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David L. Olson
Desheng Wu

Enterprise Risk Management Models

Focus on Sustainability

Fourth Edition

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To my daughter Daria Carter for all of her help on AI/machine learning

David L. Olson

Preface

Enterprise risk management has always been important. However, the events of the twenty-first century have made it even more critical. Nature has caused massive disruption, such as the tsunami that hit Fukushima in March 2011 and the Covid-19 pandemic of 2020-2022. Terrorism seems to be on the rise, with attacks occurring in the USA, Europe, and Russia with greater regularity, not to mention the even more common occurrences in the Middle East. Human activities meant to provide benefits such as food modification and medicine have led to unintended consequences. The generation of energy involves highly politicized trade-offs between efficient electricity and carbon emissions, with the macro-level risk of planetary survival at stake. Oil transport has experienced traumatic events. Risks can arise in many facets of business. Businesses in fact exist to cope with risk in their area of specialization. But chief executive officers are responsible to deal with any risk fate throws at their organization.

The first edition of this book was published in 2010, reviewing models used in management of risk in nonfinancial disciplines. It focused more on application areas, to include management of supply chains, information systems, and projects. It included review of three basic types of models: multiple criteria analysis, probabilistic analysis, and balanced scorecards to monitor risk performance. The second edition in 2017 focused more on models, with the underlying assumption that they can be applied to some degree to risk management in any context. The third edition added material on risk-adjusted loss in Chap. 2. This fourth edition updates cases in risk matrices in Chap. 2, value analysis cases in Chap. 4, data mining in Chap. 9., balanced scorecard in Chap. 10, and project management in Chap. 12. Material is added on artificial intelligence/machine learning in Chap. 11 and sustainability in Chap. 14.

The bulk of this book is devoted to presenting a number of operations research models that have been (or could be) applied to supply chain risk management. We begin with risk matrices, a simple way to sort out initial risk analysis. Then, we discuss decision analysis models, focusing on Simple Multi-attribute Rating Theory (SMART) models to better enable supply chain risk managers to trade off conflicting criteria of importance in their decisions. Monte Carlo simulation models are the obvious operations research tool appropriate for risk management. We demonstrate simulation models in supply chain contexts, to include calculation of value at risk. We then move to mathematical programming models, to include chance-constrained programming, which incorporates probability into otherwise linear programming models, and data envelopment analysis. We also discuss data mining with respect to enterprise risk management. We close the modeling portion of the book with the use of business scorecard analysis in the context of supply chain enterprise risk management.

Chapters 11 through 15 discuss risk management contexts. Financial risk management has focused on banking, accounting, and finance (Wu & Olson, 2015). There are many good organizations that have done excellent work to aid organizations dealing with those specific forms of risk. This book focuses on other aspects of risk, to include information systems and project management to supplement prior focus on supply chain perspectives (Olson & Wu, 2015). We present more in-depth views of the perspective of supply chain risk management, to include frameworks and controls in the ERM process with respect to supply chains, information systems, and project management. We also discuss aspects of natural disaster management, as well as sustainability, and environmental damage aspects of risk management.

Operations research models have proven effective for over half a century. They have been and are being applied in risk management contexts worldwide. We hope that this book provides some view of how they can be applied by more readers faced with enterprise risk.

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Contents

1 Enterprise Risk Management in Supply Chains

All human endeavors involve uncertainty and risk. Mitroff and Alpaslan (2003) categorized emergencies and crises into three categories: natural disasters, malicious activities, and systemic failures of human systems (Mitroff & Alpaslan, 2003). Nature does many things to us, disrupting our best-laid plans and undoing much of what humans have constructed. Natural disasters by definition are surprises, causing a great deal of damage and inconvenience. Nature inflicts disasters such as volcanic eruptions, tsunamis, hurricanes, and tornados. In 2007, an earthquake damaged Toyota's major supplier of key parts, leading to the shutdown of Toyota's Japanese factories as well as impacting Mitsubishi, Suzuki, and Honda. In 2010, the Icelandic volcanic activity shut down European air space for about a week, massively disrupting global supply chains. In 2011, the tsunami leading to the Fukushima disaster disrupted automakers and electronic supply chains, as well as many others. In 2020, the COVID-19 pandemic shut down economies with a special impact on supply chains. While natural disasters come as surprises, we can be prepared. Events such as earthquakes, floods, fires, and hurricanes are manifestations of the majesty of nature. In some cases, such as Mount Saint Helens or Hurricane Katrina, we have premonitions to warn us, but we never completely know the extent of what is going to happen. Emergency management is a dynamic process conducted under stressful conditions, requiring flexible and rigorous planning, cooperation, and vigilance.

Some things we do to ourselves, include revolutions, terrorist attacks, and wars. Malicious acts are intentional on the part of fellow humans who are either excessively competitive or suffer from character flaws. Wars fall within this category, although our perceptions of what is sanctioned or malicious are colored by our biases. Criminal activities such as product tampering or kidnapping and murder are clearly not condoned. Acts of terrorism are less easily classified, as what is terrorism to some of us is an expression of political behavior to others. Similar gray categories exist in the business world. Marketing is highly competitive, and positive spinning of your product often tips over to malicious slander of competitor products.

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Malicious activity has even arisen within the area of information technology, in the form of identity theft or tampering with company records.

The third category is probably the most common source of crises: unexpected consequences arising from overly complex systems (Fidanboy, 2022). Some disasters combine human and natural causes—we dam up rivers to control floods, to irrigate, to generate power, and for recreation, as at Johnstown, PA at the turn of the twentieth Century. We have developed low-pollution, low-cost electricity through nuclear energy, as at Three Mile Island in Pennsylvania and Chernobyl. The financial world is not immune to systemic failure. Financial risk importance was evidenced traumatically by the events of 2007 and 2008, when the global financial community experienced a real estate bubble collapse from which most of the world's economies are still recovering. Human investment activity seems determined to create bubbles, despite our long history of suffering (Wu & Olson, 2015). Financial investment seems to be a never-ending game of greedy players seeking to take advantage of each other, which Adam Smith assured us would lead to an optimal economic system. It is interesting that we pass through periods of trying one system, usually persisting until we encounter failure, and then move on to another system (Wu & Olson, 2015).

Unexpected Consequences

Charles Perrow (1984) contended that humans are creating technologies that are high risk because they are too complex, involving interactive complexity in tightly coupled systems. Examples include dam systems, which have provided a great deal of value to the American Northwest and Midwest, but which also create potential for disaster when dams might break; mines, which give access to precious metals and other needed materials but which have been known to collapse; and space activities, which demonstrate some of mankind's greatest achievements, as well as some of its most heartbreaking failures. Nuclear systems (power or weapon) and airline systems are designed to be highly reliable, with many processes imposed to provide checks and balances. Essentially, humans respond to high risk by creating redundant and more complex systems, which by their nature lead to a system prone to greater likelihood of systems failure.

Technological innovation is a manifestation of human progress, but efforts in this direction have yielded many issues. In the energy field, nuclear power was considered the solution to electrical supply 50 years ago. While it has proven to be a viable source of energy in France and other European countries, it has had problems in the USA (Three Mile Island) and in the former Soviet Union (Chernobyl). There is a reticence on the part of citizens to nuclear power, and the issue of waste disposal defies solution. Even in Europe, the trend is away from nuclear. The Federal Government in the USA did not license new plants for decades, despite technological advances developed by national laboratories. Coal remains a major source of electrical energy fuel, although there are very strong questions concerning the need to replace it for carbon footprint reasons. Natural gas is one alternative. Wind power is another. Solar energy has been proposed. All of these alternatives can be seen to work physically, if not economically. The question of energy was further complicated by the recent large-scale adoption of *fracking*. This technique introduces risk and uncertainty not only to itself, but its inclusion changes decision-making regarding all sectors of energy.

All organizations need to prepare themselves to cope with crises from whatever source. In an ideal world, managers would identify everything bad that could happen to them and develop a contingency plan for each of these sources of crisis. It is a good idea to be prepared. However, crises by definition are almost always the result of nature, malicious humans, or systems catching us unprepared (otherwise there may not have been a crisis). We need to consider what could go wrong and think about what we might do to avoid problems. We cannot expect to cope with every contingency, however, and need to be able to respond to new challenges.

Enterprise risk management, especially in finance and accounting (Olson & Wu, 2015), is well-covered by many sources. This book will review the types of risks faced within supply chains as identified by recent sources. We will also look at project management, information systems, emergency management, and sustainability aspects of supply chain risk. We will then look at processes proposed to enable organizations to identify, react to, and cope with challenges that have been encountered. This will include looking at risk mitigation options. One option explored in depth will be the application of value-focused analysis to supply chain risk. We will then seek to demonstrate points with cases from the literature. We will conclude this chapter with an overview.

Supply Chain Risk Frameworks

There is a rapidly growing body of literature concerning risk management. Special issues also have been devoted to sustainability and risk management (Wu et al., 2013). This literature involves a number of approaches, including some frameworks, categorization of risks, processes, and mitigation strategies. Frameworks have been provided by many.

The Treadway Commission gives the following definition of enterprise risk management:

"Enterprise risk management is a process, effected by an entity's board of directors, management and other personnel, applied in strategy setting and across the enterprise, designed to identify potential events that may affect the entity, and manage risks to be within its risk appetite, to provide reasonable assurance regarding the achievement of entity objectives (COSO, 2004, p. 2)." (COSO, 2023)

Management has the role of establishing strategic objectives, selecting strategy, and setting objectives for implementation. COSO sees four objectives:

- *Strategic*—High-level goals to support organizational mission.
- *Operations*—Seeking efficient and effective use of resources.

Table 1.1 Differences between ERM and traditional risk management (Olson & Wu, 2015)

Traditional risk management	ERM
Risk as individual hazards	Risk viewed in the context of business strategy
Risk identification and assessment	Risk portfolio development
Focus on discrete risks	Focus on critical risks
Risk mitigation	Risk optimization
Risk limits	Risk strategy
Risks with no owners	Defined risk responsibilities
Haphazard risk quantification	Monitoring and measurement of risks
"Risk is not my responsibility"	"Risk is everyone's responsibility"

- *Reporting*—Seeking reliability in communications.
- *Compliance*—Assuring laws and regulations are complied with.

COSO sees eight interrelated components of ERM:

1. *Internal environment*—Organizational tone as the basis for how risk is viewed, including risk management philosophy and risk appetite, ethics, and integrity.
2. *Objective setting*—Process for setting objectives to support the organization's mission consistent with their risk appetite.
3. *Event identification*—Monitoring and distinguishing between risks and opportunities, feeding back opportunities to modify strategy.
4. *Risk assessment*—Analysis considering likelihood and impact.
5. *Risk response*—Avoid, accept, reduce, or share risk in light of organization risk tolerance and risk appetite.
6. *Control activities*—Policies and procedures to ensure risk responses are effectively implemented.
7. *Information and communication*—Identification, capture, and communication of relevant information in a form and time enabling organizational members to fulfill their responsibilities.
8. *Monitoring*—Ongoing activities or special evaluation to assess organizational risk (COSO, 2004, pp. 3–4).

Enterprise risk can include a variety of factors with potential impact on an organization's activities, processes, and resources. External factors can result from economic change, financial market developments, and dangers arising in political, legal, technological, and demographic environments. Risks can arise over time, as the public may change their views on products or practices.

Most risks are beyond the control of a given organization, although organizations can prepare and protect themselves in time-honored ways. Internal risks include human error, fraud, systems failure, disrupted production, and other risks. Often systems are assumed to be in place to detect and control risk, but inaccurate numbers are generated for various reasons. Organizations of all types need robust, reliable systems to control risks that arise in all facets of life. Table 1.1 describes the differences between ERM and traditional risk management.

Tools of risk management can include creative risk financing solutions, blending financial, insurance, and capital market strategies. Capital market instruments include catastrophe bonds, risk exchange swaps, derivatives/options, catastrophe equity puts (cat-e-puts), contingent surplus notes, collateralized debt obligations, and weather derivatives.

Types of Risk

Risks can be viewed as threats, but businesses exist to cope with specific risks. Thus, if they encounter a risk that they are specialists in dealing with, the encounter is viewed as an opportunity. Risks have been categorized into five groups:

1. *Opportunities*—Events presenting a favorable combination of circumstances giving rise to the chance for beneficial activity.
2. *Killer risks*—Events presenting an unfavorable combination of circumstances leading to hazard or major loss or damage resulting in permanent cessation of operations.
3. *Other perils*—Events presenting an unfavorable combination of circumstances leading to hazard of loss or damage leading to disruption of operations with possible financial loss.
4. *Cross-functional risks*—Common risks leading to potential loss of reputation.
5. *Business process unique risks*—Risks occurring within a specific operation or process, such as withdrawal of a particular product for quality reasons.

Opportunities should be capitalized upon in most circumstances. Not taking advantage of opportunities leads to the growth of competitors, and thus increases risk. If opportunities are pursued, enterprise strategy can be modified to manage the particular risks involved. Killer risks are threats to enterprise survival and call for continuous risk treatment, monitoring, and reporting. The other perils require analysis to assess ownership, treatment, residual risk, measurement, and reporting.

A Framework for Risk Management

Risk management frameworks are designed to enable organizations to systematically cope with these risks. One enterprise operational framework is given below:

Step 1: Establish a risk management framework

This step involves identifying, evaluating, exploiting, financing, and monitoring risk events with the intent of focusing on value of the enterprise. It is related to the establishment of strategic objectives. Top management is responsible to direct and set controls after consulting with stakeholders, and constantly monitor operations with the intent of reducing risk and prioritizing strategic risks. It is often found beneficial to appoint a chief risk officer as a risk management champion.

Step 2: Risk requirements

The intent is to understand organizational internal and external key stakeholders and their objectives and strategies with respect to risk. Establishment of risk requirements includes assessment to include analysis and evaluation. Required data needs to be identified, along with the reason for collecting it. Risk exposure is measured through risk models. Two broad measures in enterprise risk management are solvency- and performance-related. Solvency-related measures focus on financial measures such as value at risk and shortfall risk. Performance-related risk includes cause and effect models to assess the effect of decisions, such as pro forma projections contingent upon some hazardous event occurring.

Step 3: Identify the flow of information

Threats and opportunities need to be reported. An accurate and detailed flowchart of information flow as well as the software and hardware needed by each department or location is needed, along with identification of skilled personnel required to operate them.

Step 4: Feasibility analysis

Alternative means of obtaining risk management software should be identified. The cost of the proposed system is estimated, along with system purpose and users. The ability to cope with increased workload also needs to be considered.

Step 5: Buy or lease

After feasibility analysis, decisions need to be made. There are many companies offering customized packages for specific aspects of risk management, including financial management, insurance risk, project risk, and risks in specific industries.

After risks are treated, residual reporting of treatment effectiveness is needed, monitoring the effectiveness of treatments.

Risk Context and Drivers

Supply chains can be viewed as consisting of primary and secondary levels. The primary level chain involves those that have major involvement in the delivery of goods and services (Wal-Mart itself and its suppliers). At the secondary level participants have a more indirect involvement (those who supply vendors who have contracts with Wal-Mart, or Wal-Mart's customers). The primary level participants are governed by contractual relationships, obviously tending to be more clearly stated. Risk drivers can arise from the external environment, from within an industry, from within a specific supply chain, from specific partner relationships, or from specific activities within the organization.

Risk drivers arising from the external environment will affect all organizations and can include elements such as the potential collapse of the global financial system, or wars. Industry-specific supply chains may have different degrees of exposure to risks. A regional grocery will be less impacted by recalls of Chinese products involving lead paint than will those supply chains carrying such items. Supply chain configuration can be the source of risks. Specific organizations can reduce industry risk by the way they make decisions with respect to vendor selection. Partner-specific risks include consideration of financial solvency, product quality capabilities, and compatibility and capabilities of vendor information systems. The last level of risk drivers involves internal organizational processes in risk assessment and response and can be improved by better equipping and training of staff and improved managerial control through better information systems.

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Risk Management Influencers

This level involves actions taken by the organization to improve its risk position. The organization's attitude toward risk will affect its reward system, and mold how individuals within the organization will react to events. This attitude can be dynamic over time, responding to organizational success or decline.

Decision Makers

Individuals within the organization have risk profiles. Some humans are more risk averse, others more risk seeking. Different organizations have different degrees of group decision-making. More hierarchical organizations may isolate specific decisions to particular individuals or offices, while flatter organizations may stress greater levels of participation. Individual or group attitudes toward risk can be shaped by their recent experiences, as well as by the reward and penalty structure used by the organization.

Risk Management Responses

Each organization must respond to risks, but there are many alternative ways in which the process used can be applied. Risk must first be identified. Monitoring and review require measurement of organizational performance. Once risks are identified, responses must be selected. Risks can be mitigated by an implicit tradeoff between insurance and cost reduction. Most actions available to organizations involve knowing what risks the organization can cope with because of their expertise and capabilities, and which risks they should outsource to others at some cost. Some risks can be dealt with, others avoided.

Performance Outcomes

Organizational performance measures can vary widely. Private for-profit organizations are generally measured in terms of profitability, short-run and long-run. Public organizations are held accountable in terms of effectiveness in delivering services as well as the cost of providing these services. Kleindorfer and Saad gave eight key drivers of disruption/risk management in supply chains (Kleindorfer & Saad, 2005).

Corporate image	Regulatory compliance
Liability	Community relations
Employee health and safety	Customer relations
Cost reduction	Product improvement

In normal times, there is more of a focus on high returns for private organizations and lower taxes for public institutions. Risk events can make their preparation in dealing with risk exposure much more important, focusing on survival.

Risk Categories within Supply Chains

Supply chains involve many risks. Cucchiella and Gastaldi (Cucchiella & Gastaldi, 2006) divided supply chain risks into two categories: internal (involving such issues as capacity variations, regulations, information delays, and organizational factors) and external (market prices, actions of competitors, manufacturing yield and costs, supplier quality, and political issues). Specific supply chain risks considered by various studies are given in Table 1.1.

Supply chain organizations thus need to worry about risks from every direction. In any business, opportunities arise from the ability of that organization to deal with risks. Most natural risks are dealt with either through diversification and redundancy or through insurance, both of which have inherent costs. As with any business decision, the organization needs to make a decision considering tradeoffs. Traditionally, this has involved the factors of costs and benefits. Society is more and more moving toward even more complex decision-making domains requiring consideration of ecological factors as well as factors of social equity.

Dealing with other external risks involves more opportunities to control risk sources. Some supply chains in the past have influenced political systems. Arms firms like that of Alfred Nobel come to mind, as well as petroleum businesses, both of which have been accused of controlling political decisions. While most supply chain entities are not expected to be able to control political risks like wars and regulations, they do have the ability to create environments leading to labor unrest.

Supply chain organizations have even greater expected influence over economic factors. While they are not expected to be able to control exchange rates, the benefit of monopolies or cartels is their ability to influence prices. Business organizations also are responsible to develop technologies to provide competitive advantage, and to develop product portfolios in dynamic markets with product life cycles. The risks arise from never-ending competition.

Internal risk management is more directly the responsibility of the supply chain organization and its participants. Any business organization is responsible for the management of financial, production, and structural capacities. They are responsible for programmes to provide adequate workplace safety, which has proven to be cost-beneficial to organizations as well as fulfilling social responsibilities. Within supply chains, there is a need to coordinate activities with vendors, and to some degree with customers (supported by data obtained through bar-code cash register information providing instantaneous indication of demand). Information systems technology provides effective tools to keep on top of supply chain information exchange. Another factor of great importance is the responsibility of supply chain core organizations to manage risks inherent in the tradeoff between wider participation made possible through Internet connections (providing a larger set of potential suppliers leading to lower overall costs) with the reliability provided by long-term relationships with a smaller set of suppliers that have proven to be reliable.

Supply chains in general involve many risks. These risks also impact the logistic component of supply chains. These risks include macro factors such as natural disaster, war, and the political environment, as well as many micro factors ranging from demand, supply, factors impacting production of goods or services, financial factors, and factors affecting logistics including transportation factors (fuel, skill availability) and information flow. Ho et al (Ho et al., 2015). reviewed 14 studies through 2013 categorizing supply chain risks. Olson and Wu (2020) reviewed seven studies (four overlapping with Ho et al. 2015) through 2014 doing the same. In both of these reviews, external (macro) factors involved natural disasters, political factors, and market competitors. Internal (micro) factors involved demand, manufacturing, supply, information systems, transportation, and finance. Nakano and Lau (Nakano & Lau, 2020) examined 173 studies ranging from 2001 to 2017 in their study. Silva et al (Silva et al., 2021). added environmental risks to their model. Table 1.2 gives lists of most commonly included risks included by Ho et al. (2015) and Olson and Wu (2020) sorted by factor.

Process

A process is a means to implement a risk management plan. Cucchiella and Gastaldi outlined a supply chain risk management process (Cucchiella and Gastaldi, 2006):

- Analysis: examine supply chain structure, appropriate performance measures, and responsibilities
- Identify sources of uncertainty: focus on most important
- Examine risks: select risks in controllable sources of uncertainty

Table 1.2 Supply chain risk categories

Macro/ Micro	Source	Risks
External factors	Environmental	Climate change, flood, earthquake, diseases, epidemics
	Political system	War, terrorism, customs and regulations
	Economic	Economic downturn, wage rate inflation, labor disputes, plant fire, exchange rate fluctuation, interest rate fluctuation/inflation, consumer demand volatility, short product life, customer payment
	Competition	Price fluctuation, product obsolescence, outdated technology, substitution alternatives
Internal factors	Supply chain	Cost/pricing, financial capacity/insurance, structural capacity, lack of alternative suppliers, supplier bankruptcy
	Internal operations	Forecast accuracy, safety (accidents), agility/flexibility, on-time delivery, transportation availability, customer service, quality
	Information systems	IS breakdown/delay, integration of systems, lack of transparency, Internet security

- Manage risk: develop strategies
- Individualize most adequate real option: select strategies for each risk
- Implement.

This can be combined with a generic risk management process compatible with those provided by Manuj and Mentzer (Manuj & Mentzer, 2008):

- Risk identification
  - Perceiving hazards, identifying failures, and recognizing adverse consequences
  - Security preparation and planning
- Risk assessment (estimation) and evaluation
  - Describing and quantifying risk, estimating probabilities
  - Estimating risk significance, acceptability of risk acceptance, cost/benefit analysis
- Selection of appropriate risk management strategy
- Implementation
  - Security-related partnerships
  - Organizational adaptation
- Risk monitoring/mitigation
  - Communication and information technology security

Both of these views match the Kleindorfer and Saad risk management framework (Kleindorfer and Saad, 2005):

1. The initial requirement is to specify the nature of underlying hazards leading to risks.

2. Risk needs to be quantified through disciplined risk assessment, including establishing the linkages that trigger risks.
3. To manage risk effectively, approaches must fit the needs of the decision environment.
4. Appropriate management policies and actions must be integrated with ongoing risk assessment and coordination.

In order to specify, assess and mitigate risks, Kleindorfer and Saad proposed ten principles derived from industrial and supply chain literatures:

1. Before expecting other supply chain members to control risk, the core activity must do so internally.
2. Diversification reduces risk—in supply chain contexts, this can include facility locations, sourcing options, logistics, and operational modes.
3. Robustness to disruption risks is determined by the weakest link.
4. Prevention is better than cure—loss avoidance and preemption are preferable to fixing problems after the fact.
5. Leanness and efficiency can lead to increased vulnerability.
6. Backup systems, contingency plans, and maintaining slack can increase the ability to manage risk.
7. Collaborative information sharing and best practices are needed to identify vulnerabilities in the supply chain.
8. Linking risk assessment and quantification with risk management options is crucial to understand the potential for harm and to evaluate prudent mitigation.
9. Modularity of process and product designs as well as other aspects of agility and flexibility can provide leverage to reduce risks, especially those involving raw material availability and component supply.
10. TQM principles such as Six-Sigma give leverage in achieving greater supply chain security and reduction of disruptive risks as well as reducing operating costs.

Mitigation Strategies

There are many means available to control risks within supply chains. A fundamental strategy would be to try to do a great job in the fundamental supply chain performance measures of consistent fulfillment of orders, delivery dependability, and customer satisfaction. That basically amounts to doing a good job at what you do. Of course, many effective organizations have failed when faced with changing markets or catastrophic risks outlined in the last section as external risks. Some strategies proposed for supply chains are reviewed in Table 1.3 (Olson and Wu, 2020; Ghadger et al., 2020, Gonzalez and Zapatero et al., 2021).

Tang emphasized robustness (Tang, 2006). He gave nine robust supply chain strategies, some of which were included in Table 1.3. He elaborated on the expected

Table 1.3 Supply chain mitigation strategies

CAPACITY	Expand where you have a competitive advantage			
INVENTORY	Buffers	Safety stock	Redundant suppliers	
SOURCES	Redundant suppliers	Multiple sourcing	Drop troublesome suppliers	Avoid suppliers in countries with high geopolitical risk
IT	Increase responsiveness	Information sharing	End-to-end visibility	
INSURANCE	Hedge	Disperse globally	Take on risk	Supplier development
Increase flexibility	Product differentiation	Late product differentiation	Delay resource commitment	

Table 1.4 Tang's Robust supply chain strategies

Strategy	Purpose	Normal benefits	Disruption benefits
Strategic stock	Product availability	Better supply management	Quick response
Economic supply Incentives			Can quickly adjust order quantities
Postponement	Product flexibility		Can change product configurations quickly in response to actual demand
Flexible supply base	Supply flexibility		Can shift production among suppliers quickly
Make-and-buy			Can shift production in-house or outsource
Flexible transportation	Transportation flexibility		Can switch among modes as needed
Revenue management	Control Product demand	Better demand management	Influence customer selection as needed
Dynamic assortment planning			Can influence product demand quickly
Silent product rollover	Control product exposure	Better manage both supply and demand	Quickly affect demand

benefits of each strategy, both for normal operations as well as in dealing with major disruptions, outlined in Table 1.4, organized by purpose.

Conclusions

Enterprise risk management began focusing on financial factors. After the corporate scandals in the USA in the early 2000s, accounting aspects grew in importance. This chapter discusses the importance of risk management in the context of supply chain management.

A representative risk framework was presented. It rationally begins by identifying causes (drivers) of risk, and influencers within the organization. Those responsible for decision-making are identified, and a process is outlined where risks, responses, and measures of outcomes are included.

There have been many cases involving supply chain risk management reported recently. Some were briefly reviewed, along with quantitative modeling. Typical risks faced by supply chains were extracted from sources and categorized. A process of risk identification, assessment, strategy development and selection, implementation, and monitoring is reviewed. Representative mitigation strategies were extracted from published sources.

Chap. 2 addresses the enterprise risk management process, describing the use of risk matrices. Chap. 3 describes value-focused supply chain risk analysis, with examples demonstrated in Chap. 4. Chap. 5 provides simulation modeling of supply chain inventory. Chap. 6 deals with value at risk, Chap. 7 with chance-constrained modeling, Chap. 8 with data envelopment analysis, and Chap. 9 with data mining from the perspective of enterprise risk management. Chap. 10 concludes the methods section of the book with balanced scorecards as tools to monitor implementation of risk management efforts. Domain-specific issues for machine learning and artificial intelligence are discussed in Chap. 11, for project management in Chap. 12, natural disaster response in Chap. 13, sustainability risk management in Chap. 14, and environmental damage and risk assessment in Chap. 15.

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2 Risk Matrices

There is no doubt that risk management is an important and growing area in this uncertain world. Chapter 1 discussed a number of recent events where events made doing business highly challenging. Globalization offers many opportunities, but it also means less control, operating in a wider world where the actions of others intersect with our own. This chapter looks at the enterprise risk management process, focusing on means to assess risks.

The Committee of Sponsoring Organizations of the Treadway Commission (COSO) is an accounting organization concerned with enterprise risk management (ERM). They define ERM as a process designed to identify potential events that may affect organizations and manage risk to be within that organization's risk appetite in order to provide reasonable assurance of accomplishing the organization's objectives (Prasad, 2011). Risk identification and mitigation are key components of an organization's ERM programme. Table 2.1 outlines this risk framework.

Risk Management Process

An important step is to set the risk appetite for the organization. No organization can avoid risk nor should they insure against every risk. Organizations exist to take on risks in areas where they have developed the capability to cope with risk. However, they cannot cope with every risk, so top management needs to identify the risks they expect to face and to identify those risks that they are willing to assume (and profit from successfully coping). A risk management process might consist of:

- Risk identification
- Risk assessment and evaluation
- Selection of risk management strategy
- Implementation
- Risk monitoring/mitigation

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Table 2.1 COSO risk management framework

Components	Principles
Control environment	Commitment to integrity and ethical values
	Exercise oversight
	Establish structure, authority, and responsibility
	Demonstrate commitment to competence
	Enforce accountability
Risk assessment	Specify suitable objectives
	Identify and analyze risk
	Assess fraud risk
	Identify and analyze significant change
Control	Select and develop control activities
	Select and develop controls over technology
	Deploy control through policies and procedures
Information and Communication	Use relevant information
	Communication internally
	Communicate externally
Monitoring	Conduct ongoing evaluation
	Evaluate and communicate deficiencies

The risk identification process needs to consider risks of all kinds. Typically, organizations can expect to encounter risks of the following types:

- Strategic risk
- Operations risk
- Legal risk
- Credit risk
- Market risk

Examples of these risks are outlined in Table 2.2.

Each manager should be responsible for ongoing risk identification and control within their area of responsibility. Once risks are identified, a risk matrix can be developed. Risk matrices will be explained in the next section. The risk management process is the control aspect of those risks that are identified. The adequacy of this process depends on assigning appropriate responsibilities by role for implementation. Effectiveness can be monitored by a risk-screening committee at a high level within the organization that monitors new significant markets and products. The risk review process includes a systematic internal audit, often outsourced to third-party providers responsible for ensuring that the enterprise risk management structure functions as designed. One tool to aid in risk assessment and evaluation is a risk matrix.

Table 2.2 Enterprise risk management framework

Strategic risks	Is there a formal process to identify potential changes in markets, economic conditions, regulations, and demographic change impacts on the business? Is new product innovation considered for both short- and long-run impact? Does the firm's product line cover the customer's entire financial services experience? Is research and development investment adequate to keep up with competitor product development? Are sufficient controls in place to satisfy regulatory audits and their impact on stock price?
Operations risks	Does the firm train and encourage use of rational decision-making models? Is there a master list of vendor relationships, with assurance each provides value? Is there adequate segregation of duties? Are there adequate cash and marketable securities controls? Are financial models documented and tested? Is there a documented strategic plan for technology expenditures?
Legal risks	Are patent requirements audited to avoid competitor abuse as well as litigation? Is there an inventory of legal agreements and auditing of compliance? Do legal agreements include protection of customer privacy? Are there disturbing litigation patterns? Is action taken to assure product quality sufficient to avoid class action suits and loss of reputation?
Credit risks	Are key statistics monitoring credit trends sufficient? How are settlement risks managed? Is there sufficient collateral to avoid deterioration of value? Is the incentive compensation programme adequately rewarding loan portfolio profitability rather than volume? Is exposure to foreign entities monitored, as well as domestic entity exposure to foreign entities?
Market risks	Is there a documented funding plan for outstanding lines? Are asset/liability management model assumptions analyzed? Is there a contingency funding plan for extreme events? Are core deposits analyzed for price and cash flow?

Risk Matrices

A risk matrix provides a two-dimensional (or higher) picture of risk, either for firm departments, products, projects, or other items of interest. It is intended to provide a means to better estimate the probability of success or failure and identify those activities that would call for greater control. One example might be for product lines, as shown in Table 2.3.

The risk matrix is meant to be a tool revealing the distribution of risk across a firm's portfolio of products, projects, or activities, and assigning responsibilities or mitigation activities. In Table 2.3, hedging activities might include paying for insurance, or in the case of investments, using short-sale activities. Internal controls would call for extra managerial effort to quickly identify adverse events and take action (at some cost) to provide greater assurance of acceptable outcomes.

Table 2.3 Product risk matrix

	Likelihood of risk low	Likelihood of risk medium	Likelihood of risk high
Level of risk high	Hedge	Avoid	Avoid
Level of risk medium	Control internally	Hedge	Hedge
Level of risk low	Accept	Control internally	Control internally

	Negligible	Minor	Major	Hazard	Catastrophic
Extremely improbable	A	A	A	A	A
Improbable	T	T	T	A	A
Remote	I	T	T	T	A
Occasional	I	I	T	T	T
Frequent	I	I	I	T	T

Fig. 2.1 Dudek et al. (2020) risk matrix

A risk management process was applied by Dudek et al. (2020). Their process consisted of hazard identification, risk analysis, and risk evaluation. Hazard identification was accomplished through brainstorming, using checklists, and interviews supplemented through the Delphi method. Risk analysis was supported by analysis of cause and effect, event tree analysis, and Markov probability modeling. Risk evaluation modeling included use of decision trees, Bayesian statistics and Bayesian nets, and Monte Carlo simulation. The risk matrix (Fig. 2.1) focusing on air traffic safety consisted of risk probability levels:

1. Extremely improbable—inconceivable of occurring
2. Improbable—unlikely or not known to have occurred
3. Remote—unlikely but possible, or rarely occurred
4. Occasional—likely to occur or has occurred infrequently
5. Frequent—likely to occur many times

Risk severity categories consisted of the following categories:

1. Negligible—no influence on safety, little consequence
2. Minor—inconsiderable influence on safety
3. Major—significant threat to safety
4. Hazardous—serious safety threat involving human injury or damage to equipment
5. Catastrophic—huge safety threat, multiple deaths, or equipment destruction

The mitigating actions to be taken were:

Table 2.4 Product/technology risk assessment

	1—Fully experienced	2	3—Significant change	4	5—No experience	Score
Current development capability			X			3
Technological competency		X				2
Intellectual property protection				X		4
Manufacturing and service delivery system	X					1
Required knowledge			X			3
Necessary service		X				2
Expected quality			X			3
Total						18

Table 2.5 Product/technology failure risk assessment

	1—Same as present	2	3—Significant change	4	5—Completely different	Score
Customer behavior				X		4
Distribution and sales			X			3
Competition					X	5
Brand promise					X	5
Current customer relationships					X	5
Knowledge of competitor behavior				X		4
Total						26

A—acceptable, implying no action
T—tolerable – further analysis and management decision required
I—intolerable – calling for risk management or stopping activity

Their risk matrix is shown in Fig. 2.1.

Evaluation of both scales, historical data can be used to calibrate the prediction of product success. Scaled measures for product/technology risk could be based on expert product manager evaluations as demonstrated in Table 2.4 for a proposed product, with higher scores associated with less attractive risk positions.

Table 2.5 demonstrates the development of risk assessment of the intended market.

Table 2.6 combines these scales, with risk assessment probabilities that should be developed by expert product managers based on historical data to the degree possible.

Table 2.6 Innovation product risk matrix—expert success probability assessments

	Failure <10	Failure 10–15	Failure 15–20	Failure 20–25	Failure 25–30
Technology 30–35	0.50	0.40	0.30	0.15	0.01
Technology 25–30	0.65	0.50	0.45	0.30	0.05
Technology 20–25	0.75	0.60	0.55	0.45	0.20
Technology 15–20	0.80	0.70	0.65	0.55	0.30
Technology 10–15	0.90	0.85	0.80	0.65	0.45
Technology <10	0.95	0.90	0.85	0.70	0.60

In Table 2.6, the combination of a technology risk score of 18 with a product failure risk score of 26 is in bold, indicating a risk probability assessment of 0.30.

Color Matrices

Risk matrices have been applied in many contexts. McIlwain (McIlwain, 2006) cited the application of clinical risk management in the UK arising from the National Health Service Litigation Authority creation in April 1995. This triggered a systematic analysis of incident reporting on a frequency/severity grid comparing likelihood and consequence. Traffic light colors are often used to categorize risks into three (or more) categories, quickly identifying combinations of frequency and consequence calling for the greatest attention. Table 2.7 demonstrates the use of a risk matrix that could be based on historical data, with green assigned to a proportion of cases with serious incident rates below some threshold (say 0.01), red for high proportions (say 0.10 or greater), and amber in between.

While risk matrices have proven useful, they can be misused as can any tool. Cox (Cox Jr., 2008) provided a critique of some of the many risk matrices in use. Positive examples were shown from the Federal Highway Administration for civil engineering administration (Table 2.8), and the Federal Aviation Administration applied to airport operation safety. The Federal Aviation Administration risk matrix was quite similar but used qualitative terms for the likelihood categories (frequent, probable, remote, extremely remote, and extremely improbable) and severity categories (no safety effect, minor, major, hazardous, and catastrophic).

There have been many criticisms of color risk matrices, focusing on the following issues:

- Inconsistency between risk matrices and quantitative measures (the column and row cutoffs are essentially arbitrary).
- Subjective classification in color matrices.

Table 2.7 Risk matrix of medical events

	Consequence insignificant	Consequence minor	Consequence moderate	Consequence major	Consequence catastrophic
Likelihood almost certain	Amber	Red	Red	Red	Red
Likelihood likely	Green	Amber	Red	Red	Red
Likelihood possible	Green	Amber	Amber	Amber	Red
Likelihood unlikely	Green	Green	Amber	Amber	Red
Likelihood rare	Green	Green	Green	Amber	Amber

Table 2.8 Risk matrix for Federal Highway Administration (2006)

	Very low impact	Low impact	Medium impact	High impact	Very high impact
Very high probability	Green	Yellow	Red	Red	Red
High probability	Green	Yellow	Red	Red	Red
Medium probability	Green	Green	Yellow	Red	Red
Low probability	Green	Green	Yellow	Red	Red
Very low probability	Green	Green	Green	Yellow	Red

Extracted from Cox (2008)

- Scaling of categories—Levine suggested that scales in risk matrices are often more appropriately logarithmically scaled rather than linear (Levine, 2012).
- Limited resolution often results in risk level ties.
- Use of a matrix across an organization, often in different contexts.

Some problems arise because inevitably different risk assessors will assign different ratings to the same hazard. It has been found that even after lengthy reflection, a great degree of scatter remains, due to fundamentally different beliefs and world views (Ball & Watt, 2013).

Cox identified some characteristics that should be present in risk matrices:

1. Under weak consistency conditions, no red cell should share an edge with a green cell.
2. No red cell can occur in the left column or in the bottom row.
3. A line from a green cell to a red cell must pass through a yellow cell.
4. There must be at least three colors.
5. Too many colors give spurious resolution.

Note that Table 2.8 violated characteristics 2 and 3.

Cox argued that risk ratings do not necessarily support good resource allocation decisions. This is due to the inherently subjective categorization of uncertain consequences. Thus, Cox argues that the theoretical results he presented demonstrate that quantitative and semiquantitative risk matrices (using numbers instead of categories) cannot correctly reproduce risk ratings, especially if frequency and severity are negatively correlated.

Quantitative Risk Assessment

It would be ideal to go deeper than risk matrices allow, to be able to identify the costs and benefits of risk actions. Risk matrices are simple and useful tools because most of the time, detailed cost and probability data is not available. However, if such data is available, more accurate risk assessment is possible (Cox Jr., 2012).

Risk can be characterized by the attributes of threat, vulnerability, and consequence, each of which can be expressed in terms of probability. Each of these is uncertain, and in fact these three aspects of risk may be correlated. A normative argument is that if these measures are important but are not known, the organization should invest in obtaining them. Levine demonstrated risk management of computer network security with an example comparing different types of attack in terms of frequency, consequence, and risk. Table 2.9 provides hypothetical data.

In Table 2.9, risk is defined as the product of frequency and consequence, a common approach. The risk matrix in this case can overlay treatments with cells, as in Table 2.10.

In this case, the most attention would be given to identity theft. The others either are relatively low consequence (web vandalism) or relatively low frequency (cyber espionage, denial of service). Looking at the quantitative scale of risk, a bit different outcome is obtained, with cyber espionage and identity theft both being very high, closely followed by denial of service. Web vandalism is lower on this scale. Generally, moving to a more quantitative metric is preferable, with the trade-off of requiring more data with accuracy an important factor.

To demonstrate, assume the context of a construction firm with a portfolio of ten jobs, involving some risk to worker safety. The firm has a safety programme that can be applied to reduce some of these risks to varying degrees on each job. Cox addressed four different levels of risk evaluation, depending upon the level of data

Table 2.9 Hypothetical computer network security data

Attack type	Label	Frequency	Consequence	Risk
Cyber espionage	CE	10^2 per year	\$$10^7$ per event	\$$10^9$ per year
Denial of service	DS	10^2 per year	\$$10^6$ per event	\$$10^8$ per year
Identity theft	IT	10^4 per year	\$$10^5$ per event	\$$10^9$ per year
Web vandalism	WV	10^3 per year	\$$10^2$ per event	\$$10^5$ per year

Table 2.10 Risk matrix for computer network security

	Consequence <\$$10^3$/event	Consequence \$$10^3$–≤ \$$10^5$/event	Consequence ≥\$$10^6$/event
Frequency > 10^3 per year	Green	Amber IT	Red
Frequency > 10^2–10^3 per year	Green WV	Amber	Amber
Frequency ≤ 10^2 per year	Green	Green	Green CE DS

Table 2.11 Hypothetical construction data

Job	Liability risk (k$)	Prob {injury} (frequency)	Expected loss (risk)	Reducible	Savings (k$)	Cost of reducing	RRPUC
1	250	0.30	75.0	0.7	52.50	25	2.100
2	300	0.20	60.0	0.5	30.00	20	1.500
3	320	0.15	48.0	0.6	28.80	25	1.152
4	340	0.20	68.0	0.3	20.40	15	1.360
5	370	0.11	40.7	0.5	20.35	20	1.018
6	410	0.18	73.8	0.6	44.28	25	1.771
7	440	0.33	145.2	0.4	58.08	20	2.904
8	460	0.25	115.0	0.7	80.50	30	2.683
9	480	0.20	96.0	0.5	48.00	20	2.400
10	530	0.08	42.4	0.4	16.96	18	0.942

Table 2.12 Hypothetical risk matrix

	Liability risk low	Liability risk medium	Liability risk high
Prob{injury} high	Assign safety	Assign safety	Subcontract
Prob{injury} medium	Insurance only	Assign safety	Assign safety
Prob{injury} low	Insurance only	Insurance only	Assign safety

available. The risk matrices that we have been looking at require little quantitative data, although as we have demonstrated in Table 2.6, they are more convincing if they are based on quantitative input. Table 2.11 provides full raw data for the ten construction jobs.

In Table 2.11, column 2 is the potential liability due to injury in thousands of dollars. Column 3 is the probability of an injury if no special safety improvement is undertaken. Column 4 is the product of column 2 and column 3, the expected loss without action. Column 5 is the proportion of the injury probability that can be reduced by proposed action, which leads to savings in column 6 (the product of column 4 and column 5). Column 7 is the amount of budget that would be needed to reduce risk. Column 8 (RRPUC) is the risk reduction per unit cost.

Table 2.12 gives the risk matrix in categorical terms, using the dimensions of probability of injury {below 0.19; 0.20–0.25; 0.26 and above} and liability risk {below 399; 400–599; 600 and above}.

For each combination of injury probability and risk liability risk a mitigation strategy is assigned. Insurance is obtained in all cases (even for subcontracting). Assigning extra safety personnel costs additional expenses. Subcontracting sacrifices quite a bit of expected profit, and thus is to be avoided except in extreme cases. Table 2.12 demonstrates what Cox expressed as a limitation in that while the risk matrix is quick and easy, it is a simplification that can be improved upon. Cox suggested three indices, each requiring additional accurate inputs.

The first index is to use risk (the expected loss column in Table 2.11), the second risk reduction (savings column in Table 2.11), and the third the risk reduction per

Table 2.13 Ranking by index

Risk index ranking	Budget (k$)	Risk reduction index ranking	Budget (k$)	RRPUC ranking	Budget (k$)
Job 7	20	Job 8	30	Job 7	20
Job 8	30	Job 7	20	Job 8	30
Job 9	20	Job 1	25	Job 9	20
Job 1	25	Job 9	20	Job 1	25
Job 6	25	Job 6	25	Job 6	25
Job 4	15	Job 2	20	Job 2	20
Job 2	20	Job 3	25	Job 4	15
Job 3	25	Job 4	15	Job 3	25
Job 10	18	Job 5	20	Job 5	20
Job 5	20	Job 10	18	Job 10	18

Table 2.14 Risk reductions achieved by index

Budget	Risk index	Risk reduction index	RRPUC
$100 k	247.936	247.936	247.936
$150 k	326.260	324.880	326.961

unit cost (RRPUC column in Table 2.11). These would yield different rankings of which jobs should receive the greatest attention. In all three cases, the contention is that there is a risk reduction budget available to be applied, starting with the top-ranked job and adding jobs until the budget is exhausted. Table 2.13 shows rankings and budget required for job.

If there were a budget of $100 k, using the risk ranking jobs 7, 8, 9, and 1 would be given extra safety effort, as well as a 20% effort on job 6. With the risk reduction index as well as the RRPUC index, a different order of selection would be applied, here yielding the same set of jobs. For a budget of $150 k, the risk index would provide full treatment to job 6, add job 4, and 75% of job 2. The risk reduction index would also provide full treatment to job 6, add job 2, and provide 40% coverage to job 3. The RRPUC index also would again provide full treatment to job 6, add job 2, and 2/3rds coverage to job 4. The idea of all three indices is much the same, but with more information provided. Table 2.14 shows the expected gains from these two budget levels for each index.

Given a budget of $100 k, the risk index would reduce expected losses by $58.08 k on job 7, $80.50 k on job 8, $48 k on job 9, $52.50 k on job 1, and $8.856 k on job 6, for total risk reduction of $247.936 k. As we saw, this was the same for all three indices. But there is a difference given a budget of $150 k. Here the risk index actually comes out a bit higher than the risk reduction index, but Cox has run simulations showing that risk reduction should provide a bit better performance. The RRPUC has to be at least as good as the other two, as its basis is the sorting key. The primary point is that there are ways to incorporate more complete information into risk management. The trade-off is between the availability of information and accuracy of output.

Strategy/Risk Matrix

Risk matrices can be applied to capture the essence of trade-offs in risk and other measures of value. In this case, we apply a risk matrix to a construction industry study where the original authors applied an analytic hierarchy model (Ferreira et al., 2015). The model is relatively straightforward. The construction context included a number of types of work, each with a relative rating of supply risk along with a similar weighting of strategic impact. Data is given in Table 2.15.

Construction contexts could differ widely, but we will assume an operation where the greatest profit is expected from conducting operations normally. Risk can be reduced by spending extra money in the form of added inspection and safety supervisors, but this would eat into profit. The least profit would be expected from an option to outsource construction, placing the risk on subcontractors. The criteria can be sorted in a risk matrix considering both dimensions, as in Table 2.16.

