a real system are replaced by a simulation model, i.e., a mathematical model of these real systems or parts [1–3], sometimes referred to as HIL simulators. For automotive applications, a real electronic control unit (ECU) can be evaluated by the HIL, i.e., the plant is a model but the ECU is real as shown in Fig. 10.1. In other cases of HIL, some relatively-small plants (e.g. engine, battery, fuel cell, etc.) instead of a vehicle are placed in the loop and connected to the ECU for testing if conditions permit. The HIL system is designed to offer all the stimulus signals that help to fully exercise the ECU.

The software-in-the-loop (SIL) has the capability of testing the software employed for a real processor by using a “simulation” method. It aims to conduct “in the loop” simulation in the early development phase for high operation efficiency and good brevity of code. The SIL test environment comprises the test management, test execution and version management systems. The test management system provides the notes for a new test and determines whether a single test can be started. The test execution system embedded by a test model includes a controller for decisions of test sequence. The version management system versions all documents in the test procedure to guarantee good repeatability. A typical SIL model is shown in Fig. 10.2.

If the software of the SIL simulation is capable of simulating complicated dynamic performance in different real conditions, and replacing a real system, the SIL simulation can also give a satisfactory answer on real performance verification, similar to the function of HIL simulation.

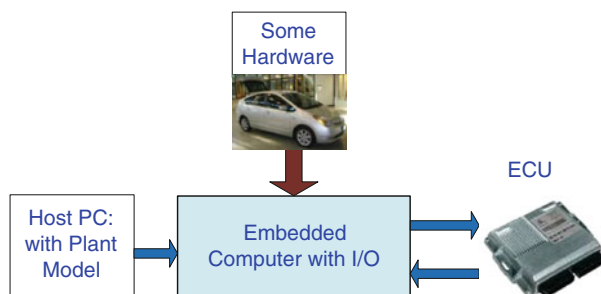


Fig. 10.1 Configuration of HIL system

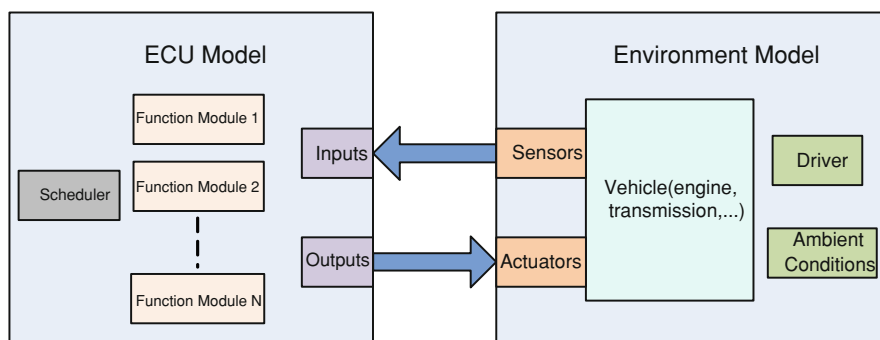


Fig. 10.2 SIL test model

10.1.1 Components in HIL and SIL

An HIL includes electrical emulation of sensors and actuators [1]. The emulations establish the relation between the plant simulation and the real systems. The plant simulation is in charge of controlling each electrically emulated sensor whose value is read by the embedded system. The control algorithms are realized in the embedded system and actuator control signals are outputted.

A typical HIL system is comprised of the following components: A mathematic model for the plant (however, a plant can also include some hardware in it as part of the HIL), sensors or sensor models, a real-time target computer, real or simulated loads, a host PC with communications link to the target computer and diagnostic link to ECU. The host computer will also contain a Graphical User Interface (GUI) for the user to develop, compile, download and control the real-time process.

Plant Model With regard to vehicle power management, the plant to be placed in the HIL could be a vehicle model, an engine model, or other models of the powertrain components. There are many software packages available for

developing these models, including the most popular simulation tool Matlab/Simulink. These models can be developed based on the physic description of the components, or based on test data of similar components. Many models today are hybrid models that are based on the physic description of the components but are validated through experiments, or supplemented by testing data.

Sensors Sensors are needed to collect feedback of the plant models. Hence, depending on whether the plant is a pure mathematic model, or partially hardware, simulated sensors and real sensors can both be used in the HIL simulators. Simulated sensors as part of the plant model will emulate real world sensors. Sensor outputs are applied to the Analog/Digital (A/D) inputs of the ECU.

Real-time target computer Real time simulations can only be run on embedded computers. Sometimes these embedded computers are placed inside the host PC, or can be standalone computers with communication link to the host PC. Embedded computers have digital and analog I/O ports to communicate with the ECU, as well as data communication with the host PC.

Loads Depending on the type of setup, loads for the HIL can be simulated or real. For example, ignition switches/coils as the load of an engine ECU can be real but others can be simulated. In simulated environment, the models can contain details of the loads, such as resistors, inductors, capacitors, diodes, and combination of those. The loads in a HIL should not only simulate the power and energy levels matching the real load, they have to represent the same transient process of the real loads.

Host PC A host PC is an important part of the HIL since much of the leg work is performed on the host PC, including model development, compilation, as well as collection, storage, and display of data.

In the automotive and aerospace engineering, HIL is often used to validate the functions of an ECU in which the vehicle or airplane is replaced with a “virtual vehicle” or a “virtual engine”. In addition to validation of normal functions of the ECU, fault diagnostics is one of the other most important functions of HIL. Hence, manmade errors are often induced in the HIL during the testing of the ECU.

The new challenge in HIL for vehicle power management is the introduction of advanced power electronics in electric and hybrid vehicles. Real-world power electronics exhibits switching actions in the tens of kilohertz range (microseconds). To reveal the behavior of the switching dynamics of power electronic switches, the real time simulators must be fast enough and with very small latency which is a challenge. Hence many power electronics-based HIL systems use averaged models instead of physics based models.

Figure 10.3 shows two different scenarios for the HIL and SIL simulations, respectively. On the right hand, the power electronics circuit is replaced by a real time simulator while the software is inside a real ECU. This platform is used to test the functions of the ECU. Hence, according to the aforementioned definition this is a HIL platform. On the left hand, the power electronics circuit is a real hardware

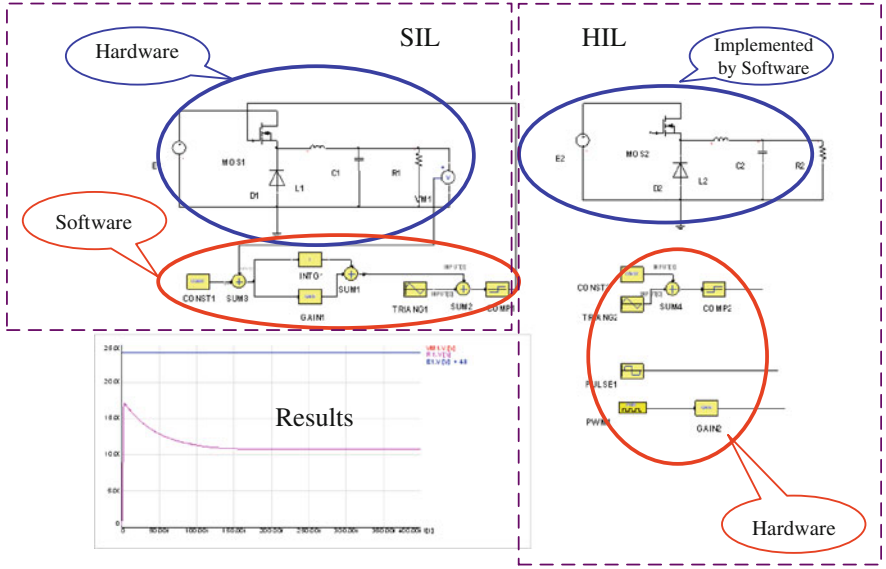


Fig. 10.3 Power electronics HIL/SIL system

but the software being developed is from a real time simulator (dSPACE). This is used to test the software inside the dSPACE real time simulators before they are implemented in a real ECU. Hence this is a typical SIL. Some times a SIL will not involve hardware at all for the plant, hence both the software and hardware can be in a simulated environment.

The SIL simulation examines behaviors of the implemented ECU software. The ECU code to be validated is embedded in an ECU model and environment model. The models receive information from the real environment. As shown in Fig. 10.2, a SIL test model is composed of an ECU model and an environment model.

The ECU model includes engine (or powertrain) control strategies, characteristics of ECU and I/O ports between the ECU and the environment models. The environment model is made up of sub-models including the driver, vehicle body, running situation (e.g. roadway type), sensors and actuators.

The model of SIL for embedded software test (SILEST) has three particular features described as follows. First, the SILEST model is integrated with the strategies considering the implementable functions and actual execution. Second, the ECU model involving interfaces to the environment model is established in SIL simulation. Third, nominal and off-nominal behaviors of sensors and actuators are modeled.

The SIL tests are for the purpose of obtaining early validation of integrated software components. Unlike HIL tests, it is impossible for SIL tests to validate all functions in a fully executed way. Therefore SIL simulation deals with the components related to the implemented functions and an environment model. However, it is possible in the early phase for automated SIL tests to examine the

software integration behavior. Eventually a test conclusion and test reports can be offered by the SIL tests.

10.1.2 Advantages of HIL and SIL

In some cases such as tight development schedules, high-burden-rate plant and early process human factors development, HIL simulation is very efficient on cost, duration and safety [4].

Sometimes research and development of new automotive or aerospace projects cannot wait for testing till a prototype is available. In this case, HIL simulation has to be employed before the completion of the plant development. Usually most of the testing work can be done when the plant development is finalized, resulting in significant time saving.

At times if an HIL system rather than the real plant is employed for a test, the cost will be much lower because the real hardware can be very expensive. HIL simulation is a basis of development of jet engines which costs millions of dollars each. However, an HIL simulator for completely testing jet engines may cost 1/10 of the expense for a jet engine.

Man-in-the-loop testing for components that will have a human interface is critical to the development of the entire system. Human-factors research focuses on collecting usability data from this testing while HIL simulation plays an essential role in the human factors development. For example, HIL simulation can be employed for the fly-by-wire flight controls development to simulate human factors. The flight simulator is connected to prototype fly-by-wire flight controls, and flight performance can be evaluated by test pilots with given parameters.

In addition, HIL can prevent equipment from damaging or hurting lives. For example, the potential over-temperature in an engine can be simulated for testing such that the ECU can have measures to avoid it. Another example is that the performance of the anti-lock braking (ABS) can be evaluated and preventive measures can be made without damaging vehicles or drivers.

HIL owns benefits as follows for the design process. SIL implements early search of software design bugs and defects, especially in control applications. After this, more sophisticated designs are ready for the following development and test phases, e.g. HIL and real on-road tests.