Table 2.15 Construction work risk and impact

Type	Supply risk	Strategic impact
Cement	0.05	0.34
Workforce	0.09	0.40
Aggregate	0.11	0.58
Transport	0.12	0.18
Demolition	0.12	0.38
Painting	0.15	0.25
Misc.	0.15	0.28
Steel	0.15	0.65
Insulation	0.16	0.18
Travel	0.17	0.29
Cast iron	0.18	0.23
Excavation	0.20	0.26
Locksmith	0.21	0.36
Floor cover	0.22	0.23
Infrastructure	0.23	0.58
Sanitary	0.23	0.70
Ceilings	0.25	0.24
Geotechnical	0.25	0.29
Electrical	0.25	0.57
Climate	0.26	0.34
Aluminum	0.31	0.24
Formwork	0.31	0.31
Concrete	0.46	0.92
Mosaic	0.51	0.26
Carpentry	0.54	0.24
Special forming	0.56	0.31
Stone	0.59	0.24
Scaffolding	0.62	0.29

Table 2.16 Risk matrix of risk/strategic impact trade-off

	Supply risk ≤ 0.2	Supply risk >0.2 to ≤0.5	Supply risk >0.5 to ≤0.8	Supply risk >0.8
Strategic impact >0.8	Add risk control	Outsource	Outsource	Outsource
Strategic impact >0.5 to ≤0.8	Add risk control	Add risk control	Outsource	Outsource
Strategic impact >0.2 to ≤0.5	Normal operation	Normal operation	Add risk control	Outsource
Strategic impact ≤ 0.2	Normal operation	Normal operation	Normal operation	Add risk control

In this case, this policy would result in outsourcing (subcontracting) concrete work, which has a supply risk rating of 0.46 and a very high strategic impact of 0.92. Added risk control would be adopted for ten other types of work: aggregate, steel, infrastructure, sanitary, electrical, mosaic, carpentry, special forming and scaffolding, and stone.

Risk-Adjusted Loss

It is better to be quantitative than qualitative—but the problem is that data is not always available. But Monat and Doremus (Monat & Doremus, 2020) have presented a risk-adjusted index approach with the following steps:

- Identify risks.
- Assign quantitative values for probability and dollar impact to each risk (subjective).
- Estimate the organization's or individual's risk tolerance using rule-of-thumb.
- Calculate Risk-Adjusted Loss (RAL formula below).
- Prioritize risks from highest RAL to lowest.

The formula for RAL is:

$$RAL = (PxI)\left[1 + \frac{I(1-P)}{2RT}\right]$$

Monat and Doremus (Monat & Doremus, 2018) include variance in the above formulation. RAL essentially adds a risk factor to the expected value based on their formulation of variance and risk aversion. Risk tolerance tries to reflect the organization's ability to absorb risk. The larger the organization, the greater its ability to absorb risk. A rule-of-thumb for risk-averse companies would be to multiply net income by 1.24 (there are other rules- of-thumbs). To demonstrate,

Table 2.17 Table of expected losses

	Impact insignificant 10,000	Impact minor 100,000	Impact moderate 500,000	Impact major 1,000,000	Impact catastrophic 10,000,000
Probability 0.95	9500	95,000	475,000	950,000	9,500,000
Probability 0.7	7000	70,000	350,000	700,000	7,000,000
Probability 0.4	4000	40,000	200,000	400,000	4,000,000
Probability 0.2	2000	20,000	100,000	200,000	2,000,000
Probability 0.01	100	1000	5000	10,000	100,000

Table 2.18 Table of RAI

	Impact insignificant 10,000	Impact minor 100,000	Impact moderate 500,000	Impact major 1,000,000	Impact catastrophic 10,000,000
Probability 0.95	9502	95,192	479,788	969,153	11,415,323
Probability 0.7	7008	70,847	371,169	784,677	15,467,742
Probability 0.4	4010	40,968	224,194	496,774	13,677,419
Probability 0.2	2006	20,645	116,129	264,516	8,451,613
Probability 0.01	100	1040	5998	13,992	499,194

consider Table 2.7 redone in terms of assessment of impact and probability in Table 2.17, showing expected losses as P x I.

This approach could make it easier to set the color limits. For instance, expected loss above \$450,000 might call for red, below \$60,000 green, and in between amber. This would vary a bit from the verbal limits given in Table 2.7, where the $P = 0.95$ Impact = Insignificant was assigned amber classification, but in Table 2.17 you can see that very little expected loss was expected. The same for $P = 0.01$ Impact Major. The red categories were similar except that $P = 0.95$ Impact Minor was here classified as Amber, as was $P = 0.7$ Impact Moderate, while they were red in

Table 2.17. With expected losses, it is less likely to get inversions of categories (although just because you quantify an estimate does not mean that you have removed all subjectivity). To apply the formula, assume an organization with a net income of 1,000,000 per year, making RT = 1,240,000. Table 2.18 gives the risk-adjusted losses for the expected losses in Table 2.17.

The formula seems to have an anomaly for high P and high I, with an inversion. This occurs because the high impact value of 10,000,000 overwhelms the RT of

Table 2.19 New cases

Probability	Impact	Expected loss	RAI	Rank
0.65	4,000,000	2,600,000	4,067,742	3
0.15	6,000,000	900,000	2,750,806	4
0.25	8,000,000	2,000,000	6,838,710	1
0.40	5,000,000	2,000,000	4,419,355	2
0.90	1,000,000	900,000	936,290	5

1,240,000, making the latter component of the formula negative. Thus there is an interesting phenomenon in the formula for high *P* and high *I*, but in reality, such cases would easily be considered high risk, and firms should be wary of taking on risks greater than twice their annual income. Further, the formula yields drastic increases over an expected loss when the Impact is 10,000,000. Not only is the inversion there for high probability, the extremely low probability outcome turns red (which might be appropriate for catastrophic loss).

Monat and Doremus also suggest using their formula to rank order new risks. For a new case with an estimated probability of 0.65 and an estimated impact of \$4,000,000, the RAI would be 2,884,375, definitely in the red zone. If a portfolio of five new projects were being considered with the estimates given in Table 2.19 (along with the RT of 1,240,000 used above), the RAI could provide a basis for ranking relative risks.

Note that the expected loss for cases 4 and 5 was the same, but the RAI is much greater for case 3, which ranked highest in risk of the five cases. Based on the expected loss, case 1 was the riskiest. Based on RAI, cases 3 and 4 are both rated riskier than case 1. Consideration of risk aversion is a valid approach but does require some assumptions just as any quantitative model.

Conclusions

The study of risk management has grown in the last decade in response to serious incidences threatening trust in business operations. The field is evolving, but the first step is generally considered to be the application of a systematic process, beginning with consideration of the organization's risk appetite. The risks facing the organization need to be identified, controls generated, and a review of the risk management process along with historical documentation and records for improvement of the process.

Risk matrices are a means to consider the risk components of threat severity and probability. They have been used in a number of contexts, basic applications of which were reviewed. Cox and Levine provide useful critiques of the use of risk matrices. That same author also suggested more accurate quantitative analytic tools. An ideal approach would be to expend such measurement funds only if they enable reducing overall cost. The interesting aspect is that we do not really know. Thus we would argue that if you have accurate data (and it is usually worth measuring whatever you can), you should get as close to this ideal as you can. Risk matrices provide valuable initial tools when high levels of uncertainty are present. Quantitative risk assessment in the form of indices as demonstrated would be preferred if data to support it is available.

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Value-Focused Supply Chain Risk Analysis

3

A fundamental premise of Keeney's book (Keeney, 1992) is that decision makers should not settle for those alternatives that are thrust upon them. The conventional solution process is to generate alternative solutions to a problem, and then focus on objectives. This framework tends to suppose an environment where decision makers are powerless to do anything but choose among given alternatives. It is suggested that a more fruitful approach would be for decision makers to take more control over this process, and use objectives to create alternatives, based on what the decision makers would like to achieve, and why objectives are important.

Hierarchy Structuring

Structuring translates an initially ill-defined problem into a set of well-defined elements, relations, and operations. This chapter is based on concepts presented in Keeney, and in Olson (Olson, 1996a).

Before we discuss hierarchies and their structure, we should give some basic definitions. Keeney and Raiffa (Keeney & Raiffa, 1976) gave the following definitions:

Objective—the preferred direction of movement on some measure of value.
Attribute—a dimension of measurement.

Keeney and Raiffa distinguish between utility models, based upon tradeoffs of return and risk found in von Neumann-Morgenstern utility theory and the more general value models allowing tradeoffs among any set of objectives and sub-objectives. Preferential independence concerns whether the decision maker's preference among attainment levels on two criteria do not depend on changes in other attribute levels. Attribute independence is a statistical concept measured by correlation. Preferential independence is a property of the desires of the decision maker, not the alternatives available.

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The simplest hierarchy would involve VALUE as an objective with available alternatives branching from this VALUE node. Hierarchies generally involve additional layers of objectives when the number of branches from any one node exceeds some certain value. Cognitive psychology has found that people are poor at assimilating large quantities of information about problems. Saaty used this concept as a principle in analytic hierarchy development, calling for a maximum of seven branches in any one node in the analytic hierarchy process (AHP) (Saaty, 1988).

Desirable characteristics of hierarchies given by Chap. 2 of Keeney and Raiffa (1976) include:

Completeness—Objectives should span all issues of concern to the decision maker, and attributes should indicate the degree to which each objective is met.

Operability—Available alternatives should be characterized in an effective way.

Decomposability—Preferential and certainty independence assumptions should be met.

Lack of Redundancy—There should not be overlapping measures.

Size—The hierarchy should include the minimum number of elements necessary.

Keeney and Saaty both suggest starting with identification of the overall fundamental objective. In the past, business leaders would focus on profit. Keeney stated that the overall objective can be the combination of more specific fundamental objectives, such as minimizing costs, minimizing detrimental health impacts, and minimizing negative environmental impacts. For each fundamental objective, Keeney suggested the question, "Is it important?"

Subordinate to fundamental objectives are means objectives—ways to accomplish the fundamental objectives. Means objectives should be mutually exclusive and collectively exhaustive with respect to fundamental objectives. When asked "Why is it important?" means objectives would be those objectives for which a clear reason relative to fundamental objectives appears. If no clear reason other than "It just is" appears, the objective probably should be a fundamental objective. Available alternatives are the bottom level of the hierarchy, measured on all objectives immediately superior. If alternative performance on an objective is not measurable, Keeney suggests dropping that objective. Value judgments are required for fundamental objectives, and judgments about facts are required for means-ends objectives (Fig. 3.1):

Decision makers should not settle for those alternatives that are thrust upon them. The conventional solution process is to generate alternative solutions to a problem, and then focus on objectives. This framework tends to suppose an environment where decision makers are powerless to do anything but choose among given alternatives. It is suggested that a more fruitful approach would be for decision makers to use objectives to create alternatives, based on what the decision makers would like to achieve, and why objectives are important.

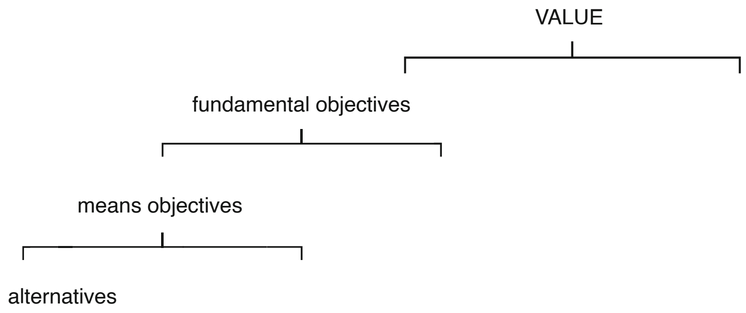

Fig. 3.1 Value hierarchy framework

Hierarchy Development Process

Hierarchies can be developed in two basic manners: top-down or bottom-up. The most natural approach is to start at the top, identifying the decision maker's fundamental objective, and developing sub-elements of value, proceeding downward until all measures of value are included (weeding out redundancies and measures that do not discriminate among available alternatives). At the bottom of the hierarchy, available alternatives can be added. It is at this stage that new and better alternatives are appropriate to consider. The top-down approach includes the following phases: (Keeney et al., 1987)

1. Ask for overall values.
2. Explain the meanings of initial value categories and interrelationships WHAT IS MEANT by this value?
   WHY IS THIS VALUE IMPORTANT?
      HOW DO AVAILABLE OPTIONS AFFECT attaining this value?
3. Get a list of concerns—as yet unstructured.

The aim of this approach is to gain as wide a spectrum of values as possible. Once they are attained, then the process of weeding and combining can begin.

The value-focused approach has been applied to supply chain risk identification (Neiger et al., 2009). Here we will present our view of value-focused analysis to a representative supply chain risk situation. We hypothesize a supply chain participant considering location of a plant to produce products for a multinational retailer. We can start looking for overall values, using the input from published sources given in Table 3.1. The first focus is on the purpose of the business—the product. Product characteristics of importance include its quality, meeting specifications, cost, and delivery. In today's business environment, we argue that service is part of the product. We represent that in our hierarchy with the concept of manufacturability and deliverability to consumer (which reflects life cycle value to the customer). The operation of the supply chain is considered next, under the phrase "management," which reflects the ability of the supply chain to communicate and to be agile in

Table 3.1 Value hierarchy for supply chain risk

Top level	Second level	Third level
Product	Quality	
	Cost	Price
		Investment required
		Holding cost/service level tradeoff
	On-time delivery	
Service	Manufacturability	Outsourcing opportunity cost/risk tradeoff
		Ability to expand production
		New technology breakthroughs
		Product obsolescence
	Deliverability	Transportation system
		Insurance cost
Management	Communication	IS breakdown
		Distorted information leading to bullwhip effect
		Forecast accuracy
		Integration
		Viruses/bugs/hackers
	Flexibility	Agility of sources
		Ability to replace sources as needed
	Safety	Plant disaster
	Labor	Risk of strikes, disputes
Political	Government	Customs and regulations
	War and Terrorism	
Economic	Overall economy	Economic downturn
		Exchange rate risk
	Specific regional economy	Labor cost influence
		Changes in competitive advantage
	Specific market	Price fluctuation
		Customer demand volatility
		Customer payment
Natural disaster		Uncontrollable disaster
		Diseases, epidemics

response to changes. There are also external risks, which we cluster into three areas of political (regulation, as well as war and terrorism), economic (overall economic climate as well as the behavior of the specific market being served), and natural disaster. Each of these hierarchical elements can then be used to identify specific risks for a given supply chain situation. We use those identified in Table 3.1 to develop a value hierarchy.

The next step in multiple attribute analysis is to generate alternatives. There are a number of decisions that might be made, including vendor selection, plant siting, information system selection, or the decision to enter specific markets by region or country. For some of these, there may be binary decisions (enter a country's market or not), or there might be a number of variants (including different degrees of entering a specific market). In vendor selection and in plant siting, there may be very many alternatives. Usually, multiple attribute analysis focuses on two to seven alternatives that are selected as most appropriate through some screening process. Part of the benefit of value analysis is that better alternatives may be designed as part of the hierarchical development, seeking better solutions performing well on all features.

Suggestions for Cases Where Preferential Independence Is Absent

If an independence assumption is found to be inappropriate, either a fundamental objective has been overlooked or means objectives are being used as fundamental objectives. Therefore, identification of the absence of independence should lead to a greater understanding of the decision maker's fundamental objectives.

Multiattribute Analysis

The next step of the process is to conduct a multiattribute analysis. There are a number of techniques that can be applied (Olson, 1996b). Multiattribute utility theory (MAUT) can be supported by software products such as Logical Decision, which are usually applied in more thorough and precise analyses. The simple multiattribute rating theory (SMART) (Edwards, 1977a) can be used with spreadsheet support and is usually the easiest method to use. Analytic hierarchy process can also be applied, as was the case in all of the cases applying multiple objective analyses. Expert Choice software is available, but allows only seven branches, so is a bit more restrictive than MAUT, and much more restrictive than SMART. Furthermore, the number of pairwise comparisons required in AHP grows enormously with the number of branches. Still, users often are willing to apply AHP and feel confident in its results (Olson et al., 1995). Here, we will demonstrate using SMART for a decision involving site selection of a plant within a supply chain.

The SMART Technique

Edwards proposed a ten-step technique. Some of these steps include the process of identifying objectives and organization of these objectives into a hierarchy. Guidelines concerning the pruning of these objectives to a reasonable number were provided.

Step 1: Identify the person or organization whose utilities are to be maximized Edwards argued that MAUT could be applied to public decisions in the same manner as was proposed for individual decision-making.

Step 2: Identify the issue or issues Utility depends on the context and purpose of the decision.

Step 3: Identify the alternatives to be evaluated. This step would identify the outcomes of possible actions, a data gathering process.

Step 4: Identify the relevant dimensions of value for evaluation of the alternatives. It is important to limit the dimensions of value to those that are important for this particular decision. This can be accomplished by restating and combining goals, or by omitting less important goals. Edwards argued that it was not necessary to have a complete list of goals. If the weight for a particular goal is quite low, that goal need not be included. There is no precise range of goals for all decisions. However, eight goals were considered sufficiently large for most cases, and 15 too many.

Step 5: Rank the dimensions in order of importance For decisions made by one person, this step is fairly straightforward. Ranking is a decision task that is easier than developing weights, for instance. This task is usually more difficult in group environments. However, groups including diverse opinions can lead to a more thorough analysis of relative importance, as all sides of the issue are more likely to be voiced. An initial discussion could provide all group members with a common information base. This could be followed by the identification of individual judgments of relative ranking.

Step 6: Rate dimensions in importance, preserving ratios The least important dimension would be assigned an importance of 10. The next-least important dimension is assigned a number reflecting the ratio of relative importance to the least important dimension. This process is continued, checking implied ratios as each new judgment is made. Since this requires a growing number of comparisons, there is a very practical need to limit the number of dimensions (objectives). Edwards expected that different individuals in the group would have different relative ratings.

Step 7: Sum the importance weights and divide each by the sum. This step allows normalization of relative importances into weights summing to 1.0.

Step 8: Measure the location of each alternative being evaluated on each dimension. Dimensions were classified into the groups: subjective, partly subjective, and purely objective. For subjective dimensions, an expert in this field would estimate the value of an alternative on a 0–100 scale, with 0 as the minimum plausible value and 100 as the maximum plausible value. For partly subjective.

dimensions, objective measures exist, but attainment values for specific alternatives must be estimated. Purely objective dimensions can be measured. Raiffa advocated the identification of utility curves by dimension (Raiffa, 1968). Edwards proposed the simpler expedient of connecting the maximum plausible and minimum plausible values with a straight line (Edwards, 1977b). It was argued that the straight-line approach would provide an acceptably accurate approximation.

Step 9: Calculate utilities for alternatives $U_j = \Sigma_k\, w_k\, u_{jk}$ where U_j is the utility value for alternative j, w_k is the normalized weight for objective k, and u_{jk} is the scaled value for alternative j on dimension k. $\Sigma_k\, w_k = 1$. The w_k values were obtained from Step 7 and the u_{jk} values were generated in Step 8.

Step 10: Decide if a single alternative is to be selected, select the alternative with maximum U_j. If a budget constraint existed, rank order alternatives in the order of U_j/C_j where C_j is the cost of alternative j. Then alternatives are selected in order of highest ratio first until the budget is exhausted.

Plant Siting Decision

Assume that a supply chain vendor is considering sites for a new production facility. Management has considered the factors that they feel are important in this decision (the criteria):

- Acquisition and building cost.
- Expected cost per unit.
- Workforce ability to produce quality product.
- Workforce propensity for labor dispute.
- Transportation system reliability.
- Expandability.
- Agility to changes in demand.
- Information system linkage.
- Insurance structure.
- Tax structure.
- Governmental stability.
- Risk of disaster.

Each of these factors needs to be measured in some way. If possible, objective data would be preferred, but often subjective expert estimates are all that are available. The alternatives need to be identified as well. There are an infinite number of sites. But the number considered is always filtered down to a smaller number. Here we will start with ten options. Each of them has estimated performances on each of the 12 criteria listed (Table 3.2).

Each of the choices involves some trade-off. With 12 criteria, it will be rare that one alternative (of the final set of filtered choices) will dominate another, meaning that it is at least as good or better on all criteria measures, and strictly better on at least one criterion.

Each measure can now be assigned a value score on a 0–1 scale, with 0 being the worst performance imaginable, and 1 being the best performance imaginable. This reflects the decision maker's perception, a subjective value. For our data (Table 3.3), a possible set of values could be:

The SMART method now needs to identify relative weights for the importance of each criterion in the opinion of the decision maker or decision-making group. This process begins by sorting the criteria by importance. One possible ranking:

- Workforce ability to produce quality products.
- Expected cost per unit.
- Risk of disaster.
- Agility to changes in demand.

Table 3.2 Plant siting data

Location	A&B	UnitC	Quality	Labor	Trans	Expand
Alabama	$20 m	$5.50	High	Moderate	0.30	Good
Utah	$23 m	$5.60	High	Good	0.28	Poor
Oregon	$24 m	$5.40	High	Low	0.31	Moderate
Mexico	$18 m	$3.40	Moderate	Moderate	0.25	Good
Crete	$21 m	$6.20	High	Low	0.85	Poor
Indonesia	$15 m	$2.80	Moderate	Moderate	0.70	Fair
Vietnam	$12 m	$2.50	Good	Good	0.75	Good
India	$13 m	$3.00	Good	Good	0.80	Good
China #1	$17 m	$3.10	Good	Good	0.60	Fair
China #2	$15 m	$3.20	Good	Good	0.55	Good
Location	Agility	IS link	Insurance	Tax	Govt	Disaster
Alabama	2 mos	Very good	$400	$1000	Very good	Hurricane
Utah	3 mos	Very good	$350	$1200	Very good	Drought
Oregon	1 mo	Very good	$450	$1500	Good	Flood
Mexico	4 mos	Good	$300	$1800	Fair	Quake
Crete	5 mos	Good	$600	$3500	Good	Quake
Indonesia	3 mos	Poor	$700	$800	Fair	Monsoon
Vietnam	2 mos	Good	$600	$700	Good	Monsoon
India	3 mos	Very good	$700	$900	Very good	Monsoon
China #1	2 mos	Very good	$800	$1200	Very good	Quake
China #2	3 mos	Very good	$500	$1300	Very good	Quake

- Transportation system reliability.
- Expandability.
- Governmental stability.
- Tax structure.
- Insurance structure.
- Acquisition and building cost.
- Information system linkage.
- Workforce propensity for labor dispute.

The SMART method proceeds by assigning the most important criterion a value of 1.0, and then assessing relative importance by considering the proportional worth of moving from the worst to the best on the most important criterion (quality) and moving from the worst to the best on the criterion compared to it. For instance, the decision maker might judge moving from the worst possible unit cost to the best possible unit cost to be 0.8 as important as moving from the worst possible quality to the best possible quality. We assume the following ratings based on this procedure (Tables 3.4 and 3.5).

Proportion is obtained by dividing each rating by the sum of ratings (6.00). The overall value for each alternative site can then be ranked by the sum-product of criterion relative importance times the matrix of scores on criteria (Table 3.6).

Table 3.3 Standardized scores for plant siting data

Location	A&B	UnitC	Quality	Labor	Trans	Expand
Alabama	0.60	0.40	0.90	0.30	0.90	1.0
Utah	0.30	0.35	0.90	0.80	0.95	0
Oregon	0.10	0.45	0.90	0.10	0.86	0.5
Mexico	0.70	0.80	0.40	0.30	1.00	1.0
Crete	0.50	0.20	0.90	0.10	0.30	0
Indonesia	0.80	0.90	0.40	0.30	0.55	0.3
Vietnam	0.90	0.95	0.60	0.80	0.50	1.0
India	0.85	0.87	0.60	0.80	0.40	1.0
China #1	0.75	0.85	0.60	0.80	0.60	0.3
China #2	0.80	0.83	0.60	0.80	0.70	1.0
Location	Agility	IS link	Insurance	Tax	Govt	Disaster
Alabama	0.8	1.0	0.70	0.80	1.0	0.5
Utah	0.6	1.0	0.80	0.70	1.0	0.9
Oregon	1.0	1.0	0.60	0.60	0.8	0.8
Mexico	0.4	0.7	1.00	0.40	0.4	0.4
Crete	0.2	0.7	0.50	0.00	0.8	0.3
Indonesia	0.6	0	0.30	0.90	0.4	0.7
Vietnam	0.8	0.7	0.50	1.00	0.8	0.7
India	0.6	1.0	0.30	0.85	1.0	0.7
China #1	0.8	1.0	0.10	0.70	1.0	0.8
China #2	0.6	1.0	0.55	0.65	1.0	0.4

Note that for the Disaster criterion, specifics for each locale can lead to different ratings for the same major risk category

Table 3.4 Ratings for top level weights

Criterion		Rating	Proportion
Workforce ability to produce a quality product	Quality	1.00	0.167
Expected cost per unit	UnitC	0.80	0.133
Risk of disaster	Disaster	0.70	0.117

Table 3.5 Ratings for all weights

Agility to changes in demand	Agility	0.65	0.108
Transportation system reliability	Trans	0.60	0.100
Expandability	Expand	0.58	0.097
Government stability	Govt	0.40	0.067
Tax structure	Tax	0.35	0.058
Insurance structure	Insurance	0.32	0.053
Acquisition and building cost	A&B	0.30	0.050
Information system linkage	IS link	0.20	0.033
Workforce propensity for labor dispute	Labor	0.10	0.017

Table 3.6 Weights and scores

Location	A&B	UnitC	Quality	Labor	Trans	Expand	Agility	IS link	Insurance	Tax	Govt	Disaster
weight	0.05	0.133	0.167	0.017	0.1	0.097	0.108	0.033	0.053	0.058	0.067	0.117
Alabama	0.6	0.4	0.9	0.3	0.9	1	0.8	1	0.7	0.8	1	0.5
Utah	0.3	0.35	0.9	0.8	0.95	0	0.6	1	0.8	0.7	1	0.9
Oregon	0.1	0.45	0.9	0.1	0.86	0.5	1	1	0.6	0.6	0.8	0.8
Mexico	0.7	0.8	0.4	0.3	1	1	0.4	0.7	1	0.4	0.4	0.4
Crete	0.5	0.2	0.9	0.1	0.3	0	0.2	0.7	0.5	0	0.8	0.3
Indonesia	0.8	0.9	0.4	0.3	0.55	0.3	0.6	0	0.3	0.9	0.4	0.7
Vietnam	0.9	0.95	0.6	0.8	0.5	1	0.8	0.7	0.5	1	0.8	0.7
India	0.85	0.87	0.6	0.8	0.4	1	0.6	1	0.3	0.85	1	0.7
China #1	0.75	0.85	0.6	0.8	0.6	0.3	0.8	1	0.1	0.7	1	0.8
China #2	0.8	0.83	0.6	0.8	0.7	1	0.6	1	0.55	0.65	1	0.4

Table 3.7 Final scores for alternatives

Rank	Site	Score
1	Vietnam	0.762
2	Alabama	0.754
3	India	0.721
4	China #2	0.710
5	Oregon	0.706
6	China #1	0.679
7	Utah	0.674
8	Mexico	0.626
9	Indonesia	0.557
10	Crete	0.394

This analysis ranks the alternatives as follows in Table 3.7.

This indicates a close result for Vietnam and Alabama, with the first seven sites all reasonably close as well. There are a couple of approaches. More detailed comparisons might be made between Vietnam and Alabama. Another approach is to look at characteristics that these alternatives were rated low on, with the idea that maybe the site's characteristics could be improved.

Conclusions

Structuring a value hierarchy is a relatively subjective activity, with a great deal of possible latitude. It is good to have a complete hierarchy, including everything that could be of importance to the decision maker. However, this yields unworkable analyses. Hierarchies should focus on those criteria that are important in discriminating among available alternatives. The key to hierarchy structuring is to identify those criteria that are most important to the decision maker, and that will help the decision maker make the required choice.

This chapter presented the value-focused approach and the SMART method. These were demonstrated in the context of the supply chain risk management decision of selecting a plant location for production of a component. The methods apply to any decision involving multiple criteria.

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Examples of Supply Chain Decisions Trading-off Criteria

4

In prior editions, we reviewed five cases of models trading off criteria, seeking to demonstrate how multiple criteria models can be applied, along with value analysis to seek improvement. Sometimes risk is dealt with directly. Other times it is implicit, especially in cases involving environmental issues. In this third edition, we present five more cases.

In the five cases to follow, we will try to demonstrate the kinds of trade-off decisions often applied in practice. A number of different multiple-criteria methodologies were applied in the original papers. We demonstrate the less complex SMART methodology, which is not often published recently because journal publication requires new approaches, and the SMART methodology is well-known (and quite useful). You can refer to the original articles if you are interested in the methodology they specifically used. We try to use their data as closely as possible.

Case 1: Lombardi Netto et al. (2021)

This paper dealt with the assessment of sustainability programmes in Brazilian textile companies. The triple bottom line is very popular, combining consideration of profitability, ecology, and social needs. A supportive movement is the circular economy, a view of business sustainability in which resource input and waste, emissions, and energy leakage are minimized by slowing, closing, and narrowing material and energy loops. Means to accomplish this include longer-lasting design of products, recycling, remanufacture, and reuse.

We will demonstrate the application of SMART to their model. They considered ten criteria related to sustainability programmes in the Brazilian textile industry. Data on six Brazilian textile companies was obtained, reflecting their sustainability performance. Scores for each were generated on a 0–1 scale, with 1 being the best imaginable performance and 0 worst imaginable performance.

Weight generation begins by rank ordering the criteria:

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Table 4.1 Lombardi Netto et al. weight generation using SMART

	From first	Wbest	From last	Wlast	Average
Auditing	100	0.203	60	0.236	**0.220**
Innovation	60	0.122	40	0.157	**0.140**
Community	50	0.101	33	0.130	**0.120**
New materials	48	0.097	30	0.118	**0.100**
Emissions	44	0.089	20	0.079	**0.085**
Wage equality	43	0.087	18	0.071	**0.080**
Gender equality	41	0.083	17	0.067	**0.075**
Water	39	0.079	15	0.059	**0.065**
EBITDA	35	0.071	11	0.043	**0.060**
Growth	33	0.067	10	0.039	**0.055**
	493		254		

$$\text{Auditing} > \text{Innovation} > \text{Community} > \text{New materials} > \text{Emissions} >$$

$$\text{Wage equality} > \text{Gender equality} > \text{Waster} > \text{EBITDA} > \text{Growth}$$

A value model can then be developed, beginning with assigning a score of 100 to the first-ranked criterion, and relative scores to the other nine in declining order, using the anchor of relative value of swinging from the worst imaginable case to the best imaginable case for each of the pair of criteria. The first estimate of weights is obtained by dividing each assigned score by the sum, which in this case turned out to be 493. A check estimate relative to the last-ranked criterion can be generated as well, beginning with assigning the last-ranked criterion (growth in this case) a score of 10, and giving others relative scores using the same swing-weighting idea as the first set of estimates. Here, the sum was 254, and each assigned score is divided by this sum, yielding a second set of weights. These weights might be averaged as in the last column shown in Table 4.1.

Scores were then multiplied by weights and summed, generating a value for each company. These scores, weights, and sums are shown in Table 4.2.

Table 4.2 shows these value scores in bold, with implied ranks on the bottom row. These match the AHP-obtained scores of Lombardi Netto et al. quite closely.

Value Analysis

Value analysis looks at the relative strengths and weaknesses of each option. The score matrix given in Table 4.2 provides a means to assess these. Company 1 was weak in auditing, innovation, new materials, and wage equality. It was relatively strong in water recycling, community involvement, and obtaining gender equality. Company 2 had relative strengths in auditing, community involvement, and wage equality, while relatively low on growth and water management. Each company's relative strengths and weaknesses are displayed by their scores, with 1 being the highest imaginable, 0 the worst imaginable. The overall values reflect these

Table 4.2 Lombardi Netto et al. Weights and Scores

Criteria	Co1	Co2	Co3	Co4	Co5	Co6	Weight
Auditing	0	1	1	0	1	0	**0.220**
Growth	0.4	0.4	0.4	0.4	0.8	0.4	**0.055**
EBITDA	0.4	0.6	0.2	0.2	0.6	0.2	**0.060**
Innovation	0.2	0.6	0.2	0.2	0.6	0.2	**0.140**
Emissions	0.4	0.6	0.4	0.2	0.2	0.2	**0.085**
Water	0.6	0.4	0.2	0.4	0.2	0.4	**0.065**
New materials	0.2	0.6	0.4	0.2	0.4	0.2	**0.100**
Community	0.6	0.8	0.2	0.6	0.4	0.6	**0.120**
Gend equality	0.6	0.6	0.6	0.2	0.6	0.4	**0.075**
Wage equality	0.2	0.8	0.2	0.2	0.4	0.2	**0.080**
VALUE	**0.300**	**0.704**	**0.454**	**0.228**	**0.579**	**0.243**	1
Rank	4	1	3	6	2	5	

measures as well as the relative importance reflected in the weights obtained by swing-weighting.

Case 2: Liu, Eckert, Yannou-Le Bris, and Petit (2019)

This case involves a larger dataset. Supplier selection is a widely popular supply chain decision supported by multiple criteria models. Liu et al. (2019) modeled sustainability balanced against economic value and social responsibility, in line with the triple bottom line approach emphasized in Europe. They combined fuzzy input into the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the analytic network process (ANP) for the task of ranking 12 types of farmers and intermediate suppliers in a pork value chain in France. In that study, two decision makers were involved, applying pairwise comparisons to the three triple bottom line factors, as well as the three groups of subcriteria.

The 12 sources varied in feeding practices, dominant feed composition, size, and horizontal or vertical storage. Twenty measures of environmental, economic, and social (the triple bottom line) aspects were considered as displayed in Table 4.3.

The 12 source alternatives were categories of suppliers in the value chain as shown in Table 4.4.

Measures were given for each criterion for each type of farmer.

The SMART methodology would begin by identifying swing weights. The first step in that process would be to rank order the 20 criteria. The rank order complying with the analytic network process values obtained in the original article were:

$$C2.4 > C3.1 > C2.1 = C2.7 > C2.5 = C2.6 > C1.7 > C3.2 = C3.3 = C3.4$$

$$> C2.2 = C2.3 > C1.6 > C1.1 = C1.8 = C1.9 > C1.3 > C1.4 = C1.5$$

Table 4.3 Pork supply chain criteria

TBL component	Criteria	Code	Measure
Environmental	Freshwater eutrophication	C1.1	Kg SO_2 eq
	Terrestrial acidification	C1.2	Kg SO_2 eq
	Human toxicity	C1.3	Kg1, 4-DB eq
	Fossil depletion	C1.4	Kg oil eq
	Water depletion	C1.5	M3
	Climate change	C1.6	Kg CO_2 eq
	Land occupation	C1.7	M2a
	Freshwater ecotoxicity	C1.8	Kg1, 4-DB eq
	Marine ecotoxicity	C1.9	Kg1, 4-DB eq
Economic	Investment <5 years	C2.1	Euro/ton
	Investment 5–9 years	C2.2	Euro/ton
	Investment 10–14 years	C2.3	Euro/ton
	Feed manufacturing cost	C2.4	Euro/ton
	Total feed system cost	C2.5	Euro/ton
	Waste	C2.6	Percentage
	Labor cost	C2.7	Euro/ton
Social	Work hours	C3.1	Hours/day
	Biodiversity varieties	C3.2	Number by formula
	Biodiversity species	C3.3	Number by formula
	Localness	C3.4	Percent by formula

Table 4.4 Types of farmers

Code	Type name	Orientation	Dominant feed	Size of feed	Type of storage
S1	Bought colza	Purchasing	Colza		
S2	Bought soy	Purchasing	Soy		
S3	Made <2500 T	Producing	Dry cereals	Silo <2500 T	
S4	Made >2500 T	Producing	Dry cereals	Silo <2500 T	
S5	Made maize Hori < 2500 T	Producing	Corn	Silo <2500 T	Horizontal
S6	Made maize Hori > 2500 T	Producing	Corn	Silo <2500 T	Horizontal
S7	Made maize Vert < 2500 T	Producing	Corn	Silo <2500 T	Vertical
S8	Made maize Vert > 2500 T	Producing	Corn	Silo <2500 T	Vertical
S9	Mix Horizontal	Mix	Dry cereals		Horizontal
S10	Mix Vertical	Mix	Dry cereals		Vertical
S11	Mix maize Horizontal	Mix	Corn		Horizontal
S12	Mix maize Vertical	Mix	Corn		Vertical

Table 4.5 Swing weighting

Criteria	Code	From max.	Weight	From min.	Weight	Compromise
Food manufacturing cost	C2.4	100	0.181	120	0.152	0.167
Work hours	C3.1	50	0.091	60	0.076	0.080
Investment <5 years	C2.1	45	0.082	55	0.070	0.075
Labor cost	C2.7	45	0.082	55	0.070	0.075
Total feed system cost	C2.5	40	0.073	50	0.063	0.068
Waste	C2.6	40	0.073	50	0.063	0.068
Land occupation	C1.7	35	0.064	45	0.057	0.060
Biodiversity varieties	C3.2	30	0.054	40	0.051	0.053
Biodiversity species	C3.3	30	0.054	40	0.051	0.053
Localness	C3.4	30	0.054	40	0.051	0.053
Investment 5–9 years	C2.2	20	0.036	35	0.044	0.040
Investment 10–14 years	C2.3	20	0.036	35	0.044	0.040
Climate change	C1.6	15	0.027	30	0.038	0.033
Freshwater eutrophication	C1.1	10	0.018	25	0.032	0.025
Freshwater ecotoxicity	C1.8	10	0.018	25	0.032	0.025
Marine ecotoxicity	C1.9	10	0.018	25	0.032	0.025
Human toxicity	C1.3	8	0.015	20	0.025	0.020
Fossil depletion	C1.4	5	0.009	15	0.019	0.015
Water depletion	C1.5	5	0.009	15	0.019	0.015
Terrestrial acidification	C1.2	3	0.005	10	0.013	0.010

$$> C1.2$$

The greatest weight was given to feed manufacturing cost (C2.4), more than double that of the second-ranked measure of work hours (C3.1). The lowest weights were given to the environmental factors, with the exception of land occupation (C1.7).

Swing weighting could be applied as shown in Table 4.5.

The next step is to obtain relative scores for each alternative on each criterion. Table 4.6 gives normalized scores where 1.0 is the best score and 0 the worst.

Liu et al. found ranks by preference as follows:

$$\text{Excellent} : S1 > S2 \text{Acceptable} : S10 > S3 > S4 \text{Poor} \\ : S12 > S7 > S8 > S11 > S5 > S6$$

Table 4.6 has the same ranking for the Excellent category, and S10 also came third. There was some difference for the intermediate-ranked categories, but quite a bit of similarity for the lower ranks.

Table 4.6 Power generation alternative scoring

Criteria	Gas	Oil	Coal	Hydro	Wind	Solar
Cost/KW-hr	0.988	0.986	0.988	1.000	0.000	0.987
Installed capacity	1.000	0.998	0.967	0.466	0.000	0.959
Life expectancy	0.025	0.988	0.250	1.000	0.000	0.013
Efficiency	0.315	0.314	0.154	1.000	0.178	0.000
GHG emission	0.516	0.515	0.000	0.979	1.000	0.987
H_2O consumption	0.971	0.971	0.941	0.000	1.000	1.000
Land use	1.000	0.995	0.918	0.000	0.990	0.000
Social benefits	1.000	0.995	0.998	0.570	0.000	0.003

Value Analysis

Value analysis is possible by identifying where each alternative has relative strengths and weaknesses. S1, the colza farmer, was strongest on six measures, including low land occupation, short-term investment, low waste, low labor cost, and work hours. It was weakest on long-term investment. The twelfth-ranked alternative, S6, was strongest on localness, but weak on human toxicity, long-term investment, waste, and labor cost. The context of this problem was to rank given alternatives. The value analysis can show why ranking was as it ended up.

Case 3: Lin et al. (2022)

Lin et al. (2022) presented an ELECTRE II analysis for the evaluation of power generation technologies in Bangladesh. Bangladesh was seeking economic growth while considering the environment. In the ELECTRE methods, weights are entered by decision makers as a means to see the impact of emphasizing various criteria. Lin et al. modified weights by considering the difference between evaluation values. The relative scores on a 0–1 scale are given in Table 4.6.

Applying the SMART method, the next step is to rank order the criteria, The rankings implied by the Lin et al. paper are:

$$\text{H2O} > \text{Cost} > \text{Capacity} > \text{GHG} > \text{Land} > \text{Social} > \text{Life} > \text{Efficiency}$$

Applying the swing-weighting method yields Table 4.7.

The next step is to multiply the weights from Table 4.7 times the scores in Table 4.6. Results are displayed in Table 4.8.

Table 4.8 displays the relative strengths and weaknesses of each alternative through the scores. The VALUE line gives the basis for ranking given the weights in the last column. Here the implication is that the Oil is the preferred alternative, with Gas a close second.

Table 4.7 Swing weighting of power generation case

Criteria	From max.	Weight	From min.	Weight	Compromise
H_20	100	0.236	50	0.239	0.235
Cost	70	0.165	35	0.167	0.166
Capacity	65	0.154	30	0.144	0.150
GHG	50	0.118	25	0.120	0.119
Land	48	0.113	24	0.115	0.114
Social	45	0.106	23	0.110	0.108
Life	25	0.059	12	0.057	0.058
Efficiency	20	0.047	10	0.048	0.050
	423		145		1

Table 4.8 Power generation value scores

Criteria	Gas	Oil	Coal	Hydro	Wind	Solar	**Weight**
Cost/KW-hr	0.988	0.986	0.988	1.000	0.000	0.987	**0.163**
Installed capacity	1.000	0.998	0.967	0.466	0.000	0.959	**0.156**
Life expectancy	0.025	0.988	0.250	1.000	0.000	0.013	**0.061**
Efficiency	0.315	0.314	0.154	1.000	0.178	0.000	**0.058**
GHG emission	0.516	0.515	0.000	0.979	1.000	0.987	**0.111**
H_2O consumption	0.971	0.971	0.941	0.000	1.000	1.000	**0.230**
Land use	1.000	0.995	0.918	0.000	0.990	0.000	**0.111**
Social benefits	1.000	0.995	0.998	0.570	0.000	0.003	**0.109**
VALUE	**0.838**	**0.895**	**0.764**	**0.526**	**0.462**	**0.652**	
Rank	2	1	3	5	6	4	

Value Analysis

In this case, there were clearly distinguished performance scores. Oil and gas had very similar scores, with Oil having a distinct advantage on life expectancy. Coal had a distinct disadvantage on greenhouse gas emissions. Solar was weak on life expectancy, efficiency, land use, and social benefits as scored in Bangladesh. Hydro was very weak on water consumption and land use. Wind had some strengths (greenhouse gas emission and water consumption) but was weak on everything else. Again, value analysis might seek ways to improve alternative weaknesses.

Case 4: Urbaniec et al. (2021)

The fourth case also deals with sustainability. In this case, Urbaniec et al. analyzed business strategies for sustainable entrepreneurship in the bioeconomy (Table 4.9).

Rank ordering these six criteria might be:

Table 4.9 Business strategy scores

Criteria	Offensive	Innovative	Defensive	Passive
Economic/Financial	0.333	0.538	0.042	0.087
Market	0.293	0.582	0.038	0.087
Technology	0.203	0.551	0.133	0.113
Ecology	0.320	0.426	0.126	0.128
Organizational	0.282	0.480	0.046	0.092
Legal	0.437	0.402	0.059	0.102

Table 4.10 Business strategy swing-weighting

Criteria	From max.	Weight	From min.	Weight	Compromise
Economic/Fin	100	0.312	50	0.370	0.340
Market	70	0.219	30	0.222	0.220
Technology	50	0.156	20	0.148	0.150
Ecology	40	0.125	15	0.111	0.120
Organizational	30	0.094	10	0.074	0.085
Legal	30	0.094	10	0.074	0.085
Total	320		135		

Table 4.11 Value score calculations for business strategy evaluation

Criteria	Offensive	Innovative	Defensive	Passive	Weights
Economic/Financial	0.333	0.538	0.042	0.087	0.370
Market	0.293	0.582	0.038	0.087	0.220
Technological	0.203	0.551	0.133	0.113	0.150
Ecology	0.320	0.426	0.126	0.128	0.120
Organizational	0.282	0.480	0.046	0.092	0.085
Legal	0.437	0.402	0.059	0.102	0.085
Value scores	0.318	0.536	0.068	0.100	0.237

$$\text{Econ/Fin} > \text{Market} > \text{Technology} > \text{Ecology} > \text{Organizational} = \text{Legal}$$

Table 4.10 gives possible swing-weighting numbers:

These weights are applied to the business strategy scores from Table 4.9 yielding the values shown in Table 4.11.

Value Analysis

Here the choice for this situation would indicate a strong recommendation for an innovative strategy. The score table also reveals relative advantages. The offensive strategy is strongest on the legal dimensions, but that had a low weight. The innovative strategy had relatively high scores on all dimensions given. The defensive and passive strategies had very low scores across the board. This would indicate that here there was little competition. But in general, that is a function of the weights used.

Case 5: Akyuz, Karahalios, and Celik (2015)

The last case involves the application of multiple criteria analysis to a balanced scorecard assessment. Balanced scorecards involve measuring performance on four perspectives (financial, operational, business process, and organizational learning and growth). These can be applied in many different contexts. The case in point involved maritime labor compliance in a British environment. Each of the four perspectives considered four or five factors. The authors applied AHP to rank order the relative importance of these 19 factors with the intent of identifying where relative emphasis might be placed in operations. In general, their model could be used to compare performance at multiple sites. Here we simply want to demonstrate multiple criteria modeling in a balanced scorecard setting. Table 4.12 gives the criteria.

Each of the four balanced scorecard perspectives consisted of critical success factors in the context of maritime labor environment assessment (Table 4.12).

Table 4.13 gives the subcriteria and swing weighting implied in the source article. This involves rank ordering the 19 subfactors, and giving assessments of relative importance.

Table 4.12 Balanced scorecard components in the Maritime Labor context

Perspective	Critical success factor	Code
Financial	Seafarer's employment agreements	FP1
	Wages	FP2
	Seafarer compensation for ship loss or foundering	FP3
	Food and catering	FP4
Labor	Recruitment and placement	LP1
	Entitlement to leave	LP2
	Repatriation	LP3
	Medical care onboard and ashore	LP4
	Social security	LP5
Internal business	Medical certificate	IBP1
	Manning levels	IBP2
	Accommodation and recreational facilities	IBP3
	Shipowner's liability	IBP4
	Health and safety and accident prevention	IBP5
Learning and growth	Minimum age	LGP1
	Training and qualifications	LGP2
	Hours of work and rest	LGP3
	Career and skill development	LGP4
	Access to shore-based welfare facilities	LGP5

Table 4.13 Implied swing weighting

	Criteria	From max.	Weight	From min.	Weight	Compromise
FP2	Wages	100	0.249	980	0.293	0.270
FP3	Seafarer compensation for ship loss or foundering	50	0.125	470	0.140	0.130
IBP5	Health and safety and accident prevention	40	0.100	340	0.102	0.110
LP5	Social security	30	0.075	250	0.075	0.075
FP4	Food and catering	28	0.070	225	0.067	0.068
IBP4	Shipowner's liability	26	0.065	190	0.057	0.060
LP4	Medical care onboard and ashore	20	0.050	142	0.042	0.045
FP1	Seafarer's employment agreements	19	0.047	140	0.042	0.044
LGP4	Career and skill development	16	0.040	101	0.030	0.035
IBP3	Accommodation and recreational facilities	13	0.032	99	0.030	0.031
LGP2	Training and qualifications	11	0.027	80	0.024	0.025
IBP2	Manning levels	10	0.025	75	0.022	0.023
LP2	Entitlement to leave	9	0.022	70	0.021	0.021
LGP3	Hours of work and rest	7	0.017	50	0.015	0.016
IBP1	Medical certificate	6	0.015	40	0.012	0.014
LP1	Recruitment and placement	6	0.015	38	0.011	0.013
LP3	Repatriation	5	0.012	30	0.009	0.010
LGP1	Minimum age	3	0.007	18	0.005	0.006
LGP5	Access to shore-based welfare facilities	2	0.005	10	0.003	0.004
		401	1	3348	1	1

Here the source author's intent was to rank order the subcriteria, identifying where emphasis would be placed. Wages clearly were the most preferred factor, reflecting a strong emphasis on financial perspectives. Summing weights by balanced scorecard perspective, Financial received 0.512 of the relative weight, Internal business pro- cesses 0.238, labor 0.164, and learning and growth 0.086. Inherently, value analysis is implied by the compromise weights to identify relative importance using the ratings given.

Value Analysis

This application differs because its intent is to provide a balanced scorecard type of model. This can be very useful, and interesting. But value analysis applies only to hierarchical development because Akyuz et al. applied AHP to performance measurement.

Conclusions

The cases presented involved multiple criteria selection decisions (with the exception of the fifth, demonstrating how balanced scorecard modeling could be supported). Multiple criteria analysis is a very good framework to describe specific aspects of risk and to assess where they impact a given decision context. The value scores might be useful as a means to select a preferred alternative, or as a performance metric that directs attention to features calling for improvement.

Value analysis can provide useful support to decision-making by first focusing on hierarchical development. In all five cases presented here, this was done in the original articles. Nonetheless, it is important to consider overarching objective accomplishment.

Two aspects of value analysis should be considered. First, if scores on available alternatives are equivalent to a specific criterion, this criterion will not matter for this set of alternatives. However, it may matter if new alternatives are added, or existing alternatives are improved. Second, a benefit of value analysis is improvement of existing alternatives. The score matrix provides useful comparisons of relative alternative performance. If decision makers are not satisfied with existing alternatives, they might seek additional choices by expanding their search or designing better alternatives. The criteria with the greatest weights might provide an area of focus in this search, and the ideal scores might give a standard for design.

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5 Simulation of Supply Chain Risk

Supply chains involve many risks, as we have seen. Modeling that risk focuses on probability, a well-developed analytic technique. This chapter addresses basic simulation models involving supply chains, including inventory modeling (often accomplished through system dynamics) and Monte Carlo simulation of vendor outsourcing decisions.

Inventory Systems

Inventory is any resource that is set aside for future use. Inventory is necessary because the demand and supply of goods usually are not perfectly matched at any given time or place. Many different types of inventories exist. Examples include raw materials (such as coal, crude oil, and cotton), semifinished products (aluminum ingots, plastic sheets, lumber), and finished products (cans of food, computer terminals, shirts). Inventories can also be human resources (standby crews and trainees), financial resources (cash on hand, accounts receivable), and other resources such as airplane seats.

The basic risks associated with inventories are the risks of stocking out (and thus losing sales), and the counter risk of going broke because excessive cash flow is tied up in inventory. The problem is made interesting because demand is almost always uncertain, driven by the behavior of the market, usually many people making spontaneous purchasing decisions.

Inventories represent a considerable investment for many organizations; thus, it is important that they be managed well. Although many analytic models for managing inventories exist, the complexity of many practical situations often requires simulation.

The two basic inventory decisions that managers face are *how much* to order or produce additional inventory, and *when* to order or produce it. Although it is possible to consider these two decisions separately, they are so closely related that a

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simultaneous solution is usually necessary. Typically, the objective is to minimize total inventory costs.

Total inventory cost can include four components: holding costs, ordering costs, shortage costs, and purchasing costs. Holding costs, or *carrying costs*, represent costs associated with maintaining inventory. These costs include interest incurred or the opportunity cost of having capital tied up in inventories; storage costs such as insurance, taxes, rental fees, utilities, and other maintenance costs of storage space; warehousing or storage operation costs, including handling, record keeping, information processing, and actual physical inventory expenses; and costs associated with deterioration, shrinkage, obsolescence, and damage. Total holding costs are dependent on how many items are stored and for how long they are stored. Therefore, holding costs are expressed in terms of *dollars associated with carrying one unit of inventory for a unit of time*.

Ordering costs represent costs associated with replenishing inventories. These costs are not dependent on how many items are ordered at a time, but on the number of orders that are prepared. Ordering costs include overhead, clerical work, data processing, and other expenses that are incurred in searching for supply sources, as well as costs associated with purchasing, expediting, transporting, receiving, and inspecting. In manufacturing operations, setup cost is the equivalent to ordering cost. Setup costs are incurred when a factory production line has to be shut down in order to reorganize machinery and tools for a new production run. Setup costs include the cost of labor and other time-related costs required to prepare for the new product run. We usually assume that the ordering or setup cost is constant and is expressed in terms of *dollars per order*.

Shortage costs, or *stock-out costs*, are those costs that occur when demand exceeds available inventory in stock. A shortage may be handled as a *backorder*, in which a customer waits until the item is available, or as a *lost sale*. In either case, a shortage represents lost profit and possible loss of future sales. Shortage costs depend on how much shortage has occurred and sometimes for how long. Shortage costs are expressed in terms of *dollar cost per unit of a short item.*

Purchasing costs are what firms pay for the material or goods. In most inventory models, the price of materials is the same regardless of the quantity purchased; in this case, purchasing costs can be ignored. However, when price varies by quantity purchased, called the *quantity discount* case, inventory analysis must be adjusted to account for this difference.

Basic Inventory Simulation Model

Many models contain variables that change continuously over time. One example would be a model of a retail store's inventory. The number of items changes gradually (though discretely) over an extended time period; however, for all intents and purposes, they may be treated as continuous. As customer demand is fulfilled, inventory is depleted, leading to factory orders to replenish the stock. As orders are received from suppliers, the inventory increases. Over time, particularly if orders are relatively small and frequent as we see in just-in-time environments, the inventory level can be represented by a smooth, continuous, and function.

We can build a simple inventory simulation model beginning with a spreadsheet model as shown in Table 5.1. Model parameters include a holding rate of 0.8 per item per day, an order rate of 300 for each order placed, a purchase price of 90, and a sales price of 130. The decision variables are when to order (when the end-of-day quantity drops below the reorder point (ROP)), and the quantity ordered (Q). The model itself has a row for each day (here 30 days are modeled). Each day has a starting inventory (column B) and a probabilistic demand (column C) generated from a normal distribution with a mean of 100 and a standard deviation of 10. Demand is made integer. Sales (column D) are equal to the minimum of the starting quantity and demand. End-of-day inventory (column E) is the maximum of 0 or starting inventory minus demand. The quantity ordered at the end of each day in column F (here assumed to be on hand at the beginning of the next day) is 0 if ending inventory exceeds ROP, or Q if ending inventory drops at or below ROP.

Profit and shortage are calculated to the right of the basic inventory model. Column G calculates holding cost by multiplying the parameter in cell B2 times the ending inventory quantity for each day and summing over the 30 days in cell G5. Order costs are calculated by day as $300 if an order is placed that day, and 0 otherwise, with the monthly total ordering cost accumulated in cell H5. Cell I5 calculates total purchasing cost, cell J5 total revenue, and cell H3 calculates net profit considering the value of starting inventory and ending inventory. Column K identifies sales lost (SHORT), with cell K5 accumulating these for the month. Note that cell H3 adjusts for beginning and ending inventory.

Crystal Ball simulation software allows introduction of three types of special variables. Probabilistic variables (assumption cells in Crystal Ball terminology) are modeled in column C using a normal distribution [CB.Normal (mean, std)]. Decision variables are modeled for ROP (cell E1) and Q (cell E2). Crystal Ball allows setting minimum and maximum levels for decision variables, as well as step size. Here, we used ROP values of 80, 100, 120, and 140, and Q values of 100, 110, 120, 130, and 140. The third type of variable is a forecast cell. We have forecast cells for net profit (H3) and for sales lost (cell K3).

The Crystal Ball simulation can be set to run for up to 10,000 repetitions for a combination of decision variables. We selected 1000 repetitions. Output is given for forecast cells. Figure 5.1 shows net profit for the combination of an ROP of 140 and a Q of 140.

Tabular output is also provided, as in Table 5.2.

Similar output is given for the other forecast variable, SHORT (Fig. 5.2; Table 5.3).

Crystal Ball also provides a comparison over all decision variable values, as given in Table 5.4.

The implication here is that the best decision for the basic model parameters would be an ROP of 120 and a Q of 130, yielding an expected net profit of $101,446 for the month. The shortage for this combination had a mean of 3.43 items per day, with a distribution shown in Fig. 5.3. The probability of shortage was 0.4385.

Table 5.1 Basic inventory model

	A	B	C	D	E	F	G	H	I	J	K
1	Hold rate	0.8		ROP	140						
2	Order rate	300		Q	140						
3	Purchase	90					Net	101,809.2		Short	0
4	Sell	130									
5							2440.8	6600	277,200	388,050	
6	Day	Start	Demand	Sales	End	Order	Hold cost	Order cost	Purchase	Revenue	SHORT
7	1	100	85	85	15	140	12	300	12,600	11,050	0
8	2	155	84	84	71	140	56.8	300	12,600	10,920	0
9	3	211	104	104	107	140	85.6	300	12,600	13,520	0
10	4	247	105	105	142	0	113.6	0	0	13,650	0
11	5	142	104	104	38	140	30.4	300	12,600	13,520	0
12	6	178	116	116	62	140	49.6	300	12,600	15,080	0
13	7	202	105	105	97	140	77.6	300	12,600	13,650	0
14	8	237	94	94	143	0	114.4	0	0	12,220	0
15	9	143	83	83	60	140	48	300	12,600	10,790	0
16	10	200	94	94	106	140	84.8	300	12,600	12,220	0
17	11	246	115	115	131	140	104.8	300	12,600	14,950	0
18	12	271	128	128	143	0	114.4	0	0	16,640	0
19	13	143	107	107	36	140	28.8	300	12,600	13,910	0
20	14	176	110	110	66	140	52.8	300	12,600	14,300	0
21	15	206	102	102	104	140	83.2	300	12,600	13,260	0
22	16	244	96	96	148	0	118.4	0	0	12,480	0
23	17	148	91	91	57	140	45.6	300	12,600	11,830	0
24	18	197	102	102	95	140	76	300	12,600	13,260	0
25	19	235	104	104	131	140	104.8	300	12,600	13,520	0

26	20	271	96	96	175	0	140	0	0	12,480	0
27	21	175	103	103	72	140	57.6	300	12,600	13,390	0
28	22	212	98	98	114	140	91.2	300	12,600	12,740	0
29	23	254	97	97	157	0	125.6	0	0	12,610	0
30	24	157	103	103	54	140	43.2	300	12,600	13,390	0
31	25	194	86	86	108	140	86.4	300	12,600	11,180	0
32	26	248	105	105	143	0	114.4	0	0	13,650	0
33	27	143	89	89	54	140	43.2	300	12,600	11,570	0
34	28	194	106	106	88	140	70.4	300	12,600	13,780	0
35	29	228	89	89	139	140	111.2	300	12,600	11,570	0
36	30	279	84	84	195	0	156	0	0	10,920	0

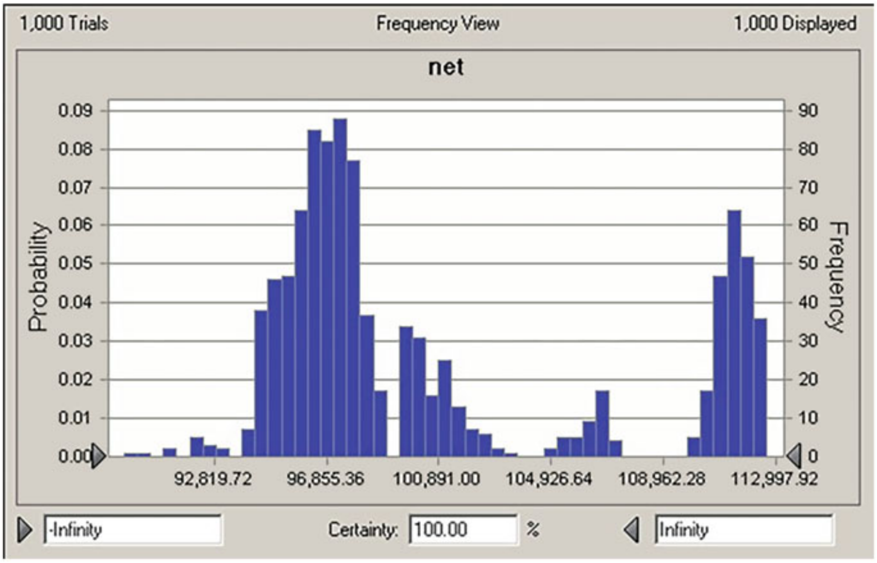

Fig. 5.1 Crystal ball output for net profit ROP 140, Q 140. © Oracle. Used with permission

Table 5.2 Statistical output for net profit ROP 140, Q 140 © Oracle. Used with permission

Statistic	Forecast values
Trials	1000
Mean	100,805.56
Median	97,732.8
Mode	97,042.4
Standard deviation	6264.80
Variance	39,247,672.03
Skewness	0.8978
Kurtosis	2.21
Coeff. of variability	0.0621
Minimum	89,596.80
Maximum	112,657.60
Mean Std. error	198.11

System Dynamics Modeling of Supply Chains

Many models contain variables that change continuously over time. One example would be a model of an oil refinery. The amount of oil moving between various stages of production is clearly a continuous variable. In other models, changes in variables occur gradually (though discretely) over an extended time period.

However, for all intents and purposes, they may be treated as continuous. An example would be the amount of inventory at a warehouse in a production–

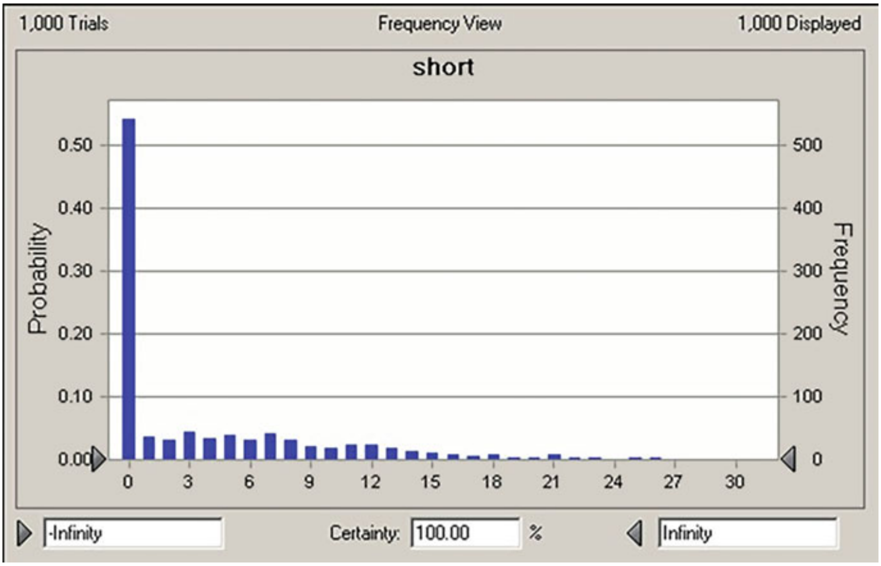

Fig. 5.2 SHORT for ROP 140, Q 140. © Oracle. Used with permission

Table 5.3 Statistical output: ROP 140, Q 140

Statistic	Forecast values
Trials	1000
Mean	3.72
Median	0.00
Mode	0.00
Standard deviation	5.61
Variance	31.47
Skewness	1.75
Kurtosis	5.94
Coeff. of variability	1.51
Minimum	0.00
Maximum	31.00
Mean Std. error	0.18

distribution system over several years. As customer demand is fulfilled, inventory is depleted, leading to factory orders to replenish the stock. As orders are received from suppliers, the inventory increases. Over time, particularly if orders are relatively small and frequent as we see in just-in-time environments, the inventory level can be represented by a smooth, continuous, and function.

Continuous variables are often called state variables. A continuous simulation model defines equations for relationships among state variables so that the dynamic behavior of the system over time can be studied. To simulate continuous systems, we use an activity-scanning approach whereby time is decomposed into small increments. The defining equations are used to determine how the state variables

Table 5.4 Comparative net profit for all values of ROP, Q

Trend Chart Overlay Chart Forecast Chart	Q (100.00)	Q (110.00)	Q (120.00)	Q (130.00)	Q (140.00)	
ROP (80.00)	99,530	99,948	99,918	100,159	101,331	*1*
ROP (100.00)	99,627	100,701	101,051	101,972	101,512	*2*
ROP (120.00)	99,519	100,429	100,919	101,446	101,252	*3*
ROP (140.00)	99,525	99,894	100,586	100,712	100,805	*4*
	1	*2*	*3*	*4*	*5*	

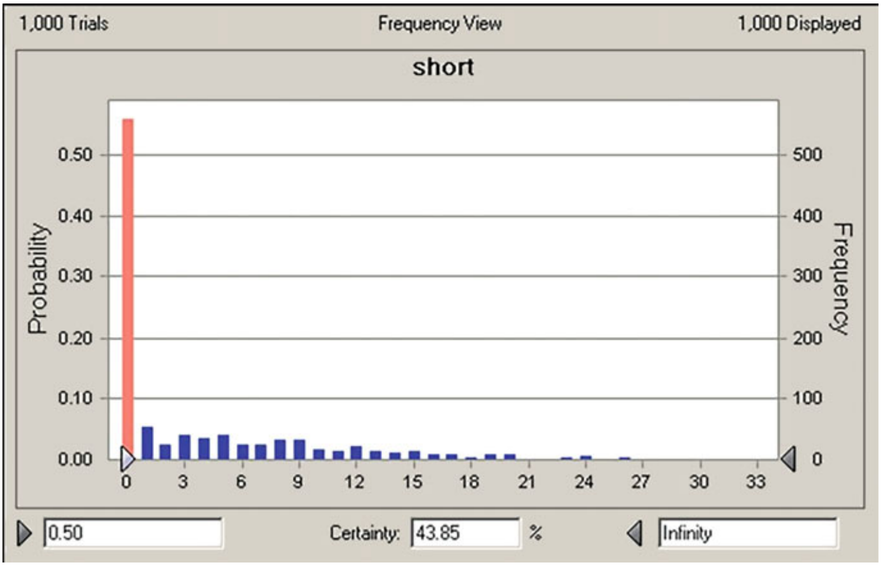

Fig. 5.3 SHORT for R = 120, Q = 130. © Oracle. Used with permission

change during an increment of time. A specific type of continuous simulation is called system dynamics, which dates back to the early 1960s and a classic work by Jay Forrester of M.I.T (Forrester, 1961). System dynamics focuses on the structure and behavior of systems that are composed of interactions among variables and feedback loops. System dynamics models usually take the form of an influence diagram that shows the relationships and interactions among a set of variables.

System dynamics models have been widely used to model supply chains, especially with respect to the bullwhip phenomenon (Sterman, 1989), which has to do with the dramatic increase in inventories across supply chains when uncertainty in demand appears. Many papers have dealt with the bullwhip effect through system dynamics models (Huang et al., 2009). These models have been used to evaluate lean systems (Agyapong-Kodua et al., 2009), Kanban systems (Claudio & Krishnamurthy, 2009), and JIT systems (Chakravarty, 2013), They also have been used to model vendor management inventory in supply chains (Mishra & Chan, 2012).

We present a four-echelon supply chain model, consisting of a vendor providing raw materials, an assembly operation to create the product, a warehouse, and a set of five retailers. We will model two systems—one a push system, the other pull in the sense that upstream activity depends on downstream demand. We will present the pull system first.

Pull System

The basic model uses a forecasting system based on exponential smoothing to drive decisions to send material down the supply chain. We use EXCEL modeling, along with Crystal Ball software to do simulation repetitions, following Evans & Olson (2002). The formulas for the factory portion of the model are given in Fig. 5.4.

Figure 5.4 models a month of daily activity. Sales of products at retail generate $100 in revenue for the core organization, at a cost of $70 per item. Holding costs are $1 at the retail level ($0.50 at wholesale, $0.40 at assembly, and $0.25 at vendors). Daily orders are shipped from each element, at a daily cost of $1000 from factory to assembler, $700 from assembler to warehouse, and $300 from warehouse to retailers. Vendors produce 50 items of material per day if inventory drops to 20 items or less. If not, they do not produce. They send material to the assembly operation if called by that element, which is modeled in Fig. 5.5 (only the first 5 days are shown). Vendor ending inventory is shown in column E, with cell E37 adding total monthly inventory.

The assembly operation calls for the replenishment of 30 units from the vendor whenever their inventory of finished goods drops to 20 or less. Each daily delivery is

	A	B	C	D	E
1	RevP	100	ROPven	20	
2	Cost	70	Qven	50	
3	Hold	1			
4		Vendor	Vendor		
5		Start	Prod	Send	End
6	Time				
7	1	40	=IF(E7<=$D$1,$D$2,0)	=IF(J7<=$I$1,$D$2,0)	=MAX(0,B7-D7)
8	=A7+1	=E7	=IF(E8<=$D$1,$D$2,0)	=IF(J8<=$I$1,$D$2,0)	=MAX(0,B8-D8)
9	=A8+1	=E8+C7	=IF(E9<=$D$1,$D$2,0)	=IF(J9<=$I$1,$D$2,0)	=MAX(0,B9-D9)
10	=A9+1	=E9+C8	=IF(E10<=$D$1,$D$2,0)	=IF(J10<=$I$1,$D$2,0)	=MAX(0,B10-D10)
11	=A10+1	=E10+C9	=IF(E11<=$D$1,$D$2,0)	=IF(J11<=$I$1,$D$2,0)	=MAX(0,B11-D11)
12	=A11+1	=E11+C10	=IF(E12<=$D$1,$D$2,0)	=IF(J12<=$I$1,$D$2,0)	=MAX(0,B12-D12)
13	=A12+1	=E12+C11	=IF(E13<=$D$1,$D$2,0)	=IF(J13<=$I$1,$D$2,0)	=MAX(0,B13-D13)
14	=A13+1	=E13+C12	=IF(E14<=$D$1,$D$2,0)	=IF(J14<=$I$1,$D$2,0)	=MAX(0,B14-D14)
15	=A14+1	=E14+C13	=IF(E15<=$D$1,$D$2,0)	=IF(J15<=$I$1,$D$2,0)	=MAX(0,B15-D15)
16	=A15+1	=E15+C14	=IF(E16<=$D$1,$D$2,0)	=IF(J16<=$I$1,$D$2,0)	=MAX(0,B16-D16)
17	=A16+1	=E16+C15	=IF(E17<=$D$1,$D$2,0)	=IF(J17<=$I$1,$D$2,0)	=MAX(0,B17-D17)
18	=A17+1	=E17+C16	=IF(E18<=$D$1,$D$2,0)	=IF(J18<=$I$1,$D$2,0)	=MAX(0,B18-D18)
19	=A18+1	=E18+C17	=IF(E19<=$D$1,$D$2,0)	=IF(J19<=$I$1,$D$2,0)	=MAX(0,B19-D19)
20	=A19+1	=E19+C18	=IF(E20<=$D$1,$D$2,0)	=IF(J20<=$I$1,$D$2,0)	=MAX(0,B20-D20)
21	=A20+1	=E20+C19	=IF(E21<=$D$1,$D$2,0)	=IF(J21<=$I$1,$D$2,0)	=MAX(0,B21-D21)
22	=A21+1	=E21+C20	=IF(E22<=$D$1,$D$2,0)	=IF(J22<=$I$1,$D$2,0)	=MAX(0,B22-D22)
23	=A22+1	=E22+C21	=IF(E23<=$D$1,$D$2,0)	=IF(J23<=$I$1,$D$2,0)	=MAX(0,B23-D23)
24	=A23+1	=E23+C22	=IF(E24<=$D$1,$D$2,0)	=IF(J24<=$I$1,$D$2,0)	=MAX(0,B24-D24)
25	=A24+1	=E24+C23	=IF(E25<=$D$1,$D$2,0)	=IF(J25<=$I$1,$D$2,0)	=MAX(0,B25-D25)
26	=A25+1	=E25+C24	=IF(E26<=$D$1,$D$2,0)	=IF(J26<=$I$1,$D$2,0)	=MAX(0,B26-D26)
27	=A26+1	=E26+C25	=IF(E27<=$D$1,$D$2,0)	=IF(J27<=$I$1,$D$2,0)	=MAX(0,B27-D27)
28	=A27+1	=E27+C26	=IF(E28<=$D$1,$D$2,0)	=IF(J28<=$I$1,$D$2,0)	=MAX(0,B28-D28)
29	=A28+1	=E28+C27	=IF(E29<=$D$1,$D$2,0)	=IF(J29<=$I$1,$D$2,0)	=MAX(0,B29-D29)
30	=A29+1	=E29+C28	=IF(E30<=$D$1,$D$2,0)	=IF(J30<=$I$1,$D$2,0)	=MAX(0,B30-D30)
31	=A30+1	=E30+C29	=IF(E31<=$D$1,$D$2,0)	=IF(J31<=$I$1,$D$2,0)	=MAX(0,B31-D31)
32	=A31+1	=E31+C30	=IF(E32<=$D$1,$D$2,0)	=IF(J32<=$I$1,$D$2,0)	=MAX(0,B32-D32)
33	=A32+1	=E32+C31	=IF(E33<=$D$1,$D$2,0)	=IF(J33<=$I$1,$D$2,0)	=MAX(0,B33-D33)
34	=A33+1	=E33+C32	=IF(E34<=$D$1,$D$2,0)	=IF(J34<=$I$1,$D$2,0)	=MAX(0,B34-D34)
35	=A34+1	=E34+C33	=IF(E35<=$D$1,$D$2,0)	=IF(J35<=$I$1,$D$2,0)	=MAX(0,B35-D35)
36	=A35+1	=E35+C34	=IF(E36<=$D$1,$D$2,0)	=IF(J36<=$I$1,$D$2,0)	=MAX(0,B36-D36)
37					=SUM(E7:E36)

Fig. 5.4 Factory model

10	4	=J9	=D9	=G9	=MIN(F10,M9)	=F10+H10-I10
11	5	=J10	=D10	=G10	=MIN(F11,M10)	=F11+H11-I11

Fig. 5.5 Core assembly model

	A	K	L	M	N	O	P
1				WholMin	20		
2				WholMax	25		
3							
4		Whol					
5	Day	Start	Demand	Order	End	Short	Sent
6				0			
7	1	=20	=20	=IF(O7>0,$N$1+INT(0.7*O7),IF(N7>$N$2,0,$N$2-N7))	=K7-P7	=IF(L7>K7,L7-K7,0)	MIN(K7,L7)
8	2	=N7+I7	=T7+Y7+AD7+AI7+AM7	=IF(O8>0,$N$1+INT(0.7*O8),IF(N8>$N$2,0,$N$2-N8))	=K8-P8	=IF(L8>K8,L8-K8,0)	MIN(K8,L8)
9	3	=N8+I8	=T8+Y8+AD8+AI8+AM8	=IF(O9>0,$N$1+INT(0.7*O9),IF(N9>$N$2,0,$N$2-N9))	=K9-P9	=IF(L9>K9,L9-K9,0)	MIN(K9,L9)
10	4	=N9+I9	=T9+Y9+AD9+AI9+AM9	=IF(O10>0,$N$1+INT(0.7*O10),IF(N10>$N$2,0,$N$2-N10))	=K10-P10	=IF(L10>K10,L10-K10,0)	MIN(K10,L10)
11	5	=N10+I10	=T10+Y10+AD10+AI10+AM10	=IF(O11>0,$N$1+INT(0.7*O11),IF(N11>$N$2,0,$N$2-N11))	=K11-P11	=IF(L11>K11,L11-K11,0)	MIN(K11,L11)

Fig. 5.6 Wholesale model

	A	Q	R	S	T	U
1		start	4		order	ROP+.7short
2		rop	4			to Tmax
3		Tmax	8			
4						
5		R1				
6		start	demand	end	order	short
7		=$R$1	=INT(CB.Exponential(0.25))	=MAX(0,Q7-R7)	=IF(S7<=$R$2,4+INT(0.7*U7),IF(S7>$R$3,0,$R$3-S7))	=IF(R7>Q7,R7-Q7,0)
8		=S7+MIN(P7,T7)	=INT(CB.Exponential(0.25))	=MAX(0,Q8-R8)	=IF(S8<=$R$2,4+INT(0.7*U8),IF(S8>$R$3,0,$R$3-S8))	=IF(R8>Q8,R8-Q8,0)
9		=S8+MIN(P8,T8)	=INT(CB.Exponential(0.25))	=MAX(0,Q9-R9)	=IF(S9<=$R$2,4+INT(0.7*U9),IF(S9>$R$3,0,$R$3-S9))	=IF(R9>Q9,R9-Q9,0)
10		=S9+MIN(P9,T9)	=INT(CB.Exponential(0.25))	=MAX(0,Q10-R10)	=IF(S10<=$R$2,4+INT(0.7*U10),IF(S10>$R$3,0,$R$3-S10))	=IF(R10>Q10,R10-Q10,0)
11		=S10+MIN(P10,T10)	=INT(CB.Exponential(0.25))	=MAX(0,Q11-R11)	=IF(S11<=$R$2,4+INT(0.7*U11),IF(S11>$R$3,0,$R$3-S11))	=IF(R11>Q11,R11-Q11,0)

Fig. 5.7 Retailing model

30 units and is received at the beginning of the next day's operations. The assembly operation takes 1 day, and goods are available to send that evening. Column J shows ending inventory to equal what starting inventory plus what was processed that day minus what was sent to wholesale. Figure 5.6 shows the model of the wholesale operation.

The wholesale operation feeds retail demand, which is shown in column L. They feed retailers up to the amount they have in stock. They order from the assembler if they have less than 25 items. If they stock out, they order 20 items plus 70% of what they were unable to fill (this is essentially an exponential smoothing forecast). If they still have stock on hand, the order to fill up to 25 items. Figure 5.7 shows one of the five retailer operations (the other four are identical).

Retailers face a highly variable demand with a mean of 4. They fill what orders they have stock for. Shortfall is measured in column U. They order if their end-of-day inventory falls to 4 or less. The amount ordered is 4 plus 70% of shortfall, up to a maximum of 8 units.

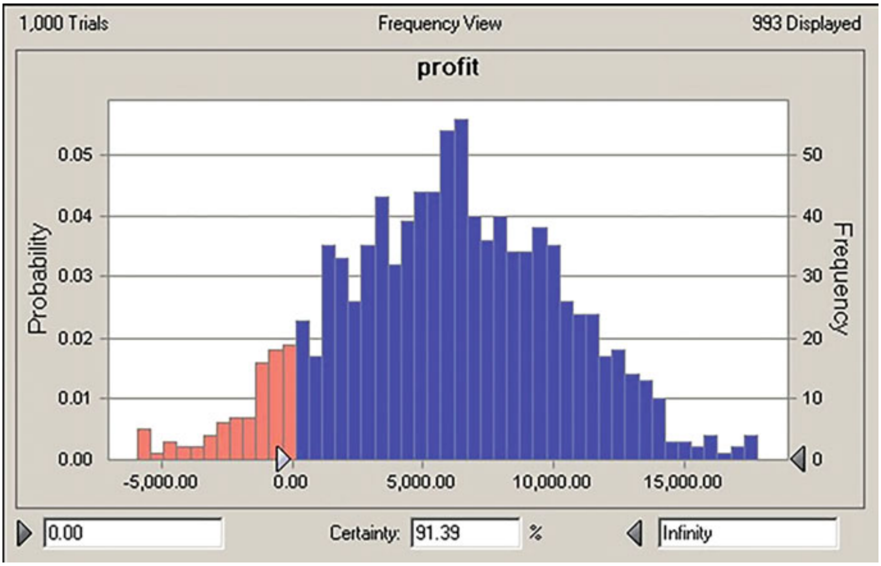

Fig. 5.8 Overall system profit for basic model. © Oracle. Used with permission

This model is run by Crystal Ball to generate a measure of overall system profit. Here, the profit formula is \$175 times sales minus holding costs minus transportation costs. Holding costs at the factory were \$0.25 times sum of ending inventory, at the assembler \$0.40 times sum of ending inventory, at the warehouse 0.50 times ending inventory, and at the retailers \$1 times sum of ending inventories. Shipping costs were \$1000 per day from factory to assembler, \$700 per day from assembler to warehouse, and \$300 per day from warehouse to retailer. The results of 1000 repetitions are shown in Fig. 5.8.

Here average profit for a month is \$5942, with a minimum loss of \$8699 and a maximum gain of \$18,922. There was a 0.0861 probability of a negative profit. The amount of shortage across the system is shown in Fig. 5.9. The average was 138.76, with a range of 33–279 over the 1000 simulation repetitions.

The central limit theorem can be shown to have an effect, as the sum of the five retailer shortfalls has a normally shaped distribution. Figure 5.10 shows a shortfall at the wholesale level, which had only one entity.

The average wholesale shortage was 15.73, with a minimum of 0 and a maximum of 82. Crystal Ball output indicates a probability of shortfall of 0.9720, meaning a 0.0280 probability of going the entire month without having a shortage at the wholesale level.

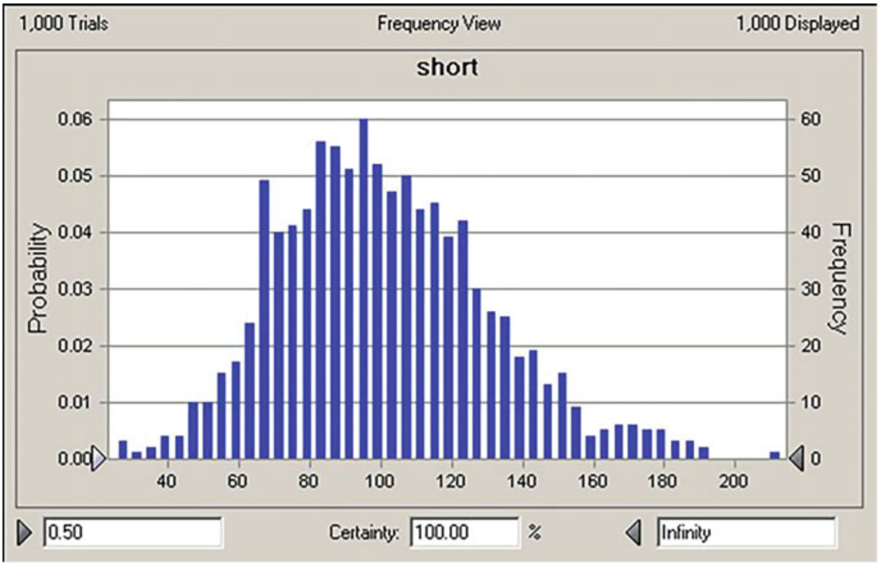

Fig. 5.9 Retail shortages for basic model. © Oracle. Used with permission

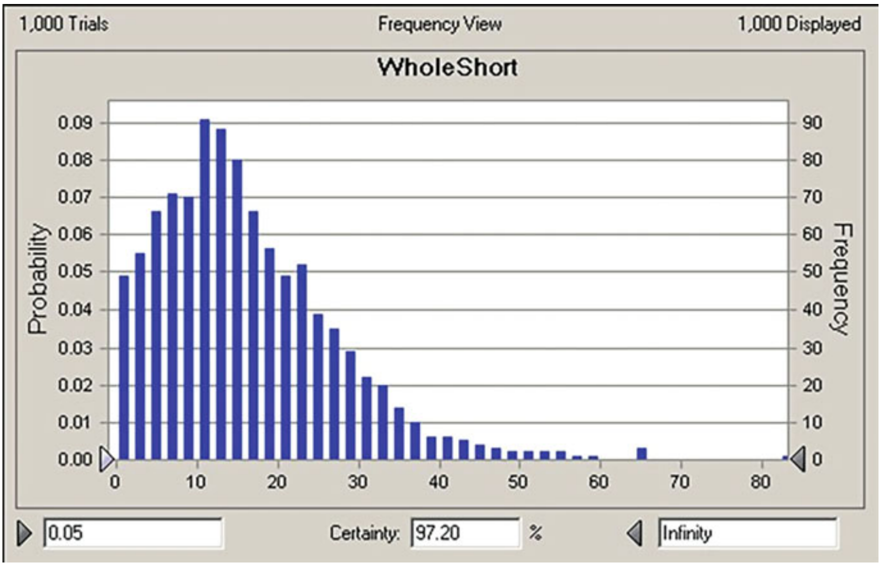

Fig. 5.10 Wholesale shortages for basic model. © Oracle. Used with permission

Push System

The difference in this model is that production at the factory (column C in Fig. 5.4) is a constant 20 per day, the amount sent from the factory to the assembler (column D in Fig. 5.4) is also 20 per day, the amount ordered by the wholesaler (column M in Fig. 5.6) is 20, the amount sent by the wholesaler to retailers (column P in Fig. 5.6) is a constant 20, and the amount ordered by the wholesaler (column T in Fig. 5.7) is a constant 20.

This system proved to be more profitable and safer for the given conditions. Profit is shown in Fig. 5.11.

The average profit was $13,561, almost double that of the more variable push system. Minimum profit was a loss of $2221, with the probability of loss 0.0052. Maximum profit was $29,772. Figure 5.12 shows shortfall at the retail level.

The average shortfall was only 100.32, much less than the 137.16 for the pull model. Shortfall at the wholesale level (Fig. 5.13) was an average of 21.54, ranging from 0 to 67.

For this set of assumed values, the push system performed better. But that establishes nothing, as for other conditions, and other means of coordination, a pull system could do better.

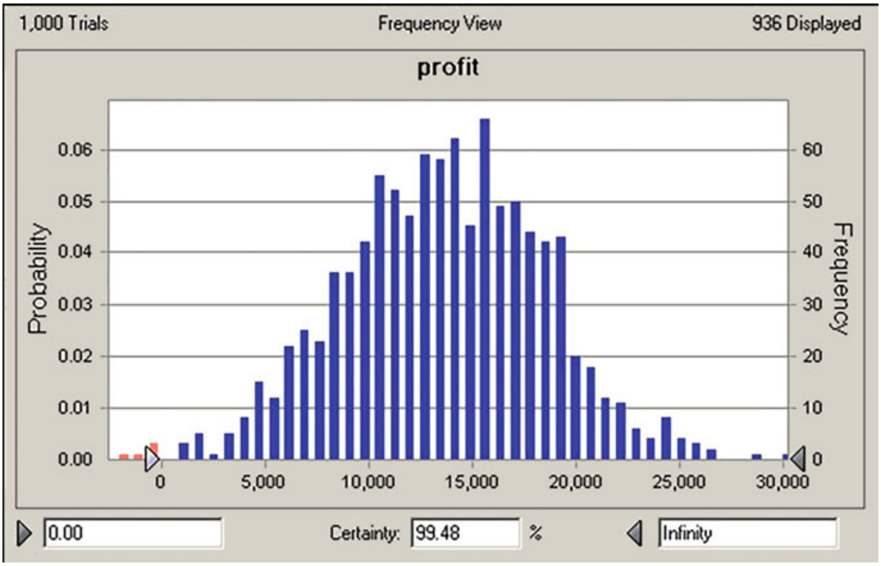

Fig. 5.11 Push system profit. © Oracle. Used with permission

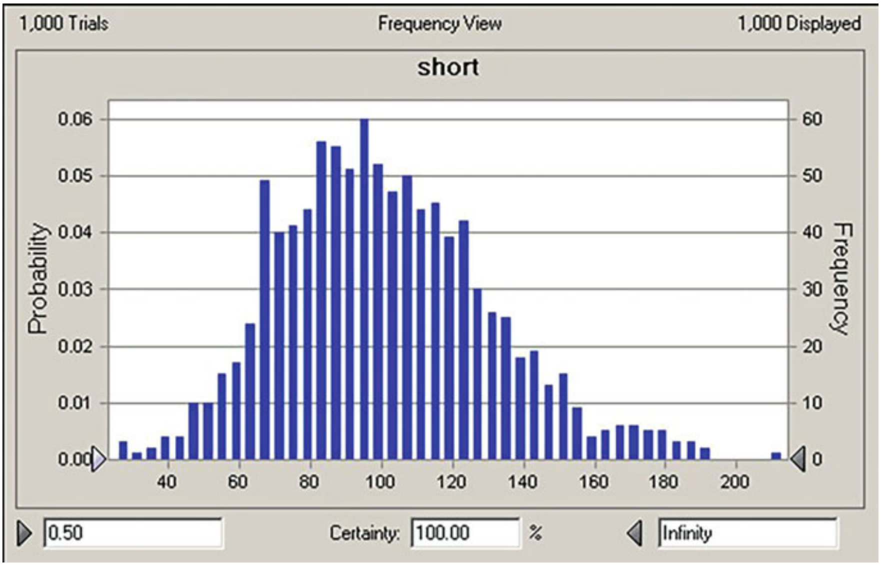

Fig. 5.12 Retail shortages for the push model. © Oracle. Used with permission

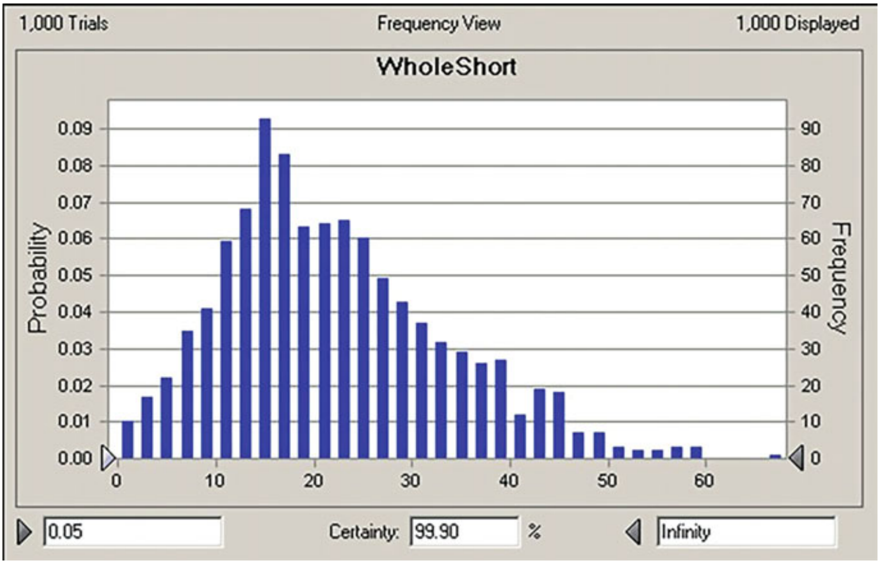

Fig. 5.13 Wholesale shortages for the push model. © Oracle. Used with permission

Monte Carlo Simulation for Analysis

Simulation models are sets of assumptions concerning the relationship among model components. Simulations can be time oriented (for instance, involving the number of events such as demands in a day) or process oriented (for instance, involving queuing systems of arrivals and services). Uncertainty can be included by using probabilistic inputs for elements such as demands, inter-arrival times, or service times. These probabilistic inputs need to be described by probability distributions with specified parameters. Probability distributions can include normal distributions (with parameters for mean and variance), exponential distributions (with parameters for a mean), lognormal (parameters mean and variance), or any of a number of other distributions. A simulation run is a sample from an infinite population of possible results for a given model. After a simulation model is built, the number of trials is established. Statistical methods are used to validate simulation models and design simulation experiments.

Many financial simulation models can be accomplished on spreadsheets, such as Excel. There are a number of commercial add-on products that can be added to Excel, such as @Risk or Crystal Ball, that vastly extend the simulation power of spreadsheet models. These add-ons make it very easy to replicate simulation runs and include the ability to correlate variables, expeditiously select from standard distributions, aggregate and display output, and other useful functions.

In supply chain outsourcing decisions, a number of factors can involve uncertainty, and simulation can be useful in gaining a better understanding of systems (Wu & Olson, 2008). We begin by looking at expected distributions of prices for the component to be outsourced from each location. China C in this case has the lowest estimated price, but it has a wide expected distribution of exchange rate fluctuation. These distributions will affect the actual realized price for the outsourced component. The Chinese C vendor is also rated as having a relatively high probability of failure in product compliance with contractual standards, in vendor financial survival, and in political stability of the host country. The simulation is modeled to generate 1000 samples of actual realized price after exchange rate variance, including having to rely upon an expensive ($5 per unit) price in case of outsourcing vendor failure.

Monte Carlo simulation output is exemplified in Fig. 5.14, which shows the distribution of prices for the hypothetical Chinese outsourcing vendor C, which was the low price vendor very nearly half of the time. Figure 5.15 shows the same for the Taiwanese vendor, and Fig. 5.16 for the safer but expensive German vendor.

The Chinese vendor C has a higher probability of failure (over 0.31 from all sources combined, compared to 0.30 for Indonesia). This raises its mean cost, because in case of failure, the $5 per unit default price is used. There is a cluster around the contracted cost of $0.60, with a minimum dropping slightly below 0 due to exchange rate variance, a mean of $0.78, and a maximum of $1.58 given survival in all three aspects of risk modeled. There is a spike showing a default price of $5.00 per unit in 0.3134 of the cases. Thus, while the contractual price is lowest for this alternative, the average price after consideration of failure is $2.10.