Besides, SIL has the advantages of agility and no real-time requirements, compared to HIL. HIL components are generally more expensive than SIL ones. In addition, there is unexpected time delay between the software development for control systems and HIL tests. However, there does not exist such delays for a SIL environment.

On contrary to HIL, SIL testing does not require that the plant is simulated in real-time environment. At this point, the modeling in SIL is simplified. Real time is not an issue when choosing the level of detail for a SIL model. A SIL model may be much more complex, which enables new applications such as simulation-based dimensioning, optimization, and application of a mechatronic system,

including failure simulation and validation of function quality based on the same model. In the meantime, simple models may produce simulations running much faster than in real-time environment such that comprehensive logic tests with fast turn around are available [5].

In spite of the above positive factors of SIL over HIL, SIL cannot completely replace HIL because in a typical SIL environment, low-level processes (e.g. ECU communication, CAN, signal processing, interrupt handling etc.) are not modeled in detail. Consequently, such processes are beyond the scope of SIL testing.

10.2 Data Acquisition, Monitoring and Control Units

In order to verify the validity of the proposed wavelet-transform-based power management strategy (see Sect. 5.3) for hybrid vehicles with multiple on-board power sources including a fuel cell, a battery and an ultracapacitor, the authors have developed an experimental platform which looks like an HIL system.

A powertrain control module (PCM), as a type of ECU, is exercised to achieve proper power split for power sources by using this platform. Models of various power sources have been established for simulation. However, in experiments designed by the authors, these models are replaced by real power sources aiming at facticity although they are capable of acting as plant models for testing. Consequently, this platform is not a standard HIL system. Nevertheless, except the plant model, other components in this proposed experimental platform such as the real-time targets and I/Os, loads, sensors, host PC, fault insertion, GUI and test automation application are almost the same as those in a typical HIL system. Therefore, description of functionality and components of such an experimental platform also can reflect features of an HIL system and enlighten readers on designing an efficient HIL system according to different requirements.

The main data acquisition and control units in this experimental platform which are often used in other typical HIL systems for vehicle powertrain control will be depicted in detail next.

10.2.1 Power Control Units

The power control unit (PCU) employed in the experimental setup is a solid-state smart switch providing point-of-load and/or circuit level distributed monitoring, control and protection of vehicle electrical loads [6]. The PCU was developed for the load power management applications. The CAN bus function is embedded in the PCU to receive data or transmit commands from/to external CAN components. The available features of PCU products made by Global ET Inc. include power control (on, off, and Pulse Width Modulation (PWM)), local current and voltage fault detection, and operation with a system level power management application (PMA) [6].

The parameters of the PCU are grouped into sets of related features. For example, all parameters concerned with the operating condition of the load are contained in the Load Status table. Each such grouping is identified with a parameter group number (PGN). The parameter group contains up to 8 bytes worth of parameter data. The choice of parameter group numbers for the PCU and other devices under development was guided by SAE recommended practices. The PGN is contained in the CAN 29-bit header: a 3 bit priority, a 1 reserved bit, a 1 bit Data Page, an 8 bit PDU Format, an 8 bit PDU Specific, and an 8 bit Source Address for the host PC. The fields of the PDU Format and PDU Specific belong to PGN. To form the PGN, the Data Page is placed in the most significant byte (MSB), followed by the PDU Format byte and then the PDU Specific byte. If the PDU Format byte is <240 , use $\times 00$ in the least significant byte (LSB).

10.2.2 Parameter Measurement and Monitoring

In the experimental setup, currents and voltages need to be measured for control loop calculations and abnormal situation monitoring (e.g. over current, over voltage, under voltage, etc.). Temperature monitoring is also essential for system safety since severely-high temperature will completely damage components. In addition, waveforms of different variables can be clearly displayed on the oscilloscope screen such that researchers may observe the transient and steady-state processes using various time resolutions and record waveforms or data for further analysis. This sub-section will give a specific introduction of these measurement and monitoring components.

10.2.2.1 Current Transducer

Current transducers for measuring direct current (DC) and alternating current (AC) often employ the compensation principle, i.e., the flux caused in the magnetic core by the current flowing in the primary winding is compensated for by a current supplied to the secondary winding. To control the secondary current, a sensor or detector is placed in the magnetic circuit to monitor the zero point of the flux of the core. A zero flux prevails in the core when the current supplied to the secondary winding compensates for the flux caused by the current of the primary winding. At higher frequencies, the current flowing in the secondary winding is directly proportional to the current to be measured in the primary winding within a wide frequency range [7].

In the afore-mentioned multi-source vehicle power system, output currents of different power sources and the current going through the bus are required to be known by the control subsystem. Measurement precision directly influences the validity of the control algorithm. Therefore choosing satisfactory current transducers with the synthetic consideration of appropriate measurement range and high

precision is very important. Thus the LA55-TP current transducer model from LEM Inc. using the closed loop Hall Effect technology comes into our sight. The properties that the primary nominal value is 50 A and maximum measuring current is 70 A definitely conform to the real system requirements. An accuracy of 0.65% can satisfy the error limitation of the control subsystem. Additionally, the supply voltage of 12–15 V is easy to obtain.

10.2.2.2 Voltage Transducer

In a voltage transducer using the Hall-Effect technology, a very small current is generated from the voltage to be measured and is driven through the primary coil. The primary current creates the magnetic flux which is balanced by a complementary flux generated by driving a current through the secondary windings. Thus, the secondary current generated from a Hall device and relevant electronic circuit exactly represents the primary voltage [8].

Similar to the current transducer discussed above, the precision level of the voltage transducer partly decides the quality of the voltage feedbacks for the control loops and further the validity of the control subsystem. Therefore effective and precise voltage transducers are greatly needed. In the multi-source vehicle power system, the voltages of power sources and the DC bus vary from about 20 V to 45 V, so the final choice is the LV100–50 model designed and manufactured by LEM Inc. due to its proper measurement range (primary nominal value is 50 V and maximum measuring value is 75 V) and exciting accuracy (0.7%). Besides in this vehicle power system, the LV100–50 model also can be applied in AC variable speed drives, DC power supplies, and so on.

10.2.2.3 Temperature Sensor

Temperature can be measured by a diverse array of sensors. All of them infer temperature by sensing some change in a physical characteristic. In general, the two main categories of these sensors are contact and noncontact style temperature sensors. Three methods of contact style temperature measurement, thermal resistors (RTD, thermistors), thermocouples and IC sensors, can generally be referred to as temperature probes [9].

Among the three contact style sensors, thermistors are inexpensive and easy to obtain. Also they are easy to use and adaptable. Thermistors are made of resistive semiconductor material sensitive to temperature. The resistance of semiconductor material changes significantly in a converse direction as the temperature increases or decreases. Because of these qualities, thermistors are selected to detect the abnormal temperature increase for protection of components such as the battery and high-frequency switching devices. Omega thermistor ON-950-44,005 with accuracy of $\pm 0.2^{\circ}\text{C}$, resistance of $3,000\ \Omega$ @ 25°C and maximum operating temperature of 100°C is the final choice meeting requirements for over temperature protection.

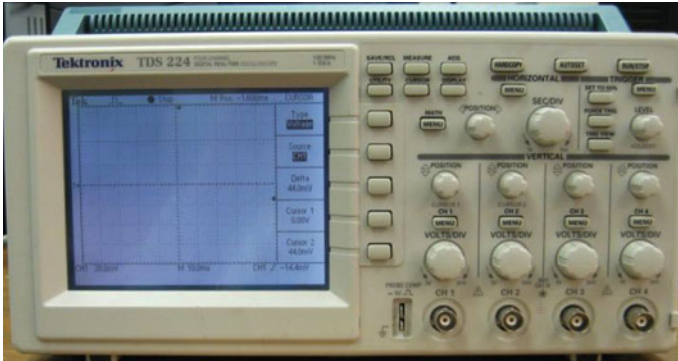


Fig. 10.4 Tektronix TD224 oscilloscope

10.2.2.4 Oscilloscope

An oscilloscope used as an electronic test instrument is capable of displaying signal voltages. Two-dimensional graph of one or more electrical potential differences (vertical axis) plotted as a function of time or of some other voltage (horizontal axis) can be viewed. Besides the amplitude of the signal, the oscilloscope can measure the frequency and show distortion, the time between two events, and the relative timing of two related signals. Modern digital storage oscilloscopes (DSOs) can analyze and display the spectrum of a repetitive event [10]. The vertical input of the DSO is converted to digital signals through the A/D port to store data in processor memory. The LCD flat panel receives and displays the processed data. The related data processing software is capable of analyzing valuable time-domain and frequency-domain characteristics, persistence maps, histograms and statistics, and many other parameters that users want.

In the experimental platform designed for the multi-source vehicle power management, a digital storage oscilloscope with fast sweep speed is required for observation of transient or steady-state voltage, current or power variables and further analysis of validity of the control strategy. The Tektronix TDS224 (see Fig. 10.4) which features bandwidth of 100 MHz, sample rate of 1GS/s and four channels is chosen as the waveform display instrument due to unbeatable combination of performance, cost, reliability and versatility.

10.2.3 Typical Tools Available for Data Acquisition and Processing

Several options including LabVIEW, RT-LAB, dSPACE, etc. are available for data acquisition and processing in the early phase of vehicle power management study. These tools can be utilized in real-time HIL environment to validate

strategies and components in users' own system. Descriptions of them are given below.

10.2.3.1 LabVIEW

LabVIEW by National Instruments Inc. is a platform and development environment for a visual dataflow programming language referred to as "G". With the help of LabVIEW, users can establish complicated measurement, tests, and control systems in the form of a flowchart by using intuitive graphical icons and wires. Considerable hardware devices and built-in libraries are provided by LabVIEW for advanced analysis and data visualization.

Users can connect different function-nodes by drawing wires to create a graphical block diagram which determines execution of the dataflow programming language. The wires propagate variables, and as soon as all input data of a node are available, the node can execute. The aforementioned G language can be executed in parallel such that multi-processing and multi-threading hardware is exploited automatically by the embedded scheduler multiplexing various operating system threads over the execution nodes.

Programs or subroutines in LabVIEW are called virtual instruments (VIs). A front panel, block diagram, and a connector panel are included in every VI. Development of front panels is introduced by LabVIEW into the design cycle. A virtual instrument can be executed as a program or a node onto the block diagram. The front panel gives the interfaces to the given nodes by using the connector panel. Thus every virtual instrument can be tested easily ahead of being incorporated into a larger program acting as a subroutine. On the other hand, simple programs can be built by dragging and dropping virtual symbols of the lab equipment, which is allowed by the graphical approach. However, for large-scale code, it is essential that the user has an extensive knowledge of the special LabVIEW syntax and the topology of its memory management. Also distributed applications are available due to the parallel nature of the G language [11].

10.2.3.2 RT-LAB

As a product by Opal-RT Inc., RT-LAB, combined with MATLAB/Simulink, implements real-time, hardware-in-the-loop (HIL) Simulink models on PC hardware. Since RT-LAB is flexible and scalable, it can be employed in any kind of virtual simulation or control strategy setup, and help simulations improve computing speed and efficiency. In the meantime, RT-LAB occupies technologies of high-speed communication, fixed-step computing, and real-time interfacing to improve time and cost in design and implementation phases.

Code generated with the Real-Time Workshop (RTW) is linked to highly-optimized runtime libraries in the RT-LAB environment. Consequently, Simulink models can be readily converted via RTW to realize real-time simulation of the models that run on multi-target computers.

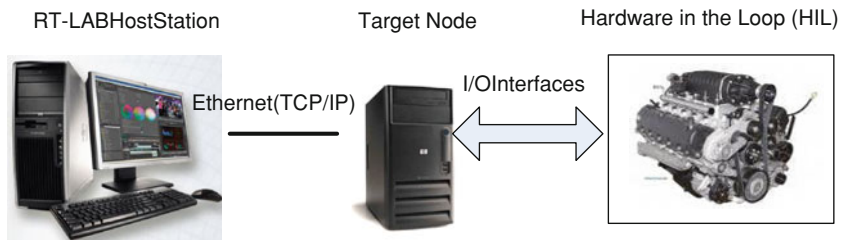


Fig. 10.5 RT-LAB single target configuration

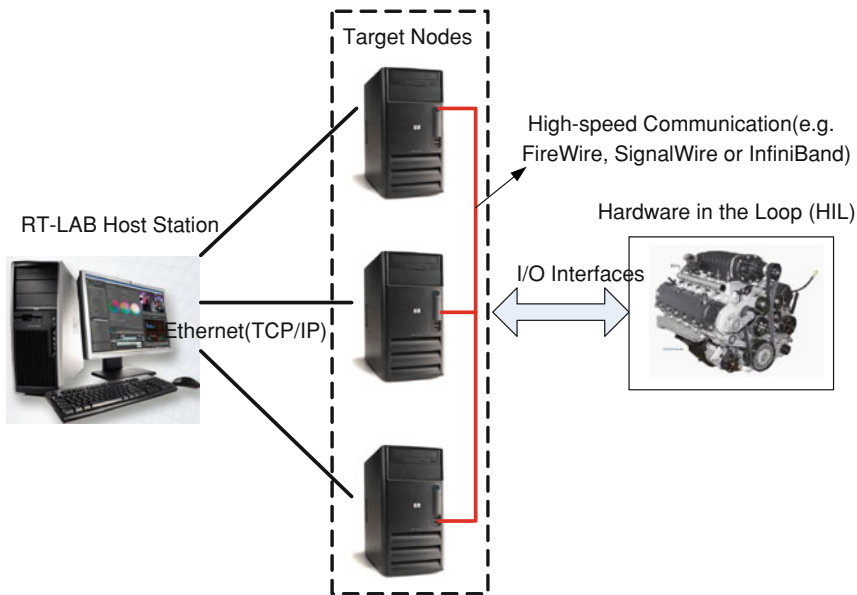


Fig. 10.6 RT-LAB distributed target configuration

The RT-LAB platform consists of compilation software, a host station, target nodes, high-speed communication links and I/O boards. The host station is usually a Windows operating system-supported PC workstation. Users can use the host station to edit and make modifications to models with MATLAB/Simulink, generate machine codes, separate codes as needed and control the simulator's Go/Stop sequences. The host station is linked to target nodes through an Ethernet link (TCP/IP network). Target nodes are computers installing real-time operating fixed-step systems e.g. QNX/Neutrino or RedHawk Linux. These nodes are interconnected by high-speed communication protocols such as FireWire, SignalWire and InfiniBand, as well as I/O boards for accessing external hardware equipments. The

compilation software is utilized to compile simulation blocks on the host station and generate C codes, load codes onto each target node, and debug the user source codes. The analog or digital I/O boards allow real connection between the target nodes and real external equipments for real-time HIL simulation [12].

According to the number of target nodes, RT-LAB configurations are classified into the single target configuration and distributed target configuration as shown in Figs. 10.5 and 10.6 respectively. It has to be noted that the maximum number of RT-LAB nodes for parallel running is 64.

10.2.3.3 dSPACE

The dSPACE prototyping systems, developed by dSPACE Inc., allow the user to optimize control designs of the real controlled system flexibly without manual programming [13]. Design faults can be found and corrected on the spot immediately. The user's design is realized automatically on dSPACE prototyping systems from a MATLAB/Simulink block diagram and calculated in real time. In addition, dSPACE provides sufficient I/O interfaces for connection between the user's design and the real world.

The dSPACE single-board hardware provides fast processors and comprehensive I/O interfaces—all on single boards that are installed directly in the PC. The dSPACE Real-Time Interface allows the user to automatically implement MATLAB/Simulink models on dSPACE hardware via code generated by Real-Time Workshop (RTW). In summary, the dSPACE prototyping systems have the following advantages: Quick and reliable real-time testing and optimization of control functions, in-vehicle capable and high-speed hardware, wide range of I/O interfaces, easy integration of CAN, LIN, and FlexRay bus systems and automatic realization of MATLAB/Simulink models on dSPACE hardware [13].

The user can select from a large number of dSPACE hardware and software types. For instance, the DS1104 connector panel designed for rapid control prototyping (RCP) is shown in Fig. 10.7. The DS1104 board, especially for design of real-time simulation and high-speed multi-variable controllers, is a standard board which provides an interface for a PC PCI slot. Based on a 603 PowerPC floating-point processor running at 250 MHz, the DS1104 can realize complete real-time functionalities. A slave-DSP subsystem using the TMS320F240 DSP microcontroller from Texas Instruments Inc. is included in the board. The real-time interface (RTI) library (i.e., rtilib1104) for the DS1104 board offers the RTI blocks to realize I/O functions in MATLAB/Simulink models. The blocks are used to decide configurations of the hardware for real-time operations. In addition, rtilib1104 offers demo models, additional RTI blocks, and required information [14]. The MASTER PPC and SLAVE DSP F240 libraries contain the I/O blocks served by the Power PC processor and Texas Instruments (TI) F240 slave DSP, respectively.

The definition of LabVIEW as general-purpose programming language is still under debate. Also LabVIEW does not include embedded functions, that are

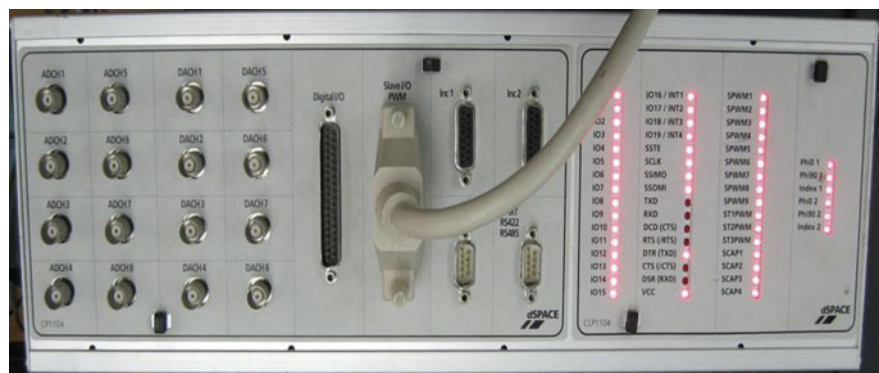


Fig. 10.7 dSPACE DS1104 connector panel

formal limits tests, reading of a limits file, and acquisition of any result for an environment heavily targeted for test. In addition, it is hard to control seemingly parallel code at a satisfactory grained level, which makes multi-interface systems unreliable and unwieldy. However RT-LAB and dSPACE can solve this problem well. RT-LAB and dSPACE, integrated with MATLAB/Simulink, have their own advantages on real-time applications, while dSPACE is employed in this book for data acquisition and processing. For example, the DS1104 R&D controller board is selected in the experimental setup for the multi-source vehicle power management. Figure 10.8a shows the Simulink library for DS1104.

In the experimental setup, ControlDesk is employed as a real-time data storing and display tool. ControlDesk is the software for seamless controller development. It performs all the necessary tasks, and gives the user a single working environment, from the start of experimentation right through to the end [15]. MATLAB/Simulink simulation is integrated in ControlDesk to validate both the offline controller models and their converted representations in the dSPACE real-time applications. The GUI and layout techniques and comprehensive online help are very friendly to the user. A ControlDesk interface designed by the authors is shown in Fig. 10.8b.

10.2.4 Electronic Load Applied for Simulating Load Profile

An electronic load is a device simulating loading on an electronic circuit. The electronic load is a current sink as a substitute for a conventional ohmic load resistor [16]. The electronic load allows the load current to be set and vary in a determined range and regulated electronically. Electric energy is consumed and transformed into heat energy by the electronic load. Coolers such as fans and water-cooled elements are required to dissipate the heat. Advanced electronic loads supply a few operating modes such as constant current, constant voltage,

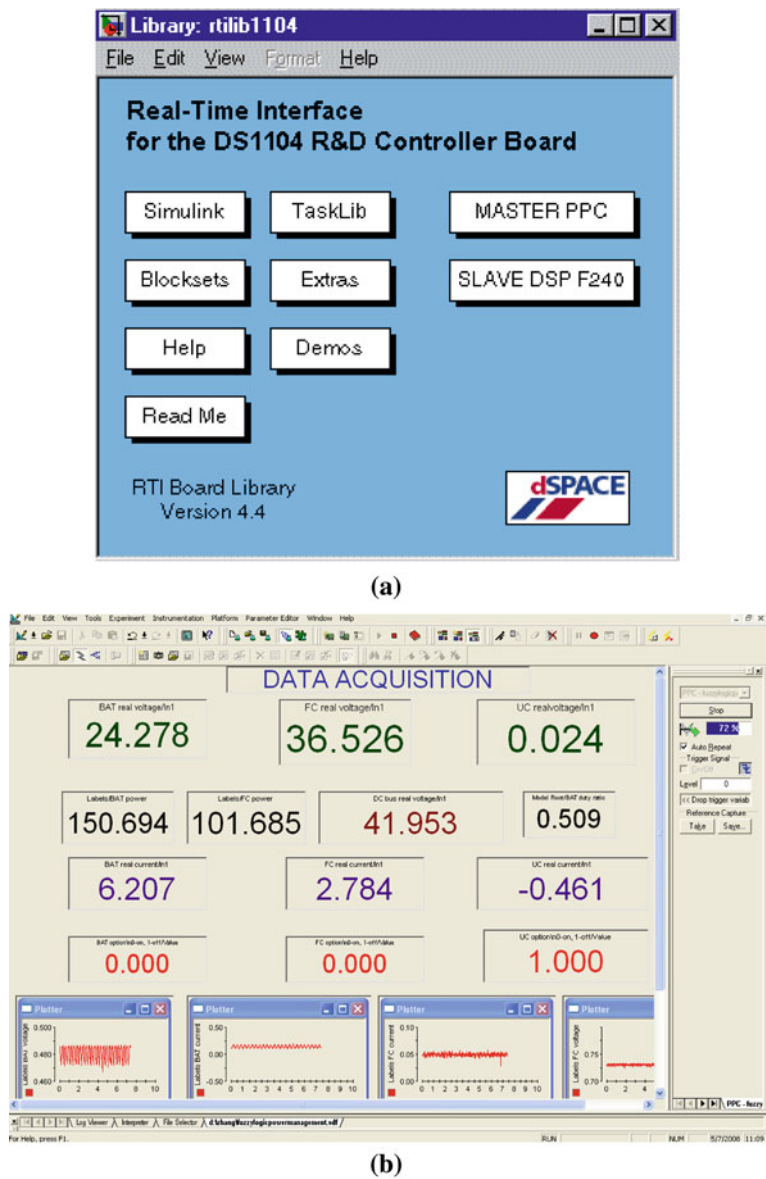


Fig. 10.8 dSPACE system. **a** RTI library for the DS1104 board. **b** ControlDesk interface for real-time data storing and display

constant power and constant resistance. A display panel is usually utilized to indicate settings and measured values. Electronic loads appear in a wide range of applications e.g. the test of power supplies and power sources. For example, in the experimental setup designed by the authors, a Chroma DC electronic load (model