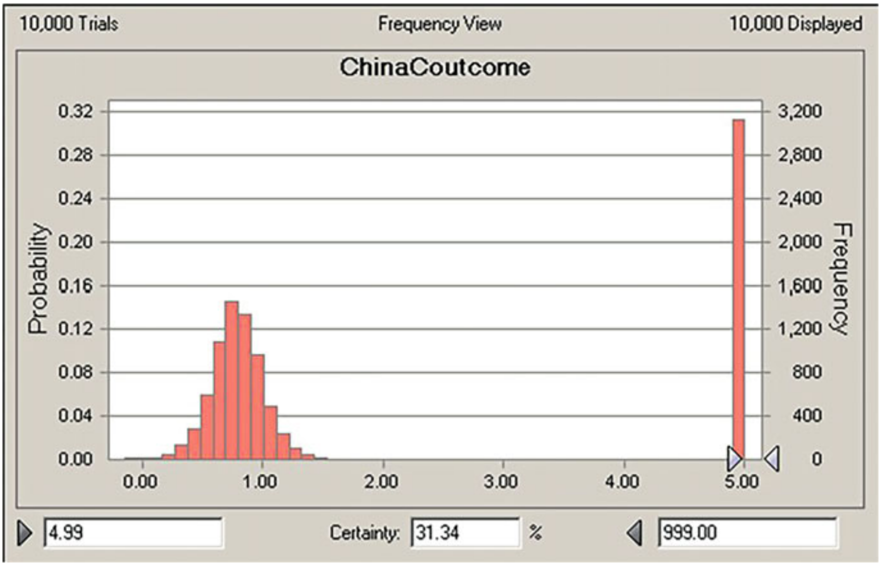

Fig. 5.14 Distribution of results for Chinese vendor C costs. © Oracle. Used with permission

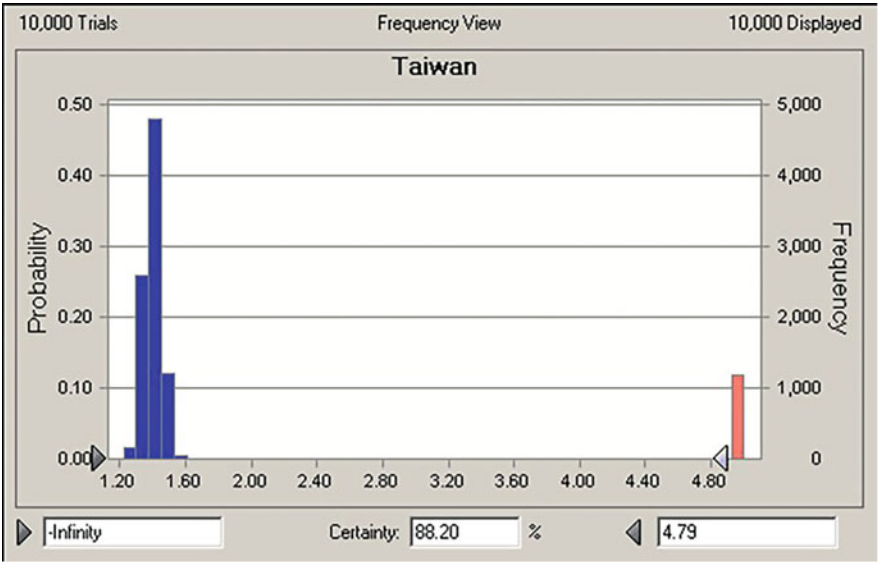

Fig. 5.15 Distribution of results for Taiwanese vendor costs. © Oracle. Used with permission

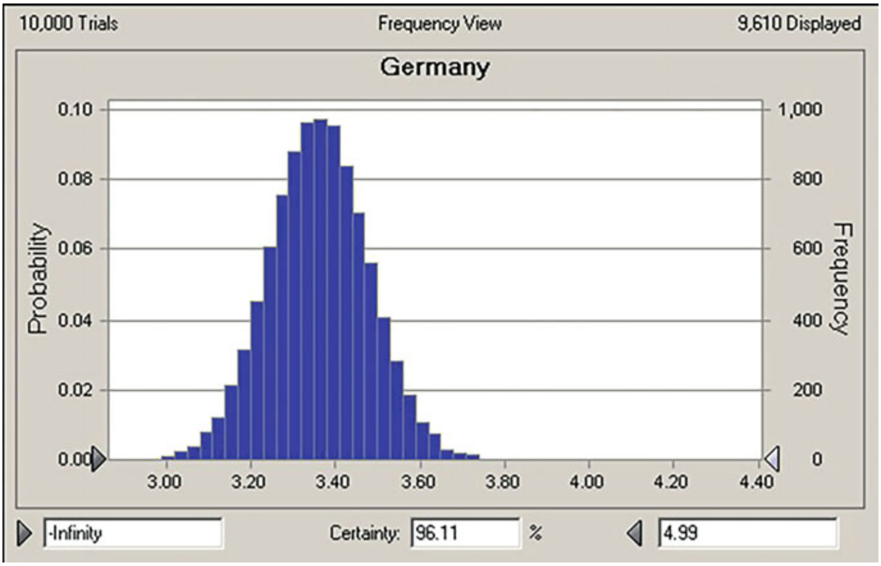

Fig. 5.16 Distribution of results for Germany vendor costs. © Oracle. Used with permission

Table 5.5 Simulation output

Vendor	Mean cost	Min. cost	Max. cost	Probability of failure	Probability low	Average cost if did not fail	Average overall
China B	0.70	−0.01	1.84	0.2220	0.1370	0.91	1.82
Taiwan	1.36	1.22	1.60	0.1180	0.0033	1.41	1.83
China C	0.60	0.05	1.58	0.3134	0.4939	0.78	2.10
China A	0.82	−0.01	2.16	0.2731	0.0188	1.07	2.14
Indonesia	0.80	0.22	1.61	0.2971	0.1781	0.96	2.16
Arizona	1.80	1.80	1.80	0.2083	0.0001	2.71	2.47
Vietnam	0.85	0.40	1.49	0.3943	0.1687	0.94	2.54
Alabama	2.05	2.05	2.05	0.2472	0		2.78
Ohio	2.50	2.50	2.50	0.2867	0		3.22
Germany	3.20	2.90	3.81	0.0389	0		3.42

Note: Average overall assumes cost of $5 to supply chain should vendor fail

Table 5.5 shows the comparative output. Simulation provides a more complete picture of the uncertainties involved.

Probabilities of being the low-cost alternative are also shown. The greatest probability was for China C at 0.4939, with Indonesia next at 0.1781. The expensive (but safer) alternatives of Germany and Alabama both were never low (and thus were dominated in the DEA model). But Germany had a very high probability of survival, and in the simulation could appear as the best choice (rarely).

Conclusion

Simulation is the most flexible management science modeling technique. It allows making literally any assumption you want, although the trade-off is that you have to work very hard to interpret results in a meaningful way relative to your decision.

Because of the variability inherent in risk analysis, simulation is an obviously valuable tool for risk analysis. There are two basic simulation applications in business. Waiting line models involve queuing systems, and software such as Arena (or many others) is very appropriate for that type of modeling. The other type is supportable by spreadsheet tools such as Crystal Ball, demonstrated in this chapter. Spreadsheet simulation is highly appropriate for inventory modeling as in push/pull models. Spreadsheet models also are very useful for system dynamic simulations. We will see more Crystal Ball simulation models in chapters covering value at risk and chance-constrained models.

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6 Value at Risk Models

Value at risk (VaR) is one of the most widely used models in risk management. It is based on probability and statistics (Jorion, 1997). VaR can be characterized as a maximum expected loss, given some time horizon and within a given confidence interval. Its utility is in providing a measure of risk that illustrates the risk inherent in a portfolio with multiple risk factors, such as portfolios held by large banks, which are diversified across many risk factors and product types. VaR is used to estimate the boundaries of risk for a portfolio over a given time period, for an assumed probability distribution of market performance. The purpose is to diagnose risk exposure.

Definition

Value at risk describes the probability distribution for the value (earnings or losses) of an investment (firm, portfolio, etc.). The mean is a point estimate of a statistic, showing historical central tendency. Value at risk is also a point estimate but offset from the mean. It requires specification of a given probability level, and then provides the point estimate of the return or better expected to occur at the prescribed probability. For instance, Fig. 6.1 gives the normal distribution for a statistic with a mean of 10 and a standard deviation of 4 (Crystal Ball was used, with 10,000 replications).This indicates a 0.95 probability (for all practical purposes) of a return of at least 3.42. The precise calculation can be made in Excel, using the NormInv function for a probability of 0.05, a mean of 10, and a standard deviation of 4, yielding a return of 3.420585, which is practically the same as the simulation result shown in Fig. 6.1. Thus, the value of the investment at the specified risk level of 0.05 is 3.42. The interpretation is that there is a 0.05 probability that things would be worse than the value at this risk level. Thus, the greater the degree of assurance, the lower the value at risk return. The value at the risk level of 0.01 would only be 0.694609.

D. L. Olson, D. Wu, *Enterprise Risk Management Models*, Springer Texts in Business and Economics, https://doi.org/10.1007/978-3-662-68038-4_6

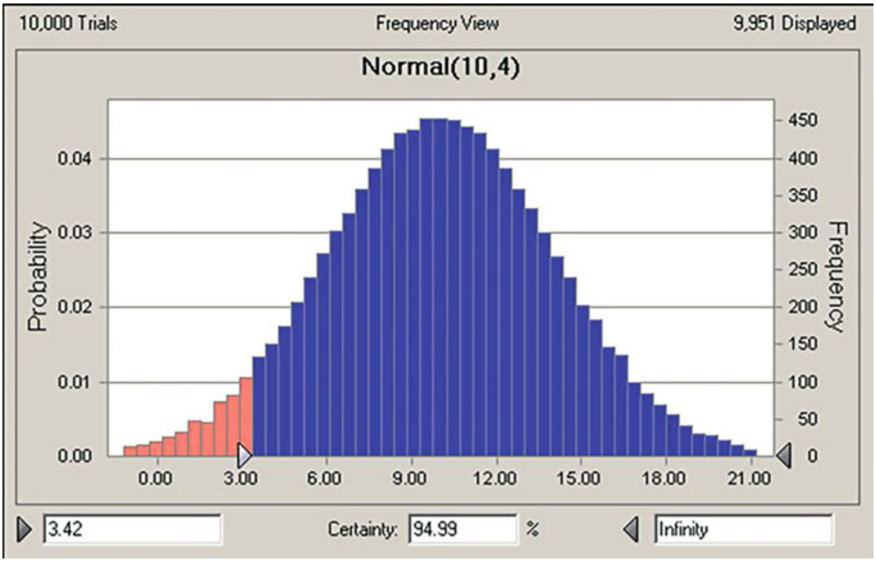

Fig. 6.1 Normal distribution (10,4). ©Oracle. used with permission

The Basel Accords

VaR is globally accepted by regulatory bodies responsible for the supervision of banking activities. These regulatory bodies, in broad terms, enforce regulatory practices as outlined by the Basel Committee on Banking Supervision of the Bank for International Settlements (BIS). The regulator that has responsibility for financial institutions in Canada is the Office of the Superintendent of Financial Institutions (OSFI), and OSFI typically follows practices and criteria as proposed by the Basel Committee.

Basel I

Basel I was promulgated in 1988, focusing on credit risk. A key agreement of the Basel Committee is the Basel Capital Accord (generally referred to as "Basel" or the "Basel Accord"), which has been updated several times since 1988. In the 1996 (updated, 1998) Amendment to the Basel Accord, banks were encouraged to use internal models to measure Value at Risk, and the numbers produced by these internal models support capital charges to ensure the capital adequacy, or liquidity, of the bank. Some elements of the minimum standard established by Basel are:

- VaR should be computed daily, using a 99th percentile, one-tailed confidence interval.

- A minimum price shock equivalent to ten trading days be used. This is called the "holding period" and simulates a 10-day period of liquidating assets in a period of market crisis.
- The model should incorporate a historical observation period of at least 1 year.
- The capital charge is set at a minimum of three times the average of the daily value-at-risk of the preceding 60 business days.

In 2001, the Basel Committee on Banking Supervision published principles for management and supervision of operational risks for banks and domestic authorities supervising them.

Basel II

Basel II was published in 2009 to deal with the operational risk management of banking. Banks and financial institutions were bound to use internal and external data, scenario analysis, and qualitative criteria. Banks were required to compute capital charges on a yearly basis and to calculate 99.9 % confidence levels (one in one thousand events as opposed to the earlier one in one hundred events). Basel II included standards in the form of three pillars:

1. Minimum capital requirements.
2. Supervisory review, to include categorization of risks as systemic, pension related, concentration, strategic, reputation, liquidity, and legal.
3. Market discipline, including enhancements to strengthen disclosure requirements for securitizations, off-balance sheet exposures, and trading activities.

Basel III

Basel III was a comprehensive set of reform measures published in 2011 with phased implementation dates. The aim was to strengthen regulation, supervision, and risk management of the banking sectors.

Pillar 1 dealt with capital, risk coverage, and containing leverage:

- Capital requirements to improve bank ability to absorb shocks from financial and economic stress:

  Common equity 0.045 of risk-weighted assets
- Leverage requirements to improve risk management and governance: Tier 1 capital 0.03 of total exposure
- Liquidity requirements to strengthen bank transparency and disclosure: High-quality liquid assets $\geq$ total net liquidity outflows over 30 days

Pillar 2 dealt with risk management and supervision.

Pillar 3 dealt with market discipline through disclosure requirements.

The Use of Value at Risk

In practice, these minimum standards mean that the VaR that is produced by the Market Risk Operations area is multiplied first by the square root of 10 (to simulate 10 days holding) and then multiplied by a minimum capital multiplier of 3 to establish capital held against regulatory requirements.

In summary, VaR provides the worst expected loss at the 99 % confidence level. That is, a 99 % confidence interval produces a measure of loss that will be exceeded only 1 % of the time. But this does mean there will likely be a larger loss than the VaR calculation two or three times in a year. This is compensated for by the inclusion of the multiplicative factors above, and the implementation of Stress Testing, which falls outside the scope of the activities of Market Risk Operations.

Various approaches can be used to compute VaR, of which three are widely used: Historical Simulation, Variance-covariance approach, and Monte Carlo simulation. The variance-covariance approach is used for investment portfolios, but it does not usually work well for portfolios involving options that are close to delta neutral. Monte Carlo simulation solves the problem of non-linearity approximation if model error is not significant, but it suffers some technical difficulties such as how to deal with time-varying parameters and how to generate maturation values for instruments that mature before the VaR horizon. We present Historical Simulation and Variance-covariance approach in the following two sections. We will demonstrate Monte Carlo Simulation in a later section of this chapter.

Historical Simulation

Historical simulation is a good tool to estimate VAR in most banks. Observations of day-over-day changes in market conditions are captured. These market conditions are represented using upwards of 100,000 points daily of observed and implied Market Data. This historical market data is captured and used to generate historical “shocks” to current spot market data. This shocked market data is used to price the Bank’s trading positions as against changing market conditions, and these revalued positions then are compared against the base case (using spot data). This simulates a theoretical profit or loss. Each day of historically observed data produces a theoretical profit/loss number in this way, and all of these theoretical P&L numbers produce a distribution of theoretical profits/losses. The (1-day) VaR can then be read as the 99th percentile of this distribution.

The primary advantage of historical simulation is the ease of use and implementation. In Market Risk Operations, historical data is collected and reviewed on a regular basis, before it is added to the historical data set. Since this data corresponds to historical events, it can be reviewed in a straightforward manner. Also, the historical nature of the data allows for some clarity of explanation of VaR numbers. For instance, the Bank’s VaR may be driven by widening credit spreads, or by decreasing equity volatilities, or both, and this will be visible in actual historical data.

Additionally, historical data implicitly contains correlations and non-linear effects (e.g., gamma, vega, and cross-effects).

The most obvious disadvantage of historical simulation is the assumption that the past presents a reasonable simulation of future events. Additionally, a large bank usually holds a large portfolio, and there can be considerable operational overhead involved in producing a VaR against a large portfolio with dependencies on a large and varied number of model inputs. All the same, other VaR methods, such as variance-covariance (VCV) and Monte Carlo simulation, produce essentially the same objections. The main alternative to historical simulation is to make assumptions about the probability distributions of the returns on the market variables and calculate the probability distribution of the change in the value of the portfolio analytically. This is known as the variance-covariance approach. VCV is a parametric approach and contains the assumption of normality, and the assumption of the stability of correlation at the same time. Monte Carlo simulation provides another tool for these two methods. Monte Carlo methods are dependent on decisions regarding model calibration, which have effectively the same problems. No VaR methodology is without simplifying assumptions, and several different methods are in use at institutions worldwide. The literature on volatility estimation is large and seemingly subject to unending growth, especially in acronyms (Danielson & de Vries, 1997; Fallon, 1996; Garman, 1996):

Variance-Covariance Approach

VCV Models portfolio returns as a multivariate normal distribution. We can use a position vector containing cash flow present values to represent all components of the portfolio and describe the portfolio. VCV approach concerns most the return and covariance matrix(Q) representing the risk attributes of the portfolio over the chosen horizon. The standard deviation of portfolio value (σ), also called volatility, is computed:

$$\sigma = \sqrt{h^2 Qh}$$

The volatility (σ) is then scaled to find the desired centile of portfolio value that is the predicted maximum loss for the portfolio or VaR:

ð2Þ

$$VaR = \sigma f(Y)$$

where $f(Y)$ is the scale vector for centile Y

For example, for a multivariate normal return distribution, $f(Y) = 2.33$ for Y = 1 %. It is then easy to calculate VaR from the standard deviation (1-day VaR=2.33s). The simplest assumption is that daily gain/losses are normally distributed and independent. The N-day VaR equals $\sqrt{N}$ times the one-day VaR. When there is autocorrelation equal to r the multiplier is increased from N to:

$$N + 2(N-1)\rho + 2(N-2)\rho^2 + 2(N-3)\rho^3 + \ldots + 2\rho^{N-1}$$

Besides being easy to compute, VCV also lends itself readily to the calculation of the marginal risk (Marginal VaR), Incremental VaR, and Component VaR of candidate trades. For a Portfolio where an amount x_i is invested in the ith component of the portfolio, these three VaR measures are computed as:

- Marginal VaR: $\frac{\partial VaR}{\partial x_i}\, i$
- Incremental VaR: Incremental effect of ith component on VaR.
- Component VaR $x_i \frac{\partial VaR}{\partial x_i}$.

VCV uses delta approximation, which means the representative cash flow vector is a linear approximation of positions. In some cases, a second-order term in the cash flow representation is included to improve this approximation (Morgan, 1996). However, this does not always improve the risk estimate and can only be done with the sacrifice of some of the computational efficiency. In general, VCV works well in calculating linear instruments such as forward, interest rate SWAP, but works quite badly in nonlinear instruments such as various options.

Monte Carlo Simulation of VaR

Simulation models are sets of assumptions concerning the relationship among model components. Simulations can be time oriented (for instance, involving the number of events such as demands in a day) or process oriented (for instance, involving queuing systems of arrivals and services). Uncertainty can be included by using probabilistic inputs for elements such as demands, inter-arrival times, or service times. These probabilistic inputs need to be described by probability distributions with specified parameters. Probability distributions can include normal distributions (with parameters for mean and variance), exponential distributions (with parameters for a mean), lognormal (parameters mean and variance), or any of a number of other distributions. A simulation run is a sample from an infinite population of possible results for a given model. After a simulation model is built, a selected number of trials is established. Statistical methods are used to validate simulation models and design simulation experiments.

Many financial simulation models can be accomplished on spreadsheets, such as Excel. There are a number of commercial add-on products that can be added to Excel, such as @Risk or Crystal Ball, that vastly extend the simulation power of spreadsheet models (Evans & Olson, 2002). These add-ons make it very easy to replicate simulation runs, and include the ability to correlate variables, expeditiously select from standard distributions, aggregate and display output, and other useful functions.

The Simulation Process

Using simulation effectively requires careful attention to the modeling and implementation process. The simulation process consists of five essential steps:

Develop a conceptual model of the system or problem under study. This step begins with understanding and defining the problem, identifying the goals and objectives of the study, determining the important input variables, and defining output measures. It might also include a detailed logical description of the system that is being studied. Simulation models should be made as simple as possible to focus on critical factors that make a difference in the decision. The cardinal rule of modeling is to build simple models first, then embellish and enrich them as necessary.

1. Build the simulation model. This includes developing appropriate formulas or equations, collecting any necessary data, determining the probability distributions of uncertain variables, and constructing a format for recording the results. This might entail designing a spreadsheet, developing a computer programme, or formulating the model according to the syntax of a special computer simulation language.
2. Verify and validate the model. Verification refers to the process of ensuring that the model is free from logical errors; that is, that it does what it is intended to do. Validation ensures that it is a reasonable representation of the actual system or problem. These are important steps to lend credibility to simulation models and gain acceptance from managers and other users. These approaches are described further in the next section.
3. Design experiments using the model. This step entails determining the values of the controllable variables to be studied or the questions to be answered in order to address the decision maker's objectives.
4. Perform the experiments and analyze the results. Run the appropriate simulations to obtain the information required to make an informed decision.

As with any modeling effort, this approach is not necessarily serial. Often, you must return to previous steps as new information arises or as results suggest modifications to the model. Therefore, simulation is an evolutionary process that must involve not only analysts and model developers but also the users of the results.

Demonstration of VaR Simulation

We use an example Monte Carlo simulation model published by Beneda (2004) to demonstrate simulation of VaR and other forms of risk. Beneda considered four risk categories, each with different characteristics of data availability:

- Financial risk—controllable (interest rates, commodity prices, currency exchange)
- Pure risk—controllable (property loss and liability)

- Operational—uncontrollable (costs, input shortages)
- Strategic—uncontrollable (product obsolescence, competition)

Beneda's model involved forward sale (45 days forward) of an investment (CD) with a price that was expected to follow the uniform distribution ranging from 90 to 110. Half of these sales (20,000 units) were in Canada, which involved an exchange rate variation that was probabilistic (uniformly distributed from 0.008 to 0.004). The expected price of the CD was normally distributed with mean 0.8139, standard deviation of 0.13139. Operating expenses associated with the Canadian operation were normally distributed with mean $1,925,000 and standard deviation $192,500. The other half of sales were in the USA. In the USA, there was a risk of customer liability lawsuits (2, Poisson distribution), with expected severity per lawsuit that was lognormally distributed with mean $320,000, standard deviation $700,000. Operational risks associated with US operations were normally distributed with mean $1,275,000, standard deviation $127,500. The Excel spreadsheet model for this is given in Table 6.1.

In Crystal Ball, entries in cells B2, B3, B7, B10, B21, B22, and B23 were entered as assumptions with the parameters given in column C. Prediction cells were defined for cells B17 (Canadian net income) and B29 (Total net income after tax). Results for cell B17 are given in Fig. 6.2, with a probability of 0.9 prescribed in Crystal Ball so that we can identify the VaR at the 0.05 level.Statistics are given in Table 6.2.

The value at risk at the 0.95 level for this investment was 540,245.40, meaning that there was a 0.05 probability of doing worse than losing $540,245.50 in US dollars. The overall investment outcome is shown in Fig. 6.3.Statistics are given in Table 6.3.

On average, the investment paid off, with a positive value of $96,022.98. However, the worst case of 500 was a loss of over $14 million. (The best was a gain of over $1.265 million.) The value at risk shows a loss of $1.14 million, and Fig. 6.3 shows that the distribution of this result is highly skewed (note the skewness measures for Figs. 6.2 and 6.3).

Beneda proposed a model reflecting hedging with futures contracts, and insurance for customer liability lawsuits. Using the hedged price in cell B4, and insurance against customer suits of $640,000, the after-tax profit is shown in Fig. 6.4.Mean profit dropped to $84,656 (standard deviation $170,720), with a minimum -$ 393,977 (maximum gain $582,837). The value at risk at the 0.05 level was a loss of $205,301. Thus, there was an expected cost of hedging (mean profit dropped from $96,022 to $84,656), but the worst case was much improved (loss of over $14 million to loss of $393,977) and value at risk improved from a loss of over $1.14 million to a loss of $205 thousand.

Table 6.1 Excel model of investment

	A	B	C
1	Financial risk	Formulas	Distribution
2	Expected basis	−0.006	Uniform (−0.008,-0.004)
3	Expected price per CD	0.8139	Normal (0.8139,0.13139)
4	March futures price	0.8149	
5	Expected basis 45 days	=B2	
6	Expected CD futures	0.8125	
7	Operating expenses	1.925	Normal (1,925,000,192,500)
8	Sales	20,000	
9			
10	Price $US	100	Uniform (90,110)
11	Sales	20,000	
12	Current	0.8121	
13	Receipts	=B10 * B11/B12	
14	Expected exchange rate	=B3	
15	Revenues	=B13 * B14	
16	COGS	=B7 * 1,000,000	
17	Operating income	=B15 - B16	
18			
19	Local sales	20,000	
20	Local revenues	=B10 * B19	
21	Lawsuit frequency	2	Poisson (2)
22	Lawsuit severity	320,000	Lognormal (320,000,700,000)
23	Operational risk	1,275,000	Normal (1,275,000,127,500)
24	Losses	=B21 * B22 + B23	
25	Local income	=B20 - B24	
26			
27	Total income	=B17 + B25	
28	Taxes	=0.35 * B27	
29	After-Tax Income	=B27 - B28	

Conclusions

Value at risk is a useful concept in terms of assessing probabilities of investment alternatives. It is a point estimator, like the mean (which could be viewed as the value at risk for a probability of 0.5). It is only as valid as the assumptions made, which include the distributions used in the model and the parameter estimates. This is true of any simulation. However, value at risk provides a useful tool for financial investment. Monte Carlo simulation provides a flexible mechanism to measure it, for any given assumption.

However, Value at risk has undesirable properties, especially for gain and loss data with non-elliptical distributions. It satisfies the well-accepted principle of

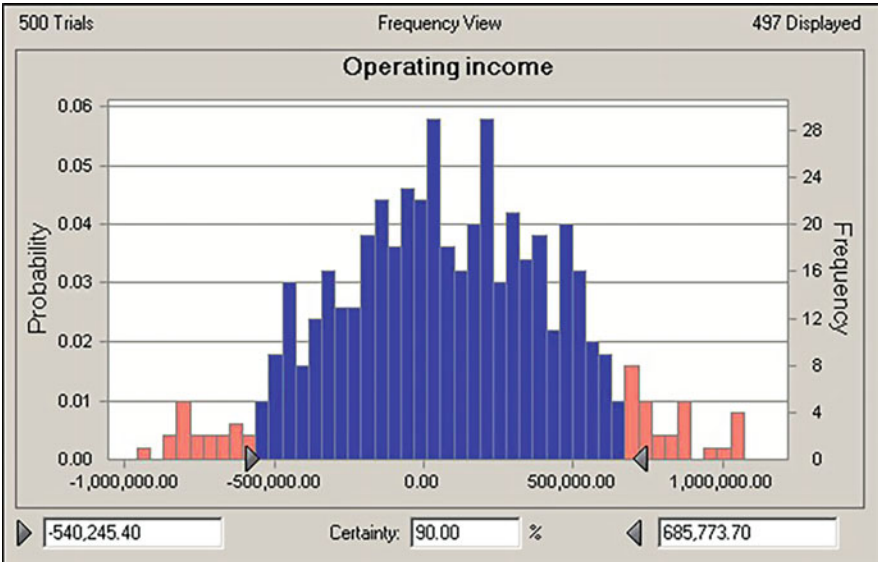

Fig. 6.2 Output for Canadian investment. ©Oracle. used with permission

Table 6.2 Output statistics for operating income

Forecast	Operating income
Statistic	Forecast values
Trials	500
Mean	78,413.99
Median	67,861.89
Mode	–
Standard Deviation	385,962.44
Variance	148,967,005,823.21
Skewness	−0.0627
Kurtosis	2.99
Coefficient of variability	4.92
Minimum	−1,183,572.09
Maximum	1,286,217.07
Mean standard error	17,260.77

diversification under the assumption of normally distributed data. However, it violates the widely accepted subadditive rule; i.e., the portfolio VaR is not smaller than the sum of component VaR. The reason is that VaR only considers the extreme percentile of a gain/loss distribution without considering the magnitude of the loss. As a consequence, a variant of VaR, usually labeled *Conditional-Value-at-Risk* (or CVaR), has been used. With respect to computational issues, optimization CVaR can be very simple, which is another reason for the adoption of CVaR. This pioneering work was initiated by Rockafellar and Uryasev (2002), where CVaR constraints in optimization problems can be formulated as linear constraints. CVaR

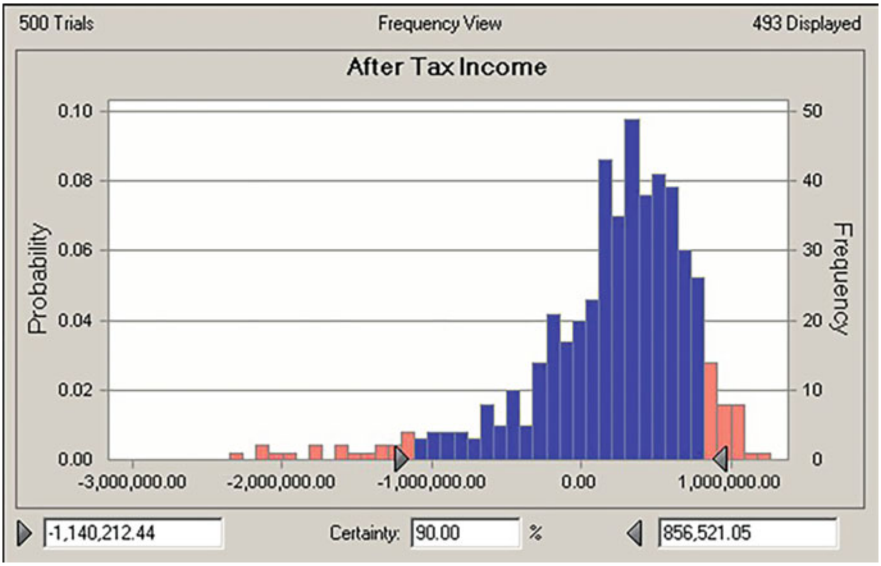

Fig. 6.3 Output for after-tax income. ©Oracle. used with permission

Table 6.3 Output statistics for after-tax income

Forecast	Operating income
Statistic	Forecast values
Trials	500
Mean	96,022.98
Median	304,091.58
Mode	–
Standard Deviation	1,124,864.11
Variance	1,265,319,275,756.19
Skewness	−7.92
Kurtosis	90.69
Coefficient of variability	11.71
Minimum	−14,706,919.79
Maximum	1,265,421.71
Mean standard error	50,305.45

represents a weighted average between the value at risk and losses exceeding the value at risk. CVaR is a risk assessment approach used to reduce the probability a portfolio will incur large losses assuming a specified confidence level. CVaR has been applied to financial trading portfolios (Al Janabi, 2009), implemented through scenario analysis (Sawik, 2011), and applied via system dynamics (Mehrjoo & Pasek, 2016). A popular refinement is to use copulas, multivariate distributions permitting the linkage of a huge number of distributions (Guégan & Hassani, 2012). Copulas have been implemented through simulation modeling (Hsu et al., 2012) as well as through analytic modeling (Kaki et al., 2014).

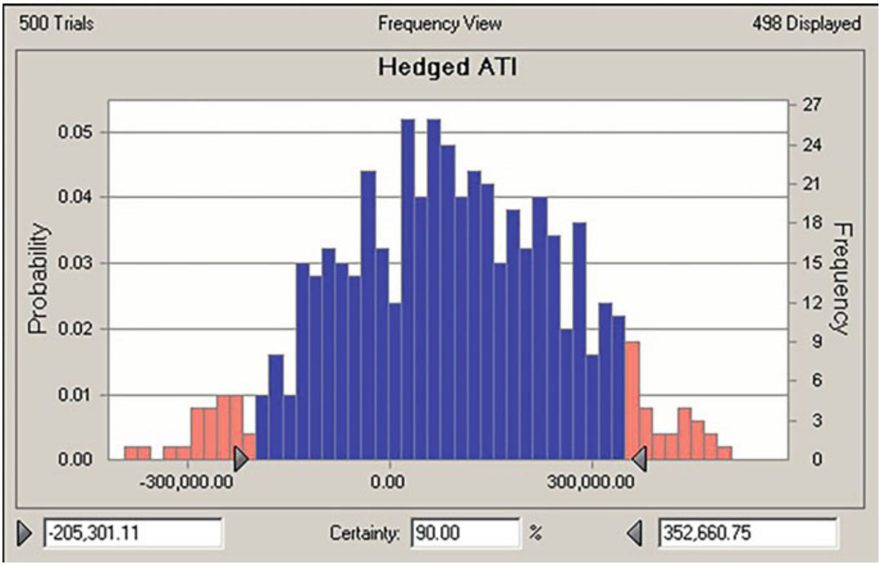

Fig. 6.4 After-tax profit with hedging and insurance. ©Oracle. used with permission

We will show how specified confidence levels can be modeled through chance constraints in the next chapter. It is possible to maximize portfolio return subject to constraints including Conditional Value-at-Risk (CVaR) and other downside risk measures, both absolute and relative to a benchmark (market and liability based). Simulation CVaR-based optimization models can also be developed.

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7 Chance-Constrained Models

Chance-constrained programming was developed as a means of describing constraints in mathematical programming models in the form of probability levels of attainment (Charnes & Cooper, 1959, 1962). Consideration of chance constraints allows decision makers to consider mathematical programming objectives in terms of the probability of their attainment. If α is a predetermined confidence level desired by a decision maker, the implication is that a constraint will be violated at most (1-α) of all possible cases. Chance constraints are thus special types of constraints in mathematical programming models, where there is some objective to be optimized subject to constraints. A typical mathematical programming formulation might be:

$$\text{Maximize} f(X)$$

$$\text{Subject to}: Ax \leq b$$

The objective function *f(X)* can be profit, with the function consisting of n variables X as the quantities of products produced and *f(X)* including profit contribution rate constants. There can be any number m of constraints in Ax, each limited by some constant b. Chance constraints can be included in Ax, leading to a number of possible chance constraint model forms. Charnes and Cooper presented three formulations (Charnes & Cooper, 1963):

1. Maximize the expected value of a probabilistic function

$$\text{Maximize E}[Y] \text{ where } (Y = f(X))$$

$$\text{Subject to}: \Pr\{Ax \leq b\} \geq \alpha$$

Any coefficient of this model (Y, A, b) may be probabilistic. The intent of this formulation would be to maximize (or minimize) a function while assuring α probability that a constraint is met. While the expected value of a function usually

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involves a linear functional form, chance constraints will usually be nonlinear. This formulation would be appropriate for many problems seeking maximum profit subject to staying within resource constraints at some specified probability.

2. Minimize variance

$$\text{Min Var}[Y]$$

$$\text{Subject to : Pr}\{Ax \leq b\} \geq \alpha$$

The intent is to accomplish some functional performance level while satisfying the chance constraint set. This formulation might be used in identifying portfolio investments with minimum variance, which often is used as a measure of risk.

3. Maximize the probability of satisfying a chance constraint set

$$\text{Max Pr}\{Y \geq \text{target}\}$$

$$\text{Subject to : Pr}\{Ax \leq b\} \geq \alpha$$

This formulation is generally much more difficult to accomplish, especially in the presence of joint chance constraints (where simultaneous satisfaction of chance constraints is required). The only practical means to do this is running a series of models seeking the highest α level yielding a feasible solution.

All three models include a common general chance constraint set, allowing probabilistic attainment of functional levels:

$$\text{Pr}\{Ax \leq b\} \geq \alpha$$

This set is nonlinear, requiring nonlinear programming solution. This inhibits the size of the model to be analyzed, as large values of model parameters m (number of constraints) and especially n (number of variables) make it much harder to obtain a solution.

Most chance-constrained applications assume normal distributions for model coefficients. Goicoechea and Duckstein presented deterministic equivalents for non-normal distributions (Goicoechea & Duckstein, 1987). However, in general, chance-constrained models become much more difficult to solve if the variance of parameter estimates increases (the feasible region shrinks drastically when more dispersed distributions are used). The same is true if α is set at too high a value (for the same reason—the feasible region shrinks).

Chance-constrained applications also usually assume coefficient independence. This is often appropriate. However, it is not appropriate in many investment analyses. Covariance elements of coefficient estimates can be incorporated within chance constraints, eliminating the need to assume coefficient independence. However, this requires significantly more data and vastly complicates model data entry.

Chance-Constrained Applications

Chance-constrained models are not nearly as widespread as linear programming models. A number of applications involve financial planning, including retirement fund planning models (Booth, 2004). Chance constraints have also been applied to stress testing value-at-risk (and CVaR) (Dupaĉová & Polivka, 2007). Beyond financial planning, chance-constrained models have been applied to supplier selection (Bilsel & Ravindran, 2011) in operations, as well as in project selection in construction (Wibowo & Kochendoerfer, 2011). A multi-attribute model for the selection of infrastructure projects in an aerospace firm seeking to maximize company performance subject to probabilistic budget constraints has been presented (Gurgur & Morley, 2008). There are green chance-constrained models seeking efficient climate policies considering available investment streams and renewable energy technologies (Held et al., 2009).

Chance constraints have been incorporated into data envelopment analysis models (Cooper et al., 2002). Chance-constrained programming has been compared with data envelopment analysis and multi-objective programming in a supply chain vendor selection model (Wu & Olson, 2008).

Portfolio Selection

Assume a given sum of money to be invested in n possible securities. We denote by $x = (x_1, \ldots, x_n)$ as an investment proportion vector (also called a portfolio). As for the number of securities n, many large institutions have “approved lists” where n is anywhere from several hundred to a thousand. When attempting to form a portfolio to mimic a large broad-based index (like S&P500, EAFE, Wilshire 5000), n can be up to several thousand, denoted by r_i the percent return of i-th security; other objectives to characterize the i-th security could be:

- s_i is social responsibility of i-th security
- g_i is growth in sales of i-th security
- a_i is amount invested in R&D of i-th security
- d_i is dividends of i-th security
- q_i is liquidity of i-th security

Consideration of such investment objectives will lead to utilization of multi-objective programming models. The investor tries to select several possible securities from the n securities to maximize his/her profit, which leads to the investor’s decision problem as:

$$Max\ r_p = \sum_{i=1}^{n} r_i x_i$$

$$\text{Subject to}: Ax \leq b$$

- r_p is percent return on a portfolio over the holding period.
- $Ax \leq b$ is the feasible region in decision space.

In the investor's decision problem (1), the quantity r_p to be maximized is a random variable because r_p is a function of the individual security r_i random variables. Therefore, Eq. (1) is a *stochastic programming problem*. Stochastic programming models are similar to deterministic optimization problems where the parameters are known only within certain bounds but take advantage of the fact that probability distributions governing the data are known or can be estimated. To solve a stochastic programming problem, we need to convert the stochastic programming to an equivalent *deterministic programming problem*. A popular way of doing this is to use utility function $U(\cdot)$], which maps stochastic terms into their deterministic equivalents. For example, by use of the means μ_i, variances σ_{ii}, and covariances σ_{ij} of the r_i, a portfolio selection problem is to maximize expected utility.

$$E\left[U\left(r_p\right)\right] = E\left[r_p\right] - \lambda \mathrm{Var}\left[r_p\right]$$

where $\lambda \geq 0$ is a risk reversion coefficient and may be different for different investors. In other words, a portfolio selection problem can be modeled by a trade-off between the mean and variance of random variable r_p:

$$\begin{aligned} \text{Max } E\left[U\left(r_p\right)\right] &= E\left[r_p\right] - \lambda \mathrm{Var}\left[r_p\right] \\ \text{Max } E\,U\,r_p &= E\,r_p - \lambda \mathrm{Var}\,r_p, \\ \lambda &\geq 0 \\ Ax &\leq b \end{aligned}$$

Assuming $[U(r_p)]$ is an expandable Taylor series, the validity of $E[U(r_p)]$ and thus the above problem can be guaranteed if $[U(r_p)]$ is the expandable Taylor series of $r = (r_1, \ldots, r_n)$ follows the multinormal distribution. Another alternative to Markowitz's mean-variance framework, chance-constrained programming was employed to model the portfolio selection problem. We will demonstrate the utilization of chance-constrained programming to model the portfolio selection problem in the next section.

Demonstration of Chance-Constrained Programming

The following example was taken from Lee and Olson (2006). The Hal Chase Investment Planning Agency is in business to help investors optimize their return from investment, including consideration of risk. By using nonlinear programming models, Hal Chase can control risk.

Hal deals with three investment mediums: a stock fund, a bond fund, and his own Sports and Casino Investment Plan (SCIP). The stock fund is a mutual fund

Table 7.1 Hal Chase investment data

	Stock S	Bond B	SCIP G
Average return	0.148	0.060	0.152
Variance	0.014697	0.000155	0.160791
Covariance with S		0.000468	−0.002222
Covariance with B			−0.000227

investing in openly traded stocks. The bond fund focuses on the bond market, which has a much stabler return, although a significantly lower expected return. SCIP is a high-risk scheme, often resulting in heavy losses, but occasionally coming through with spectacular gains. In fact, Hal takes a strong interest in SCIP, personally studying investment opportunities and placing investments daily. The return on these mediums, as well as their variance and correlation, are given in Table 7.1.

Note that there is a predictable relationship between the relative performance of the investment opportunities, so the covariance terms report the tendency of investments to do better or worse given that another investment did better or worse. This indicates that variables S and B tend to go up and down together (although with a fairly weak relationship), while variable G tends to move opposite to the other two investment opportunities.

Hal can develop a mathematical programming model to reflect an investor's desire to avoid risk. Hal assumes that returns on investments are normally distributed around the average returns reported above. He bases this on painstaking research he has done with these three investment opportunities.

Maximize Expected Value of Probabilistic Function

Using this form, the objective is to maximize return:

$$\text{Expected return} = 0.148\,\text{S} + 0.060\,\text{B} + 0.152\,\text{G}$$

subject to staying within budget:

$$\text{Budget} = 1\,\text{S} + 1\,\text{B} + 1\,\text{G} \leq 1000$$

having a probability of positive return greater than a specified probability:

$$\Pr\{\text{Expected return} \geq 0\} \geq \alpha$$

with all variables greater than or equal to 0:

$$\text{S}, \text{B}, \text{G} \geq 0$$

The solution will depend on the confidence limit α. Using EXCEL, and varying α from 0.5, 0.8, 0.9, and 0.95, we obtain the solutions given in Table 7.2.

The probability level determines the penalty function α. At a probability of 0.80, the one-tailed normal z-function is 0.842, and thus the chance constraint is:

Table 7.2 Results for chance-constrained formulation (1)

Probability {return ≥0}	α	Stock	Bond	Gamble	Expected return
0.50	0	–	–	1000.00	152.00
0.80	0.842	585.19	–	414.81	149.66
0.90	1.282	863.18	–	136.82	148.55
0.95	1.645	515.28	427.39	57.33	110.62
0.99	2.326	260.87	707.91	31.21	85.83

$$0.148\,\mathrm{S} + 0.060\,\mathrm{B} + 0.152\,\mathrm{G} - 0.842^{*}\mathrm{SQRT}\Big(0.014697\,\mathrm{S}^2 + 0.000936\,\mathrm{SB} - 0.004444\,\mathrm{SG} + 0.000155\,\mathrm{B}^2 - 0.000454\,\mathrm{BG} + 0.160791\,\mathrm{G}^2\Big)$$

The only difference in the constraint set for the different rows of Table 7.2 is that α is varied. The effect seen is that investment is shifted from the high-risk gamble to a bit safer stock. The stock return has low enough variance to assure the specified probabilities given. Had it been higher, the even safer bond would have entered into the solution at higher specified probability levels.

Minimize Variance

With this chance-constrained form, Hal is risk averse. He wants to minimize risk subject to attaining a prescribed level of gain. The variance–covariance matrix measures risk in one form, and Hal wants to minimize this function.

$$\text{Min}\quad 0.014697\,\mathrm{S}^2 + 0.000936\,\mathrm{SB} - 0.004444\,\mathrm{SG} + 0.000155\,\mathrm{B}^2 - 0.000454\,\mathrm{BG} + 0.160791\,\mathrm{G}^2$$

This function can be constrained to reflect other restrictions on the decision. For instance, there typically is some budget of available capital to invest.

$$\mathrm{S} + \mathrm{B} + \mathrm{G} \le 1000 \quad \text{for} \quad \text{a \$1000 budget}$$

Finally, Hal only wants to minimize variance given that he attains a prescribed expected return. Hal wants to explore four expected return levels: \$50/\$1000 invested, \$100/\$1000 invested, \$150/\$1000 invested, and \$200/\$1000 invested. Note that these four levels reflect expected returns of 5%, 10%, 15%, and 20%.

$$0.148\,\mathrm{S} + 0.06\,\mathrm{B} + 0.152\,\mathrm{G} \ge r \qquad \text{where } r = 50, 100, 150, \text{and } 200$$

Solution Procedure

The EXCEL input file will start off with the objective, MIN followed by the list of variables. Then we include the constraint set. The constraints can be stated as you want, but the partial derivatives of the variables need to consider each constraint stated in less-than-or-equal-to form. Therefore, the original model is transformed to:

$$\mathrm{Min}\left[0.014697\,S^2 + 0.000936\,SB - 0.004444\,SG + 0.000155\,B^2 - 0.000454\,BG\right.$$

$$+0.160791G^2$$

$$\text{s.t.} S + B + G \leq 1000 \quad \text{budget constraint}$$

$$0.148\,S + 0.06\,B + 0.152\,G \geq 50 \quad \text{gain constraint}$$

$$S, B, G \geq 0$$

The solution for each of the four gain levels is given in Table 7.3.

The first solution indicates that the lowest variance with an expected return of $50 per $1000 invested would be to invest $20.25 in S (stocks), 778.56 in B (the bond fund), $1.90 in G (the risky alternative), and keeping the 199.29 slack. The variance is $100.564. This will yield an average return of 5% on the money invested. Increasing the specified gain to $100 yields the designed expected return of $100 with a variance of $2807. Raising the expected gain to 150 yields the prescribed $150 with a variance of $43,872. Clearly, this is a high-risk solution. But it also is near the maximum expected return (if all $1000 was placed on the riskiest alternative, G, the expected return would be maximized at $152 per $1000 invested). A model specifying a gain of $200 yields an infeasible solution, and thus by running multiple models, we can identify the maximum gain available (matching the linear programming model without chance constraints). It can easily be seen that lower variance is obtained by investing in bonds, then shifting to stocks, and finally to the high-risk gambling option.

Maximize Probability of Satisfying Chance Constraint

The third chance-constrained form is implicitly attained by using the first form example above, stepping up α until the model becomes infeasible. When the probability of satisfying the chance constraint was set too high, a null solution was generated (do not invest anything—keep all the $1000). Table 7.4 shows solutions

Table 7.3 Results for chance-constrained formulation (2)

Specified gain	Variance	Stock	Bond	Gamble
≥50	100.564	20.25	778.56	1.90
≥100	2807.182	413.28	547.25	39.47
≥150	43,872	500.00	–	500.00
≥152	160,791	–	–	1000.00

Table 7.4 Results for chance-constrained formulation (3)

α	Stock	Bond	Gamble	Expected return
3	157.84	821.59	20.57	75.78
4	73.21	914.93	11.86	67.53
4.5	38.66	953.02	8.32	64.17
4.8	11.13	983.38	5.48	61.48
4.9 and up	–	–	–	0

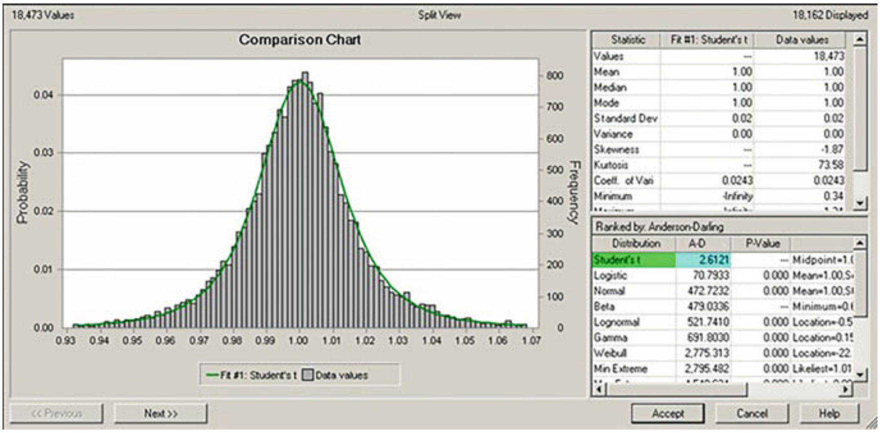

Fig. 7.1 Data distribution fit Student's-*t*. © Oracle. Used with permission

obtained, with the highest α yielding a solution being 4.8, associated with a probability very close to 1.0 (0.999999 according to EXCEL).