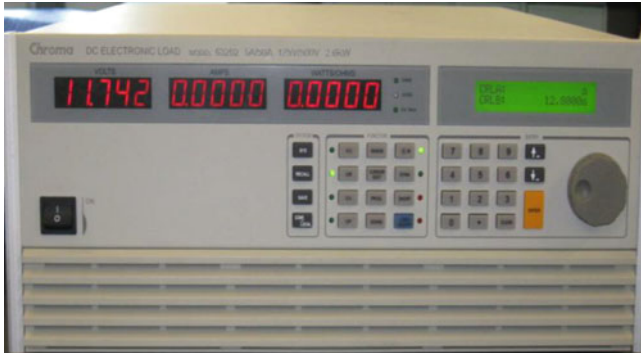


Fig. 10.9 Chroma 63202 DC electronic load model

number: 63202, see Fig. 10.9) acts as a load of the DC bus in a vehicle power system with multiple on-board power source, i.e., a fuel cell, a battery and an ultracapacitor, simulating a scaled-down load profile in a drive cycle. The Chroma 63202 mode which can consume 2.6 kW power has four modes, i.e., constant current, constant voltage, constant power and constant resistance. The current can go up to 50 A and the voltage range is from 0 to 500 V. Furthermore, this model can supply necessary measurement functions and short circuit simulation extending the test capability for even the most demanding engineering tests and applications. Besides, remote control via GPIB, RS-232 or Analog Programming (APG) interfaces is available.

10.2.5 Power Converter Setup for Power Split

A power converter is a power supply unit (PSU) that incorporates a switching regulator. The power converter can be a DC/DC converter, an AC/DC rectifier, an AC/AC frequency converter or a DC/AC inverter depending on various input constraints and output requirements. The power converters are comprised of high-power fast-response semiconductor devices such as the bipolar junction transistor (BJT), metal oxide semiconductor field effect transistor (MOSFET), insulated gate bipolar transistor (IGBT), silicon-controlled rectifier or thyristor (SCR), gate turn-off SCR (GTO) and MOS-controlled thyristor (MCT). These solid-state devices as on–off electronic switches are configured in a certain circuit topology to convert the fixed supply voltage into variable voltage and variable frequency supply. All these devices can be turned on and off through a control input gate or base, which is decided by the controller command.

Power converters have been widely used in the automobile industry to meet current, voltage, power or frequency requirements inside vehicles [17–19].

Fig. 10.10 Unidirectional DC/DC boost converter

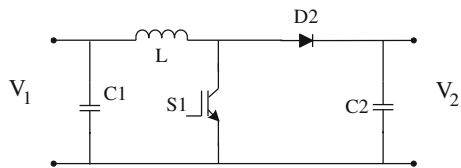
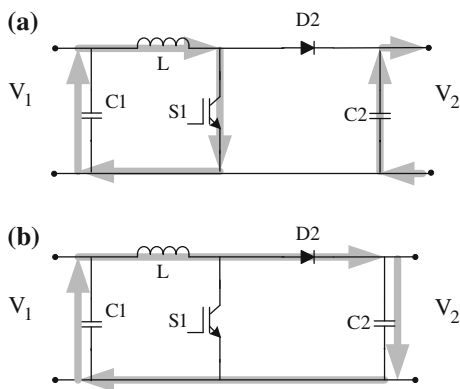


Fig. 10.11 Operation of a DC/DC boost converter (from V_1 to V_2). **a** Current paths when S1 is on. **b** Current paths when S1 is off



For example, in the multi-source vehicle power management system, a unidirectional DC/DC boost converter and two bi-directional DC/DC converters are directly connected to the fuel cell, battery and ultracapacitor, respectively for appropriate power split among these power sources.

As shown in Fig. 10.10, an IGBT S1 is employed in the topology of the unidirectional DC/DC boost converter for power tracking of the fuel cell (V_1 side). The power from the fuel cell to the DC bus (V_2 side) can be determined by inputting proper pulse width modulation (PWM) drive signals to S1. The operating principle of the DC/DC boost converter is described as follows.

In Fig. 10.11a, when S1 is on, the voltage source (V_1 side) supplies the current flowing through inductor L and IGBT S1. The inductor produces a back electromotive force (EMF), making the current rise. The output capacitor C2 discharges to supply the load (V_2 side). When S1 is off (see Fig. 10.11b), the energy stored in inductor L keeps the current flowing through inductor L, diode D2 and the load. In the meantime, the output capacitor C2 is charged with a portion of the current. The current decreases due to the difference between the input voltage V_1 (low) and output voltage V_2 (high). The “on” and “off” times for IGBT S1 are T_{ON} and T_{OFF} , respectively. Define the duty cycle D as the proportion of time when S1 is on, i.e., $D = T_{ON}/(T_{ON} + T_{OFF})$. The output voltage V_2 is obtained by:

$$V_2 = \frac{T_{ON} + T_{OFF}}{T_{OFF}} V_1 = \frac{1}{1 - D} V_1 \quad (10.1)$$

By adding IGBT S2 and diode D1, the unidirectional DC/DC converter changes to a bi-directional converter, as shown in Fig. 10.12. For power tracking

Fig. 10.12 Bi-directional DC/DC converter topology

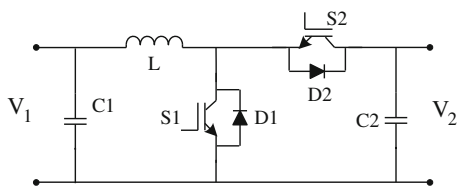
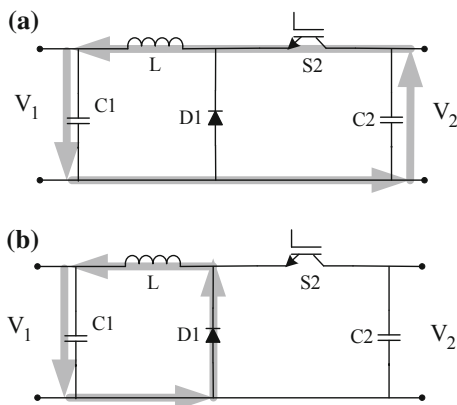


Fig. 10.13 Operation of a DC/DC buck converter (from V_2 to V_1). **a** Current paths when S2 is on. **b** Current paths when S2 is off



applications of the battery and ultracapacitor, the battery and ultracapacitor are located on the V_1 side, and the other side V_2 is connected to the DC bus. So the voltage from the power sources is boosted on the DC bus at the aim of voltage regulation. If power is required to flow from power sources (V_1 side) to the DC bus (V_2 side), IGBT S1 is operated under the PWM switching mode and IGBT S2 is turned off all the time. The operating principle has been introduced above. If the regenerative power from the DC bus (V_2 side) needs to charge the battery and ultracapacitor (V_1 side), S2 is used as an active switching device and S1 is permanently disabled, which results in a DC/DC buck converter (from V_2 to V_1). The operating principle is introduced below.

When S2 is on, the voltage source (V_2 side) supplies the current flowing through S2, inductor L and the load (V_1 side) as shown in Fig. 10.13a. The inductor current increases due to the back EMF produced by the inductor. Then S2 is turned off as shown in Fig. 10.13b, and the energy stored in inductor L keeps the current flowing through the load (V_1 side) and diode D1. Assume the “on” and “off” time for IGBT S2 are T_{ON} and T_{OFF} , respectively. Define the duty cycle D as the proportion of time when S2 is on, i.e., $D = T_{ON} / (T_{ON} + T_{OFF})$. The output voltage V_1 is derived from the input voltage V_2 as:

$$V_1 = \frac{T_{ON}}{T_{ON} + T_{OFF}} V_2 = D V_2 \quad (10.2)$$

10.3 Global Description and Analysis for a Vehicle Power Management System¹

10.3.1 System Configuration

Figure 10.14 shows a typical hybrid energy system consisting of a fuel cell, a battery and an ultracapacitor. A unidirectional DC/DC converter and two bi-directional DC/DC converters are directly connected to the fuel cell, battery and ultracapacitor, respectively. The power demand of the vehicle can be satisfied by controlling the direction and amount of output power (power-oriented-control) of each power component. The optional bi-directional DC/DC converter placed between the DC bus and the load is for the purpose of voltage regulation to keep the DC load voltage stable. The required power of the fuel cell, battery and ultracapacitor is calculated by the wavelet-transform based algorithm (see details in “Fuel Cell/Battery-Powered Electric Vehicle” of both Sects. 5.3.1 and 5.3.2).

The terminal voltage and output current of each power source, which help to obtain the instantaneous power, are sampled and provided as inputs to the data acquisition (DAQ) and control system for comparison with the desired power. The DC voltage on the load side is sampled and fed back to the DC load voltage regulator located in the DAQ and control system. The PWM signals generated from the PID controllers are used to control the four DC/DC converters respectively for power tracking and voltage regulation. If there are only three DC/DC converters without the optional DC/DC converter connected between the load and DC bus, the DC load voltage can be stabilized by choosing the voltage-oriented-control for the converter connected to the battery considering its voltage robustness, and power-oriented-control for the other two converters connected to the fuel cell and ultracapacitor. If the state of charge (SOC) of the battery or ultracapacitor falls below a predetermined threshold, the switch between the fuel cell and the battery/ultracapacitor is closed for SOC increase, and the power control unit (PCU) connected to the battery/ultracapacitor is disabled prohibiting power flow from the battery/ultracapacitor to the DC bus, until the voltage returns within the desired limits.

The output current from the fuel cell module is limited by its maximum value. The battery and ultracapacitor are initially charged to sufficient voltage to ensure that the voltage difference between the fuel cell and the battery or the ultracapacitor is within an acceptable range when the switch turns on. This helps ensure that the surge current is within allowable limits and the membrane of the fuel cell module is not damaged.

¹ Portion of the material in this section are from Xi Zhang, Chunting Mi, Abul Masrur, and David Daniszewski, “Wavelet based power management of hybrid electric vehicles with multiple onboard power sources,” *Journal of Power Sources*, vol. 185, no. 2, pp. 1533–1543, 2008. © [2009], with permission, from *Journal of Power Sources*.

10.3.2 Drive Cycle Selection

ADVISOR simulation tool is employed to help set up a power demand model of the proposed power management system in an HEV. The Orange County Cycle (OCC) is chosen as a sample cycle for modeling. The speed curve and load profile (for a certain vehicle) during the OCC can be found in Figs. 20 and 21, respectively. For the convenience of design, the load profile is considered as the power demand. It can be seen from Fig. 21 that the load profile consists of many transients derived from the speed variations.

10.3.3 Control Concepts

In this power management system (see Fig. 10.14), three power sources (i.e., fuel cell, battery and ultracapacitor) and corresponding power flow control are independent. The required power demand suitable for the characteristics of an individual power source can be met precisely. The specific control concepts are described below:

- The three-level Haar wavelet transform is utilized for decomposition of the total power demand.
- The proton exchange membrane fuel cell (PEMFC) module deals with the majority of the positive portion of the low-frequency components of power demand derived from the wavelet decomposition. The power flow from the fuel cell is determined by switch duty cycle of the unidirectional DC/DC converter. The duty cycle is obtained by the DAQ and control system.
- The battery satisfies the negative portion (during regeneration) and some of the positive portion of the low-frequency components of power demand derived from the wavelet decomposition. The battery not only absorbs the slow-variation power from the load but also helps the fuel cell provide the required power to reduce the burden of the fuel cell.
- All the high-frequency components of the power demand are met by the ultracapacitor. The amount and direction of required fast-variation power is determined by properly controlling an individual switch existing in the bi-directional DC/DC converter. The switch status and switch duty cycle are outputs of the DAQ and control system.
- When the SOC of the battery drops to 0.5 because of over-discharging, switch S_{bat} in Fig. 10.14 turns on (i.e., connected to the upper diode attached to the fuel cell) and the PCU connected to the battery (see Fig. 10.17) is disabled until the battery voltage reaches the fuel cell module terminal voltage. During this process, the battery is charged through the diode D_{bat} and switch S_{bat} from the fuel cell module, and the power flow from the battery to the DC bus is prohibited. When the SOC of the ultracapacitor decreases to 0.25, switch S_{UC} in Fig. 10.14 turns on (i.e., connects to D_{UC}) and the PCU linked to the ultracapacitor is shut off until the ultracapacitor voltage reaches the fuel cell module terminal voltage.

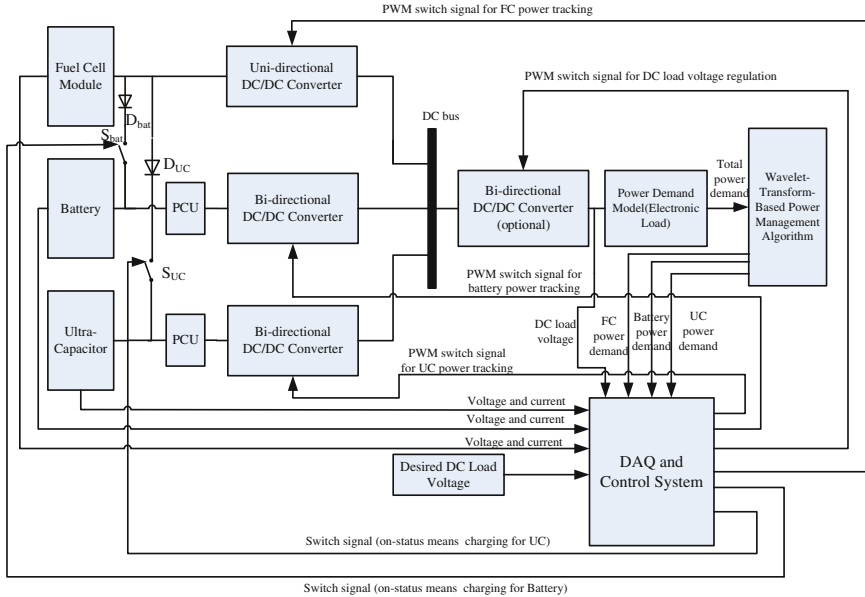


Fig. 10.14 System configuration of the multi-source vehicle power system

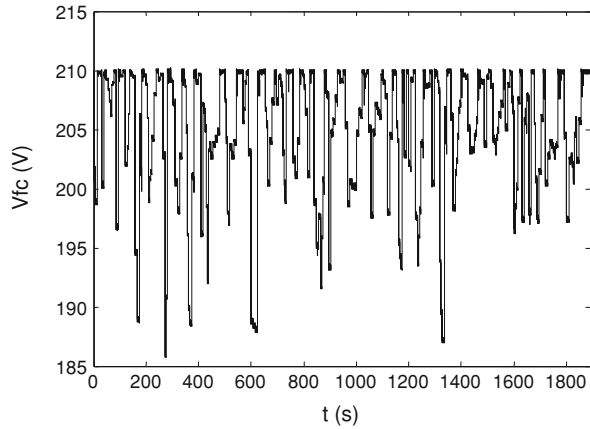
The ultracapacitor is then charged from the fuel cell module, thus avoiding the voltage collapse. Meanwhile no power is drawn from the ultracapacitor to the DC bus.

- If the SOC of the battery or ultracapacitor increases to 0.95, the other two power sources (the ultracapacitor & fuel cell, or the battery & fuel cell) are removed from the power train, and the battery or ultracapacitor satisfies all the power demand as the only power source until its SOC drops to 0.85.
- The output current from the fuel cell module is limited to its maximum value. Meanwhile, the battery and ultracapacitor are initially charged to sufficient voltage, and the battery and ultracapacitor are also charged from the load during the energy regeneration process. Thus, the SOC of the ultracapacitor/battery will not decrease widely and the voltage difference between the fuel cell and battery/ultracapacitor will be within an acceptable range when the charging switch (S_{bat} or S_{uc}) turns on. These measures and conditions guarantee that the destructive surge current can be avoided.

10.3.4 Analysis of Simulation and Experimental Results

The fuel cell parameters are derived from the data obtained of a fuel cell module NexaTM manufactured by Ballard. The open cell voltage $E_{0,cell} = E_{0,cell}^0 - k_E(T - 298) \approx 0.6V$. The no-load terminal voltage of the FC module is reconstructed to be 212 V,

Fig. 10.15 FC terminal voltage



so the number of FCs in series is $N_0 = 353$. To completely satisfy the load demand shown in Fig. 5.28, two Ballard FC modules are connected in parallel. The rated output power per cell is 210.3 W. As a result, the rated power of the FC system is 19.3 kW. Consequently, the required power in Fig. 5.28 can be completely satisfied.

The lithium-ion battery parameters are based on experimental data of a Sony US18650 battery. The nominal voltage of this battery is 3.7 V. Accordingly the number of batteries in series is calculated to be 58 since the terminal voltage of the battery stack is 212 V in our design. To obtain the sufficient current outputting ability, we place 40 US18650 cells in parallel. Additionally the nominal capacity of a US18650 cell is 1.4 Ah, and the reference current for battery modeling is set to 1.4 A. So the nominal power of the battery stack is 12 kW. Meanwhile the maximum current of the US18650 battery can reach a few ten amperes. Thus the maximum instantaneous power of the stack exceeds 100 kW.

The maximum float voltage of the ultra capacitor MAXWELL PC7223 is 2.3 V. Therefore 105 cells of PC7223 UCs are chosen so that the terminal voltage of the UC bank is equal to 212 V. The total UC internal resistance $R_{UCbank} = 0.00085 \times 105 = 0.0892 \Omega$ and the total capacitance $C_{UCbank} = 2700/105 = 25.71 \text{ F}$. The rated current of the PC7223 model is 400 A. Therefore the maximum output power is larger than $400 \times 212 = 84.8 \text{ kW}$. This can adequately satisfy the power demand depicted in Fig. 5.28.

Figures 10.15, 10.16, 10.17 and 10.18 show the voltage variations of the FC system, battery stack, UC and DC load side. Due to the required power, the voltages of the three power sources change accordingly. The battery shows good voltage stabilization performance in the whole drive cycle except a few moments. The increase in assigned power decreases the FC terminal voltage. The UC terminal voltage increases from 197 V to 215 V as a whole because of regenerative