Real Stock Data

To check the validity of the ideas presented, we took real stock data from the Internet, taking daily stock prices for six dispersed, large firms, as well as the S&P500 index. Data was manipulated to obtain daily rates of return over the period 1999 through 2008 (2639 observations—dividing closing price by closing price of the prior day).

$$r = \frac{V_t}{V_{t-1}}$$

where V_t = return for day t and V_{t-1} = return for the prior day. (The arithmetic return yields identical results, only subtracting 1 from each data point.)

$$V_{\text{arith}} = \frac{V_t - V_{t-1}}{V_{t-1}}$$

We first looked at possible distributions. Figure 7.1 shows the Crystal Ball best fit for all data (using the Chi-square criterion—same result for Kolmogorov–Smirnov

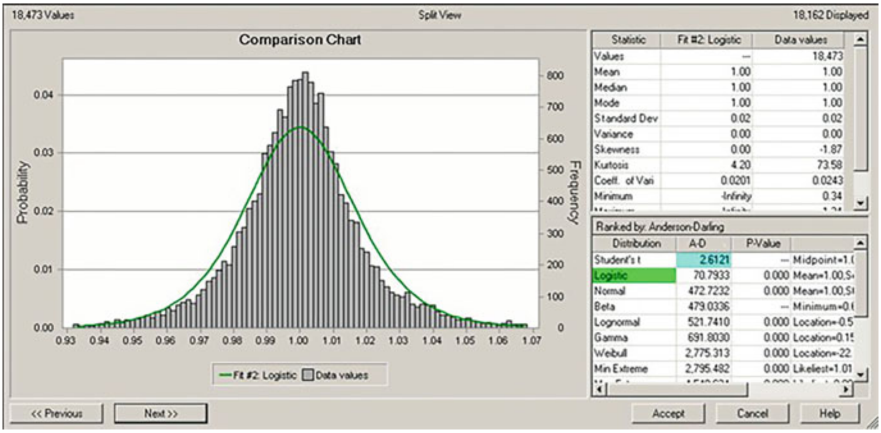

Fig. 7.2 Logistic fit. © Oracle. Used with permission

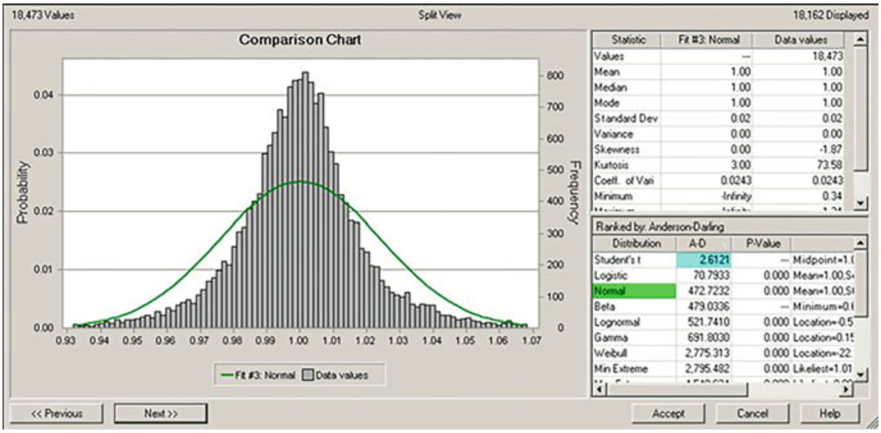

Fig. 7.3 Normal model fit to data. © Oracle. Used with permission

or Anderson criteria), while Fig. 7.2 shows fit with the logistic distribution, and Fig. 7.3 with the normal distribution.

The parameters for the Student's-*t* distribution fit were a scale of 0.01, and 2.841 degrees of freedom. For the logistic distribution, the scale parameter was 0.01.

The data had a slight negative skew, with a skewness score of −1.87. It had a high degree of kurtosis (73.65), and thus much more peaked than a normal distribution. This demonstrates "fat tail" distributions that are often associated with financial returns. Figures 7.1–7.3 clearly show how the normal assumption is too spread out for probabilities close to 0.5, and too narrow for the extremes (tails). The logistic distribution gives a better fit, but Student's-*t* distribution does better yet.

Table 7.5 shows the means standard deviations and covariances of these investments.

Table 7.5 Daily data

	Ford	IBM	Pfizer	SAP	WalMart	XOM	S&P
Mean	1.00084	1.00033	0.99935	0.99993	1.00021	1.00012	0.99952
Std. dev	0.03246	0.02257	0.02326	0.03137	0.02102	0.02034	0.01391
Min	0.62822	0.49101	0.34294	0.81797	0.53203	0.51134	0.90965
Max	1.29518	1.13160	1.10172	1.33720	1.11073	1.17191	1.11580
Cov(Ford)	0.00105	0.00019	0.00014	0.00020	0.00016	0.00015	0.00022
Cov(IBM)		0.00051	0.00009	0.00016	0.00013	0.00012	0.00018
Cov(Pfizer)			0.00054	0.00011	0.00014	0.00014	0.00014
Cov(SAP)				0.00098	0.00010	0.00016	0.00016
Cov(WM)					0.00044	0.00011	0.00014
Cov(XOM)						0.00041	0.00015
Cov(S&P)							0.00019

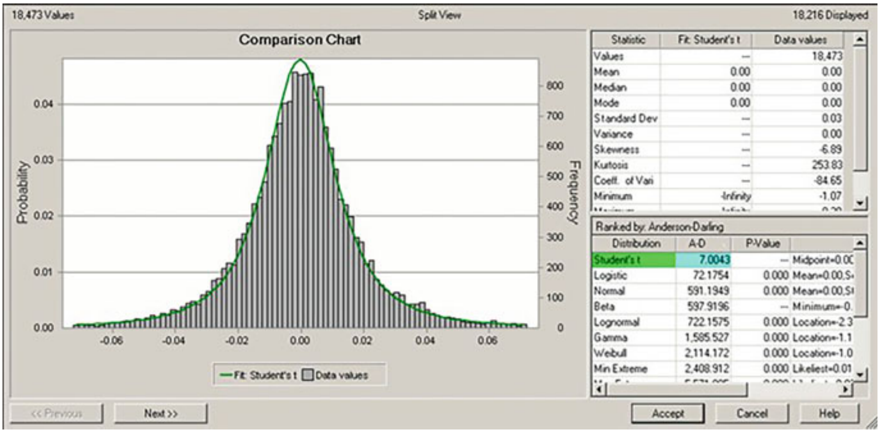

Fig. 7.4 Distribution comparison from Crystal Ball. © Oracle. Used with permission

An alternative statistic for returns is the logarithmic return, or continuously compounded return, using the formula:

$$r_{log} = ln\left(\frac{V_f}{V_i}\right)$$

The Student's-t distribution again had the best fit, followed by logistic and normal (see Fig. 7.4). This data yields slightly different data, as shown in Table 7.6.

Like the arithmetic return, the logarithmic return is centered on 0. There is a difference (slight) between logarithmic return covariances and arithmetic return covariances. The best distribution fit was obtained with the original data (identical to arithmetic return), so we used that data for our chance-constrained calculations. If logarithmic return data was preferred, the data in Table 7.6 could be used in the chance-constrained formulations.

Table 7.6 Daily data for logarithmic return

	Ford	IBM	Pfizer	SAP	WalMart	XOM	S&P
Mean	−0.00029	0.00015	−0.00084	−0.00038	0.00006	−0.00017	−0.00068
Std. dev	0.03278	0.02455	0.02852	0.03087	0.02254	0.02219	0.01392
Min	−0.46486	−0.71130	−1.07021	−0.20093	−0.63105	−0.67073	−0.09470
Max	0.25865	0.12364	0.09687	0.29058	0.10502	0.15863	0.10957
Cov(Ford)	0.00107	0.00019	0.00013	0.00020	0.00016	0.00015	0.00022
Cov(IBM)		0.00060	0.00009	0.00015	0.00013	0.00012	0.00018
Cov(Pfizer)			0.00081	0.00011	0.00014	0.00013	0.00014
Cov(SAP)				0.00095	0.00010	0.00016	0.00016
Cov(WM)					0.00051	0.00011	0.00014
Cov(XOM)						0.00049	0.00015
Cov(S&P)							0.00019

Chance-Constrained Model Results

We ran the data into chance-constrained models assuming a normal distribution for data, using means, variances, and covariances from Table 7.5. The model included a budget limit of \$1000, all variables ≥0, (chance constrained to have no loss), obtaining results shown in Table 7.7.

Maximizing return is a linear programming model, with an obvious solution of investing all available funds in the option with the greatest return (Ford). This has the greatest expected return, but also the highest variance.

Minimizing variance is equivalent to chance-constrained form (2). The solution avoided Ford (which had a high variance), and spread the investment out among the other options, but had a small loss.

A series of models using chance-constrained form (1) were run. Maximizing expected return subject to investment S1000 as well as adding the chance constraint Pr{return ≥970} was run for both normal and *t*-distributions.

$$\begin{aligned} &\text{Max expected return} \\ &\text{s.t.} \quad \text{Sum investment} \leq 1000 \\ &\qquad \Pr\{\text{return} \geq 970\} \geq 0.95 \\ &\qquad \text{All investments} \geq 0 \end{aligned}$$

It can be seen in Table 7.6 that the *t*-distribution was less restrictive, resulting in more investment in the riskier Ford option, but having a slightly higher variance (standard deviation). The chance constraint was binding in both assumptions (normal and Student's-*t*). There was a 0.9 probability return of 979.50, and a 0.8 probability of return of 988.09 by *t*-distribution. Further chance constraint models were run assuming *t*-distribution. For the model:

$$\begin{aligned} &\text{Max expected return} \\ &\text{s.t.} \quad \text{Sum investment} \leq 1000 \\ &\qquad \Pr\{\text{return} \geq 970\} \geq 0.95 \\ &\qquad \Pr\{\text{return} \geq 980\} \geq 0.9 \\ &\qquad \text{All investments} \geq 0 \end{aligned}$$

The expected return was only slightly less, with the constraint Pr{return ≥980} ≥ 0.9 binding. There was a 0.95 probability of a return of 970.73, and a 0.8 probability of return of 988.38. A model using three chance constraints was also run:

Table 7.7 Model results

Model	Ford	IBM	Pfizer	SAP	WM	XOM	S&P	Return	Std Dev
Max return	1000.000	–	–	–	–	–	–	1000.84	32.404
Min variance	–	45.987	90.869	30.811	127.508	116.004	588.821	999.76	13.156
Normal Pr{>970} > 0.95	398.381	283.785	–	–	222.557	95.277	–	1000.49	18.534
t Pr{>970} > 0.95	607.162	296.818	–	–	96.020	–	–	1000.63	23.035
t Pr{>970} > 0.95 Pr{>980} > 0.9	581.627	301.528	–	–	116.845	–	–	1000.61	22.475
t Pr{>970} > 0.95 Pr{>980} > 0.9 Pr{>990} > 0.8	438.405	279.287	–	–	220.254	62.054	–	1000.51	19.320
Max Pr{>1000}	16.275	109.867	105.586	38.748	174.570	172.244	382.711	999.91	13.310

$$\begin{aligned}&\text{Max expected return}\\&\text{s.t.}\qquad \text{Sum investment S 1000}\\&\qquad \Pr\{\text{return} \geq 970\} \geq 0.95\\&\qquad \Pr\{\text{return} \geq 980\} \geq 0.9\\&\qquad \Pr\{\text{return} \geq 990\} \geq 0.8\\&\qquad \text{All investments} \geq 0\end{aligned}$$

This yielded a solution where the 0.95 probability of return was 974.83, the 0.9 probability of return was 982.80, and the 0.8 probability of return was 990 (binding). Finally, a model was run to maximize the probability of return ≥1000 (chance-constrained model type 3).

$$\begin{aligned}&\text{Minimize } D\\&\text{s.t.}\qquad \text{Sum investment} \leq 1000\\&\qquad \Pr\{\text{return} \geq 970\} \geq 0.95\\&\qquad \Pr\{\text{return} \geq 980\} \geq 0.9\\&\qquad \text{D} = 1000\text{–return}[\Pr\{\text{return} \geq 1000\} \geq 0.8]\\&\qquad \text{All investments} \geq 0\end{aligned}$$

This was done by setting the deviation from an infeasible target. The solution yielded a negative expected return at a low variance, with the 0.95 probability of return 982.22, the 0.9 probability of return 987.71, and the 0.8 probability of return 992.67.

Conclusions

A number of different types of models can be built using chance constraints. The first form is to maximize the linear expected return subject to attaining specified probabilities of reaching specified targets. The second is to minimize variance. This second form is not that useful, in that the lowest variance is actually to not invest. Here we forced investment of the 1000 capital assumed. The third form is to maximize the probability of attaining some target, which in order to be useful, has to be infeasible. Chance-constrained models have been used in many applications. Here we have focused on financial planning, but there have been applications whenever statistical data is available in an optimization problem.

The models presented were solved with EXCEL SOLVER. In full disclosure, we need to point out that chance constraints create nonlinear optimization models, which are somewhat unstable relative to linear programming models. Solutions are very sensitive to the accuracy of input data. There also are practical limits to model size. The variance–covariance matrix involves a number of parameters to enter into EXCEL functions, which grow rapidly with the number of variables. In the simple example, there were three solution variables, with six elements to the variance–covariance matrix. In the real example, there were seven solution variables (investment options). The variance–covariance matrix thus involved 28 nonlinear expressions.

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Data Envelopment Analysis in Enterprise Risk Management

8

Charnes, Cooper, and Rhodes (1978a) first introduced DEA (CCR) for efficiency analysis of Decision-making Units (DMU). DEA can be used for modeling operational processes, and its empirical orientation and absence of a priori assumptions have resulted in its use in a number of studies involving efficient frontier estimation in both nonprofit and private sectors. DEA is widely applied in banking (Banker et al., 2010; Gunay, 2012; Yang, 2014) and insurance (Segovia-Gonzalez et al., 2009). DEA has become a leading approach for efficiency analysis in many fields, such as supply chain management (Ross & Droge, 2002; Wu & Olson, 2010; Dong & Yuan, 2023) petroleum distribution system design (Ross & Droge, 2004), and government services (Narasimhan et al., 2005). DEA and multicriteria decision-making models have been compared and extended (Lahdelma & Salminen, 2006; Olson & Wu, 2011).

Moskowitz et al (2000). presented a vendor selection scenario involving nine vendors with stochastic measures given over 12 criteria. This model was used by Wu and Olson (2008) in comparing DEA with multiple criteria analysis. We start with a discussion of the advanced ERM technology, i.e., value-at-risk (VaR) and view it as a tool to conduct risk management in enterprises.

While risk needs to be managed, taking risks is fundamental to doing business. Profit by necessity requires accepting some risk (Alquier & Tignol, 2006). ERM provides tools to rationally manage these risks. We will demonstrate multiple criteria and DEA models in the enterprise risk management context with a hypothetical nuclear waste repository site location problem.

Basic Data

For a set of data including a supply chain needing to select a repository for waste dump siting, we have 12 alternatives with four criteria. Criteria considered include cost, expected lives lost, risk of catastrophe, and civic improvement. Expected lives

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Table 8.1 Dump site data

Alternatives	Cost (billions)	Expected lives lost	Risk	Civic improvement
Nome AK	40	60	Very high	Low
Newark NJ	100	140	Very low	Very high
Rock Springs WY	60	40	Low	High
Duquesne PA	60	40	Medium	Medium
Gary IN	70	80	Low	Very high
Yakima Flats WA	70	80	High	Medium
Turkey TX	60	50	High	High
Wells NE	50	30	Medium	Medium
Anaheim CA	90	130	Very high	Very low
Epcot Center FL	80	120	Very low	Very low
Duckwater NV	80	70	Medium	Low
Santa Cruz CA	90	100	Very high	Very low

Table 8.2 Scores used

Alternatives	Cost	Expected lives lost	Risk	Civic improvement
Nome AK	60	80	0	25
Newark NJ	0	0	100	100
Rock Springs WY	40	100	80	80
Duquesne PA	40	100	50	50
Gary IN	30	60	80	100
Yakima Flats WA	30	60	30	50
Turkey TX	40	90	30	80
Wells NE	50	110	50	50
Anaheim CA	10	10	0	0
Epcot Center FL	20	20	100	0
Duckwater NV	20	70	50	25
Santa Cruz CA	10	40	0	0

lost reflect workers as well as expected local (civilian bystander) lives lost. The hierarchy of objectives is:

Overall

Cost   Lives Lost   Risk   Civic Improvement

The alternatives available, with measures on each criterion (including two categorical measures), are given in Table 8.1.

Models require numerical data, and it is easier to keep things straight if we make higher scores better. So, we adjust the Cost and Expected Lives Lost scores by subtracting them from the maximum, and we assign consistent scores on a 0–100 scale for the qualitative ratings given Risk and Civic Improvement, yielding Table 8.2.

Non-dominated solutions can be identified by inspection. For instance, Nome AK has the lowest estimated cost, so is by definition non-dominated. Similarly, Wells NE has the best-expected lives lost. There is a tie for risk of catastrophe (Newark NJ and Epcot Center FL have the best ratings, with a trade-off in that Epcot Center FL has better cost and lives lost estimates while Newark NJ has better civic improvement rating, and both are non-dominated). There also is a tie for best civic improvement (Newark NJ and Gary IN), and a tradeoff in that Gary IN has better cost and lives lost estimates while Newark NJ has a better risk of catastrophe rating), and again both are non-dominated. There is one other non-dominated solution (Rock Springs WY), which can be compared to all of the other 11 alternatives and shown to be better on at least one alternative.

Multiple Criteria Models

Non-dominance can also be established by a linear programming model. We create a variable for each criterion, with the decision variables weights (which we hold strictly greater than 0, and to sum to 1). The objective function is to maximize the sum-product of measure values multiplied by weights for each alternative site in turn, subject to this function being strictly greater than each sum-product of measure values time weights for each of the other sites. For the first alternative, the formulation of the linear programming model is:

$$Max \sum_{i=1}^{4} w_i y_1$$

$$s.t. \sum_{i=1}^{4} w_i = 1$$

For each j from 2 to 12: $\sum_{i=1}^{4} w_i y x_1 \geq \sum_{i=1}^{4} w_i y_j + 0.0001$

$$w_i \geq 0.0001$$

This model was run for each of the 12 available sites. Nondominated alternatives (defined as at least as good on all criteria, and strictly better on at least one criterion relative to all other alternatives) are identified if this model is feasible. The reason to add the 0.0001 to some of the constraints is that strict dominance might not be identified otherwise (the model would have ties). The solution for the Newark NJ alternative was as shown in Table 8.3:

The set of weights was minimum for the criteria of Cost and Expected Lives lost, with roughly equal weights on Risk of Catastrophe and Civic Improvement. That makes sense because Newark NJ had the best scores for Risk of Catastrophe and Civic Improvement and low scores on the other two Criteria.

Running all 12 linear programming models, 6 solutions were feasible, indicating that they were not dominated {Nome AK, Newark NJ, Rock Springs WY, Gary IN,

Table 8.3 MCDM LP solution for Nome AK

	Criteria	Cost	Lives	Risk	Improve	
Object	Newark NJ	0	0	100	100	99.9801
Weights		0.0001	0.0001	0.4975	0.5023	1.0000
	Nome AK	60	80	0	25	12.5708
	Rock Springs WY	40	100	80	80	79.9980
	Duquesne PA	40	100	50	50	50.0040
	Gary IN	30	60	80	100	90.0385
	Yakima Flats WA	30	60	30	50	40.0485
	Turkey TX	40	90	30	80	55.1207
	Wells NE	50	110	50	50	50.0060
	Anaheim CA	10	10	0	0	0.0020
	Epcot Center FL	20	20	100	0	49.7567
	Duckwater NV	20	70	50	25	37.4422
	Santa Cruz CA	10	40	0	0	0.0050

Table 8.4 LP solution for Duquesne PA

	Criteria	Cost	Lives	Risk	Improve	
Object	Duquesne PA	40	100	50	50	99.9840
Weights		0.0001	0.9997	0.0001	0.0001	1.0000
	Nome AK	60	80	0	25	79.9845
	Newark NJ	0	0	100	100	0.0200
	Rock Springs WY	**40**	**100**	**80**	**80**	**99.9900**
	Gary IN	30	60	80	100	60.0030
	Yakima Flats WA	30	60	30	50	59.9930
	Turkey TX	40	90	30	80	89.9880
	Wells NE	**50**	**110**	**50**	**50**	**109.9820**
	Anaheim CA	10	10	0	0	9.9980
	Epcot Center FL	20	20	100	0	20.0060
	Duckwater NV	20	70	50	25	69.9885
	Santa Cruz CA	10	40	0	0	39.9890

Wells NE, and Epcot Center FL}. The corresponding weights identified are not unique (many different weight combinations might have yielded these alternatives as feasible). These weights also reflect the scale (here the range for Cost was 60, and for Lives Lost was 110, while the range for the other two criteria was 100—in this case this difference is slight, but the scales do not need to be similar. The more dissimilar, the more warped are the weights.) For the other six dominated solutions, no set of weights would yield them as feasible. For instance, Table 8.4 shows the infeasible solution for Duquesne PA.

Here Rock Springs WY and Wells NE had higher functional values than Duquesne PA. This is clear by looking at criteria attainments. Rock Springs WY is equal to Duquesne PA on Cost and Lives Lost, and better on Risk and Civic Improvement.

Scales

The above analysis used input data with different scales. Cost ranged from 0 to 60, Lives Lost from 0 to 110, and the two subjective criteria (Risk, Civic Improvement) from 0 to 100. While they were similar, there were slightly different ranges. The resulting weights are one possible set of weights that would yield the analyzed alternative as non-dominated. If we proportioned the ranges to all be equal (divide Cost scores in Table 8.2 by 0.6, Expected Lives Lost scores by 1.1), the resulting weights would represent the implied relative importance of each criterion that would yield a non-dominated solution. The non-dominated set is the same, only weights varying. Results are given in Table 8.5.

Stochastic Mathematical Formulation

Value-at-risk (VaR) methods are popular in financial risk management (Duffie & Pan, 2001). VaR models were motivated in part by several major financial disasters in the late 1980s and 1990s, including the fall of Barings Bank and the bankruptcy of Orange County. In both instances, large amounts of capital were invested in volatile markets when traders concealed their risk exposure. VaR models allow managers to quantify their risk exposure at the portfolio level and can be used as a benchmark to compare risk positions across different markets. Value-at-risk can be defined as the expected loss for an investment or portfolio at a given confidence level over a stated time horizon. If we define the risk exposure of the investment as L, we can express VaR as:

Table 8.5 Results using scaled weights

Alternative	Cost	Lives	Risk	Improve	Dominated by
Nome AK	0.9997	0.0001	0.0001	0.0001	
Newark NJ	0.0001	0.0001	0.4979	0.5019	
Rock Springs WY	0.0001	0.7673	0.0001	0.2325	
Gary IN	0.00001	0.0001	0.0001	0.9997	
Wells NE	0.0001	0.9997	0.0001	0.0001	
Epcot Center FL	0.0002	0.0001	0.9996	0.0001	
Duquesne PA					Rock Springs WY Wells NE
Yakima Flats WA					Six alternatives
Turkey TX					Rock Springs WY
Anaheim CA					All but Newark NJ
Duckwater NV					Five alternatives
Santa Cruz CA					Eight alternatives

$$Prob\{L \leq VaR\} = 1 - \alpha$$

A rational investor will minimize expected losses or the loss level at the stated probability (1 – α). This statement of risk exposure can also be used as a constraint in a chance-constrained programming model, imposing a restriction that the probability of loss greater than some stated value should be less than (1 – α).

The standard deviation or volatility of asset returns, σ, is a widely used measure of financial models such as VaR. Volatility σ represents the variation of asset returns during some time horizon in the VaR framework. This measure will be employed in our approach. Monte Carlo Simulation techniques are often applied to measure the variability of asset risk factors (Crouhy et al., 2001). We will employ Monte Carlo Simulation for benchmarking our proposed method.

Stochastic models construct production frontiers that incorporate both inefficiency and stochastic error. The stochastic frontier associates extreme outliers with the stochastic error term and this has the effect of moving the frontier closer to the bulk of the producing units. As a result, the measured technical efficiency of every DMU is raised relative to the deterministic model. In some realizations, some DMUs will have a super-efficiency larger than unity (Olesen & Petersen, 1995; Cooper et al., 1996, 2002):

Now we consider the stochastic vendor selection model. Consider N suppliers to be evaluated, each has s random variables. Note that all input variables are transformed into output variables, as was done in Moskowitz et al (2000). The variables of supplier j (j = 1,2.. .N) exhibit random behavior represented by $\widetilde{y_j} = (\widetilde{y_{1j}}, \ldots \widetilde{y_{sj}})$ where each $\widetilde{y_{rj}}$ (r = 1,2, ..., s) has a known probability distribution. By maximizing the expected efficiency of a vendor under evaluation subject to VaR being restricted to be no worse than some limit, the following model is developed:

$$Max \sum_{i=1}^{4} w_i y_1$$
$$s.t. \sum_{i=1}^{4} w_i = 1$$

For each j from 2 to 12: Prob$\{\sum_{i=1}^{4} w_i y x_1 \geq \sum_{i=1}^{4} w_i y_j + 0.0001\}$≥(1-α)

$$w_i \geq 0.0001$$

Because each $\widetilde{y_j}$ is potentially a random variable, it has a distribution rather than being a constant. The objective function is now an expectation, but the expectation is the mean, so this function is still linear, using the mean rather than the constant parameter. The constraints on each location's performance being greater than or equal to all other location performances is now a nonlinear function. The weights w_i are still variables to be solved for, as in the deterministic version used above.

The scalar α is referred to as the modeler's risk level, indicating the probability measure of the extent to which Pareto efficiency violation is admitted as most α proportion of the time. The α_j ($0 \leq \alpha_j \leq 1$) in the constraints are predetermined scalars which stand for an allowable risk of violating the associated constraints, where $1 - \alpha_j$ indicates the probability of attaining the requirement. The higher the value of α, the higher the modeler's risk and the lower the modeler's confidence about the 0th vendor's Pareto efficiency and vice visa. At the $(1 - \alpha)\%$ confidence level, the 0th supplier is stochastic efficient only if the optimal objective value is equal to one.

To transform the stochastic model into a deterministic DEA, Charnes and Cooper (1959; Huang & Li, 2001) employed chance-constrained programming (Charnes et al., 1958). The transformation steps presented in this study follow this technique and can be considered as a special case of their stochastic DEA (Cooper et al., 1999), where both stochastic inputs and outputs are used. This yields a nonlinear programming problem in the variables w_i, which has computational difficulties due to the objective function and the constraints, including the variance-covariance yielding quadratic expressions in constraints. We assume that y_j follows a normal distribution N(y_j, $\mathrm{B_{jk}}$), where $\widetilde{\overline{y}}_j$ is its vector of expected value and $\mathrm{B_{jk}}$ indicates the variance–covariance matrix of the jth alternative with the kth alternative. The development of stochastic DEA is given by Wu and Olson (2008). We adjust the data set used in the nuclear waste siting problem by making cost a stochastic variable (following an assumed normal distribution, thus requiring a variance). The mathematical programming model decision variables are the weights on each criterion, which are not stochastic. What is stochastic is the parameter on costs. Thus the adjustment is in the constraints. For each evaluated alternative y_j compared to alternative y_k:

$$\mathrm{w}_{\mathrm{cost}(}y_{j\,cost} – \mathrm{z}^{*}\mathrm{SQRT}\left(\mathrm{Var}\left[y_{j\,cost}\right]\right) + w_{lives}y_{j\,lives} + w_{risk}y_{j\,risk} + w_{imp}y_{j\,imp} \geq$$

$$\begin{aligned}&\mathrm{w}_{\mathrm{cost}(}y_{k\,cost} – \mathrm{zSQRT}(\mathrm{Var}[y_{k\,cost}] + 2^{*}\mathrm{Cov}\left[y_{j\,cost}, y_{k\,cost}\right]\\&+\mathrm{Var}[y_{k\,cost}] + w_{lives}y_{k\,lives} + w_{risk}y_{k\,risk} + w_{imp}y_{k\,imp}\end{aligned}$$

These functions need to include the covariance term for costs between alternative y_j compared to alternative y_k.

Table 8.6 shows the stochastic cost data in billions of dollars, and the converted cost scores (also billions of dollars transformed as \$100 billion minus the cost measure for that site) as in Table 8.2. The cost variances will remain as they were, as the relative scale did not change.

The variance–covariance matrix of costs is required (Table 8.7).

The degree of risk aversion used (α) is 0.95, or a z-value of 1.645 for a one-sided distribution. The adjustment affected the model by lowering the cost parameter proportional to its variance for the evaluated alternative, and inflating it for the other alternatives. Thus, the stochastic model required a 0.95 assurance that the cost for the evaluated alternative is superior to each of the other 11 alternatives, a more difficult standard. The DEA models were run for each of the 12 alternatives. Only two of the six alternatives found to be non-dominated with deterministic data above were still non-dominated {Rock Springs WY and Wells NE}. The model results in Table 8.8 show the results for Rock Springs WY, with one set of weights {0, 0.75,

Table 8.6 Stochastic data

Alternative	Cost measure	Mean cost	Cost variance	Expected lives lost	Risk	Civic improvement
S1 Nome AK	N(40,6)	60	6	80	0	25
S2 Newark NJ	N (100,20)	0	20	0	100	100
S3 Rock Springs WY	N(60,5)	40	5	100	80	80
S4 Duquesne PA	N(60,30)	40	30	100	50	50
S5 Gary IN	N(70,35)	30	35	60	80	100
S6 Yakima Flats WA	N(70,20)	30	20	60	30	50
S7 Turkey TX	N(60,10)	40	10	90	30	80
S8 Wells NE	N(50,8)	50	8	110	50	50
S9 Anaheim CA	N(90,40)	10	40	10	0	0
S10 Epcot Center FL	N(80,50)	20	50	20	100	0
S11 Duckwater NV	N(80,20)	20	20	70	50	25
S12 Santa Cruz CA	N(90,40)	10	40	40	0	0

Table 8.7 Site covariances

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1	6	2	4	2	2	3	3	3	2	1	3	2
S2		20	3	10	9	5	2	1	4	5	1	4
S3			5	2	1	2	3	3	2	1	3	2
S4				30	10	8	2	2	6	5	1	4
S5					35	9	3	2	5	6	1	4
S6						20	3	2	10	8	2	12
S7							10	3	2	1	3	2
S8								8	2	1	3	2
S9									40	5	1	12
S10										50	2	8
S11											20	2
S12												40

0.25, 0} yielding Rock Springs with a greater functional value than any of the other 11 alternatives. The weights yielding Wells NE as non-dominated had all the weight on Lives Lost.

One of the alternatives that was non-dominated with deterministic data {Nome AK} was found to be dominated with stochastic data. Table 8.9 shows the results of the original deterministic model for Nome AK.

Table 8.8 Output for Stochastic Model for Rock Springs WY

Object	Rock Springs WY	36.322	100	80	80	94.99304
Weights		0.0001	0.7499	0.24993	0.0001	1
	Nome AK	67.170	80	0	25	59.999
	Newark NJ	9.158	0	100	100	25.004
	Duquesne PA	50.272	100	50	50	87.494
	Gary IN	40.660	60	80	80	64.999
	Yakima Flats WA	38.858	60	30	30	52.497
	Turkey TX	47.538	90	30	30	74.994
	Wells NE	57.170	110	50	50	94.993
	Anaheim CA	21.514	10	0	0	7.501
	Epcot Center FL	32.418	20	100	100	40.004
	Duckwater NV	29.158	70	50	50	64.995
	Santa Cruz CA	21.514	40	0	0	29.997

Table 8.9 Nome AK alternative results with original model

Object	Nome AK	60	80	0	25	64.9857
Weights		0.7500	0.2498	0.0001	0.0001	1
	Newark NJ	0	0	100	100	0.020
	Rock Springs WY	40	100	80	80	54.994
	Duquesne PA	40	100	50	50	54.988
	Gary IN	30	60	80	100	37.505
	Yakima Flats WA	30	60	30	50	37.495
	Turkey TX	40	90	30	80	52.491
	Wells NE	50	110	50	50	64.986
	Anaheim CA	10	10	0	0	9.998
	Epcot Center FL	20	20	100	0	20.006
	Duckwater NV	20	70	50	25	32.492
	Santa Cruz CA	10	40	0	0	17.491

The stochastic results are shown in Table 8.10.

Wells NE is shown to be superior to Nome AK at the last set of weights the SOLVER algorithm in EXCEL attempted. Looking at the stochastically adjusted scores for cost, Wells NE now has a superior cost value to Nome AK (the objective functional cost value is penalized downward, the constraint cost value for Wells NE and other alternatives are penalized upward to make a harder standard to meet).

DEA Models

DEA evaluates alternatives by seeking to maximize the ratio of efficiency of output attainments to inputs, considering the relative performance of each alternative. The mathematical programming model creates a variable for each output (outputs

Table 8.10 Nome AK alternative results with a stochastic model

Object	Nome AK	55.97	80	0	25	55.965
Weights		0.9997	0.0001	0.0001	0.0001	1
	Newark NJ	9.009	0	100	100	9.027
	Rock Springs WY	47.170	100	80	80	47.182
	Duquesne PA	50.403	100	50	50	50.408
	Gary IN	41.034	60	80	100	41.046
	Yakima Flats WA	39.305	60	30	50	39.307
	Turkey TX	47.715	90	30	80	47.721
	Wells NE	57.356	110	50	50	57.360
	Anaheim CA	21.631	10	0	0	21.625
	Epcot Center FL	32.527	20	100	0	32.529
	Duckwater NV	29.305	70	50	25	29.310
	Santa Cruz CA	21.631	40	0	0	21.628

designated by u_i) and input (inputs designated by v_j). Each alternative k has performance coefficients for each output (y_{ik}) and input (x_{jk}).

The classic Charnes, Cooper, and Rhodes (CCR) (Charnes et al., 1978b) DEA model is:

Max Efficiency$_\mathrm{k}$ $= \sum_{i=1}^{2} u_i y_{ik} / \sum_{j=1}^{2} v_j x_{jk}$

s.t. for each k from 1 to 12: $\sum_{i=1}^{2} u_i y_{ik} / \sum_{j=1}^{2} v_j x_{jk} \leq 1$

$$u_i, v_j \geq 0$$

The Banker, Charnes and Cooper (BCC) DEA model includes a scale parameter to allow for economies of scale. It also releases the restriction on the sign for u_i, v_j.

Max Efficiency$_\mathrm{k}$ $= \sum_{i=1}^{2} u_i y_{ik} + \gamma / \sum_{j=1}^{2} v_j x_{jk}$

s.t. for each k from 1 to 12: $\sum_{i=1}^{2} u_i y_{ik} + \gamma / \sum_{j=1}^{2} v_j x_{jk} \leq 1$

u_i, v_j unrestricted in sign

A third DEA model allows for super-efficiency. It is the CCR model without a restriction on efficiency ratios.

Max Efficiency$_\mathrm{k}$ $= \sum_{i=1}^{2} u_i y_{ik} / \sum_{j=1}^{2} v_j x_{jk}$

s.t. for each k from 1 to 12: $\sum_{i=1}^{2} u_i y_{ik} / \sum_{j=1}^{2} v_j x_{jk} \leq 1$ for $l \neq k$

$$u_i, v_j \geq 0$$

The traditional DEA models were run on the dump site selection model, yielding results shown in Table 8.11.

These approaches provide rankings. In the case of CCR DEA, the ranking includes some ties (for first place and eleventh place). The non-dominated Nome AL alternative was ranked tenth, behind dominated solutions Turkey TX, Duquesne PA, Yakima Flats WA, and Duckwater NV. Nome dominates Anaheim CA and Santa Cruz CA, but does not dominate any other alternative. The ranking in tenth place is probably due to the smaller scale for the Cost criterion, where Nome AK has

Table 8.11 Traditional DEA model results

	CCR DEA		BCC DEA		Super-CCR	Super-CCR
Alternative	Score	Rank	Score	Rank	Score	Rank
Nome AK	0.43750	10	1	1	0.43750	10
Newark NJ	0.75000	6	1	1	0.75000	6
Rock Springs WY	1	1	1	1	1.31000	1
Duquesne PA	0.62500	7	0.83333	8	0.62500	7
Gary IN	1	1	1	1	1.07143	2
Yakima Flats WA	0.5	8	0.70129	9	0.5	8
Turkey TX	0.97561	3	1	1	0.97561	3
Wells NE	0.83333	5	1	1	0.83333	5
Anaheim CA	0	11	0.45000	12	0	11
Epcot Center FL	0.93750	4	1	1	0.93750	4
Duckwater NV	0.46875	9	0.62500	10	0.46875	9
Santa Cruz CA	0	11	0.48648	11	0	11

the best score. BCC DEA has all dominated solutions tied for first. The rankings for 7th through 12 reflect more of an average performance on all criteria (affected by scales). The rankings provided by BCC DEA after the first are affected by criteria scales. Super-CCR provides a nearly unique ranking (tie for 11th place).

Conclusion

The importance of risk management has vastly increased in the past decade. Value-at-risk techniques have been becoming the frontier technology for conducting enterprise risk management. One of the ERM areas of global business involving high levels of risk is global supply chain management.

Selection in supply chains by its nature involves the need to trade off multiple criteria, as well as the presence of uncertain data. When these conditions exist, stochastic dominance can be applied if the uncertain data is normally distributed. If not normally distributed, simulation modeling applies (and can also be applied if data is normally distributed).

When the data is presented with uncertainty, stochastic DEA provides a good tool to perform efficiency analysis by handling both inefficiency and stochastic error. We must point out that the main difference for implementing investment VaR in financial markets such as the banking industry and our DEA VaR used for supplier selection is that the underlying asset volatility or standard deviation is typically a managerial assumption due to lack of sufficient historical data to calibrate the risk measure.

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9 Data Mining Models and Enterprise Risk Management

Data mining applications to businesses cover a variety of fields (Olson & Shi, 2006). Risk-related applications are especially strong in insurance, specifically fraud detection (Debreceny & Gray, 2010; Jan et al., 2011). Fraud detection modeling includes text mining (Holton, 2009). There are many financial risk management applications, with a heavy interest in developing tools to support investment. Automated trading has been widely applied in practice for decades. More recent efforts have gone into sentiment analysis, mining text of investment comments to detect patterns, especially related to investment risk (Groth & Muntermann, 2011; Chan & Franklin, 2011; Hagenau et al., 2013; Wu et al., 2014).

There are a number of data mining tools. This includes a variety of software, some commercial (powerful and expensive) as well as open source. Open-source classification software tools have been published (Olson, 2016). There are other modeling forms as well, including application of clustering analysis in fraud detection (Jans et al., 2010). We will use an example dataset involving data mining of bankruptcy, a severe form of financial risk.

Bankruptcy Data Demonstration

This data concerns 100 US firms that underwent bankruptcy (Olson et al., 2012). All of the sample data are from the USA companies. About 400 bankrupt company names were obtained from the Compustat database, focusing on the companies that went bankrupt over the period January 2006 through December 2009. This yielded 99 firms. Using the company Ticker code list, financial data ratios over the period January 2005–December 2009 were obtained and used in prediction models of company bankruptcy. The factor collected contains total assets, book value per share, inventories, liabilities, receivables, cost of goods sold, total dividends, earnings before interest and taxes, gross profit (loss), net income (loss), operating income after depreciation, total revenue, sales, dividends per share, and total market value. To obtain non-bankrupt cases for comparison, the same financial ratios for

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Table 9.1 Attributes in bankruptcy data

No	Short name	Long name
1	fyear	Data year—Fiscal
2	cik	CIK number
3	at	Assets—Total
4	bkvlps	Book value per share
5	invt	Inventories—Total
6	Lt	Liabilities—Total
7	rectr	Receivables—Trade
8	cogs	Cost of goods sold
9	dvt	Dividends—Total
10	ebit	Earnings before interest and taxes
11	gp	Gross profist (loss)
12	ni	Net income (loss)
13	oiadp	Operating income after depreciation
14	revt	Revenue—Total
15	sale	Sales-turnover (net)
16	dvpsx_f	Dividends per share—Ex-date—Fiscal
17	mkvalt	Market value—Total—Fiscal
18	prch_f	Price high—Annual—Fiscal
19	bankruptcy	Bankruptcy (output variable)

200 non-failed companies were gathered for the same time period. The LexisNexis database provided SEC fillings after June 2010, to identify firm survival with CIK code.

The CIK code list was input to the Compustat database to obtain financial data and ratios for the period January 2005–December 2009 to match that of failed companies.

The data set consists of 1321 records with full data over 19 attributes as shown in Table 9.1. The outcome attribute is bankruptcy, which has a value of 1 if the firm went bankrupt by 2011 (697 cases), and a value of 0 if it did not (624 cases).

This is real data concerning firm bankruptcy, which could be updated by going to web sources.

Software

R is a widely used open-source software. Rattle is a GUI system for R (also open source) that makes it easy to implement R for data mining.

To install R, visit https://cran.rstudio.com/ Open a folder for R.

Select Download R for Windows.

Rattle instructions will vary with time. The best way is to go to: https://www.togaware.com

Select the installation instructions for your computer. The togaware site usually helps. When running Rattle a number of other packages will be downloaded and

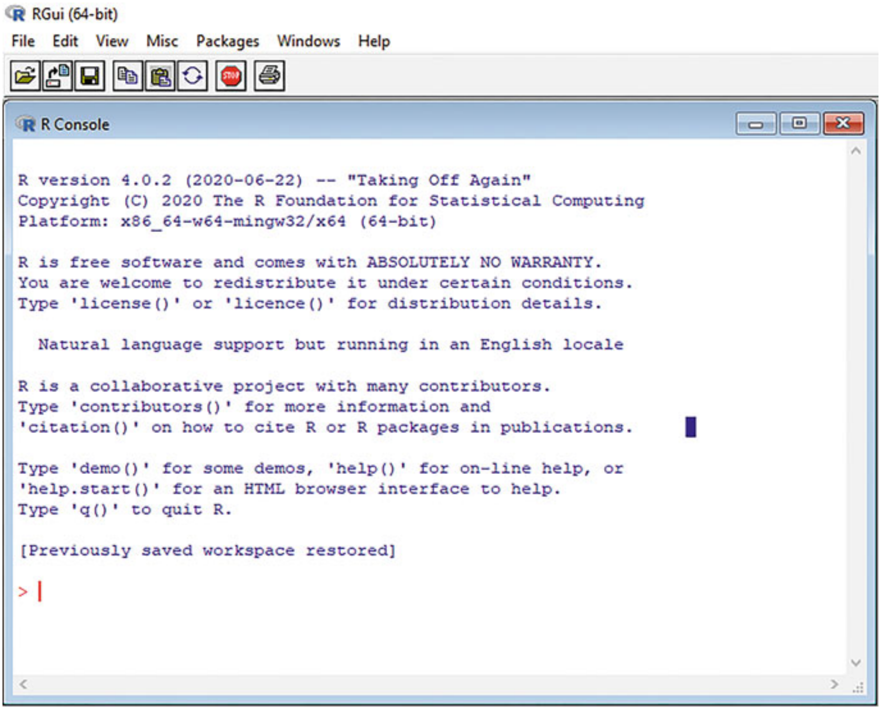

Fig. 9.1 R console

installed as needed, with Rattle asking for the user's permission before doing so. They only need to be downloaded once. The installation has been tested to work on Microsoft Windows, 32 bit and 64 bit, XP, Vista, and 7 with R 3.1.1, Rattle.

3.1.0 and RGtk2 2.20.31. If you are missing something, you will get a message from R asking you to install a package. I read nominal data (string), and was prompted that I needed "stringr". On the R console (see Fig. 9.1), click on the "Packages" word on the top line: Give the command "Install packages" which will direct you to HTTPS CRAN mirror. Select one of the sites (like "USA(TX) [https]") and find "stringr" and click on it. Then upload that package. You may have to restart R.

Data mining practice usually utilizes a training set to build a model, which can be applied to a test set. In this case, 1178 observations (those through 2008) were used for the training set and 143 observations (2009 and 2010) held out for testing. To run a model, on the Filename line, click on the icon and browse for the file "bankruptcyTrain.csv". Click on the Execute icon on the upper left of the Rattle window. This yields (Fig. 9.2). Bankrupt is a categoric variable, and R assumes that is the Target (as we want). We could delete other variables if we choose to, and redo the Execute step for the Data tab. We can Explore—the default is Summary. Execute yields macrodata, identify data types as well as descriptive statistics (minima,

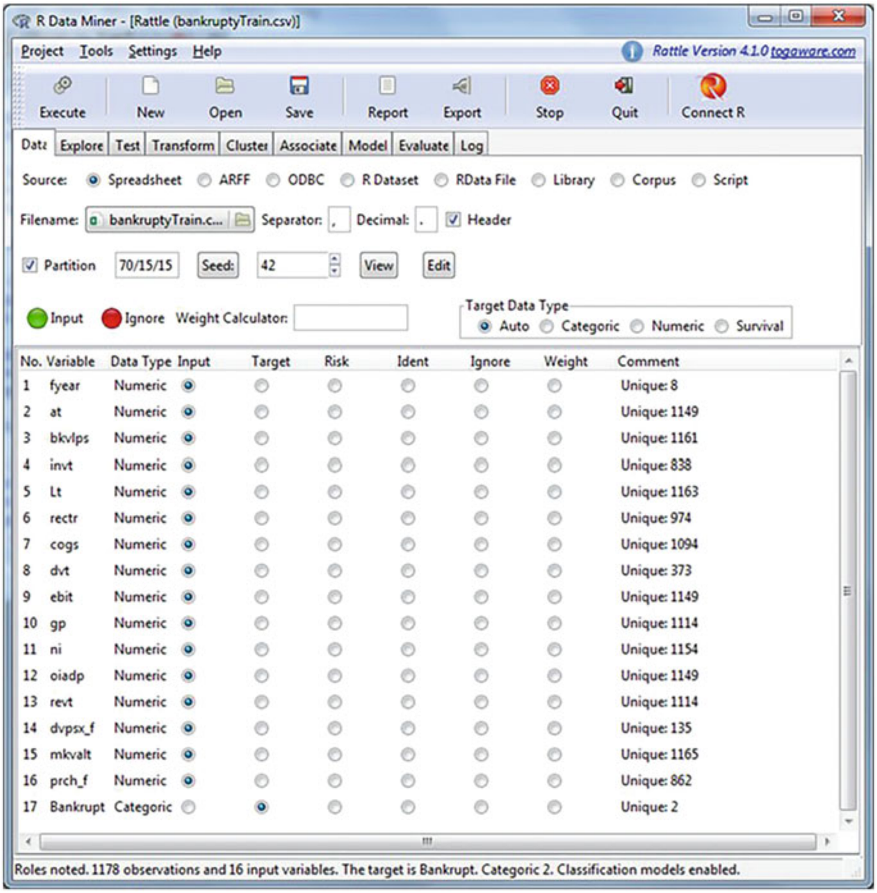

Fig. 9.2 LoanRaw.csv data read

maxima, medians, means, and quartiles). R by default holds out 30% of the training data as an intermediate test set, and thus builds models on the remaining 70% (here 824 observations). The summary identifies the outcome of the training set (369 not bankrupt, 455 bankrupt).