Fig. 10.16 Battery terminal voltage

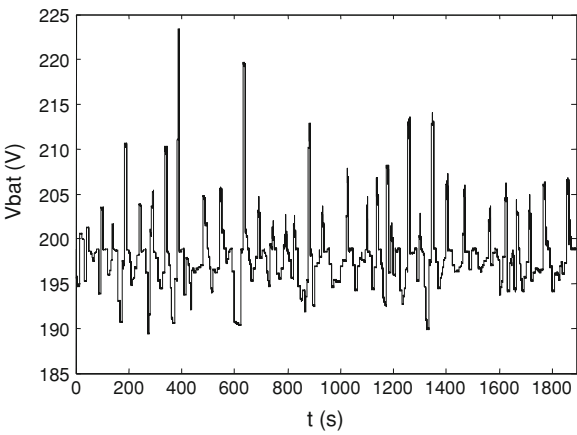


Fig. 10.17 UC terminal voltage

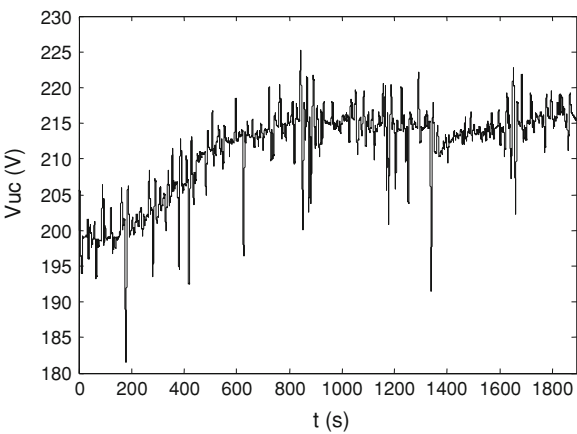


Fig. 10.18 Regulated DC load voltage

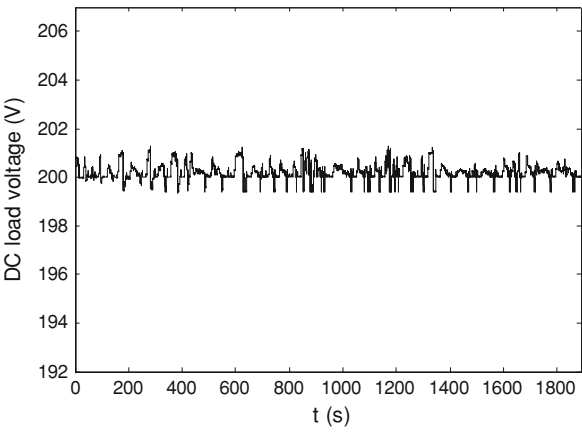


Fig. 10.19 FC output power

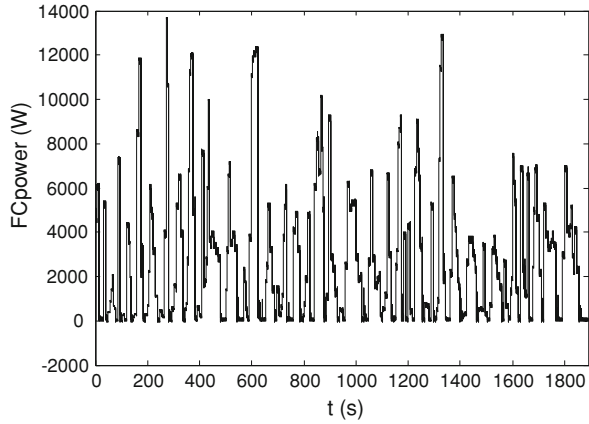
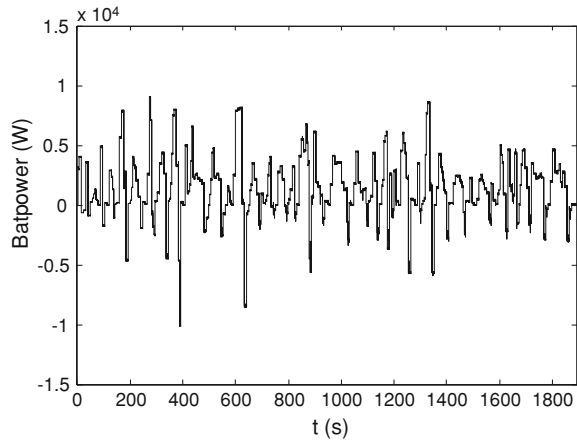


Fig. 10.20 Charging and discharging power of battery



energy. The DC voltage on the load side remains at 200 V with the help of the bi-directional DC/DC converter for voltage regulation.

The power tracking performance of the three power sources (i.e., the FC, battery and UC) is shown in Figs. 10.19, 10.20, and 10.21. By comparing these power tracking curves to the required power curve, it is found that the power demands are adequately satisfied. The power variations are within the maximum limitations of the power sources as mentioned above. According to Fig. 10.21, the UC absorbs the entire 110 kJ energy for a small-scale voltage increase. The fact that the DC output power trajectory matches the load profile as shown in Fig. 10.18 proves the validity and correctness of the proposed power-sharing algorithm as evidenced in Fig. 10.22.

Fig. 10.21 Charging and discharging power of ultra-capacitor

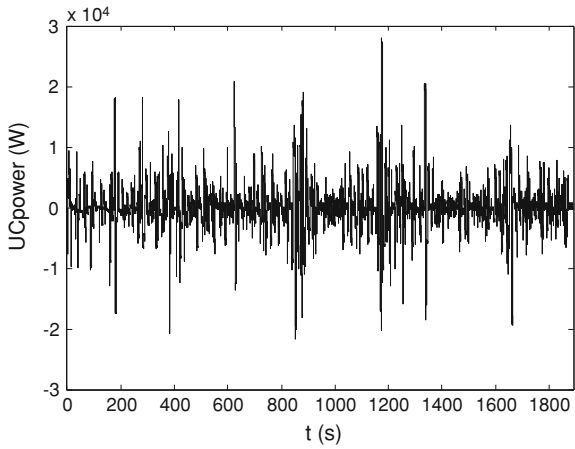


Fig. 10.22 Total output power for load demand

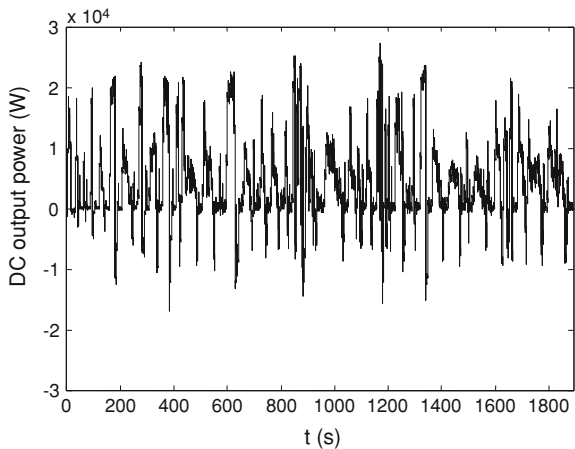


Fig. 10.23 Downscaled total power demand at a certain time interval of OCC

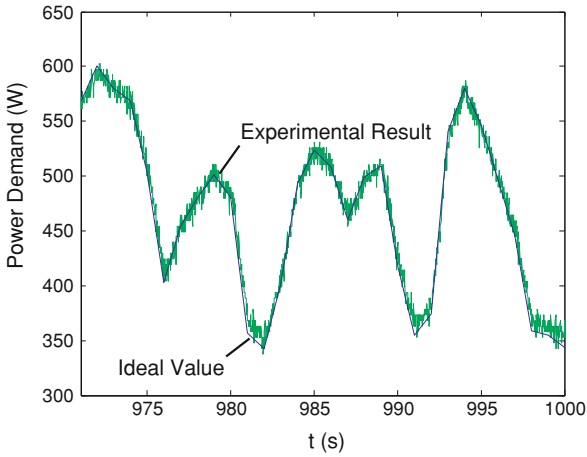
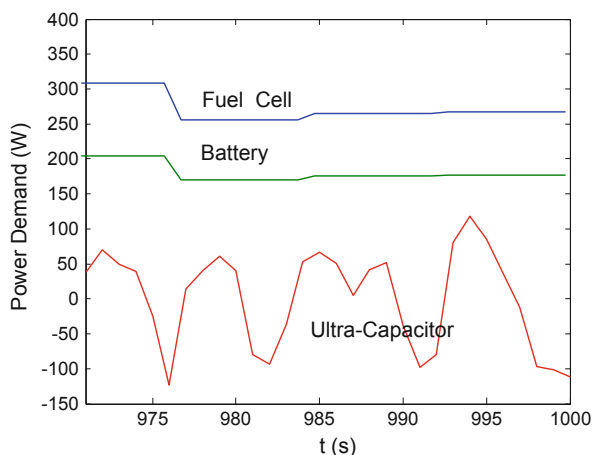


Fig. 10.24 Calculated power distribution for three power sources



10.3.5 Experimental Results

A scaled-down experimental setup was developed in the laboratory to validate the proposed algorithm. The power sources consist of a 1.2 kW fuel cell module (the rated operating voltage is 26 V), a lithium-ion battery pack ($V_{\text{nominal}} = 25.2$ V, Capacity = 32.4 Ah) and an ultracapacitor (the capacitance is 95 F). For the sake of simplicity of experimental verification, a certain time interval (971st–1000th second) is extracted from the OCC drive cycle to be analyzed. Meanwhile the power demand is scaled down because the power source voltage is low and the current can't exceed some value due to the device limitation. The power demand in the experiment is 1/20 of that in the real OCC drive cycle, which is implemented by an electronic load (Chroma 63202 model, $P_{\text{max}} = 2.6$ kW) operating as a load simulator. Three DC/DC converters controlled by a real time controller board (dSPACE DS1104) are connected to three power sources respectively, switching at 10 kHz. The control program is compiled and downloaded to the DS1104 board for sending and receiving signals. Currents and voltages are monitored and fed back into the DS1104 board where the power is calculated as a product of the current and voltage. The real instantaneous power (in form of analog voltage) can be measured via digital-to-analog (DAC) ports on the real time controller board.

The ideal power demand and the real power consumed by the electronic load are shown and compared in Fig. 10.23. The electronic load shows good power tracking precision to guarantee persuasion of experiments. The designed 1 kW hardware prototype is capable of meeting the requirements since the maximum power demand is 600 W. The power demands allocated to the fuel cell, battery and ultracapacitor are calculated using the proposed wavelet transform and shown in Fig. 10.24. It can be seen that the high-frequency components are assigned for the

Fig. 10.25 Experimental results of power distribution

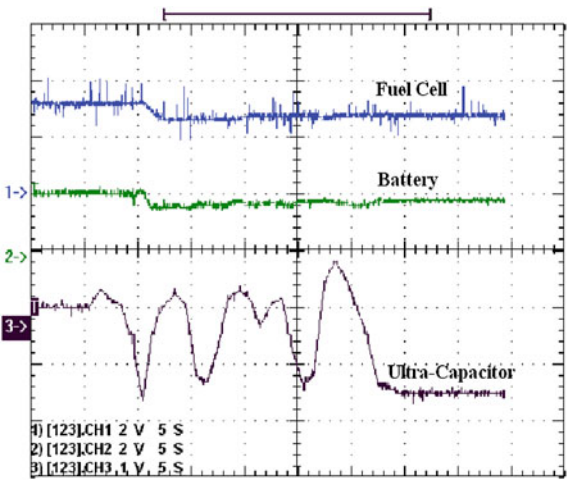
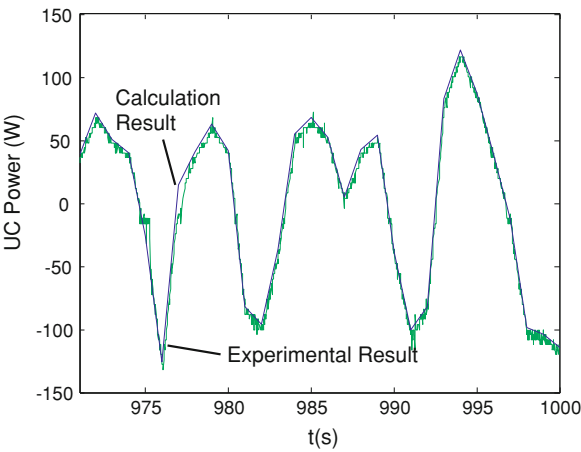


Fig. 10.26 Comparison of ultracapacitor power between calculation and experimental results



ultracapacitor, while the fuel cell and battery cooperate with each other to share the low-frequency components obeying the aforementioned principle (see Eqs. 5.85 and 5.87). Figure 10.25 shows the measured waveforms of power possessed by the fuel cell, battery and ultracapacitor, respectively. To sufficiently prove validity of the experimental setup, the measured ultracapacitor power is compared to the calculated ultracapacitor power in Fig. 10.26 with the same scale. High similarity between the experimental result and the theoretical value exists not only during the positive power transferring process (outputting power) but during the negative power transferring process (absorbing power). Consequently, the experimental results validate that the proposed wavelet-transform-based power sharing algorithm is applicable to the real hardware environment.

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Chapter 11

Future Trends in Vehicle Power Management

The automobile industry has been focusing on developing clean, efficient and sustainable vehicles as a substitute for conventional vehicles that are based on internal combustion engines (ICE), thanks to government regulations, consumer interests, environmental concerns, and economical issues. The concept of battery-powered electric vehicles (EVs) works well with this tide because of high efficiency, quiet operation and zero emissions. However, energy storage is still a bottleneck for EVs today due to the limitations of batteries such as size, weight, charging time, and cost. In particular, the high cost of batteries makes EVs unable to compete with conventional vehicles. These barriers hinder the commercialization of EVs.

Thus, integrated with benefits of both EVs and conventional vehicles, hybrid electric vehicles (HEVs) incorporating an engine and one or more electric motors were developed to take advantages of a conventional vehicle and an electric vehicle while mitigating their limitations. HEVs are superior due to dramatic extension of driving ranges and rapid refueling of gasoline or diesel compared with EVs. Although HEVs lose the zero-emission concept, they are vastly less polluting and have much less fuel consumption than ICE-based vehicles. They can also work as EVs with zero emissions when the engine is shut off. The complex configuration of HEVs where there is more than one power source gives more freedom to applications of power management strategies for satisfactory performance.

In the mean time, hydrogen as an attractive long-term fuel option is being considered for utilization in vehicles as well. So research and development of fuel cell electric vehicles (FCEVs) using hydrogen as fuel is being pursued. In addition to high cost of fuel cell and low energy density of hydrogen storage, another major drawback of FCEVs is imperfect transient performance. Consequently, the combination of fuel cell and other power sources, e.g. a battery or an ultracapacitor, is a good choice in terms of transient performance. This “hybridization” configuration for FCEVs leaves enough space for effective power management strategies aiming at certain requirements such as improvement of fuel economy, lifetime extension of power sources, reliability, and so on.

Recently, automakers and governments have shown lively interests on plug-in hybrid electric vehicles (PHEVs). PHEVs differ from regular HEVs with their ability to use off-board electric power sources to recharge the on-board batteries. In addition to the charge-sustaining mode of regular HEVs, PHEVs use the stored electrical energy in a charge-depleting mode. The operating strategy for the charge-depleting mode will greatly influence the component attributes and the value of the PHEV technology [1]. How to best use the fuel converter in a charge-depleting operating manner must be decided by a power management strategy until the PHEV exhausts the stored electric energy obtained through external charging. Thus appearance of PHEVs raises a new preposition for vehicle power management.

There exist some good power management approaches for HEVs and FCEVs, however problems are still obvious due to the intrinsic defects of each strategy and the lack of complete real-time characteristics. Meanwhile, new technologies upon materials science, electrochemistry, mechanics etc. propel development of power sources and other devices, and new power management strategies and requirements related to these changes have to be up to date. Besides, potential power management strategies need to be developed for and implemented in PHEVs as mentioned above. This chapter will introduce and think over these aspects, and intend to draw a picture for readers about trends in vehicle power management.

11.1 Existing Problems in Present Vehicle Power Management

So far optimal control strategies especially dynamic programming (DP) and artificial intelligent (i.e., fuzzy logic and neural networks) supervisory systems have been successfully applied to vehicle power management by considerable researchers for certain objectives. In addition, in this book, the authors proposed a wavelet-transform-based strategy aiming at performance improvement in battery-powered EVs, HEVs and FCEVs. However, there exist some problems in these control and optimization methodologies due to their intrinsic drawbacks.

In an optimal control scheme for a vehicle, optimization laws are established based on cost functions of the vehicular system [2–4]. However, optimal controllers are somehow sensitive to parameter variations and measurement noises. Stability problems may be caused by any small measurement problem. All the dynamic and static behaviors of the vehicle components have to be taken into account for the optimization process. Sometimes assumptions are introduced for simplification of calculations due to the complexity of some problems. But optimal solutions are obtained only under these assumptions beyond real-world conditions. The discrete time event strategy is used in the optimal controller since it is simple and more robust. The system behaviors move from one state to another decided by certain rules. Nevertheless only a partial optimal solution is obtained since the

discrete time event strategy employs the binary (on/off) mode and the resolution of rules determines the system performance.

The fuzzy logic control is the most popular artificial intelligent systems approach used in vehicle power management. Fuzzy logic control with a nonlinear structure suitable for the power split problem serves more flexibility to optimization and brings more robustness than other methods [5, 6]. However, the optimization and mathematical manipulation of the defuzzification process brings a problem to fuzzy logic control. Also the defuzzification process consumes memory and time in the controller. In addition, fuzzy logic control is difficult to scale to larger problems because there are some problems with conditional possibility.

Artificial neural network (ANN) models are utilized for prediction of vehicle behaviors with the desire to incorporate fuel consumption or emissions as a design criterion [7, 8]. The problem is that they require a large diversity of training for real-world operation. Consequently considerable processing and storage resources need to be committed to implement large and effective ANN on line.

The analytical approach is developed for the plug-in hybrid electric vehicle (PHEV) to minimize fuel consumption. The simplified and unified analytical solutions to this optimization problem are derived through analysis on constant-speed driving and standard driving cycles, respectively. The constant battery energy-based strategy is preferred to the constant engine power-based strategy due to higher system efficiency. Nevertheless, precise and detailed models are required by the analytical approach. This will somehow constrain the wide applications of the analytical approach to the real-world objects e.g. hybrid vehicles running on the road.

The wavelet technology has been successfully applied to vehicle power management in this book. It can identify high-frequency transients from power demand of the drive line. A proper power split can be achieved to improve system efficiency and life expectancy of power sources. However, in most cases, an ultra-capacitor has to participate in this wavelet-transform-based power management system due to its high power density and superiority in dealing with transient processes. This structure constraint obstructs the wavelet technology to be applied more broadly to vehicle power management.

In general, the common defect of the above technologies is absence of true on-line solutions and good real-time performance. Although these approaches look perfect and can be used as a benchmark for other strategies' performance, the entire drive cycle is assumed already known in the initial design process for controllers. Even if some existing predictive methods are incorporated into the power management system to get future roadway conditions, the quality of prediction is an issue to be concerned, which determines the success of the power management strategy. In most cases, the measurement and prediction problems affect strategy execution and system performance. So in summary, future vehicle power management requires new advanced control and optimization strategies as well as nearly-perfect prediction approaches to be implemented more effectively and precisely in real-time vehicular systems.

Fig. 11.1 BMW hydrogen internal combustion engine.
Source [10]. Courtesy BMW



11.2 Future Energy Sources and Energy Storage Systems

Researchers and manufacturers are making efforts to develop novel energy converters or energy storage systems (ESS) at the aim of larger energy capacity, higher power density, higher efficiency, lower cost, better reliability and durability compared to mature existing energy converters or ESS placed in the powertrain of all types of vehicles today. New technologies bring significant progresses on functionality and reliability of energy converters and ESS all the time, but due to the limited space, we only introduce several representative and prospective energy converters and ESS in this section as follows.

11.2.1 *Hydrogen Internal Combustion Engine*

The hydrogen internal combustion engine (H_2ICE), where liquefied hydrogen is used as an automotive fuel, is a modified traditional ICE, and is a potential environment-friendly and near-term option and bridge to hydrogen fuel cell vehicles. Near-zero emissions except a little amount of NO_x and low cost is a very attractive feature. Additionally, the H_2ICE -powered vehicles are capable of using the existing manufacturing infrastructure for gasoline/diesel ICEs [9]. A hydrogen internal combustion engine produced by BMW is shown in Fig. 11.1.

The high auto-ignition temperature of hydrogen indicates that hydrogen is very suitable as a fuel for spark ignition (SI) engines. The direct-injection (DI) SI H_2ICE has the potential to avoid many problems related to the use of hydrogen in port-fuel-injected (PFI) engines such as pre-ignition and back-flash. Here pre-ignition is

defined as combustion prior to spark discharge, and back-flash (also referred as backfire) is an explosion generated from the intake manifold of the engine, or expelled from the exhaust pipe at the rear of the vehicle [11]. Besides, because the fuel is injected after the intake valve closes, a DI H_2 ICE avoids the power-density loss associated with the displacement of air by lighter hydrogen. A DI H_2 ICE can deliver approximately 115% the power of a gasoline-fueled ICE at stoichiometry.

The drawback with DI H_2 ICEs is that in-cylinder injection requires H_2 /air mixing in a very short time while incomplete mixing can produce some problems such as misfire, high NO_x emissions, reduced efficiency, and power loss. On the other hand, hydrogen does not come as a pre-existing source of energy like fossil fuels, but is first produced and then stored as a carrier. Either renewable or non-renewable energy sources are needed to produce hydrogen for vehicle use. In the mean time, because of hydrogen's potential detonations, storage, transport and distribution of hydrogen are also challenges facing the application of H_2 ICEs in vehicles.

11.2.2 Internally Radiating Impulse Structure (IRIS) Engine

The internally radiating impulse structure (IRIS) engine, as a new type of internal combustion engine (ICE), changes the combustion chamber's design from one piston in a cylinder to six "chordons" which act as expanding walls [12]. This design innovation can reduce waste heat and increase the surface area reacting productively to torque. In an IRIS engine, an average of more than 70% of the chamber's surface area, in comparison to less than 25% of that in a traditional engine, is productive. In addition, the IRIS engine also captures energy that previously flowed out the exhaust pipe. The simplicity of a two-stroke combustion cycle with the efficiency of a four-stroke engine is also offered by the IRIS engine. The innovative valve/vent structure brings the IRIS engine more efficiency than the traditional piston-in-cylinder configuration. The IRIS engine design is compatible with existing infrastructure and built with conventional materials and machining. Alternative fuels such as biodiesel, natural gas and hydrogen is expected to be used in the future IRIS engine. The IRIS technology can also be employed to create dramatically more efficient pumps, compressors and medical devices. In summary, IRIS provides a viable solution to some severe problems facing the automobile industry.

However, despite of a concept, no real IRIS prototype exists to the authors' best knowledge. Though the IRIS engine schematic and its analysis look perfect, no test data support its validity in real-world application. Conceivers of the IRIS hope to build an IRIS prototype soon. Let's look forward to the moment when it comes to reality.