We can further explore the data through correlation analysis. Figure 9.3 shows the R screen with the correlation radio button selected. Execute on this screen yields output over the numerical variables as shown in Fig. 9.4.

Figure 9.4 indicates high degrees of correlation across potential independent variables, and further analysis might select some for elimination. Numerical correlation values are also provided by R. The dependent variable was alphabetical, so R did not include it, but outside analysis indicates a low correlation between bankruptcy and all independent variables—the highest in magnitude being 0.180 with cost of goods sold (cogs) and with total revenue (revt).

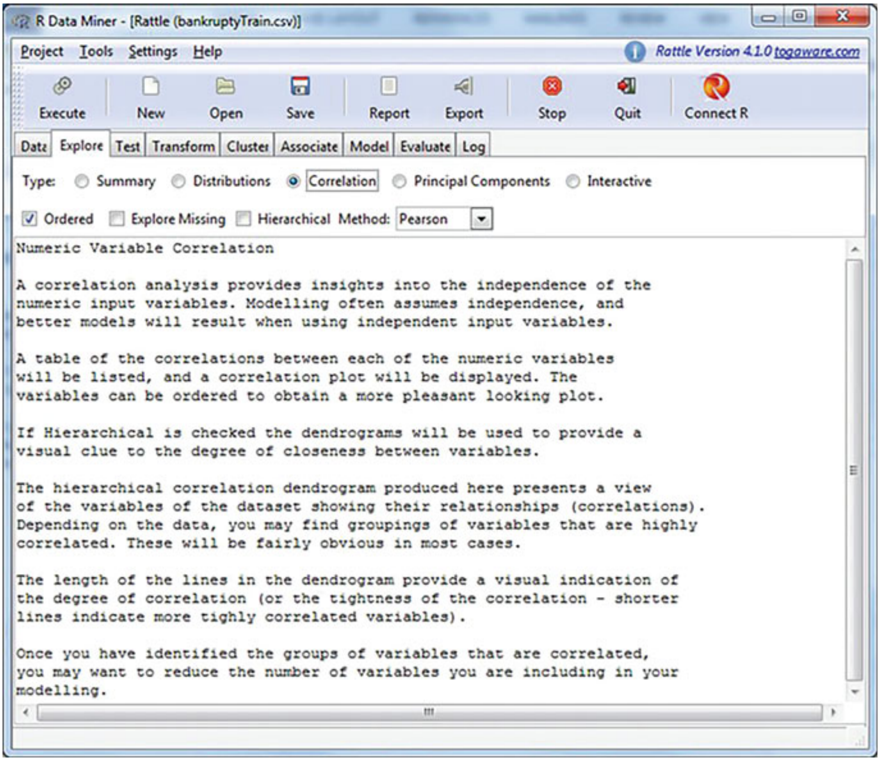

Fig. 9.3 Selecting correlation

Decision Tree Model

We can click on the Model tab and run models. Data mining for classification models has three basic tools—decision trees, logistic regression, and neural network models. To run a decision tree, select the radio button as indicated in Fig. 9.5. Note that the defaults are to require a minimum of 20 cases per rule, with a maximum number of 30 branches. These can be changed by entering desired values in the appropriate window. Execute yields Fig. 9.6. Rattle also provides a graphical display of this decision tree, as shown in Fig. 9.7. This model begins with the variable revt, stating that if revt is less than 78, the conclusion is that bankruptcy

would not occur. This rule was based on 44% of the training data (360 out of 824), over which 84% of these cases were not bankrupt (count of 304 no and 56 yes).

On the other branch, the next variable to consider is dvpsx_f. If dvpsx_f was less than 0.215 (364 cases of 464, or 44% of the total), the conclusion is bankruptcy (340 yes and 24 no, for 93%).

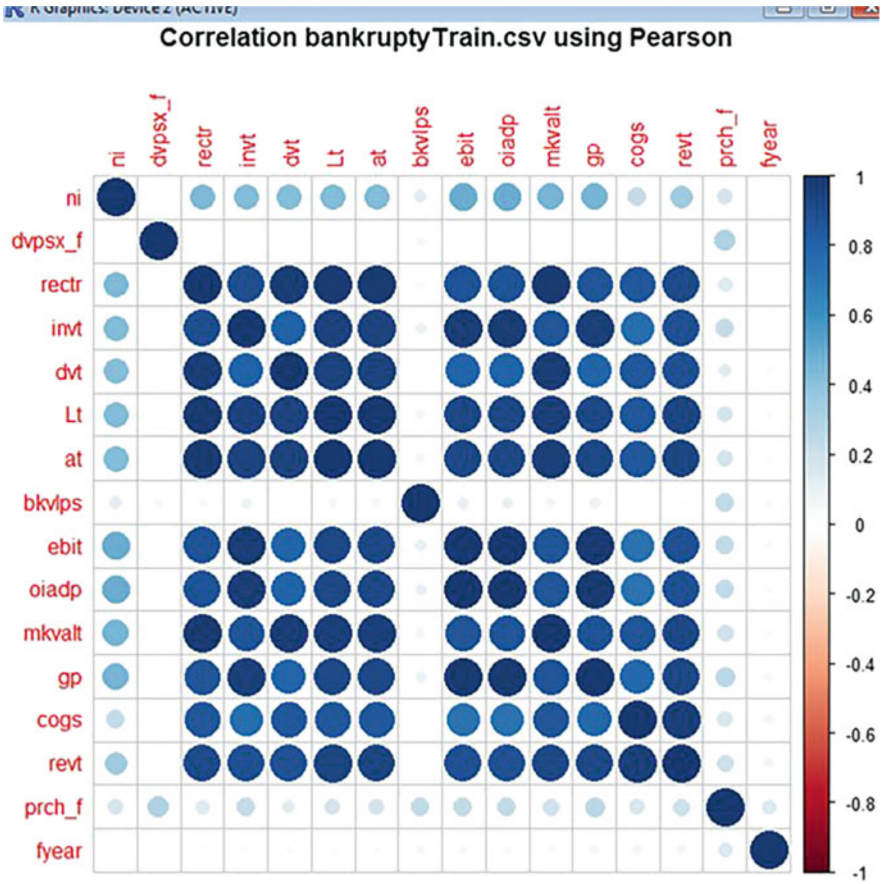

Fig. 9.4 Correlation plot

If revt ≥78 and dvpsx_f ≥ 0.215 (100 cases), the tree branches on variable at. If at ≥4169.341, the conclusion is bankruptcy (based on 31 of 31 cases). If at<4169.341, the model branches on variable invt.

For these 69 cases, if invt <16.179 (23 cases), there is a further branch on variable at. For these 23 cases if at <818.4345, the conclusion is bankruptcy (based on 13 of 13 cases). If at ≥818.4345, the conclusion is no bankruptcy (based on 7 of 10 cases).

If invt ≥16.179 (46 cases), the model splits further on invt. If invt <74.9215, the conclusion is no bankruptcy (based on 18 of 18 cases). If invt ≥74.9215, there is further branching on variable mkvalt. For mkvalt <586.9472, the conclusion is bankruptcy based on 11 of 14 cases. If mkvalt ≥586.9472, the conclusion is no bankruptcy (based on 13 of 14 cases).

This demonstrates well how a decision tree works. It simply splits the data into bins, and uses outcome counts to determine rules. Variables are selected by various algorithms, often using entropy as a basis to select the next variable to split on

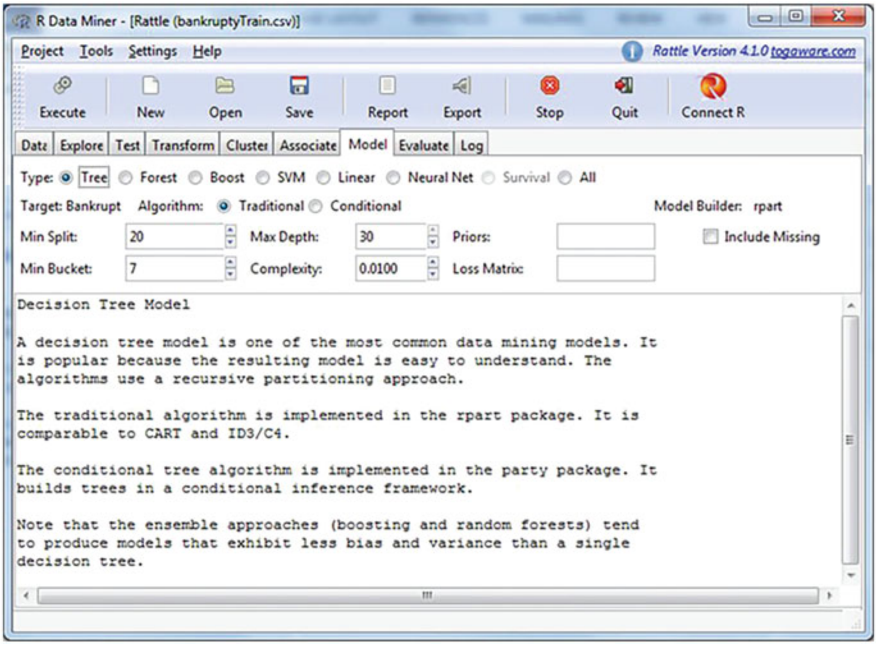

Fig. 9.5 Selecting decision tree

(Table 9.2). This model shows overall accuracy of 164/176, or 0.932. This validation data was over the same period as the model was built upon, up to 2008. We now test on a more independent testing set (2009–2010) as shown in Table 9.3. Here the overall correct classification rate is 126/143, or 0.881. The model was correct in 80 of 90 cases where firms actually went bankrupt (0.889 correct). For test cases where firms survived, the model was correct 46 of 53 times (0.868 correct).

Logistic Regression Model

We can obtain a logistic regression model from Rattle by clicking the Linear button in Fig. 9.8, followed by the Logistic button. Execute yields Fig. 9.9 output.

Note that R threw out two variables (oiadp and revt), due to detected singularity. This output indicates that variables rectr and gp are highly significant. Further refinement of logistic regression might consider deleting some variables in light of correlation output. Here we are simply demonstrating running models, so we will evaluate the above model on both the validation set (Table 9.4) and the test set. This model shows overall accuracy of 158/176, or 0.898. This is slightly inferior to the decision tree model. We now test on a more independent testing set (2009–2010) as shown in Table 9.5. Here the overall correct classification rate is 111/143, or 0.776. The model was correct in 78 of 90 cases where firms actually went bankrupt (0.867

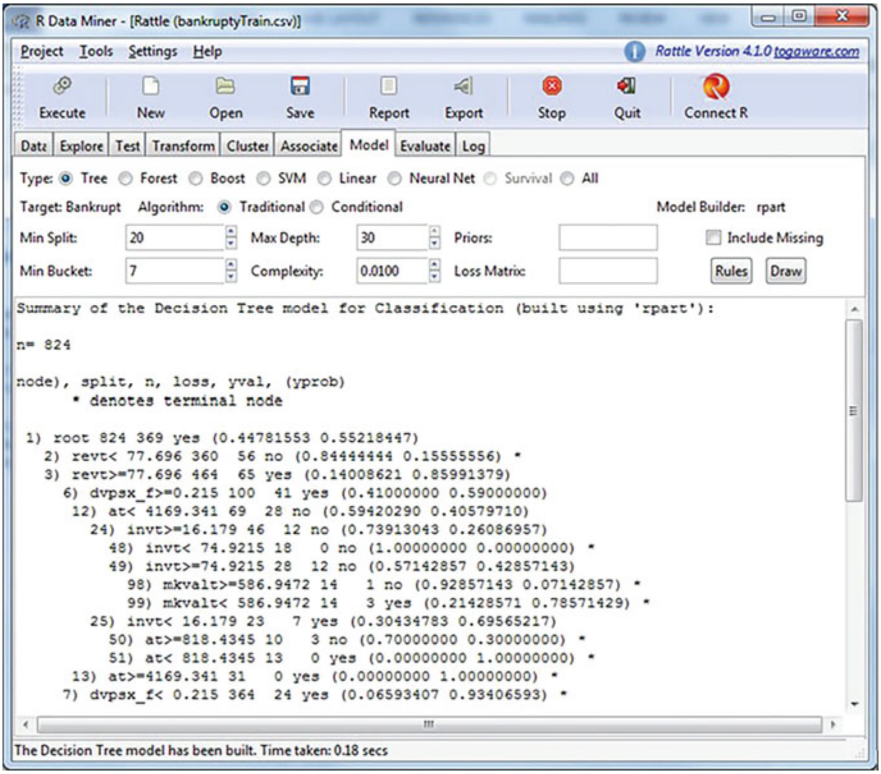

Fig. 9.6 Default decision tree model

correct). For test cases where firms survived, the model was correct 33 of 53 times (0.623 correct).

Neural Network Model

To run a neural network, on the Model tab, select the neural net button (see Fig. 9.10). Execute yields a lot of values, which usually are not delved into. The model can be validated and tested as with the decision tree and logistic regression models. Table 9.6 shows validation results. This model shows overall accuracy of 156/176, or 0.886. This is slightly inferior to the decision tree model. We now test on a more independent testing set (2009–2010) as shown in Table 9.7. Here the overall correct classification rate is 121/143, or 0.846. The model was correct in 75 of 90 cases where firms actually went bankrupt (0.833 correct). For test cases where firms survived, the model was correct 46 of 53 times (0.868 correct).

Here the decision tree model fits best, as shown in Table 9.8, comparing all three model test results. All three models had similar accuracies, on all three dimensions

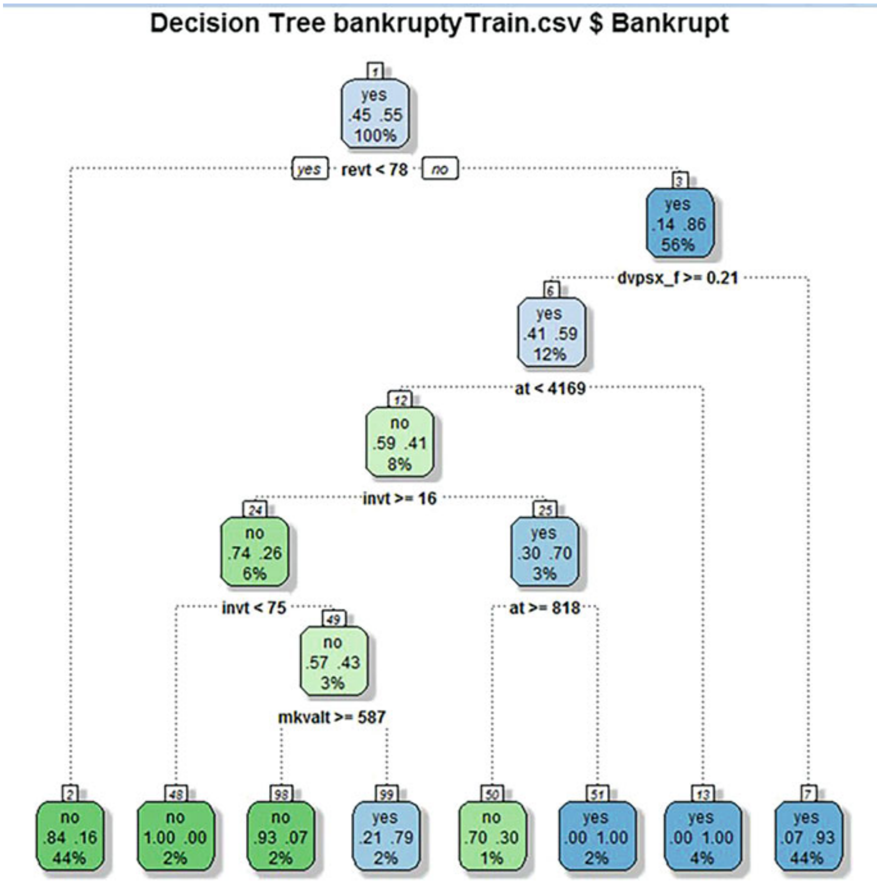

Fig. 9.7 Rattle graphical decision tree

Table 9.2 Coincidence matrix for the validation set of decision tree model

	Model not bankrupt	Model bankrupt	
Actual not bankrupt	70	6	76
Actual bankrupt	6	94	100
	76	100	176

Table 9.3 Coincidence matrix for test set of decision tree model

	Model not bankrupt	Model bankrupt	
Actual not bankrupt	80	10	90
Actual bankrupt	7	46	53
	87	56	143

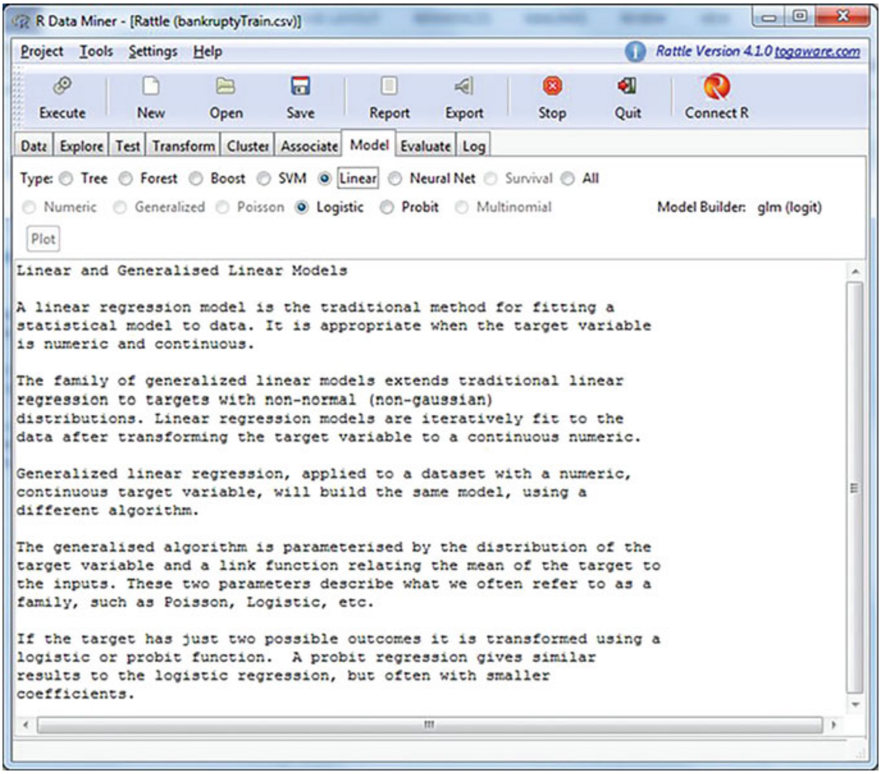

Fig. 9.8 Selecting logistic regression

(although the decision tree was better at predicting high expenditure, and correspondingly lower at predicting low expenditure). The neural network did not predict any high expenditure cases, but it was the least accurate at doing that in the test case. The decision tree model predicted more high cases. These results are typical and to be expected—different models will yield different results, and these relative advantages are liable to change with new data. That is why automated systems applied to big data should probably utilize all three types of models. Data scientists need to focus attention on refining parameters in each model type, seeking better fits for specific applications.

Of course, each model could be improved with work. Further, with time, new data may diverge from the patterns in the current training set. Data mining practice is usually to run all three models (once the data is entered, software tools such as Rattle make it easy to run additional models and to change parameters) and compare results. Note that another consideration not demonstrated here is to apply these models to new cases. For decision trees, this is easy—just follow the tree with the values for the new case. For logistic regression, the formula in Fig. 9.9 could be used, but it requires a bit more work and interpretation. Neural networks require entering

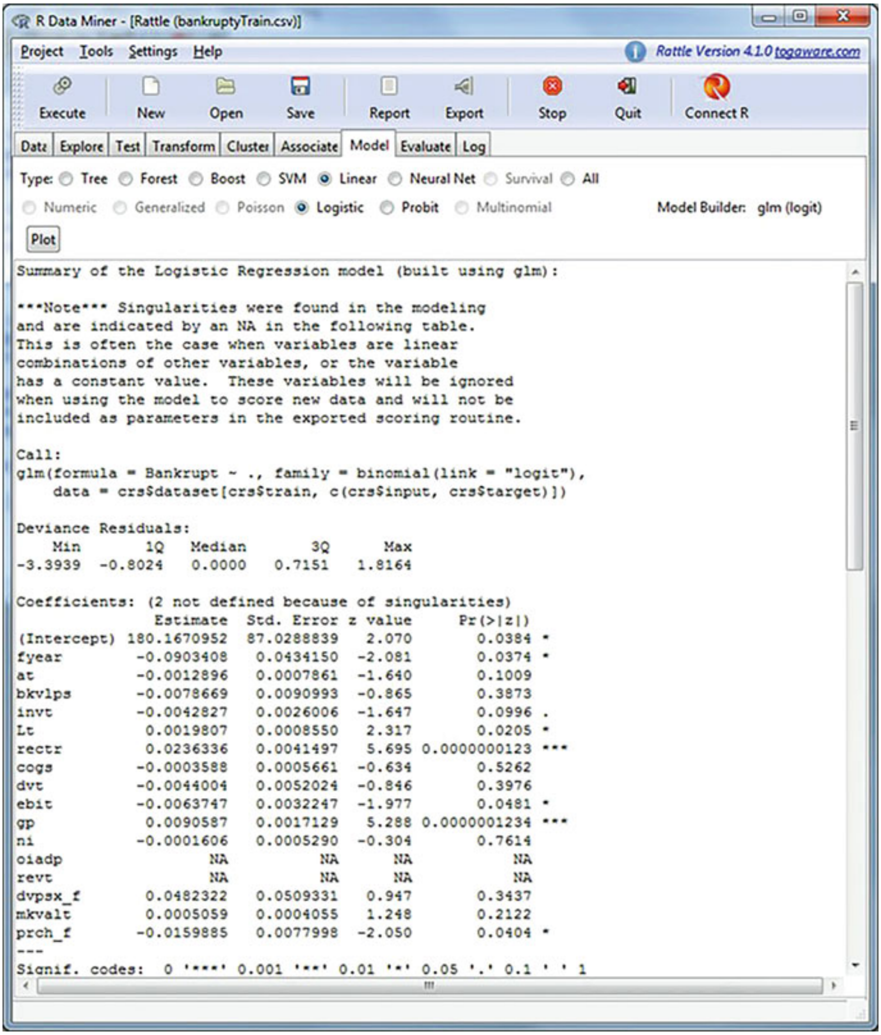

Fig. 9.9 Logistic regression output

Table 9.4 Coincidence matrix for validation set of logistic regression model

	Model not bankrupt	Model bankrupt	
Actual not bankrupt	72	4	76
Actual bankrupt	14	86	100
	86	90	176

Table 9.5 Coincidence matrix for test set of logistic regression model

	Model not bankrupt	Model bankrupt	
Actual not bankrupt	78	12	90
Actual bankrupt	20	33	53
	98	45	143

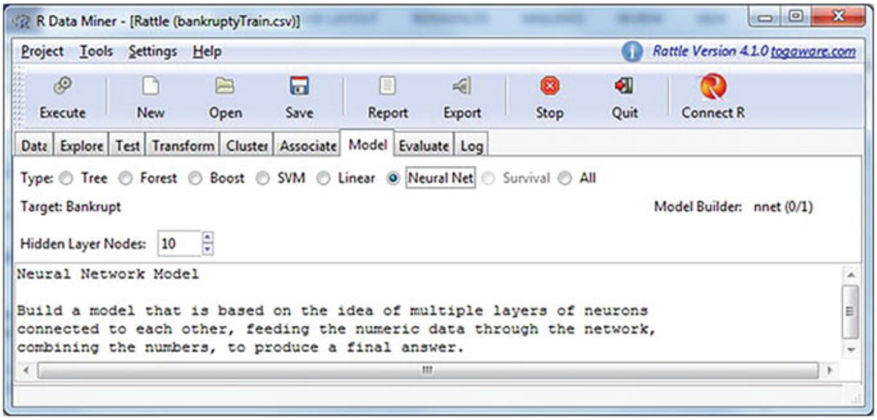

Fig. 9.10 Selecting neural network model

Table 9.6 Coincidence matrix for validation set of neural network model

	Model not bankrupt	Model bankrupt	
Actual not bankrupt	67	9	76
Actual bankrupt	11	89	100
	78	98	176

Table 9.7 Coincidence matrix for test set of neural network model

	Model not bankrupt	Model bankrupt	
Actual not bankrupt	75	15	90
Actual bankrupt	7	46	53
	82	61	143

Table 9.8 Comparative test results

Model	Correct not bankrupt	Correct bankrupt	Overall
Decision tree	0.889	0.868	0.889
Logistic regression	0.867	0.623	0.776
Neural network	0.833	0.867	0.846

new case data into the software. This is easy to do in Rattle for all three models, using the Evaluate tab and linking your new case data file.

Descriptive Data Mining Studies Involving Climate Change

This chapter reviews three papers applying descriptive data mining in one form or another to general climate change, and a fourth paper applying predictive time series forecasting. The first applies an input-output model with descriptive statistics to analyze the impact of coal-use reduction in Europe. The second applies association rule modeling, the third is cluster analysis. Thus all three are in the descriptive data mining category. The fourth is a time series forecasting model that is predictive.

Coal Phase-out in Europe

In order to reach greenhouse gas abatement targets, several European countries plan to phase out coal-fired power plants. This action will have several side effects, including disruption of the supply chain of coal to Europe and will increase trade with China in solar technology. Vögele et al. (2023) used input-output modeling and econometric analysis to study the environmental, economic, and societal impact of phasing out coal-fired power plants.

The European Union has been a major user of coal. As local resources have depleted, imports have grown. In 2018, steam coal for heat and power accounted for 63% of imports, while coking coal for steel had a 27% share. Some European countries (Belgium, France, Sweden) use little coal for electricity generation, but others (the Czech Republic, Germany, Poland, The Netherlands) continue to rely heavily on coal-fired plants. While coal imports for electricity generation have declined, this is counterbalanced by an even greater increase in its use for steel production.

Steel production is a heavy generator of greenhouse gases in Europe. Mitigation efforts have included reducing the use of coking coal as well as capture and storage of CO_2 emissions. Shifting production processes to hydrogen-direct reduction and the use of more secondary steel (recycling through electric arc furnace production) would reduce the use of coking coal. Carbon capture would not. Steel production in Europe is also facing strong competition from Chinese steel production, which makes the future production demand questionable.

European coal imports of steam coal come primarily from Colombia and Russia, with the USA and South Africa also notable sources. Coking coal has been imported primarily from the USA and Australia. Vögele et al. studied the impact on coal exporters at the local economy, mining sector, and national economic levels. Local economic impact was derived from literature reviews of specific coal mining sites. At the sector level, an input-output model was used to study direct and indirect links between countries and sectors, including production values, employment, water consumption, and greenhouse gas emissions. National economic impact was studied based on overall economic activity measures. Data was obtained from EIOBASE, a multi-regional environmentally extended input-output table, supplemented by the World Input-Output database. Measurement of sustainability development goals differs by study. Those used by Vögele et al. are given in Table 9.9:

Table 9.9 Measures used in the input-output coal model

SDG	Goal	Measure
SDG1	No poverty	Compensation for low-skilled employees
SDG2	Zero hunger	Arable area (crops, pastures, forest)
SDG3	Health	Total suspended particles
SDG4	Quality education	Not used
SDG5	Gender equality	Women's share of employment
SDG6	Clean water	Share of gray water
SDG7	Clean energy	Share of renewable energy consumption
SDG8	Economic growth	Value added per capita
SDG9	Industry infrastructure	CO_2 emission per unit of value added
SDG10	Inequality reduction	Change in income of low-skilled vs. high-skilled employees
SDG11	Sustainable cities	Total suspended particles
SDG12	Consumption and production	Materials over value added
SDG13	Climate action	CO_2
SDG14	Life in water	Not used
SDG15	Life on land	Forest area
SDG16	Peace and justice	Not used
SDG17	Partnerships	Not used

The study found that a decline in European coal demand would lower salaries in coal-exporting countries. The assumption that more imports would come from China resulted in a slight positive impact on Chinese employment and on renewable energy. Using GDP as an explanatory variable in the level 2 model resulted in lower scores for SDGs 1, 3, 4, 6, 7, and 9, and an increase in SDG 12 scores. Russia would be impacted the most, followed by Indonesia and South Africa. Australia would experience the most positive effects, followed by Russia and Canada. All of these impacts would be small. In general, decommissioning coal mining creates additional agricultural use capacity. The impact of coal use reduction in Europe on coal-exporting countries is described in Table 9.10.

The Vögele et al. study found that there were negative impacts on income and employment in coal-exporting countries, but a number of positive effects in the form of carbon dioxide reduction, water management, biodiversity, conservation, and societal improvements. However, the scale of these positive impacts was found to be small, both for coal-exporting countries and China.

Association Rule Mining of Adaptation Options

Ghazali et al. (2021) studied household perceptions of climatic and environmental variables among the Kashkooli nomads in Iran. Kashkooli nomads live in the Sepidan plain on the slopes of the Zagros mountains in southern Iran. The main source of livelihood for the Kashkooli is traditional ranching on natural rangelands.

Table 9.10 Impacts on Coal-exporting Countries by SDG

SDG	Goal	Level 1	Level 2	Level 3
SDG1	No poverty	Negative	Negative	Negative
SDG2	Zero hunger	Insignificant		Positive
SDG3	Health	Positive	Negative	Positive
SDG4	Quality education		Low negative	
SDG5	Gender equality	Low positive		Low positive
SDG6	Clean water	Low positive	Low negative	Positive
SDG7	Clean energy	Indifferent	Low negative	Positive
SDG8	Economic growth	Low negative		Low negative
SDG9	Industry infrastructure	Low positive	Negative	Indifferent
SDG10	Inequality reduction	Positive		
SDG11	Sustainable cities	Positive		Low positive
SDG12	Consumption and production	Positive	Positive	Positive
SDG13	Climate action	Positive		Positive
SDG14	Life in water			
SDG15	Life on land	Insignificant		Positive
SDG16	Peace and justice			Positive
SDG17	Partnerships			

This area has experienced decreases in precipitation and increases in temperature that have made it necessary to consider changes in operations.

Reducing vulnerability to climate change is expedited by properly understanding regional climate and anticipating climatic hazards before they occur. Coping strategies can be anticipatory (proactive measures to preserve and protect existing systems), and reactive, adopted after climate change impacts.

Methods used to adapt to climate change identified by Ghazali et al. included:

Southern Mexico, where adaptations adopted were promotion of coffee growing methods, forest restoration payments, diversification of income, fire management, crop insurance, and strengthening local capacity. The Mexican government provided credit resources, information, and promotional services on coping strategies and invested in climate smart and resilient projects.

In Bangladesh, riverine island residents are vulnerable to climate change. Coping options used were homestead gardening, altering cultivation patterns, planting trees, and migration. Government support was applied in the form of development programmes and disaster management projects.

In Nepal, rural communities adopted coping strategies in the form of natural forest conservation, tree planting, waste conservation, construction of conservation ponds, forest protection, construction of irrigation channels, planting drought-resistant crops, and maintaining a clean environment. Surveying Kashkooli nomads identified the following adaptation options:

Reduced spending on unnecessary things	98.7%
Saving water consumption	96.0%

(continued)

Reduced spending on unnecessary things	98.7%
Selling surplus livestock	95.1%
Supplementary feedstuff	92.9%
Borrowing money	81.3%
Substituting sheep for goats	48.9%
Occupation in other jobs	37.8%
Rangeland evacuation	34.2%
Livestock insurance	24.4%
Rangeland regeneration	22.78%
Immigration to better rangeland	21.4%
Construction of water ponds	13.3%

Four co-occurrence combinations showed that 95% of sampled nomads who reduced spending on unnecessary items practiced one of the coping strategies of saving water consumption, rangeland regeneration, and immigrating to other rangelands. Three co-occurrence combinations showed that sampled nomads who moved to other rangelands practiced rangeland regeneration and reduced spending.

Association rule mining was adopted to recommend options using support (probability of the joint occurrence of antecedent and consequent), confidence (probability of joint occurrence given the antecedent), and lift (relative propensity for the joint occurrence).

$$\mathrm{Support}(\mathrm{B}\square\mathrm{A}) = \mathrm{prob}\{\mathrm{A} \cup \mathrm{B}\}$$

$$\mathrm{Confidence}(\mathrm{B}\square\mathrm{A}) = \frac{\mathrm{prob}\{\mathrm{A} \cup \mathrm{B}\}}{\mathrm{prob}\{\mathrm{A}\}.}$$

$$\mathrm{Lift}(\mathrm{B}\square\mathrm{A}) = \frac{\mathrm{prob}\{\mathrm{A} \cup \mathrm{B}\}}{\mathrm{prob}\{\mathrm{A}\}\mathrm{xprob}(\mathrm{B})}$$

They applied a conventional a priori algorithm, using IBM SPSS Modeler 18 software, using minimum support and minimum confidence levels to control the number of rules obtained. Using minimum support of 0.1 and minimum confidence of 0.8 yielded 182 rules, too many. Increasing minimum support to 0.2 while holding minimum confidence at 0.8 yielded 124 rules. Minimum support of 0.3 with minimum confidence of 0.8 reduced the number of rules to 60. Minimum support of 0.3 and minimum confidence of 1.0 yielded the 16 rules given in Table 9.11.

These association rules distinguished causality effects, with the inference that antecedent conditions led to consequent actions. A major point is that when faced with climate change, catastrophe is not automatic. Humans have had to adapt for millenia and will continue to do so.

Table 9.11 Rules for Minimum Support 0.8, Minimum Confidence 1.0

Rule	Consequent	Antecedent	Spt	Conf	Lift
1	Sell surplus	Supp feed, save water	0.91	1	1.07
2	Sell surplus	Supp feed, Reduce spending	0.91	1	1.07
3	Sell surplus	Borrow, Supp feed, Save water	0.75	1	1.07
4	Sell surplus	Borrow, Supp feed, Reduce spending	0.75	1	1.07
5	Sell surplus	Supp feed, save water, Reduce spending	0.91	1	1.07
6	Sell surplus	Borrow, Supp feed, save water, reduce spending	0.75	1	1.07
7	Save water	Sell surplus	0.93	1	1.06
8	Save water, livestock insurance	Borrow, sell surplus	0.77	1	1.06
9	Save water, rangeland regeneration	Supp feed, sell surplus	0.91	1	1.06
10	Save water	Supp feed, reduce spending	0.91	1	1.06
11	Save water	Sell surplus, Reduce spending	0.93	1	1.06
12	Save water, immigrate rangeland	Borrow, supp feed, sell surplus	0.75	1	1.06
13	Save water	Borrow, supp feed, reduce spending	0.75	1	1.06
14	Save water	Borrow, sell surplus, reduce spending	0.77	1	1.06
15	Save water, rangeland regeneration	Supp feed, sell surplus, reduce spending	0.91	1	1.06
16	Save water, immigrate rangeland	Borrow, supp feed, sell surplus, reduce spending	0.75	1	1.06

Cluster Analysis

There has been increased pressure on businesses to take action with respect to climate change. Before the Kyoto Protocol of 2005, companies for the most part focused on socio-political actions in the form of non-market responses such as influencing law-making procedures to favor their profitability. But the number and stringency of climate regulations have increased, along with rising environmental public awareness and investor requests for transparency on greenhouse gas emissions and strategies to reduce them. Thus, there has been a shift toward proactive managerial and technological measures for greenhouse gas reduction, to include carbon inventories, investment in green products, and cleaner production processes.

The transportation sector accounted for 22% of global carbon dioxide emissions at the time of the study. Passenger and freight transport accounted for about three-quarters of emissions in the transportation sector. Policies adopted to mitigate CO_2 emissions include adoptions of fuel economy standards and emission-based taxes on vehicles. New technologies that have helped include alternative propulsion systems, fleet management, and altered usage patterns such as car sharing.

Damert and Baumgartner (2018) looked at 11 categories of climate change activities adopted in the transportation industry. These were grouped into four areas of strategic intent as follows:

Governance:

1. Greenhouse gas management and policy development
2. Organizational involvement
3. Risk management

Innovation

4. Process improvement
5. Product improvement
6. New markets and product development

Compensation

7. Supplier involvement
8. Emissions trading and compensation

Legitimation

9. Sector and stakeholder cooperation
10. Corporate reporting
11. Political activity

The specific measures and practices identified by Damert and Baumgartner are given in Table 9.12.

Damert and Baumgarten utilized three determinants for corporate climate chain strategies: the institutional environment, supply chain position, and firm size/financial performance. They sampled a database of the 550 largest automotive companies worldwide. They assess supplier shares of automotive sales using corporate financial data. They then collected publicly available company documents, with the Carbon Disclosure Project as the main source. Databases were screened from national and international automotive trade associations and business initiatives and gathered data on each firm's home country quality of climate mitigation policies.

Data analysis began with qualitative content analysis of company documents, using the 11 activities shown in Table 9.4. The second step of analysis was to assess the implementation level for each firm on each of these 11 activities. Then a two-step

Table 9.12 Measures adopted by corporations in response to climate change

Strategy	Activity	Measures
Governance	GHG management, policy development	Emission inventory
		Emission reduction targets
		Disinvesting from carbon intensive
	Organizational involvement	Assign climate change responsibilities
		Raising awareness
		Monetary reward for emission performance
		Non-monetary energy-efficiency awards
	Risk management	Assess challenges and opportunities
		Integrate climate change into risk management
		Design risk mitigation strategies
Innovation	Product improvement	Lifecycle analysis
		Product innovation policy
		Decrease carbon-intensive products
		Substitute carbon-intensive inputs
	Process improvement	Assess production process emissions
		Retrofit to energy-efficient equipment
		Switch to sustainable energy sources
	New markets and products	Partner to develop low-carbon products
Compensation	Supplier involvement	Suppliers implement environmental management
		Set emission reduction targets with suppliers
		Assist suppliers in implementing measures
	Emission trading	Acquire emission allowances
Legitimation	Sector and stakeholder cooperation	Collaborate with companies, political actors, NGOs
		Voluntary initiatives with local communities
		Stakeholder dialogue
	Reporting political activity	Disclose climate information
		Lobby, fund research or political parties
		Voluntary commitment to self-regulation

cluster analysis was conducted using the scores of the four strategic intents as inputs. Hierarchical cluster analysis identified four clusters as appropriate. A Mann-Whitney U test and ANNOVE were used to statistically analyze differences between OEMs and suppliers with the different strategy clusters. Firm size was measured by the natural logarithm of annual sales, financial performance was measured by return on assets and return on equity.

Table 9.13 Damert and baumgarten automotive clusters and strategy scores

Strategy	All-round enhancer	Legitimating reducer	Emergent innovator	Introverted laggard
Governance	3.83	3.73	2.98	2.08
Innovation	3.91	3.75	3.78	2.42
Compensation	3.42	1.37	1.17	0.48
Legitimation	3.52	3.02	2.19	1.6
Number	25	27	36	28

The four clusters obtained with relative scores (on a 1–5 scale) are displayed in Table 9.13.

All-round enhancers were the most proactive. Legitimating reducers were active in building up governance capabilities for climate change and innovating to reduce carbon emissions, but their initiatives related to emission credit acquisition and reducing supplier emissions were still in the planning phase. Emergent innovators prioritized innovation to achieve a reduction in carbon emissions, but their governance capabilities were less developed. The introverted laggard cluster scored lowest on all measures—they were aware of their carbon footprint but had not yet implemented measures to reduce emissions.

OEMs were generally more proactive than suppliers. This was attributed to being closer to consumers and thus to public scrutiny. European automobile manufacturers were mainly all-round enhancers, possibly due to higher regulatory pressure. Japanese and South Korean firms were found more in the emergent innovator cluster, as were US and Canadian firms. Other regions were predominant in the Introverted laggard cluster.

Inferences drawn were that more globalized companies are exposed to a greater variety of institutional settings and they tended to exhibit more ambitious action on climate change to legitimate their business. Japanese South Korean and other countries were innovative, but otherwise less active in seeking emission reduction. Larger companies faced greater visibility and exposure (and also had more resources), and thus were more proactive. The relationship between financial performance and corporate climate action was inconclusive.

Time Series Forecasting

Akyol and Uçar (2021) forecast Turkish greenhouse gas emission for the period 2018–2030 using predictive data mining models. Their forecasts found estimated greenhouse gas emission below Paris Accord targets for Turkey. But other forecasts are less optimistic, and policies need to continue to be given to greenhouse gas emission abatement. Akyol and Uçar recommended Turkish government policies to protect the environment by identifying possible carbon emission targets, using scientific methods to implement low carbon development policies with consideration given to lowering costs and effects on the country's economy. Policy packages recommended included carbon tax, a renewable energy investment fund, and energy efficiency tools.

The global treatment of energy policies in the world divides countries into categories of developed and developing, the effect of scale is at work. Each country tries to realize economic growth, increasing production while technology is stable in the developing period, which uses proportionally more resources and energy in their production process, which releases more greenhouse gases. As growth continues, there is a structural transformation of the economy and environmental destruction starts to decrease with more use of technology in the energy sector (the structural effect). Ultimately, as the share of R&D investments increases, a technological transformation is experienced and environmental quality is improved by reducing carbon footprint through the use of clean technology (the technological effect).

Turkey saw a rapid industrialization after January 1980, with efforts made to integrate with the global economy. Increasing population saw increased energy use needed to increase production, thus increasing destruction of the environment. Carbon footprint is measured as carbon dioxide emissions released into the atmosphere. Its increase is credited with melting glaciers that increase sea level, reduce water resources, and induce global warming. Turkey has committed to reduce carbon footprint and seeks estimates of national greenhouse gas emissions by 2030 and its impact on its economy. Akyol and Uçar (2021) applied WEKA open-source data mining software to analyze Turkish greenhouse gas emissions. Data for the period 1990 through 2017 was used with the variables population, gross domestic product (in ABD dollars), primary energy consumption (million tons of fuel oil equivalent), energy production (gigawatt hours), and rate of greenhouse gas emission in million tons of CO_2 equivalent. In the Paris Climate Convention, Turkey agreed to a target of 929 metric tons of CO_2 equivalent by 2030.

Pabuçcu and Bayramoğlu (2017) applied neural network forecasting for greenhouse gas emissions for Turkey and 28 EU countries for the period 2020–2030. Their forecast was 1244.13 million ton for Turkey in 2030, well above the agreed target. Time series modeling applied by Akyol and Uçar (2021) included application of linear regression, a neural network model in the form of multilayer perceptron, and sequential minimal optimization applying a support vector machine. These models were applied to a training set using the data for the period 1990–2008 and tested on three segments of 3-year data (2009–2011, 2012–2014, 2015–2017). The most successful model was selected based on the average of mean square error and mean absolute percentage error by time segment. Table 9.14 gives results.

Table 9.14 gives the dependent variable in the GHG column, and forecasts for each year for the linear regression, neural network (MLP—multilayer perceptron) and support vector machine (SMOreg) models. The model that was closest to actual is in bold. Note that all forecasts were lower than actual observations. The support vector machine model was lowest in six of the nine forecasts, while the multilayer perceptron model was lowest the other three. Thus, the SMOreg model was used to forecast greenhouse gas emissions for each year for the period 2018 through 2030.

In Turkey, the industrial sector has a high proportion of energy use, and accounts for 70% of greenhouse gas emissions. Turkey is seeking economic development

Table 9.14 Akyol and Uçar (2021) forecasting model results

Year	GHG	LR	MLP	SMOreg
2009	395,515	321,515	393,451	**395,390**
2010	398,661	340,958	386,199	**399,283**
2011	427,572	353,595	352,237	**394,080**
2012	446,935	297,805	**429,298**	421,472
2013	438,969	337,171	**435,890**	428,162
2014	457,962	389,265	433,282	**433,943**
2015	472,191	409,853	490,697	**475,696**
2016	498,469	431,825	**492,369**	489,132
2017	526,253	403,513	493,494	**507,349**

growth while using sustainable development utilizing renewable energy in the form of hydraulic, solar, wind, and geothermal energy. But Turkish renewable energy sources can provide only a small portion of needed energy.

Summary

We have demonstrated data mining on a financial risk set of data using R (Rattle) computations for the basic classification algorithms in data mining. The advent of big data has led to an environment where billions of records are possible. We have not demonstrated that scope by any means, but it has demonstrated the small-scale version of the basic algorithms. The intent is to make data mining less of a black box exercise, thus hopefully enabling users to be more intelligent in their application of data mining.

We have demonstrated an open-source software product. R is a very useful software, widely used in industry and has all of the benefits of open-source software (many eyes are monitoring it, leading to fewer bugs; it is free; it is scalable). Further, the R system enables widespread data manipulation and management.

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10 Balanced Scorecards to Measure Enterprise Risk Performance

Balanced scorecards are one of a number of quantitative tools available to support risk planning (Kaplan & Norton, 1996, 2006). Olhager and Wikner (Olhager & Wikner, 2000) reviewed a number of production planning and control tools, where scorecards are deemed as the most successful approach in production planning and control performance measurement. Various forms of scorecards, e.g., company-configured scorecards and/or strategic scorecards, have been suggested to monitor performance in a number of areas, including sustainability (Myung et al., 2019). This chapter demonstrates some ways in which balanced scorecards have been applied in the area of sustainability management.

While risk needs to be managed, taking risks is fundamental to doing business. Profit by necessity requires accepting some risk (Alquier & Tignol, 2006). The monitoring aspect of enterprise risk management has been widely supported through the use of balanced scorecards, including franchise operations (Kumar Raj & Kaur Singh, 2020), auditing (Hegazy et al., 2020), and finance (Song, 2022). Enterprise risk can include a variety of factors with potential impact on an organization's activities, processes, and resources. External factors can result from economic change, financial market developments, and dangers arising in political, legal, technological, and demographic environments. Most of these are beyond the control of a given organization, although organizations can prepare and protect themselves in time-honored ways. Internal risks include human error, fraud, systems failure, disrupted production, and other risks. Often systems are assumed to be in place to detect and control risk, but inaccurate numbers are generated for various reasons. ERM brings a systemic approach to risk management. This systemic approach provides more systematic and complete coverage of risks (far beyond financial risk, for instance). ERM provides a framework to define risk responsibilities, and a need to monitor and measure these risks. That is where balanced scorecards provide a natural fit in the measurement of risks that are key for the organization.

D. L. Olson, D. Wu, *Enterprise Risk Management Models*, Springer Texts in Business and Economics, https://doi.org/10.1007/978-3-662-68038-4_10

ERM and Balanced Scorecards

Beasley et al (Beasley et al., 2006). argued that balanced scorecards broaden the perspective of enterprise risk management. While many firms focus on Sarbanes-Oxley compliance, there is a need to consider strategic, market, and reputation risks as well. Balanced scorecards explicitly link risk management to strategic performance. To demonstrate this, Beasley et al. provided an example balanced scorecard for supply chain management, outlined in Table 10.1.

Sustainability Performance Measurement

Sustainability has received increased emphasis with the onset of global warming. We present three papers that propose the application of modified balanced scorecards to support the monitoring of performance in the environmental area.