11.2.3 Lithium Iron Phosphate Battery

The lithium iron phosphate battery (LFP) using $LiFeO_4$ as a cathode material is a type of lithium-ion (Li-ion) battery with the advantages of low weight, high energy density, low self-discharge rate and no memory effect. Currently, most lithium-ion

batteries used in consumer products are lithium cobalt oxide (LiCoO_2) batteries. Compared to LiCoO_2 , the major advantages of LiFePO_4 include improved safety through higher resistance to thermal runaway, longer cycle and calendar life, higher current or peak-power rating, and use of iron and phosphate which have lower environmental impact than cobalt. LiFePO_4 is an intrinsically safer cathode material than LiCoO_2 and manganese spinel because the Fe–P–O bond is stronger than the Co–O bond so that the oxygen atoms are much harder to remove when abused e.g. short-circuited, overheated, etc. Despite of lower voltage and energy density than LiCoO_2 batteries, slower rate of capacity loss of LiFePO_4 can compensate this drawback [13]. In summary, the LiFePO_4 battery is definitely a prospective alternative candidate for energy storage systems in the powertrain of future vehicles [14].

11.2.4 Nanotechnology in Batteries

Nanotechnology is being used by battery companies to design new anode and cathode materials which can dramatically increase the amount and rate of energy transferred to a battery and reduce the recharge time as well [15]. The surface area of the electrode is increased thereby allowing more current to flow between the electrode and chemicals in the battery. Nanotechnology helps batteries store more energy than previous types, which significantly increases the efficiency of electric or hybrid vehicles due to the reduced weight of batteries. The separation between liquids in the battery and the solid electrodes when the battery is free can prevent the low level discharge that occurs in conventional batteries. Consequently the shelf life of the battery increases greatly. Additionally nanotechnology provides less flammable electrode material reducing the possibility of batteries catching fire. Specifically A123Systems produces lithium-ion batteries with the cathode made from nano-phosphate [16]; Altair Nano makes lithium-ion battery anode composed of lithium titanate spinel nano particles [17]; Nanoexa uses nanocomposite electrodes in the lithium-ion battery [18], and so on. All these new technologies result in higher power, quicker recharge and less combustible than standard lithium-ion batteries. Hopefully nanotechnology batteries will bring a real revolution to the battery industry in the future. Other battery technologies, such as lithium air batteries, are also being developed with the promise of dramatically increase energy and power density.

11.3 Plug-In Hybrid Electric Vehicle

As we discussed in several chapters in this book, a plug-in hybrid electric vehicle (PHEV) is a hybrid electric vehicle with a plug which is connected to an electric power source to recharge batteries inside the vehicle. A PHEV is sometimes called a grid-connected hybrid, gas-optional hybrid, or GO-HEV. It combines the functions of traditional hybrid electric vehicles (HEV) and battery-powered electric vehicles (EV).

With the employment of rechargeable batteries, PHEVs can dramatically reduce air pollution, dependence on fossil fuels, and greenhouse gas emissions compared to conventional vehicles. In addition, PHEVs are cheaper to run and cheaper to maintain than conventional vehicles and regular HEVs. The batteries in PHEVs are mostly recharged at night while overnight electricity is available at a lower cost in most areas of the world. According to statistics, the cost for electricity to power PHEVs for all-electric operation has been estimated at less than one quarter of the cost of gasoline. Another advantage of PHEVs is that they can improve load balance or send power back to the grid during peak periods, which is realized with vehicle-to-grid (V2G) technology. During peak periods, excess battery energy is sent back to the grid, and during off peak periods, batteries are recharged using cheaper electric power. Both utilities and PHEV owners will benefit from this. Other benefits include improved national energy security, convenience of home recharging, and fewer fill-ups at the filling station and so on.

Due to the significant benefits and potential profits that PHEVs bring, considerable automakers have announced their schedule for mass production or have already manufactured PHEVs for sale. At the end of 2008, the world's first mass-produced PHEV, BYD F3DM, appeared in the domestic Chinese market. General Motors, Ford, Chrysler, Toyota, and almost all other major OEMs plan to produce and sell their PHEVs between 2010 and 2012.

PHEVs are capable of several operation modes, i.e., charge-depleting, charge-sustaining, blended and mixed modes. As can be seen from previous chapters, the use of these modes has a direct effect on the size and type of batteries due to their management on batteries' discharge strategy. In charge-depleting mode, a fully charged PHEV operates exclusively (or almost exclusively) on electric power until the battery SOC drops to a predetermined level. Charge-sustaining mode is employed by HEVs and combines the operation of two power sources in such a manner that the vehicle operates efficiently and the battery SOC stays inside a predetermined band. Whenever a PHEV exhausts its all-electric range in charge-depleting mode, it will switch into charge-sustaining mode. Blended mode is a kind of charge-depleting mode which is employed when vehicles do not have enough electric power to sustain high speeds only using batteries. It increases the distance from stored grid electricity compared to charge-depleting mode. Mixed mode is related to a trip in which all the above three modes are combined [19].

Different from regular HEVs, PHEVs need deeper battery charging and discharging cycles, which may somehow negatively influence battery life. Thus design issues and trade-offs against battery life, capacity, heat dissipation, weight, costs and safety need to be solved. Technology progresses on all types of batteries promise larger energy densities by mass and volume and better battery life expectancy.

A PHEV has an onboard battery charger that plugs into an electric outlet or it can be plugged into a charger installed in a garage. In the future, automakers may provide docking stations for automatic charging without a plug when the vehicle rides onto the docking platform. However, the problem is that many people living in apartments, condominiums and townhouses do not have garages and they need

access to electric outlets to recharge PHEV batteries. Consequently, electric outlets near their places of residence, or in commercial or public parking lots or streets need to be installed for them to enjoy full advantages of PHEVs. Another option is to build massive public charging stations for fast charging. Electric utility companies need to cooperate with automakers to formulate unified standards for building charging stations.

11.4 Thoughts of Future Vehicle Power Management

Due to the problems of present vehicle power management strategies and new characteristics of future energy sources and energy storage systems, changes are required in vehicle power management to face these challenges. This section will discuss some thoughts from the authors on development of future vehicle power management.

Though each existing vehicle power management strategy has its intrinsic defects, the hybridization of two or multiple strategies or injection of other methods balancing off these drawbacks under certain conditions may be a relatively good option. For instance, combination of optimal control and fuzzy logic control seems to be a good consideration for avoiding the sensitivity problem of optimal control. Stability problems may be caused by parameter variations in an optimal controller. If the fuzzy logic controller is put into use to generate required results instead of the optimal controller when insignificant parameter variations are found, the stability of the system can be guaranteed relatively. We may consider this in a simple way that, both controllers operate to output results all the time, and the results of one controller are selected in turn according to predetermined conditions e.g. parameter variations for calculation and optimization of the entire system.

Some new characteristics of future energy sources and energy storage systems have to be incorporated into the vehicle power management design process as constraints. For example, the danger of explosion in the hydrogen internal combustion engine (H_2ICE) needs to be addressed when designing a power management strategy for the powertrain control. In some cases such as low load and low speed operations, there exists a possibility that moisture becomes a severe problem and hydrogen gets past the piston ring and works its way into the oil pan. Hydrogen can accumulate in the oil and hydrogenate the oil or, even worse, cause an explosion. The power management strategy should involve this as a constraint, and allocate proper power demand for the H_2ICE and control engine speed appropriately to avoid the problem. Similarly, the safety of batteries in EV, HEV and PHEV are critical factors to be considered in designing the power management strategy.

Plug-in hybrid electric vehicles (PHEVs) bring new requirements to vehicle power management due to a new charge-depleting operation mode. How to best use two power sources (fuel and stored electricity) in a charge-deleting operating

manner will significantly affect the component attributes and the value of the PHEV technology. According to the driving demand situation and power capability of the motor and battery, different strategies may be utilized in the charge-depleting mode. Detailed design for the control strategies is under development with the consideration of expected driving distances and tradeoffs between the electric components' cost and zero-emission criteria.

Battery state of charge (SOC) is critical to hybrid vehicle power management. Normally, in hybrid vehicles, the SOC determines when the engine is switched on and off. SOC errors over 5% could seriously affect the system efficiency and driveability. Therefore high precision of battery SOC is expected for operations of power management strategies. An efficient battery management system (BMS) is needed to monitor status and acquire information of the battery. At the present time most methods used in the BMS for obtaining SOC depend on measuring some convenient parameter which varies with the SOC. In the future, more effective and precise SOC calculation or estimation algorithms will be in great need due to higher requirements for status monitoring and relevant effects. Synthetic methods using multiple parameters with respect to battery SOC may be a good choice for improving the calculation or estimation precision of battery SOC.

For implementation of vehicle power management strategies in real-time operations, driving patterns need to be predicted. Because the road type and traffic condition, trend and style, and vehicle operating modes have various degrees of impacts on vehicle fuel consumptions, prediction of these driving patterns are of great importance for validity of real-time vehicle power management strategies. Only recently some researchers have started focusing on this issue [20–23]. Roadway types can be predicted and classified in contrast to the existing drive cycles in terms of maximum speed, maximum acceleration, maximum deceleration and so on in a short term. Driving trends, operation modes and drive styles can be predicted using features such as average speed, average acceleration, the standard deviation of acceleration and so on. Several intelligent systems approaches were developed for driving pattern prediction, including the neural network, learning vector quantization network and fuzzy classifier. Future on-line driving pattern prediction needs to be faster and more precise to meet the real-time requirements, by simplifying the classification process and reducing the number of required features which may lead to significant prediction malfunction due to measurement errors.

On the other hand, the global positioning system (GPS), “connected vehicles” and other telematic systems can be introduced to vehicle power management for acquisition of driving patterns. The GPS has become a widely used aid to navigation worldwide and a useful tool for map-making and land surveying. Based on the functions of GPS, the authors have some original thoughts for the application of GPS in driving pattern prediction. Features of roads such as types of roadways (e.g. freeway, arterial, local, etc.), positions of traffic signs and levels of traffic congestions can be provided in real time by the automobile navigation system using GPS. The combination of the traffic environment information and other vehicle real-time operation information such as speed, acceleration, deceleration

and so on will help predict vehicle propulsion load or some other variables in the next time instant. Since the information e.g. roadway type and levels of traffic congestions, is obtained from the automobile navigation system directly rather than from estimation or calculation, the entire prediction precision can increase dramatically. “Connected vehicles” are vehicles connected to one another, the roadside, and beyond, via wireless communication pipelines. This technology keeps drivers and passengers connected to information through cellular and next generation of wireless technology (4G), WiFi, or worldwide interoperability for microwave access (WiMAX). “Connected vehicles” promises many useful applications such as lane departure warnings, blind-spot warnings, automated braking when needed to avoid a crash and so on. Beyond safety, it can provide real-time roadway features (e.g. pavement, bridges, traffic lights, etc.) and traffic information (e.g. traffic congestion). As discussed above, this will benefit prediction precision of vehicle propulsion load or some other variables and further quality of vehicle power management.

As a result, due to the increase of processing accuracy, the vehicle power management system will play a more efficient and more important role in the real-time driving environment for improvement of fuel economy, reduction of emissions, life extension of energy sources or energy storage systems, etc.

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