Da Silva Neiva et al. (2021) Urban Sustainability

The United Nations views sustainable development as that which meets all of our needs without compromising future generations. Sustainability has received increased emphasis with the onset of global warming. The triple bottom line of economic, ecological, and social goals attainment is key to that effort. Da Silva Neiva et al. (2021) considered strategic management of sustainable cities.

In 2008, the global urban population outnumbered rural population for the first time. For each 10% increase in expansion, there is a 5.7% carbon dioxide emission increase and a 9.6% increase in pollution per capita. The UN recommends that around 20% of urban centers by area should be allocated to public spaces, in addition to between 30 and 35% for building streets.

Cities are complex dynamic systems with many interacting components. Sustainable cities have robust economic growth, prosperity, and competitiveness while protecting ecosystems and natural resources. This means mitigation of greenhouse gas emissions, as well as promoting inclusion and habitability. Urban planning seeks innovative, affordable means for cities to face sustainability challenges. The World Bank (2018) proposes a four-step approach:

1. Diagnosis and analysis of sustainability status quo.
2. Setting goals with priorities for attaining sustainability.
3. Develop a plan with funding to attain goals.
4. Monitor and evaluate attainment.

It is this fourth step that calls for a balanced scorecard analysis, modified to reflect sustainability. They adapted the balanced scorecard as follows:

Table 10.1 Supply chain management balanced scorecard

BSC element	Goals	Measures
Learning and growth for employees To achieve our vision, how will we sustain our ability to change and improve?	Increase employee ownership over process	Employee survey scores
	Improve information flows across supply chain stages	Changes in information reports, frequencies across supply chain partners
	Increase employee identification of potential supply chain disruptions	Comparison of actual disruptions with reports about drivers of potential disruptions
	Risk-related goals:	
	Increase employee awareness of supply chain risks	Number of employees attending risk management training
	Increase supplier accountabilities for disruptions	Supplier contract provisions addressing risk management accountability and penalties
	Increase employee awareness of integration of supply chain and other enterprise risks	Number of departments participating in supply chain risk identification and assessment workshops
Internal business processes to satisfy our stakeholders and customers, where must we excel in our business processes?	Reduce waste generated across the supply chain	Pounds of scrap
	Shorten the time from start to finish	Time from raw material purchase to product/service delivery to customer
	Achieve unit cost reductions	Unit costs per product/service delivered, % of target costs achieved
	Risk-related goals:	
	Reduce the probability and impact of threats to supply chain processes	Number of employees attending risk management training
	Identify specific tolerances for key supply chain processes	Number of process variances exceeding specified acceptable risk tolerances
	Reduce the number of exchanges of supply chain risks to other enterprise processes	Extent of risks realized in other functions from supply chain process risk drivers
Customer satisfaction To achieve our vision, how should we appear to our customers?	Improve product/service quality	Number of customer contact points
	Improve timeliness of product/service delivery	Time from customer order to delivery
	Improve customer perception of value	Customer scores of value
	Risk-related goals:	
	Reduce customer defections	Number of customers retained

(continued)

Table 10.1 (continued)

BSC element	Goals	Measures
	Monitor threats to product/ service reputation	Extent of negative coverage in business press of quality
	Increase customer feedback	Number of completed customer surveys about delivery comparisons to other providers
Financial performance To succeed financially, how should we appear to our stakeholders?	Higher profit margins	Profit margin by supply chain partner
	Improved cash flows	Net cash generated over supply chain
	Revenue growth	Increase in number of customers and sales per customer; % annual return on supply chain assets
	Risk-related goals:	
	Reduce threats from price competition	Number of customer defections due to price
	Reduce cost overruns	Surcharges paid, holding costs incurred, overtime charges applied
	Reduce costs outside the supply chain from supply chain processes	Warranty claims incurred, legal costs paid, sales returns processed

Developed by Beasley et al. (2006)

Dimension	Target
Social	Increase social justice
	Encourage sustainable production and consumption
	Increase level of employment
Environmental	CO_2 reduction
	Waste recycling
	Land use policy
	Renewable energy policy
	Access to drinking water
Infrastructure	Sustainable transport
	Sustainable urban spaces
	Accessibility
Economic/financial	Access to health
	Access to quality education
	Promotion of public transport

Da Silva Neiva et al. conducted a literature review followed by text analysis to generate a multicriteria tree for sustainable cities. Table 10.2 displays the result.

Table 10.2 Da Silva Neiva et al. (2021) urban sustainability goals

	Goals	Measures
Environment	Waste	Recycled waste Waste reduction Access to basic sanitation Municipal waste production
	Land use	Urban density Green public spaces Accessibility to parks
	Greenhouse gas emission	CO_2 emission CO_2 reduction CO_2 intensity Industrial pollution Air quality policies
	Energy	Renewable energy policies Renewable energy consumption
	Water resources	Water waste rate Water efficiency Public water supply Access to drinking water
Social	Transparency	Economic development Public finance Social justice
	Social equity	Employment Child mortality Quality of life Families below poverty line
	Community involvement	Territorial resilience Sustainable production/consumption Culture
Economic	Governance	Public participation Sustainable construction Education Urban planning
	Access to public goods	Access to education Security Access to health
	Transport	Average travel time and cost Vehicles per unit of paved road Alternative mobility Public transport

Lu et al. (2022) Sustainability Balanced Scorecard

This study focused on supporting green energy companies. They also generated a multiple criteria view of quantitative and qualitative elements, resulting in the framework shown in Table 10.3.

Table 10.3 Lu et al. (2022) sustainability balanced scorecard

Aspect	Elements	Measures
Social	Customer relationship management	Customer satisfaction Customer loyalty
	Employee job security	Create friendly work environment Employee safety
	Impact on society	Degree of public health influence Community development Education
Growth and learning	Employee skills	Professional knowledge Green energy skills
	Employee education	Improve quality performance
	Research and development	Scientific works Patents
Environmental	Noise	Noise measure
	Carbon emissions	Emission reduction
	Environmental policy	Natural resource use Environmental protection Certifications
Internal processes	Efficiency	On-time delivery Quality attainment
	Employee productivity	Production per resource input
	Risk management	Managed risks/identified risks
Financial	Net profit	Current period net profit Revenue income
	Return on investment	Net income Investment
	Financial transparency	Meaningful and timely disclosures

Lu et al. (2022) applied a fuzzy DEMATEL model reflecting these five aspects as criteria. Scores of attainment were obtained from interviews with a dozen specialists working in green energy companies. From our perspective, the interest is in the modification of the balanced scorecard idea to incorporate a focus on sustainability.

Pereira Ribeiro et al. (2021) Balanced Scorecard to Measure Attainment of SDGs

As the world's population continues to increase, there is added pressure on the consumption and usage of resources. It is expected that by 2030 there will be an increase in demand for energy of 40% and an increase of 30% for the use of water, while food production will have to increase by 70% to provide food security by 2050 (Leese & Meish, 2015; Miralles-Wilhelm, 2016). SDG 2 seeks to end hunger and achieve food security and improved nutrition as well as promote sustainable agriculture. Pereira Ribeiro et al. (2021) addressed the interchange between water, food, and energy.

Table 10.4 Pereira Ribeiro et al. (2021) SBG sustainability balanced scorecard

SBG	Goal	Policy area
2	Hunger and sustainable agricultural	Ensure proper function of food commodity markets
		Prevent trade restrictions in agricultural markets
		Maintain genetic diversity of crops
		Ensure sustainable food production systems
		Increase investment in rural infrastructure in LDCs
		Double productivity of small-scale food producers
12	Sustainable Consumption and Production	Halve per capita food waste
		Sustainable management of natural resources
14	Marine resources	Sustainable fisheries, aquaculture and tourism
		Access to small-scale fishers to marine resources and markets
15	Terrestrial ecosystem	Restore degraded land and soil

The United Nations has put forth a great deal of effort in the form of sustainable development goals (SDGs). SDG 2 seeks to protect, restore and promote sustainable use of terrestrial ecosystems by sustainably managing forests and combatting desertification. SDG 12 involves sustainable consumption and production. Its focus is on what public policies are needed to ensure sustainable consumption and production patterns. SDG 14 addresses the sustainable management of marine resources. SDG 15 considers the goal of eliminating hunger through sustainable agriculture in order to attain food security and improved nutrition. Pereira Ribeiro et al. (2021) conducted a literature review of Brazilian efforts in accomplishing these four sustainability development goals followed by text mining of SBGs as outlined in Table 10.4. They then applied balanced scorecard reasoning to Brazilian attainment of SDGs.

The study concluded that proper functioning of policies seeking attainment of these four SDGs requires investment in mitigation and climate change adaptation, conservation of water, energy, and land resources, modernizing of irrigation systems, guarantee of domestic food supply, and reform of the global food trade market. A holistic and integrative effort would be needed to solve challenges raised by scarce resources, calling for international cooperation and coordination.

Conclusions

The value of balanced scorecards to risk management is in monitoring organizational unit performance. Balanced scorecard analysis provides a means to measure multiple strategic perspectives. The basic principle is to select four (or five) diverse areas of strategic importance, and within each, to identify concrete measures that managers can use to gauge organizational performance on multiple scales. This allows consideration of multiple perspectives or stakeholders. Examples given included supply chain risk analysis and policy analysis of natural gas vehicle adoption. This chapter focused on examples of sustainability performance.

Balanced scorecards have been widely applied in general, but not often specifically to enterprise risk management. This chapter demonstrates how the balanced scorecard can be applied to evaluate the risk management posture of a particular organization. Balanced scorecards offer the flexibility to include any type of measure key to the production planning and operations of any type of organization.

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11 Machine Learning and Artificial Intelligence Risk

A great deal of attention has been given to the growth of artificial intelligence and machine learning. Applications in the form of artificial intelligence, robotics, specialized software, and cloud computing have led to higher labor productivity and lower labor shares. Artificial intelligence (AI) makes machines intelligent in the sense that they can perceive, analyze, and select a response appropriate to their environment. This was found to have led to 14.4% higher labor productivity for adopters (Acemoglu et al., 2022). Forms of AI technology include robotic equipment (automatically controlled, reprogrammable, and multipurpose) used in automated operations in industrial and/or service environments as well as cloud-based computing systems that apply computing resources over the Internet. Industrial robots are fully autonomous without the need for a human operator and can be programmed to perform tasks such as welding, painting, assembly, and materials handling.

Computer science has accomplished a great deal since the Turing machines of the 1940s. Kurzweil (Kurzweil, 2005) reviewed five paradigms of computing:

1. Electromechanical calculators (early twentieth century if not earlier—Babbage machines)
2. Relay-based computing (1940s)
3. Vacuum tubes
4. Discrete transistors
5. Integrated circuits

These forms of computation yielded a highly nonlinear explosion in capacity. Kurzweil predicted that by 2045, nonbiological intelligence created by AI would be a billion times more powerful than all human intelligence today. This implies that computers may jump past humans in knowledge, calculation speed, and accuracy on the road to computer self-awareness. We have already seen tremendous gains in the application of computer technology to keep accounting records, extended to run manufacturing plants (by robotic machines controlled by computers), to guide supersonic aircraft and rockets to space (beyond the capacity of human pilots), to

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trade stocks in nanoseconds, to control the vehicles that we drive, to create an Internet to communicate and trade files globally, to a cloud to store seemingly infinite bits and bytes of data, and social media. Some of these are due to artificial intelligence.

Artificial intelligence received a great deal of attention in the 2016 US Presidential election when Cambridge Analytica was found to have tapped the private data of Facebook users to custom tailor influencing messages and influencing voters, while Internet Research Agency in Russia similarly used social media to target voters (Siebecker, 2022). Businesses utilize machine learning/artificial intelligence to automate production lines (operations management), manage customer relationships (marketing), and mitigate market risks (finance).

Machine learning algorithms are methods that learn from data without human intervention and improve based on experience. Learning tasks may include mapping inputs to outputs, discovering hidden structures in unlabeled data, or generating category labels for new instances by comparing them with training data stored in memory (Ray, 2019). Instance-based learning, also known as nearest-neighbor learning, does not generate abstract results from specific instances. This chapter reviews definitions and then describes some popular machine learning approaches. This is followed by a review of some AI applications, and by a discussion of the expected impact of AI on human employment.

Definitions

The general definition of artificial intelligence is computer actions indistinguishable from that of a real human. A practical definition is unsupervised computer data analysis and autonomous computer decision-making. Smart technologies are capable of learning from their environment, at least in the sense that they adjust actions based on past results. They can detect patterns to make predictions and recommendations rather than simply run programmed instructions. There are two extreme views of the role of artificial intelligence. The conservative view is that computers are man-made devices (artifices, and thus artificial) and could never do what human brains do. Larson argued that AI can apply deduction and induction, but the abductive activity involved in general intelligence is beyond computer program capability (Larson, 2021). A more liberal perspective is taken by Kurzweil and others that computer intelligence will fly past human capacity very soon.

Artificial intelligence has reached a high level of technological maturity in the business field. Sampson proposed that humans maintain an advantage over AI when creative skills or interpersonal skills are needed (Sampson, 2021). In the field of robotics, Huang and Rust saw an evolution of AI development from mechanical to thinking and to feeling (Huang & Rust, 2021). They saw mechanical service being performed mostly by mechanical AI and less by humans, thinking activities shared by AI and humans, and feeling still in the realm of human activity. AI does well in environments with high levels of structure, but less well at dealing with people.

Manufacturing, with high levels of structure, has seen high levels of automation, but other less structured domains also have seen AI progress.

Use of AI in services is still evolving. Integrated enterprise resource planning systems control most sizable businesses today, extending beyond individual firms to coordinate global supply chains. Systems are capable of dealing with masses of data, creating industries to store and recover data as a service beyond firm capabilities of operating. This ability to deal with masses of data has led to the concept of big data, and the development of business analytics systems capable of wading through data in real time (from cash register to decision-making in terms of setting prices, controlling inventories, monitoring demand, and the need for new sources). Predictive analysis is usually driven by machine learning and artificial intelligence. Merging mathematical, statistical, and optimization techniques with artificial intelligence can lead to intelligent environments capable of transforming the delivery of business services.

Kurzweil pointed to three overlapping revolutions. The field of genetics may involve the opportunity to apply somatic gene therapy to custom design babies. This maybe is not such a good thing, but the ability to modify genetics is near. In the parallel field of animal genetics, there may be opportunities to alleviate world hunger by producing desired animal sources of food. Nanotechnology is a second revolution, with the use of nanobots in 2004 for mission-critical software systems to control nuclear power plants and guide missiles. Artificial intelligence driving robots has revolutionized many manufacturing applications. AI tools such as expert systems, Bayesian networks, neural network models, genetic algorithms, and recursive search have been used to generate all sorts of dramatic applications in military and intelligence, space exploration, medicine, and even business finance and manufacturing. Kurzweil's argument is that we are building machines with powers far greater than the sum of their parts by combining self-organizing design principles of the natural world with accelerating powers of human-initiated technology. Kurzweil's goal is a singularity where artificial intelligence attains the ability to irreversibly transform human life.

Common Machine Learning Algorithms

Several common machine learning algorithms are illustrated below.

Linear Regression

In the field of machine learning, the fundamental objective revolves around discerning the connection between inputs denoted as "x" and an output referred to as "y," with the ultimate goal of quantitatively characterizing this relationship. Linear regression, as a prominent technique in this realm, endeavors to determine an optimal line of fit that traverses a given set of data points and holds the capacity to make predictions for future observations. This process is achieved by formulating an equation that defines the association between the input and the output through the identification of specific weights, termed coefficients and symbolized as "beta." Several methodologies, such as ordinary least squares for minimizing the sum of squared residuals and leveraging linear algebra solutions with gradient descent optimization, are employed to acquire a linear regression model from the available data (Singhal & Kumar, 2023).

Linear regression finds its applicability in various predictive scenarios involving continuous variable output, including forecasting stock prices or product sales quantities (Ray, 2019). Nevertheless, it should be noted that linear regression, despite its simplicity and efficacy in prediction, might not be universally applicable. The assumption of a linear relationship between the independent and dependent variables, which underlies the method, may not be universally valid, posing limitations on its applicability to more intricate problems. Additionally, the sensitivity of linear regression to outliers can lead to significant discrepancies in model accuracy, as extreme values deviating from the overall data trend can exert a disproportionate influence. Linear regression can be considered in the following scenarios:

- Estimating the time required to travel from one location to another.
- Predicting the sales of a particular product in the next month.
- Assessing the impact of alcohol content in blood on coordination abilities.
- Forecasting the sales of gift cards each month and improving the estimation of annual income.

Python code for linear regression.

```
  # Import necessary libraries
From sklearn import linear_model

# Load Train and Test datasets
# Identify feature and response variables
x_train = input_variables_values_training_datasets
y_train = target_variables_values_training_datasets
x_test = input_variables_values_tedt_datasets

# Create linear regression object
linear = linear_model.LinearRegression()

# Train the model using the training sets and check score
linear.fit(x_train, y_train)
score = linear.score(x_train, y_train)

# Equation coefficient and Intercept
print('Coefficient:\n', linear.coef_)
print('Intercept:\n', linear.intercept_)
```

```
# Predict output
predicted = linear.predict(x_test)
print('Predicted Values:\n', predicted)
```

Logistic Regression

Logistic regression, in contrast to linear regression, is employed to predict discrete outcomes through a transformation function, making it suitable for binary classification problems where the output variable assumes values of 0 or 1, with 1 representing the default class (Alarsan & Younes, 2019). This technique is commonly applied in scenarios such as event occurrence prediction or disease status determination, where a value of 1 indicates the presence of the event or condition. The algorithm derives its name from the logistic function, which generates an S-shaped curve. Unlike linear regression, which directly predicts continuous values, logistic regression provides output as probabilities ranging from 0 to 1, with "y" being the probability of belonging to the default class. This probability is computed by applying the logarithmic transformation of the input "x" using the logistic function. To convert the probability into a binary classification outcome, a threshold is applied. Coefficients in a logistic regression model are determined through model training using an optimization algorithm, such as gradient descent, which minimizes the cost function, typically the logarithmic loss. Once the model is trained, it can make predictions by inputting new data and calculating the probability of the outcome being 1. The threshold for classifying the result as 1 or 0 is usually set around 0.5 (Almamy et al., 2016). Logistic regression can be considered in the following scenarios:

- Predicting customer churn
- Credit scoring and fraud detection
- Evaluating the effectiveness of marketing campaigns

Python code for logistic regression.

```
  # Import necessary libraries
From sklearn.linear_model import LogisticRegression

# Create logistic regression object
model = LogisticRegression()

# Train the model using the training sets and check score
model.fit(X, y)
score = model.score(X, y)

# Equation coefficient and Intercept
print('Coefficient:\n', model.coef_)
print('Intercept:\n', model.intercept_)
```

```
# Predict output
predicted = model.predict(x_test)
print('Predicted Values:\n', predicted)
```

The K-Nearest Neighbors Algorithm

When presented with a new data instance, KNN identifies the "k" nearest neighbors, or the most similar samples, based on distance measures such as Euclidean or Hamming distance. For regression tasks, KNN computes the average value of output results, while for classification problems, it predicts the class with the highest frequency among the "k" nearest neighbors. The key assumption of KNN is that data instances in proximity within the feature space exhibit similar characteristics or belong to the same class (Ray, 2019). It operates on the principle of "neighbors influence," utilizing the local structure of data to make predictions and generalizations (Zhang et al., 2021).

The strengths of KNN lie in its simplicity and ease of implementation, as it requires no explicit training or complex parameter tuning, and it can handle both regression and classification tasks. However, the algorithm has limitations, such as computational expense, especially with large datasets due to distance calculations for each new instance. The choice of "k" is crucial, as small values may cause overfitting, while large values may lead to oversimplification and reduced sensitivity to local patterns. KNN finds utility in diverse applications, including recommendation systems, pattern recognition, anomaly detection, and data clustering (Idoje et al., 2021). Its effectiveness is contingent on domain-specific considerations, the selection of distance metrics, and the appropriate setting of the "k" parameter (Khalil et al., 2022). Python code for a K-nearest neighbor algorithm:

```
  # Import necessary libraries
From sklearn.neighbors import KNeighborsClassifier

# Create KNeighbors classifier object model with n_neighbors set to
6
model = KNeighborsClassifier(n_neighbors=6)

# Train the model using the training sets
model.fit(X, y)

# Predict output
predicted = model.predict(x_test)
print('Predicted Values:\n', predicted)
```

Multi-layer Perceptron Artificial Neural Networks (MLP-ANNs)

The Artificial Neural Network (ANN) model represents a nonparametric prediction method based on nonlinear and non-parametric statistical multivariate techniques. Under certain conditions, the early warning effect of the ANN model surpassed that of parametric and non-parametric models, overcoming the limitations of traditional quantitative prediction methods as it does not require sample and variable distribution assumptions. The ANN model performs nonlinear mapping between input (database) and output (result), capturing unknown relationships between variables to construct a discriminant learning model. Various types of ANN models exist, such as multi-layer perceptron (MLP) and radial basis function (RBF), with MLP being more widely accepted (KTechniques, 2011).

The structure of an ANN model comprises three processing neuron units or nodes: the input node, hidden layer node, and output node (Chakraborty & Tudu, 2010). The input node processes external observations or independent variables, and activation functions like the softmax function establish connections between the input node and hidden layer node, as well as between the hidden layer node and output node. Information flows from the input node to the hidden layer node and then to the output node. The output node communicates the information processed by the neural network to external systems, and the output is compared with the expected values to fine-tune parameters (Patra et al., 1999). The hidden layer node can have multiple layers, and the accuracy of predictions heavily relies on the number of hidden layers. Therefore, the determination of the number of hidden layers requires iterative training and adjustments. Figure 11.1 depicts a schematic representation of a three-tier MLP-ANN.

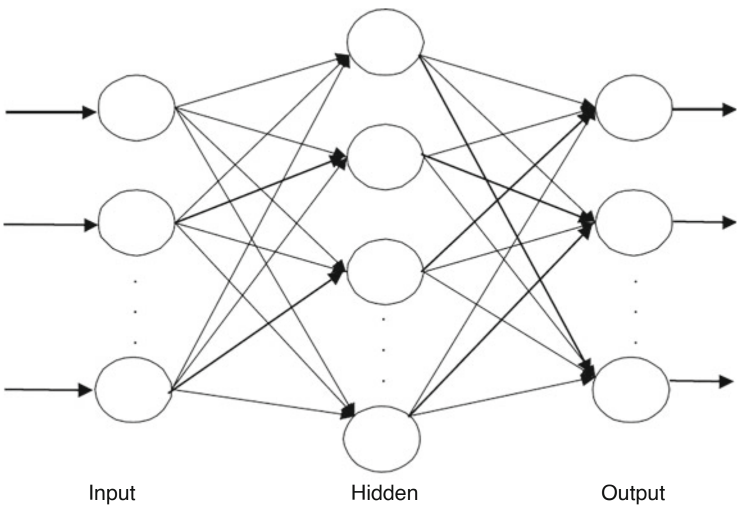

Fig. 11.1 A three-layer neural network schematic

Despite the opaque nature of its internal workings, the Multi-Layer Perceptron Artificial Neural Networks (MLP-ANNs) tool exhibits versatility in accommodating various data types and effectively handling nonlinear relationships between variables, owing to its strong learning, error tolerance, and prediction capabilities. However, MLP-ANNs also manifest notable drawbacks, including prolonged training times, intricate computations, reduced stability, and limited interpretability. Moreover, the tool may lack generalization abilities, making it susceptible to local optima and overfitting issues (Zanchettin et al., 2011).

Support Vector Machines

Support Vector Machines (SVM) are a widely acclaimed and extensively studied supervised learning algorithm. Its central concept involves identifying a boundary that efficiently separates distinct classes in the data. The hyperplane, representing the dividing line in the input variable space, is determined to optimize the separation of classes (class 0 or class 1) based on the input variable classes. In two dimensions, this corresponds to a line that effectively separates all input points. The SVM learning algorithm seeks coefficients that enable the hyperplane to achieve the optimal class separation, with the margin representing the distance to the nearest data points. To achieve the best hyperplane, relevant support vectors are utilized, which define and support the hyperplane. Optimization techniques are employed to find the coefficient values that maximize the margin.

SVM proves particularly advantageous when data is not linearly separable, meaning a straight line cannot separate it (Liang et al., 2022). SVM excels in high-dimensional spaces, making it valuable in text classification problems with high-dimensional input variables (Ray, 2019). Memory efficiency is another advantage, as SVM only requires storage of the support vectors rather than the entire dataset. This leads to high accuracy and helps prevent overfitting. However, SVM's performance depended on factors including kernel function and algorithm parameters. It may also exhibit lengthy training times, rendering it less suitable for large datasets. Moreover, SVM is memory-intensive, difficult to interpret, and challenging to fine-tune (Khalil et al., 2022). In real-world applications, SVM can be used for:

- Identifying people with common diseases like diabetes.
- Handwritten character recognition.
- Text classification, such as organizing articles into topics.
- Stock market price prediction.

Python Code for SVM:

```
  # Import necessary libraries
From sklearn.linear_model import svm
```

```
# Create SVM classification object
model = svm.SVC()

# Train the model using the training sets
model.fit(X, y)

# Check score (accuracy) on the training data
score = model.score(X,y)

# Predict output
predicted = model.predict(x_test)
print('Predicted Values:\n', predicted)
```

Random Forest

Random Forest, a tree-based ensemble method, serves as an advancement over individual bagged decision trees (Ray, 2019). It adeptly handles both regression and classification problems, particularly with extensive datasets, while effectively discerning the most crucial variables from a large pool of input features. Notably, Random Forest exhibits remarkable scalability, making it well-suited for data of any dimension and often yielding commendable performance. Furthermore, other genetic algorithms, such as microbial genetic algorithms, also demonstrate scalability to data of varying dimensions and types with minimal prior knowledge about the data itself. However, the learning speed of Random Forest may be hindered (depending on parameter settings), and it should be noted that this approach does not iteratively refine the generated model. Random Forest finds applications in various real-world scenarios, such as:

- Predicting high-risk patients.
- Predicting component failures in production.
- Predicting individuals likely to default on loans.

Python Code for a random forest classifier:

```
  # Import necessary libraries
From sklearn.ensemble import RandomForestClassifier

# Create Random Forest object
model = RandomForestClassifier()

# Train the model using the training sets
model.fit(X, y)
```

```
# Check score (accuracy) on the training data
score = model.score(X,y)

# Predict output
predicted = model.predict(x_test)
print('Predicted Values:\n', predicted)
```

Principal Component Analysis

Principal Component Analysis (PCA) is a data exploration technique that reduces the number of variables, enhancing visual accessibility (Zhu et al., 2022). It achieves this by extracting data with the highest variance into new coordinates termed "principal components." These components represent new linear combinations of the original variables and possess statistical independence, with correlation coefficients of 0. PCA serves as a powerful tool for data dimensionality reduction, particularly when dealing with highly correlated features, as employing a large number of data points in a model may lead to overfitting. In such cases, PCA can be employed to mitigate the issue. Python code for PCA:

```
  # Import necessary libraries
From sklearn.decomposition import PCA

# Assume you have training and test datasets as train and test

# Create PCA object with the desired number of components k
(default values)
pca = PCA(n_components=k)

# For factor analysis, you can use the following line instead of
PCA
# from sklearn.decomposition import FactorAnalysis
# fa = FactorAnalysis()

# Reduce the dimension of the training dataset using PCA
Train_reduced = pca.fit_transform(train)

# Reduce the dimension of the test dataset
test_reduced = pca.transform(test)
```

Integrated Z-Score and MLP-ANN Models

The two-stage hybrid neural discriminant technique involves using the Z-score model to select characteristic variables for distinguishing between "failed" and "non-failed" firms. From the Z-score model, five significant variables (WCTA, RETA, EBITTA, MVETA, and STA) are identified and used as input units in the neural network model, forming an input layer with five nodes. The default risk prediction model is established based on this neural network configuration. The sample companies are categorized into three groups: the financial health group (coded as 2), the gray area group (coded as 1), and the financial distress group (coded as 0) using the Z-score model's discriminant results. In the hybrid neural network model, the output layer consists of three neuron nodes, representing the three situations corresponding to the three groups of companies. The hyperbolic tangent function is adopted as the excitation function for the hidden layer, and the softmax function is utilized as the activation function for the output layer. The hybrid model is designed to overcome certain shortcomings of using either the neural network model or the Z-score model in isolation. A graphical representation of the architecture of the 3-layer 5-5-3 neural network is shown in Fig. 11.2.

Case Study

In this section, we combined Z-Score and Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) models to forecast the financial health of companies listed in China's A-share market to see how the machine learning methods affect in practice. Additionally, we conducted a comparative analysis of the prediction outcomes of the Z-Score model, MLP-ANN model, and the integrated model. The aim was to identify variations in the predictive capabilities of each model and determine the most suitable approach for forecasting the health of companies in the Chinese stock market.

We utilize financial statement data from all companies listed on the Shenzhen and Shanghai stock exchanges during the period from 2016 to 2020, resulting in a total of 17,206 observations after addressing missing values through the use of average values. The listed Chinese companies are categorized into two groups: the financial distress group (coded as 0) and the financial health group (coded as 1), based on whether the companies are marked by *ST and ST or not. All financial data used are obtained from the CSMAR database.

The evaluation of enterprise performance encompasses solvency, operating capacity, profitability, and development capacity, which can be assessed through various financial ratios; however, the relative importance of these ratios remains uncertain (Altman, 1968). Notably, Almamy et al. (2016). have highlighted that an increase in financial factors does not necessarily enhance the model's explanatory power and predictive accuracy. Previous research has utilized principal factor analysis to select significant financial indicators with strong correlations. In this study, five Altman independent variables are directly employed to predict the

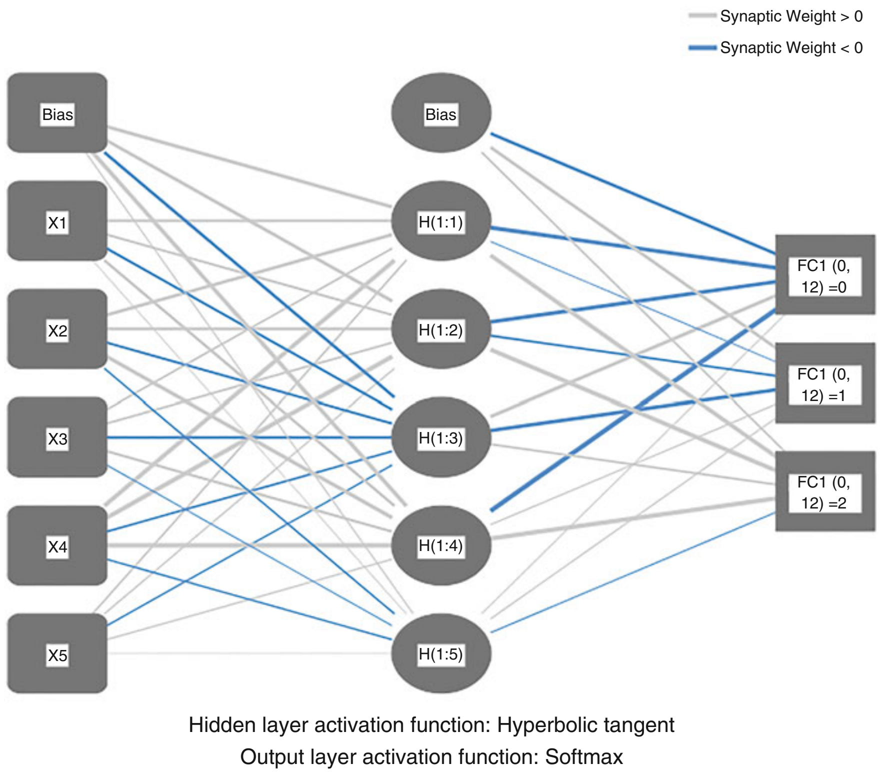

Fig. 11.2 The three-layer hybrid neural model

financial distress condition, and the definition and computation of these variables are detailed in Table 11.1.

In this case, companies designated as ST or *ST before their names are classified as financially distressed (failed) companies, amounting to 16,913 observations (98.30%). On the other hand, financially healthy (non-failed) companies comprise 293 observations (1.70%), as depicted in Table 11.2. The study employs five independent variables as predictors, namely WCTA (working capital to total assets ratio), RETA (retained earnings to total assets ratio), EBITDA (EBITDA to total assets ratio), MVETA (market value of equity to total liabilities ratio), and STA (sales to total assets ratio), as illustrated in Table 11.3. The response variable represents the financial condition of the listed company, categorized as financial distress (coded as 0) or financial health (coded as 1). The dataset is divided into a 7:3 ratio, with 12,055 observations assigned for training and the remaining 5151 retained for testing purposes.

The summarized results can be shown in Table 11.4.

From the results revealed in Table 11.4, we might conclude that the integrated Z-score and MLP-ANNs model has the best prediction power in terms of the average

Table 11.1 Model variable definitions

Variables	Classification	Index		Explanation/Computation
Dependent Variable		Financial Condition	Y	Financial Distress = 0Others = 1
Independent Variables	Short-term Solvency	WCTA	X1	WC=CA-CLThe more current capital, the less risk of insolvency.
	Profitability	RETA	X2	Firms with a high RE/TA ratio have a low default probability. RE=undistributed profits + surplus reserve
	Operating Capacity	EBITTA	X3	EBIT=Total profits + Financial expensesThis ratio measures the production capacity of an enterprise's assets without considering the influence of taxation and financing. The higher the ratio, the better the asset utilization effect and the higher the management level.
	CapitalStructure/ Leverage	MVETL	X4	MVE= Market value of stocks * Total number of stocks This ratio reflects the relative relationship between the capital provided by shareholders and creditors. The higher the ratio, the lower ratio the risk level.
	Profitability/ DevelopmentCapacity	STA	X5	The higher the index, the higher the utilization rate of assets, indicating that enterprises have a good effect in increasing income.

Note: *WCTA* working capital over total assets, *RETA* retained earnings over total assets, *EBITTA* earnings before interest and taxes (operating profit) to total assets, *MVETL* market value of equity to total liabilities, and *STA* sales to total assets

Table 11.2 Description statistics of the dependent variable

Classify	Frequency	Percent	Cum.
0 (ST or *ST)	293	1.70	1.70
1 (others)	16,913	98.30	100
Total	17,206	100	

Table 11.3 Summary of statistics for independent variables

Variable	Observations	Minimum	Maximum	Mean	Std. Deviation
WCTA	17,206	−147.7538	0.9587	0.2237	1.1835
RETA	17,206	−184.8072	0.8268	0.0872	1.9531
EBITTA	17,206	−29.2880	8.1491	0.0373	0.4102
MVETL	17,206	0.5951	698.1363	8.1741	16.1666
STA	17,206	−0.0502	11.6019	0.5967	0.5080

Table 11.4 Prediction results of the three constructed models

Risk prediction models	Risk prediction results
	Average correct classification rate
Altman Z-score model	86.54%
Multilayer perceptron artificial neural networks	98.26%
Integrated Z-score and MLP-ANN model	99.40%

classification rate in comparison with Altman Z-score model and pure ANN models. However, relative model results are highly dataset dependent. Note that here dataset imbalance is eliminated by using the Z-score scale.

Artificial Intelligence Support to Supply Chains

Supply chains provide a great deal of efficiency by linking organizations, drawing upon cost-effective contributions across the globe. Contemporary products often involve tens of thousands of specialty parts, some of which may require rare earths being mined in only a few places. Attaining efficiency often involves just-in-time operations which by their nature involve low inventories which imply risk. Supply chains generally are vulnerable to any sort of disruption. The recent pandemic demonstrated this risk to a high degree, as sources in China were often locked down, disrupting supplies. Further, logistic networks were often disrupted, with ripple effects threatening production worldwide.

Artificial intelligence and machine learning have been cited as having the potential to improve supply chain operations by sensing disruptive risks and triggering action in real time. Coping with supply chain risk calls for agility and resilience, which AI and analytics may often be able to provide. Intelligent automation of stores, warehouses, manufacturing plants, and even office buildings offers a great deal of benefit.

AI enables sharing of data through supply chain transparency. Sharing data is good business. Support from blockchain technology maybe even better as it enables control over who can see your data. With supply chain transparency business data can be distributed and shared in a trusted and secure manner, increasing speed, accuracy, and connectivity. An example is food, where networks of growers, processors, wholesalers, distributors, manufacturers, retailers, and other stakeholders improve visibility and accountability, enabling timely delivery of food products to grocery stores.

AI also has improved the ability of manufacturers to deal with production delays arising from issues such as inventory or labor shortages. Technology can provide on-site cameras or drones to sense problems, and feed AI-powered equipment and computer models to take real-time action. Reactive maintenance can be costly. Predictive data-based monitoring can reduce downtime and enable companies to react before maintenance problems shut down operations. AI can sense problems early, enabling the identification of problems in time to allow real-time action. They can help obtain better supply chain designs enabling reengineering of products to gain benefits in cost and resiliency.

A major issue in modern supply chains is the shortage of human skilled workers. A solution that is often used in robotics, controlled by artificial intelligence. This has had a noticeable impact on skilled employment. Acemoglu and Restropo found that one additional robot per thousand workers had reduced the employment/population ratio by 0.2% points, and wages by 0.12% (Acemoglu & Restrepo, 2020). Hicks and Deveraj reported that between 2000 and 2010 US manufacturing employment declined by 5.6 million jobs, 88% of which was attributed to productivity improvements from automation (Hicks & Deveraj, 2015). One aspect is that people are out of jobs. Maybe a more reasonable view is that they have opportunities to find new careers (although most of us do not appreciate the need to change when we do not want to). The COVID-19 pandemic magnified labor uncertainties. Change has been present forever and will continue forever.

Even experienced data scientists cannot determine which algorithm will perform best without trying different ones. While there are many other machine learning algorithms, this chapter discusses the most popular ones and the simple coding implementation in Python, together with a case study using machine learning methods to predict the financial health of companies listed in China's A-share market. The case study indicates that the hybrid model attained the highest average correct classification rate of 99.40% compared to the Z-score model (86.54%) and the pure neural network method (98.26%). The MLP-ANNs model displayed a high overall classification success rate, which was influenced by its application to an imbalanced data set. Although the MLP-ANNs model did not degenerate by labeling all cases as safe from bankruptcy, it did generate infrequent predicted bankruptcies. However, the integrated model's Z-score component effectively addressed the data set imbalance.

Artificial Intelligence Applications

Computer software has become endemic. Many of us rely on devices such as Siri or Alexa to help us around the house. IBM's Watson defeated leading human champions at the quiz game Jeopardy. Computer software has bested world chess champions. But in addition to personal assistants and game show contestants, artificial intelligence has grown to be part of our culture. In the supply chain field, production delays can be avoided through the application of artificial intelligence and machine learning to sense problems early, allowing action to be taken in real time. AI/machine learning can also help firms develop greater agility and resilience through the use of video streams from on-site cameras and drones. Investing in technology to automate stores, warehouses, manufacturing facilities, and office buildings can yield great benefits. AI-driven predictive analytics can better track material flows. There also is the obvious application of robotics to replace human workers. This has been extended beyond the factory floor to office facilities as well. Sestino and de Mauro (Sestino & de Mauro, 2021) conducted a text mining exercise of academic papers reporting the use of artificial intelligence in business. They organized the applications they found into six categories:

1. Business Impact—Data-driven decision-making and automation have been leveraged for some decades in the form of decision-support systems. These applications can involve automation of administrative, financial, and bureaucratic activity, and identify hidden patterns in data. Through the use of chat boxes and other connections, they can increase employee or customer emotional involvement in business activities.
2. Human resource management has to support human work. Some service desk activities can be automated. The optimistic view of such replacement of human work with automation is that it ensures better more interesting work for humans, and it decreases cost.
3. Industrial applications are widespread, with many impressive accomplishments supporting the medical sciences. They have led to the identification of cures for cardiology and radiology problems and have aided in prevention and control of epidemics. They have aided discovery in pharmaceuticals as well as in politics and finance. They improve inventory management for businesses and can provide better pricing. They provide ways to connect devices on the Internet of Things.
4. Social applications include understanding consumer social behavior. The positive side of customer relationship management is providing end consumers with better choices with increasing value.
5. Predictive models such as regression and/or classification models improve sales forecasting. Sentiment analysis and opinion mining extract subjective information from comments online.
6. Machine learning has supported pattern recognition, a key element of customer relationship management. Pattern recognition also can aid in identification of fraud and reduce the risks involved in extending credit.

The 2019 National Bureau of Economic Research report (Acemoglu et al., 2022) concluded that the adoption of automation technologies could be low due to the high specificity of tasks that are fully automatable, as well as organizational barriers in the form of worker resistance. There is a high fixed cost in adopting automation, leading to greater use by larger higher-wage firms. Adopters of AI are likely to experience lower labor shares and higher labor productivity. The impact of overall employment involves tradeoffs among the productivity effect of higher sales at lower cost increasing the demand for labor countered by a displacement effect of fewer jobs. Automation has been applied to lower-skill work, although advances in artificial intelligence applications continue to appear in new areas.

The Downside of AI

While Kurzweil and those who share his views see AI as a very positive development, there are concerns expressed by many. Studies have found that a slight majority of customers have been unwilling to undergo surgeries selected solely by AI, and even fewer have been comfortable using AI to make financial decisions (Ghosh & Chanda, 2020). Automation can threaten privacy, as companies and governments have more ability to dig into private lives. Some studies have found evidence that poor governance of AI and poor data quality can lead to operational inefficiency and competitive disadvantage (Ghasemaghaei & Turel, 2021). Berleant argued that preparing applications to government regulatory agencies for permission to commercially grow genetically engineered plants currently costs millions of dollars (Berbeant, 2013). Thus with rare exceptions, only modifications to major commodity crops like corn and soy are cost-effective to commercialize. Only large agribusinesses can afford the costs, and they have no reason to object as it preserves the status quo. Large agribusiness therefore is interested in keeping costs of obtaining permission so high as to keep out smaller innovative organizations. They can thus obtain predictable profits, which is their legal obligation.

Crawford expressed concern about the impact of artificial intelligence on the decision-making systems of social institutions such as education, health care, finance, government, hiring and the workplace, and the justice system (Crawford, 2021). Robots have been noted to replace humans—their proponents point to elimination of dangerous jobs, those opposed points to reductions in payroll and the creation of an idle and unemployed class. Further, Crawford argues that humans are being treated like robots at an increasing rate. Amazon has applied AI to create Mechanical Turk to tap a large number of people at miniscule labor rates to perform temporary jobs. Data is used to expand facial recognition, modulate health insurance, penalize distracted drivers, and fuel predictive policing. Crawford argues for control of the use of artificial intelligence to retain human control. Without such control, she sees increased discrimination to amplify hierarchies and encode narrow classifications of humans.

Challenges and Opportunities

Du and Xie addressed ethical issues involving AI and machine learning (Du & Xie, 2021). When there is a high degree of interactivity (health devices such as Fitbit; personal digital assistants such as Alexa and Siri), they saw high risks to privacy, autonomy, and cybersecurity. For applications with lower levels of interaction, such as Amazon.com recommendation systems, there is a risk of the system building in bias. More advanced AI capable of activities such as autonomous vehicles or IBM's Watson has attained impressive ways for systems to work without humans but leave questions concerning the impact on employment. Du and Xie viewed opportunities for AI users to alleviate these risks at three levels: product, consumer, and society. At the product level, greater transparency about AI training data and algorithms would

Table 11.5 Artificial intelligence support to knowledge management

Process	Function	Examples
Knowledge creation	Self-learning New pattern relationships	Forecasting Customer relationship management
Knowledge storage/ retrieval	Harvest, classify, organize Knowledge reuse	Legal precedents Troubleshooting
Knowledge sharing	Connect people More coordination	Feedback Peer review
Knowledge application	Search Voice-based assistants	Scan manuals Chatbots

make humans more comfortable and enable an audit process to provide quality control. At the consumer level, fair and transparent privacy policies would reduce human concerns and offer consumers greater control over data collection and management. At the societal level, awareness of digital addiction and tools to fight it would help, as would reskilling programming and continuous learning to provide new and better employment to those humans who may lose their jobs to AI.

Trunk et al. (2020) gave an overview of the possibilities of integrating artificial intelligence into organizational decision-making, especially in the area of risk management (Trunk et al., 2020). Artificial intelligence was suggested as a means to implement predictive information into business processes, aided by risk simulation, enabling a self-thinking management system for supply chains to continuously monitor performance. This generates a great deal of probabilistic information. The primary purpose of knowledge management is to wade through all of this noise to pick out useful patterns. That is data mining in a nutshell. Thus, we view knowledge management as:

- Gathering appropriate data
  – Filtering out noise
- Storing data (DATABASE MANAGEMENT)
- Interpret data and model (DATA MINING)
  – Generate reports for repetitive operations
  – Provide data as inputs for special studies

Jarrahi et al. gave a framework seeking to uncover opportunities to implement artificial intelligence systems to aid knowledge management (Jarrahi et al., 2023):

Table 11.5 gives a general framework of knowledge management processes that might be supported by artificial intelligence. Each organization faces its own circumstances, but success will likely come to those that are able to figure out how to effectively implement artificial intelligence into their systems.

Our conclusions are summarized in Table 11.6, following Olson and Araz (Olson & Araz, 2023). The integration of predictive and prescriptive modeling in decision-support systems for ORM is a trend in practical applications. Systems integration and real-time data processing tools will be in higher demand for operational management. The specific areas of ORM that data analytics can help deserves deeper

Table 11.6 Knowledge management features

Classification categories	Major findings	Future directions	Key research questions
Application fields	• Disaster management: Mobile technologies and crowdsourcing with prescriptive analytics in disaster management operations. • Public health risk management: Integration of data collection and processing tools for real-time decision-making. • Food safety: Blockchain applications in food supply chain offer improved risk identification and mitigation. • Social welfare: While in the early development stages, there is high potential in measuring and improving social welfare using analytics with big data technologies. • Transportation: Prescriptive analytics dominate applications.	• Real-time data streaming and processing are becoming factors in all sectors. • Operational risk assessment tools will evolve for disaster management, public health, food security, social welfare, public and commercial transportation applications. • Incorporating uncertainty into optimization models with predictive analytics for robust solutions.	• How do real-time data streaming and processing technologies support healthcare? • What are new risk assessment schemes in public health and other disaster management situations? • How to establish predictive analytics for robust solutions incorporating uncertainty into optimization models for healthcare?
Analytics techniques	• High interest in leveraging real-time emerging data. • Need for more surveillance systems for predicting future impact. • Many studies on prescriptive analytics for strategic and logistical decisions for effective planning.	• Data streaming and processing in predictive and prescriptive analytics. • More surveillance systems. • Data-driven operational risk analysis.	• What are the critical data-driven techniques that can be applied? What are their impacts?
Analytics strategies	• Human–technology relationship tools are critical for successfully implementing knowledge management. • Information systems have evolved into ERP systems.	• Research on human involvement in operational protocol development along with artificial intelligence tools. • High demand for systems integration and real-time data	• What can artificial intelligence bring? What is the role of humans? • How to integrate existing systems with real-time data processing? • What are the values

(continued)

Table 11.6 (continued)

Classification categories	Major findings	Future directions	Key research questions
	• More tools seeking integration of organizational reporting and single-sourced real-time data.	processing tools for risk analysis. • The deployment strategies of new and disruptive technologies, e.g., blockchain.	and impacts of deploying disruptive technologies (e.g., blockchain)?

explorations. In addition, real-time data streaming and processing are becoming the major interests of all sectors and operational risk assessment tools will continue to evolve for disaster management, public health, food security, social welfare, and public and commercial transportation applications. The deployment of new technologies, such as blockchain, will see more use in the future.

Artificial intelligence is being applied everywhere. We see some failed efforts, but we also see steady progress as machine intelligence takes over more and more jobs that used to require human effort. We have focused on artificial intelligence applications in the medical, project management, and supply chain management fields, but they appear in many other fields as well. There are serious issues to be dealt with. One is that artificial intelligence leaps to conclusions that are often wrong. The upside is that they can learn and correct such errors. But they can do serious damage in the meantime, calling for close human observation of their performance. A second major issue is that they are replacing human jobs. Eliminating dangerous and tedious work is a good thing. But they do create a serious problem of what we are going to do to maintain human ability to earn a living.

It is evident that machine learning plays a crucial role in addressing a wide range of problems and applications. Both supervised and unsupervised learning encompasses several popular and widely applied algorithms. However, it is important to recognize that machine learning is not a universal solution, and selecting the appropriate algorithm for a specific problem still requires in-depth domain knowledge and experience. Furthermore, data preprocessing is an indispensable stage in the machine learning workflow, encompassing tasks such as standardization, normalization, handling missing values, and addressing imbalanced data, all of which contribute to improving model performance and generalization capabilities. When applying machine learning algorithms, it is essential to be mindful of the discrepancy between training error and testing error in order to avoid overfitting issues. Finally, machine learning is a rapidly evolving field, and with the emergence of novel algorithms and technologies, we will be better equipped to tackle complex data and challenges, leading to innovative advancements across various industries.

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Enterprise Risk Management in Projects 12

Project management inherently involves high levels of risk because projects by definition are being done for the first time. There are a number of classical project domain types, each with its own characteristics. For instance, construction projects focus on inanimate objects, such as materials that are transformed into some purposeful objects. There are people involved, although as time passes, more and more work is done by machinery, with diminishing human control. Thus, construction projects are among the more predictable project domains. Government projects often involve construction, but extend beyond that to processes, such as the generation of nuclear material, or more recently, the processing of nuclear wastes. Government projects involve high levels of bureaucracy, and the only aspect increasing predictability is that overlapping bureaucratic involvement of many agencies almost ensures long time frames with high levels of change. There is a very wide spectrum of governmental projects. They also should include civil works, which drive most construction projects. A third project domain is information system project management, focusing on the development of software tools to do whatever humans want. This field, like construction and governmental projects, has been widely studied. It is found to involve higher levels of uncertainty than construction projects because software programming is a precise activity, and getting a computer code to work without bugs is a precise activity. Seyedhoseini et al (2008). reviewed risk management processes within projects, using the contexts of general project management, civil engineering, software engineering, and public application. Those authors looked at 16 risk management processes published over the period 1990–2005, spread fairly evenly over their four context areas, identifying methodologies. These contexts all involve basic project management, but we argue that each context is quite different. Project management in civil engineering is usually easier to manage, as the uncertain elements involve natural science (geology, weather). However, there are many different types of risk involved in any project, including political aspects (Skorupka, 2008) and financial aspects (Kong et al., 2008). While these sources provide more than enough uncertainty for project managers, there is a much more difficult task facing software engineering project managers (Chua,

D. L. Olson, D. Wu, *Enterprise Risk Management Models*, Springer Texts in Business and Economics, https://doi.org/10.1007/978-3-662-68038-4_12

2009). We argue that this is because people are more fundamental to the software engineering production process, in the form of developing systems, programming them, and testing them, each activity involving high degrees of uncertainty (Olson, 2004). Public application projects are also unique unto themselves, with high levels of bureaucratic process that take very long periods of time as the wheels of bureaucracy grind slowly and thoroughly. Slowly enough that political support often shifts before a project is completed, and thoroughly enough that opposition of the "not- in-my-backyard" is almost inevitably uncovered prior to project completion.

Project Management Risk

The Project Management Institute views risk as general to projects and through the Project Management Body of Knowledge (PMBOK) (Project Management Institute, 2013), which develops standards, policies, and guidelines for project management. It focuses on tools and techniques related to project management skills and capabilities. Project management responsibilities include achieving cost, and schedule performance objectives. Risk management is a major element of PMBOK, with major categories:

- Planning
- Risk identification
- Quantitative risk analysis
- Quantitative risk analysis
- Risk response planning
- Risk monitoring and control

The Project Risk Analysis and Management (PRAM) Guide in the UK is very similar in approach (Chapman, 2006), and fits the description of a typical risk management programme from other sources. Each of these categories applies to all projects to some degree, although the level of uncertainty can make variants of tools applied appropriate. A number of papers have proposed risk assessment methodologies in construction, based on an iterative process of risk identification, risk analysis and evaluation, risk response development, and administration (Schatteman et al., 2008). The key is to keep systematic records over time to record risk experiences, with systematic updating (Choi & Mahadevan, 2008).

Risk Management Planning

As with any process, inputs need to be gathered to organize the development of a cohesive plan. Things such as the project purpose and stakeholders need to be identified, followed by the identification of tasks to be accomplished. This applies to every kind of project. These tasks are cohesive activities, usually accomplished by a specific individual or group, and for each task estimation of duration and resources required, as well as immediate predecessor activities is needed. This is the input needed for critical path analysis, to be demonstrated in this chapter. That quantitative approach deals with risk in the form of probability distributions for durations (demonstrated in this chapter through simulation).

But other risk aspects need to be considered. It is important to consider the organization's attitude toward risk, and qualitatively identify things that can go wrong. Risk attitude depends upon stakeholders. Identification of what might go wrong and stakeholder preference for dealing with them can affect project management team roles and responsibilities.

Risk management planning concludes with a risk management plan. This plan should define methodologies for dealing with project risks. Such methodologies can include training internal staff, outsourcing activities that other organizations are better equipped to deal with, or insurance in various forms. Ultimately, every organization has to decide which risks they are competent to manage internally (core competencies), and which risks they should offload (at some expected cost).

Risk Identification

Once the risk management plan is developed, it can naturally lead to the next step, risk identification. The process of risk identification identifies major potential sources of risk for the specific project. The risk management plan identifies tasks with their risks, as well as project team roles and responsibilities. Historical experience should provide guides (usually implemented in the form of checklists) to things that can go wrong, as well as the organization's ability to cope with them.

Specific types of risk can be viewed as arising in various ways. A classical view is the triumvirate of quality, time, and budget. Software projects are often said to allow any two of the three—you can get code functioning as intended on time, but it usually involves more cost than expected; you can get functional code within budget as long as you are patient; you can get code on time and within budget as long as you do not expect it to work as designed. This software engineering project view often generalizes to other projects but with some different tendencies. In construction, there is less duration variance, although unexpected delays from geology or the weather commonly create challenges for project managers. If weather delays are encountered, the trade-off is usually whether to wait for better weather or to pay more overtime or extra resources. If geological elements are creating difficulties, more time and money is usually required. The functionality of the project is usually not degraded. Governmental projects may involve emergency response, where time is not something that can be sacrificed. The trade-off is between quality of response and cost. Usually, emergency response teams do the best they can within available resources, and public outcry almost always criticizes the insufficiency of the effort. There are a number of techniques that can be used to identify risks. Some qualitative approaches include interviews of experts or stakeholders, supplemented by techniques such as brainstorming, the nominal group technique, the Delphi method, or SWOT analysis (strengths, weaknesses, opportunities, and threats). Each of these

Table 12.1 Construction project risks

Phase	Ganbat et al.		Qazi and Dikmen
Design	Specification	Incomplete design, long review	
	Contract	Ambiguity, permitting	Scope change
Estimate	Cost, time		Inaccurate estimate, site conditions
Climate	Socio-political	Corruption; strikes; inhospitality	
	Government	Permit delays, policy changes	Bureaucracy, working time limits
	Payment	Capital restrictions, supplier permits	Funding problems
	Public	Legal, cultural opposition	
Operations	Materials	Cost inflation, unavailability, supplier default	Material price inflation
	Progress	Schedule delay	Tight schedule
		Weather	Inclement weather
		Equipment damage or failure	
		Subcontractor performance	Subcontractor incompetence
	Workforce	Safety, health	Labor competence, quality
Environmental	Compliance	Unanticipated utilities, waste disposal	Disposal, air, noise, water

methods is relatively easy to implement, and the quality of output depends on the participation of a diverse group of stakeholders. Historical data can also be used if the organization has experience with past projects similar to the current activity. This works well if past experiences are well-documented and retrieved efficiently.

Projects can arise in a number of contexts. In construction, there are building projects, road projects, and major facility projects such as airports. Software projects can involve a variety of levels of complexity, up to enterprise resource planning system development. There also are more ad hoc types of projects, including movies or concerts. The procedures and risks involved can vary considerably, but projects inherently have high levels of risk. To demonstrate risk identification, we will show risks identified by three sources. Ganbat et al. (2020) applied a literature review and questionnaire to identify risks in international construction projects, followed by network modeling to identify relationships. Qazi and Dikmen (2019) used a literature review to generate a list of construction project risks and surveyed practitioners concerning their use in a workshop. Simplifying and collating these two lists yields a representative list of construction project risks shown in Table 12.1.

Li et al. (2023) studied the impact of COVID-19 on Chinese real estate development projects. There were obvious shutdowns from lockdown policies and subsequent shortages in labor and supplies. There was a need to provide pandemic protection to workers, and stricter design specifications. They also found that the market for buildings changed dramatically, with less demand for office space.

The output from risk identification is a more complete list of risks expected in the project, as well as possible responses along with their expected costs. This results in a set of responses that can be reviewed as events develop, allowing project managers to more intelligently select appropriate responses. While success can never be guaranteed, it is expected that organizational project performance will improve.

Qualitative Risk Analysis

After a more precise estimation of project element risk is identified, the relative probabilities and risk consequences can be addressed. Initial estimations usually require reliance on subjective expert opinion. Historical records enable more precision, but one project element of importance is that projects by definition almost always involve new situations and activities. Experts have to judge the applicability of historical records to current challenges.

A qualitative risk analysis can be used to rank overall risks to the organization. A priority system can be used to identify those risks that are most critical, and thus require the greatest degree of managerial attention. In critical path analysis terms, critical path activities would seem to call for the greatest managerial attention. Behaviorally, humans tend to work hardest when the boss is watching. However, the fallacy of this approach is that other activities that are not watched may become critical too if they delay too far beyond their expected duration.

Qualitative risk analysis can provide a valuable screening to cancel projects that are just too risky for an organization. It also can affect project organization, with more skilled personnel assigned to tasks that call for more careful management. It also can be a guide to look for means to offload risk, either through subcontracting, outsourcing, or insurance.

Quantitative Risk Analysis

We will present more formal quantitative tools in the following sections. Quantitative analysis requires data. The critical path method calls for a specific duration estimate, which we will demonstrate. Simulation is less restrictive, calling for probability distributions. But this is often more difficult for humans to estimate, and usually only works when there is some sort of historical data available with which to estimate probability distributions.

Quantitative risk analysis, as will be demonstrated, can be used to estimate probabilities of project completion times, as well as other items of interest that can be included in what is essentially a spreadsheet model. These examples focus on time. It is also possible to include cost probabilities.

Risk Response Planning

Once risk analysis (qualitative, quantitative, or both) is conducted, project managers are hopefully in a more educated position to make plans and decisions to respond to events. Risk response planning is the process of developing options and reducing threats if possible. The severity of risks, as well as cost, time, and impact on project output (quality), should be considered.

A broad categorization of risk treatment strategies includes:

- Risk avoidance (adopting alternatives that do not include the risk at issue)
- Risk probability reduction (act to reduce the probability of adverse event occurrence)
- Risk impact reduction (act to reduce the severity of the risk)
- Risk transfer (outsourcing)
- Risk transfer (insurance)
- Add buffers to the project schedule

The process of project risk management is for project decision makers to trade off the costs of each risk avoidance strategy in light of organizational goals. The key to success is for organizations to adopt those risks internally where they have competency in dealing with the risk at issue, and to pay some price to offload those risks outside of their core competencies.

The output of risk response planning can be a prioritized list of risks with potential responses. It also can include assignment of specific individual responsibilities for monitoring events and triggering planned responses.

Risk Monitoring and Control

This category of activity is the implementation of all prior categories. Accounting is the first line of measurement of cost activity. Operational project management personnel also need to keep on top of time and quality performance as the project proceeds. When adverse events are identified, corrective action (either adoption of contingency plans or development of alternative actions) needs to be applied. In the long run, it is important to document projects, both in terms of specific time and cost experiences, as well as qualitative case data to enable the organization to do better on future projects.

Project Management Tools

A variety of risk management implementation tools have been applied. We referred to PMBOK earlier, which is intended to provide a process model for generic risk management projects. There are other process models, including the Software Engineering Institute's capability maturity model (CMM). The five levels of the CMMI are shown in Table 12.2.

Table 12.2 Capability maturity model for software engineering processes

Level	Features	Key processes
1 Initial	Chaos	Survival
2 Repeatable	Individual control	Software configuration management software quality assurance software subcontract management Software project tracking & oversight Software project planning requirements management
3 Defined	Institutionalized process	Peer reviews intergroup coordination Software product engineering integrated software management training programme Organization process definition Organization process focus
4 Managed	Process measured	Quality management Process measurement and analysis
5 Optimizing	Feedback for improvement	Process change management Technology innovation defect prevention

Source: Olson (2004)

The CMM level 1 covers software engineering organizations that do nothing. The other four levels involve distinctly different process areas, leading to better control over software development. It should be noted that attaining each level involves an organizational cost in added bureaucracy, which requires a business decision on the part of each organization. However, there is a great deal of research that indicates that in the long run, software quality is improved dramatically by moving from any level to the next higher level, and that overall development cost and development time are improved. This is a clear example of risk management—paying the price of more formality to yield reduced risk in terms of product output. Other process risk management models in software engineering include Boehm's spiral model (Boehm, 1988), which provides iterative risk analysis throughout the phases of the software development.

Bannerman (2008) categorized software project risk management into the three areas of process models (reviewed above), analytical frameworks (based on some dimension such as risk source, the project life cycle, or model elements), and checklists. Checklists are often found as the means to implement risk management, with evidence of positive value (Keil et al., 2008). Checklists can be (and have been) applied in any type of project. To work well, the project must repeat a domain, as each type of project faces its own list of specific risks. The value of a checklist of course improves with the depth of experience upon which it is based.

Simulation Models of Project Management Risk

We will focus on demonstrating quantitative tools to project risk management. We will demonstrate how simulation can be used to evaluate the time aspect of project management risk. The models are based on a critical path, which can be modeled in Excel, enabling the use of distributions through Crystal Ball simulation. We begin

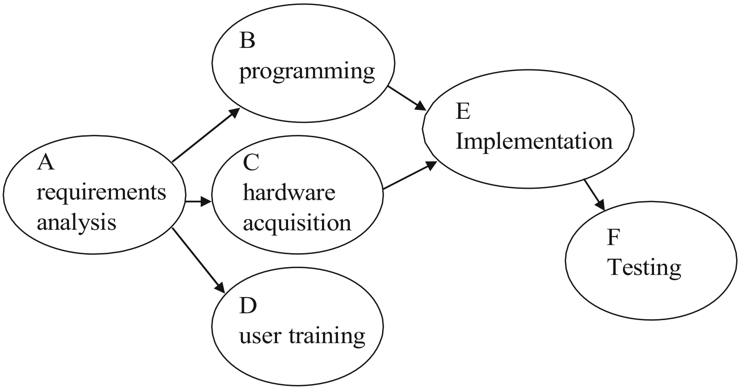

Fig. 12.1 Network for software installation example

Table 12.3 Software installation input data

Activity	Duration	Distribution	Predecessors
A Requirements analysis	3 weeks	Normal (3,0.3)	None
B Programming	7 weeks	Lognormal (1, 7)	A
C Hardware acquisition	3 weeks	Normal (3,0.5)	A
D User training	12 weeks	Constant	A
E Implementation	5 weeks	Exponential (5)	B,C
F Testing	1 week	Exponential (1)	E

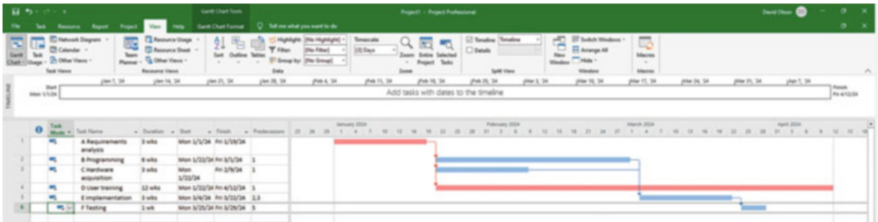

Fig. 12.2 Microsoft Project model output

with a basic software engineering project using a traditional waterfall model. Figure 12.1 gives a schematic of the activities and their precedence relationships.

Table 12.3 gives the input information, along with distributions assumed for each activity. These distributions should be based on historical data if possible, subjective expert judgment if historical data is not available.

Figure 12.2 gives the Microsoft Project output for this model.

The Excel model based on critical path analysis is given in Table 12.4.

Some modeling adjustments were needed. For all distributions, durations in weeks were rounded up in the Duration column of Table 12.1. For normal distributions, a minimum of 0 was imposed. Note that the lognormal distribution

Table 12.4 Crystal Ball model of the software installation project. ©Oracle. Used with permission

Activity	Distribution	Duration	Start	Finish
A Requirements analysis	=CB.Normal (3,0.3)	=INT(MAX(0, B2) + 0.99)	=0	=D2 + C2
B Programming	=CB.Lognormal (1, 5, 7)	=INT(B3 + 0.99)	=E2	=D3 + C3
C Hardware acquisition	=CB.Normal (3, 5)	=INT(MAX(0, C2) + 0.99)	=E2	=D4 + C4
D User training	12	=B5	=E2	=D5 + C5
E Implementation	=CB.Exponential (0.2)	=INT(B6 + 0.99)	=MAX (E3,E4)	=D6 + C6
F Testing	=CB.Exponential (1)	=INT(B7 + 0.99)	=E6	=D7 + C7
				=MAX (E2:E7)

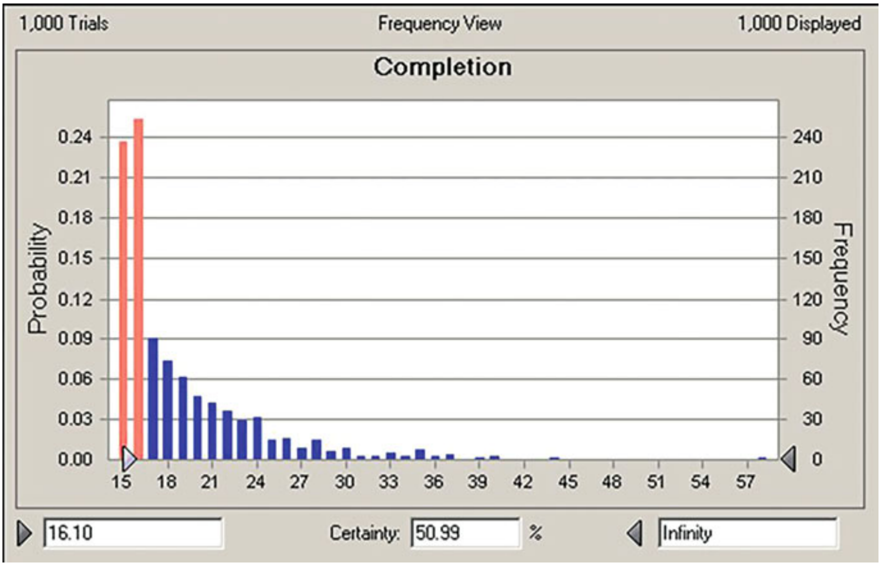

Fig. 12.3 Simulated software installation completion time. ©Oracle. Used with permission

in Crystal Ball requires a shape parameter (constrained to be less than the mean). Here the shape parameter is 5, the mean 7, and standard deviation 1. Also note that the exponential distribution's mean is inverted, so for E Implementation, 5 weeks becomes 0.2. Figure 12.3 gives the simulation results (based on 1000 replications). The average for this data was 18.62 weeks, compared to the critical path analysis of 16 weeks (which was based on assumed duration certainty). There was a minimum of 15 weeks (0.236 probability) and a maximum of 58 weeks. There was a 0.490 probability of exceeding 16 weeks.

There are other simulation systems used for project management. Process simulation allows contingent sequences of activities, as used in the Project Assessment by Simulation Technique (PAST) (Cates & Mollaghasemi, 2007).

Governmental Project

We assume a very long-term project to dispose of nuclear waste, with activities, durations, and predecessor relationships given in Table 12.5.

Table 12.6 gives the Excel (Crystal Ball) model for this scheduling project. Normal distributions were used for project manager controllable activities, and lognormal distributions were used for activities beyond project manager control (Figs. 12.4, 12.5, and 12.6).

Minimum completion time based on 1000 replications was 280 months, and the maximum was 391 months. The mean was 332 months, with a standard deviation of 16 months. The distribution of completion times appears close to normal. Table 12.7 gives the probabilities of completion in 10-month intervals.

Conclusions

We have argued that there are a number of distinct project types, including more predictable projects such as those encountered in civil engineering, highly unpredictable projects such as those encountered in software engineering, and projects involving massive undertakings or emergency response typically faced by

Table 12.5 Nuclear waste disposal project

Activity	Duration	Distribution	Predecessors
A Decision staffed	60 weeks		None
B EIS	70 weeks		A
C Licensing study	60 weeks		A
D NRC	30 weeks		A
E Conceptual design	36 weeks		A
F Regulation compliance	70 weeks		E
G Site selection	40 weeks		A
H Construction permit	0	Constant	D,F,G
I Construction	100 weeks		H
J Procurement	70 weeks		F SS, I SS + 5 weeks
K Install equipment	72 weeks		I
L Operating permit	0		K
M Cold start test	16 weeks		K
N Readiness test	36 weeks		M
O Hot test	16 weeks		N
P Begin conversion	0		L,O

Table 12.6 Model for governmental project

	A	B	C	D	E
1	Activity	Duration		Start	End
2	A Decision staffed	=INT(CB. Normal (60,5))	None	0	=D2 + B2
3	B EIS	=INT(CB. Lognormal (70,10))	A	=E2	=D3 + B3
4	C Licensing study	=INT(CB. Lognormal (60,10))	A	=E2	=D4 + B4
5	D NRC	=INT(CB. Lognormal(30,5))	A	=E2	=D5 + B5
6	E Conceptual design	=INT(CB. Normal (36,6))	A	=E2	=D6 + B6
7	F Regulation compliance	=INT(CB. Normal (70,10))	E	=E6	=D7 + B7
8	G Site selection	=INT(CB. Normal (40,5))	A	=E2	=D8 + B8
9	H Construction permit	=0	D,F,G	=MAX(D5, D7,D8)	=D9 + B9
10	I Construction	=INT(CB. Lognormal (100,10))	H	=D9	=D10 + B10
11	J Procurement	=INT(CB. Normal (70,5))	F SS, I SS + 5 weeks	=MAX(D7, D10 + 5)	=D11 + B11
12	K Install equipment	=INT(CB. Normal (72,5))	I	=E10	=D12 + B12
13	L Operating permit	=0	K	=E12	=D13 + B13
14	M Cold start test	=INT(CB. Lognormal(16,6))	K	=E12	=D14 + B14
15	N Readiness test	=INT(CB. Lognormal(36,6))	M	=E14	=D15 + B15
16	O Hot test	=INT(CB. Lognormal(16,6))	N	=E15	=D16 + B16

government bureaucracies. There are many other types of projects, of course. For instance, we did not discuss military procurement projects, which are extremely important in themselves. This type of project is a specific kind of governmental project, but here we focused more on emergency management (which military operations is closer to).

We also presented a framework for project risk analysis, based on PMBOK. This included a number of qualitative elements which can be extremely valuable in project management. But they are less concrete, and therefore we found it easier to focus on quantitative tools. We want to point out that qualitative tools are also very important.

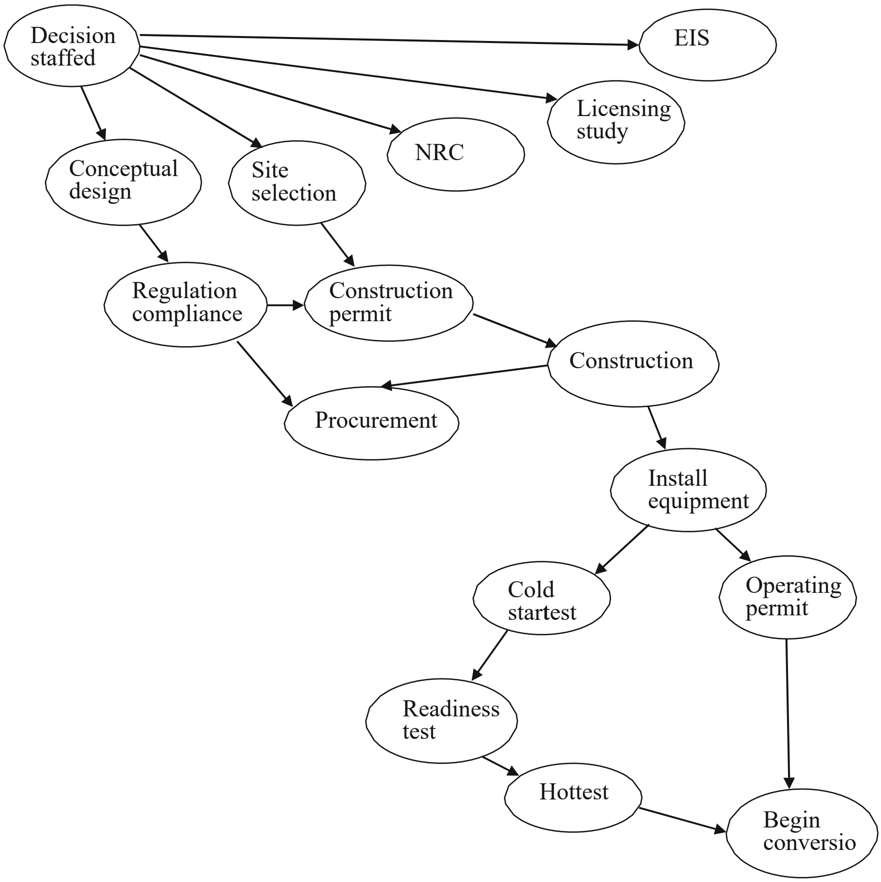

Fig. 12.4 Network for governmental project

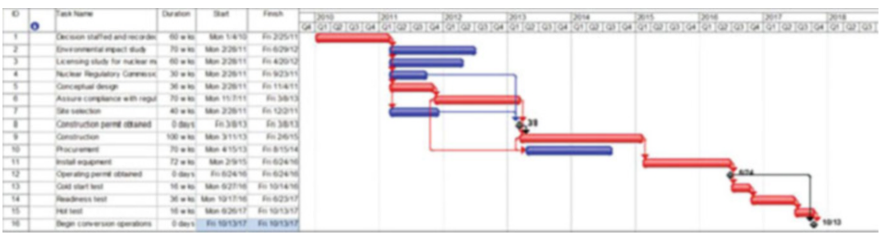

Fig. 12.5 Gantt chart for governmental project

The qualitative tools presented start with the deterministic critical path method, which assumes no risk in duration or in resource availability. We present simulation as a very useful means to quantify project duration risk. Simulation allows any kind

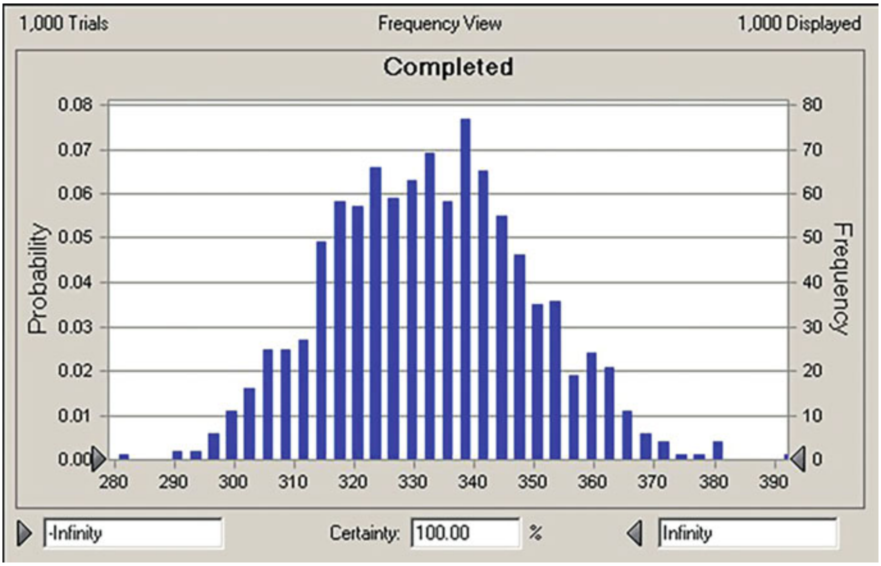

Fig. 12.6 Histogram of governmental project completion time in months. ©Oracle. Used with permission

Table 12.7 Probability of completion

Months	Probability
310	0.912
320	0.759
330	0.550
340	0.329
350	0.153
360	0.057
370	0.011
380	0.005

of assumption, and could also incorporate some aspects of resource availability risk through spreadsheet models.

While the ability to assess the relative probability of risk is valuable, the element of subjectivity should always be kept in mind. A simulation model can assign a probability of any degree of precision imaginable, but such probabilities are only as accurate as the model inputs. These probabilities should be viewed as subject to a great deal of error. However, they provide project managers with initial tools for identification of the degree of risk associated with various project tasks.

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13 Natural Disaster Risk Management

We have considered business operational risks in the context of supply chains, information systems, and project management. By definition, natural disasters are surprises and cause inconvenience and damage. Some things we do to ourselves, such as revolutions, terrorist attacks, and wars. Some things nature does to us, include hurricanes, tornados, volcanic eruptions, and tsunamis. Some disasters are caused by combinations of human and natural causes. We dam rivers to control floods, to irrigate, to generate power, and for recreation, but dams have burst causing immense flooding. We have developed low-pollution, low-cost (at the time) electricity through nuclear power. Yet with plant failure, new protective systems have made the price very high, and we have not figured out how to acceptably dispose of the waste. While natural disasters come as surprises, we can be prepared. This chapter addresses natural domain risks in the form of disaster management.

Emergency Management

Natural disaster management is the domain of government, fulfilling its responsibility to protect the general welfare. Local, State, and Federal agencies in the USA are responsible for responding to natural and man-made disasters. This is coordinated at the Federal level through the Federal Emergency Management Agency (FEMA). While FEMA has done much good, it is almost inevitable that more is expected of them than they deliver in some cases, such as hurricane recovery. In 2006, Hurricane Katrina provided one of the greatest tests of the emergency management system in the USA:

1. Communications outages disrupted the ability to locate people
2. Reliable transportation was disrupted or at least restricted
3. Electrical power was disrupted, cutting off computers
4. Multiple facilities were destroyed or damaged

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5. Some bank branches and ATMs were flooded for weeks
6. Mail was disrupted for months.

Disasters are abrupt and calamitous events causing great damage, loss of lives, and destruction. Emergency management is accomplished in every country to some degree. Disasters occur throughout the world, in every form of natural, man-made, and combination of disasters. Disasters by definition are unexpected, and tax the ability of governments and other agencies to cope. A number of intelligence cycles have been promulgated, but all are based on the idea of:

1. Identification of what is not known.
2. Collection—gathering information related to what is not known.
3. Production—answering management questions.
4. Dissemination—getting the answers to the right people (Mueller III, 2004).

Information technology has been developing at a very rapid pace, creating a dynamic of its own. Many technical systems have been designed to gather, process, distribute, and analyze information in emergencies. These systems include communications and data. Tools to aid emergency planners to communicate include telephones, whiteboards, and the Internet. Tools to aid in dealing with data include database systems (for efficient data organization, storage, and retrieval), data mining tools (to explore large databases), models to deal with specific problems, and a combination of these resources into decision support systems to assist humans in reaching decisions quickly or expert systems to make decisions rapidly based on human expertise. The role of information technology in disaster management includes the functions of (Hristidis et al., 2010):

- Information Extraction—gathering data from a variety of sources and storing them in efficient databases.
- Information Retrieval—efficiently searching and locating key information during crises.
- Information Filtering—focusing on pertinent data in a responsive manner.
- Data Mining—extract patterns and trends.
- Decision Support—analyze data through models to make better decisions.

Emergency Management Support Systems

A number of software products have been marketed to support emergency management. These are often various forms of a decision support system. The Department of Homeland Security in the USA developed a National Incident Management System. A similar system used in Europe is the Global Emergency Management Information Network Initiative (Thompson et al., 2006). While many systems are available, there are many challenges due to unreliable inputs at one end of the spectrum and overwhelmingly massive data content at the other extreme.

Systems in place for emergency management include the US National Disaster Medical System (NDMS), providing virtual centers designed as a focal point for information processing, response planning, and inter-agency coordination. NDMS is a federally coordinated system augmenting disaster medical care. Its purpose is to supplement an integrated National medical response capacity to assist State and local authorities in dealing with medical impacts of major peacetime disasters, as well as supporting military and Veterans Affairs medical systems in casualty care. EMSS has also been implemented in Europe (Lee et al., 2011). Intelligent emergency management systems are appearing as well (Amailef & Lu, 2011).

An example decision support system directed at aiding emergency response is the Critical Infrastructure Protection Decision Support System (CIPDSS) (Santella et al., 2009). CIPDSS was developed by Los Alamos, Sandia, and Argonne National Laboratories sponsored by the Department of Homeland Security in the USA. The system includes a range of applications to organize and present information, as well as system dynamics simulation modeling of critical infrastructure sectors, such as water, public health, emergency services, telecom, energy, and transportation. Primary goals are:

1. To develop, implement, and evolve a rational approach to prioritize CIP strategies and resource allocations through modeling, simulation, and analyses to assess vulnerabilities, consequences, and risks.
2. To propose and evaluate protection, mitigation, response, and recovery strategies and options.
3. To provide real-time support to decision makers during crises and emergencies.

A key focus is to aid decision makers by enabling them to understand the consequences of policy and investment options prior to action. Decision support systems provide tools to examine trade-offs between the benefits of risk reduction and the costs of protection action. Factors considered include threat information, vulnerability assessments, and disruptive consequences. Modeling includes system dynamics, simulation, and other forms of risk analysis. The system also includes multi-attribute utility functions based upon interviews with infrastructure decision makers. CIPDSS thus serves as an example of what can be done in the way of an emergency management support system.

Other systems in place for emergency management include the US National Disaster Medical System (NDMS), providing virtual centers designed as a focal point for information processing, response planning, and inter-agency coordination. Systems have been developed for forecasting earthquake impact (Aleskerov et al., 2005) or the time and size of bioterrorism attacks. This demonstrates the need for DSS support not only during emergencies but also in the planning stage.

Example Disaster Management System

Sahana is a foundation offering a suite of free open-source web-based disaster management system software for disaster response (www.sahana.lk/overview, 2010). The primary aim of the system is to alleviate human suffering and help save lives through the efficient use of information technology. Sahana Eden is a humanitarian platform customizable to integrate with local systems for planning or coping with crises. Vesuvius is a disaster preparedness and response software providing support to family reunification as well as hospital triage. Mayon provides emergency planning agencies with tools to plan preparedness, response, recovery, and mitigation. Sahana can bring together government, emergency management, nongovernment organizations, volunteers, and victims in disaster response. It is intended to empower victims, responders, and volunteers to more efficiently utilize their efforts while protecting victim data privacy.

Sahana is a free open-source software system initially built by Sri Lankan volunteers after the 2004 Asian tsunami (Morelli et al., 2009). It has the following main applications:

1. Missing persons registry—bulletin board of missing and found persons, and information of who is seeking individuals.
2. Organization registry—a tool to coordinate and balance the distribution of relief organization to affected areas.
3. Request/Pledge management system—log of incoming requests for support, tracking relief provided, and linking donors to relief requirements.
4. Shelter registry—tool to track location and number of victims by temporary location.
5. Volunteer coordination—tool to coordinate contact information, skills, and assignments of volunteers and responders.
6. Inventory management—tool to track location, quantities, and expiration dates of supplies.
7. Situation awareness—a geographic information system showing current status.

Sahana has been successfully deployed in many disasters including after the tsunami as shown in Table 13.1.

The Sahana system uses plug-in architecture, which allows third-party groups easy access to system components, while simplifying overall integration. The system does not need to be installed but can be run as a portable application from a USB drive (using a USB flash drive). The system can be translated into any language. Granular security is provided through an access control system. The user interface can be viewed through a number of devices including a PDA.

Table 13.1 Sahana deployments (Wikipedia, n.d.)

Location	Year	Event	Details
Sri Lanka	2005	Tsunami	Deployed for the Government of Sri Lanka
Pakistan	2005	Earthquake	Deployed for the Government of Pakistan
The Philippines	2006	Mudslide	Southern Leyte
Indonesia	2006	Earthquake	Yogyakarta
New York City	2007–2008	Hurricanes	Coastal storm planning
Peru	2007	Earthquake	Ica
China	2008	Earthquake	Chendu-Shizuan province
Myanmar	2008	Cyclone	Monsoon disaster planning
Haiti	2010	Earthquake	Disaster planning

Table 13.2 Seismic risk management criteria (Wikipedia, n.d.)

Economic/Social criteria	Technical criteria
Installation cost	Skilled labor required
Maintenance cost	Need for foundation intervention
Disruption of use	Significance of risk damage
Functional capability	Significance of limitations

Disaster Management Criteria

We review criteria sets used by two disaster management applications involving multiple criteria. The first involved the engineering decision of protecting buildings from earthquake damage (Tesfamariam et al., 2010). This of course is a more technical decision than what we described in the banking industry, but the point is that risks appear in almost every walk of life. Here the decision was to design buildings to be as secure as possible. Earthquakes are common. Building codes in the past have been insufficient. Building design retrofit alternatives have been developed to modify performance in terms of stiffness, strength, and ductility. Criteria that could be applied to seismic risk management are given in Table 13.2.

Their model would enable building designers to score alternatives on each of these eight risks and to express decision maker preferences.

The US Water Resource Council (Karvetski et al., 2011) has a comprehensive set of 20 performance criteria for infrastructure policies and investments given in Table 13.3.

A generic multiple-criteria model was developed within this list (Wikipedia, n.d.) with the criteria of:

- Protection from coastal inundation
- Protection of public infrastructure systems
- Protection against storm surges and flooding
- Protection of wetlands and environment
- Protection of recreational activities

Table 13.3 US Water Resource Council criteria

Provide protection for and reduce displacement of residents	Provide protection for and reduce displacement of residents
Provide protection for and reduce displacement of residents	Ensure long-term economic productivity
Provide urban and agricultural flood damage protection	Provide protection and reduce displacement of businesses and farm
Ensure employment/income distribution and equality	Protect wetlands, fish, and wildlife habitats
Protect commercial fishing and water transportation	Provide agricultural drainage, irrigation, and erosion control
Ensure power production, transmission, and efficiency	Provide floodplain protection
Protect recreational activities	Provide drought protection
Protect against natural disasters	Protect endangered and threatened species and habitats
Protect air quality	Protect prime and unique farmland protection
Protect historic and cultural values	Protect wildlife and scenic rivers

This model was to be used for specific coastal protection evaluations, with normal options of building different types of revetments, seawalls, or nourishing beaches or dunes. The evaluation they provided included evaluation under different scenarios.

Multiple Criteria Analysis

Once criteria pertinent to the specific decision are identified, analysis can be selection of a preferred choice from a finite set of alternatives, making it a selection decision. (Finite alternatives could also be rank ordered by preference.) Multiple objective programming is the application of optimization over an infinite set of alternatives considering multiple objectives, a mathematical programming application (see the chapter on DEA as one type). Chap. 3 presented the SMART multiple criteria method, which fits with this case as well.

We can use a petroleum supply chain case to demonstrate the SMART procedure (Briggs et al., 2012). We begin with three alternatives relative to risk management in the petroleum supply chain:

1. Accept and control risk
2. Terminate operations
3. Transfer or share risk

The hierarchy of criteria could be as follows, to minimize risks:

- Exploration/production risk
- Environmental and regulatory compliance risk
- Transportation risk

- Availability of oil resource risk
- Geopolitical risk
- Reputational risk

We can create a decision matrix that can express the relative performance of each alternative on each criterion through scores.

Scores

Scores in SMART can be used to convert performances (subjective or objective) to a zero-one scale, where zero represents the worst acceptable performance level in the mind of the decision maker, and one represents the ideal, or possibly the best performance desired. Thus a higher score indicates lower risk. Note that these ratings are subjective, a function of individual preference. Scores for the criteria could be as in Table 13.4.

Table 13.4 indicates that the benefits of accepting the risk involved in this project would have very good potential to obtain sufficient oil. If the project was to be abandoned (the "Terminate" alternative), oil availability would be quite low. Hedging in some manner (the "Transfer" alternative) such as subcontracting, would reduce oil availability significantly, although this is expected to be better than abandoning the project. With respect to environmental/regulatory factors, the greatest risk reduction would be to not adopt the project. Transferring risk through subcontracting would also be much more effective than taking on the project alone. Transportation risk could be avoided entirely by abandoning the project. Much of this risk could be transferred. The firm has the ability to cope with some transportation issues, but the score is lowest for the option of Accept and Control Transportation Risk. Accessing oil would be highest for adopting the project, with a slight advantage to the Accept option as it provides more control than the Transfer option. Terminating the project would require obtaining oil on the market at a higher cost. Geopolitical risk would be eliminated by terminating the project. The other two options are rated equal on this dimension. Risk to reputation could also be eliminated by terminating the project. The firm would have more control over risk response if they retained complete control over the project than if they transferred through insurance or subcontract.

Table 13.4 Relative scores for each option by criteria

Criteria	Accept	Terminate	Transfer
Exploration/production	0.8	0.2	0.5
Environment/regulatory	0.1	1.0	0.6
Transportation	0.2	1.0	0.9
Oil availability	0.9	0.2	0.6
Geopolitical	0.3	1.0	0.4
Reputation	0.2	1.0	0.5

The score matrix given in Table 13.4 provides a tabular expression of relative value of each of the alternatives over each of the selected criteria. It can be used to identify tradeoffs among these alternatives.

Weights

The next phase of the analysis ties these ratings together into an overall value function by obtaining the relative weight of each criterion. In order to give the decision maker a reference about what exactly is being compared, the relative range between best and worst on each scale for each criterion should be explained. There are many methods to determine these weights. In SMART, the process begins with rank ordering the three criteria. A possible ranking for a specific decision maker might be as given in Table 13.5.

Swing weighting could be used to identify weights (Edwards, 1977). Here, the scoring was used to reflect 1 as the best possible and 0 as the worst imaginable. Thus, the relative rank ordering reflects a common scale and can be used directly in the order given. To obtain relative criterion weights, the first step is to rank-order criteria by importance, indicated by the order of Criteria in Table 13.6. Estimates of weights can be obtained by assigning 100 points to move from the worst measure to the best measure on the most important criterion (here oil availability). Then each of the other criteria is assessed in a similar comparative manner in order, assuring that more important criteria get at least as much weight as other criteria down the ordinal list. Here we might assign moving from the worst measure on Exploration/ production 80 points compared to Oil availability's 100. For purposes of demonstration, assume the assigned values given in Table 13.6.

Table 13.5 Worst and best measures by criteria

Criteria	Worst measure	Best measure
Oil availability	Oil embargo	Successful project—In-house
Exploration/production	No project	Successful project—In-house
Environment/regulatory	Oil spills	No project
Reputation	Oil spills	No project
Transportation	Oil spills	No project
Geopolitical	War in drilling area	No project

Table 13.6 Weight estimation from the perspective of most important criterion

Criteria	Assigned value	Weight
1 Oil availability	100	0.282
2 Exploration/production	90	0.254
3 Environment/regulatory	70	0.197
4 Reputation	60	0.169
5 Transportation	20	0.056
6 Geopolitical	15	0.042
Total	355	1.000

The total of the assigned values is 355. An estimate of relative weights is obtained by dividing each assigned value by 355.

Value Score

The next step of the SMART method is to obtain value scores for each alternative by multiplying each score on each criterion for an alternative by that criterion's weight and adding these products by alternative. Table 13.7 shows this calculation:

In this example, terminate was ranked first, followed by the option of transferring (outsourcing), followed by accepting risk. However, these are all quite close, implying that the decision maker could think more in terms of other objectives, or possibly seek more input, or even other options.

Natural Disaster and Financial Risk Management

Risk is the probability of an adverse event occurring with the potential to result in loss to an exposed element. Natural hazards are meteorological or geological phenomena that due to their location, frequency, and severity, have the potential to affect economic activities. A natural event that results in human and economic losses is an environmental problem contributed by the development in the region. Natural catastrophe risk is generally characterized by low frequency and high severity, though the level of severity varies quite significantly. The extent of the development contributes to the financial vulnerability to the catastrophic effects of the natural disaster. On the same token, the vulnerability of a firm to hazard events depends on the size of its investment and revenue exposures in the region. Natural hazards can be characterized by location, timing, magnitude, and duration. The principal causes of vulnerability include imprudent investments and ineffective public policies.

Natural disaster losses are the result of mismanaged and unmanaged disaster risks that reflect current conditions and historical factors (Alexander, 2000). Disaster risk exposure comes from the interaction between a natural hazard (the external risk factor) and vulnerability (the internal risk factor) (Cardona, 2001). Proactive disaster risk management requires a comprehensive process that encompasses a

Table 13.7 Value score calculations

Criteria	Weight	Accept	Terminate	Transfer
1 Oil availability	0.282	×0.9 = 0.254	×0.2 = 0.051	×0.6 = 0.152
2 Exploration/production	0.254	×0.8 = 0.203	×0.2 = 0.051	×0.5 = 0.127
3 Environment/regulatory	0.197	×0.1 = 0.020	×1.0 = 0.197	×0.6 = 0.118
4 Reputation	0.169	×0.2 = 0.034	×1.0 = 0.169	×0.5 = 0.084
5 Transportation	0.056	×0.2 = 0.011	×1.0 = 0.056	×0.9 = 0.051
6 Geopolitical	0.042	×0.3 = 0.013	×1.0 = 0.042	×0.4 = 0.017
Totals		0.534	0.566	0.549

comprehensive pre-disaster evaluation involving the three broad steps involving the following activities:

- Identification of the potential natural hazards and evaluation of investment at risk.
- Risk reduction measures to address the vulnerability.
- Risk transfer to minimize financial losses.

The need to integrate disaster risk management into investment strategy is necessary to manage corporate value and reduce risk in the future. These should be supported by effective governance (e.g., policies and planning), supplemented by effective information and knowledge-sharing mechanisms among different stakeholders.

First, risk identification involves creating awareness and quantification of risk through understanding vulnerabilities and exposure patterns. The process also includes an analysis of the risk elements and the underlying causes of the exposure. This knowledge is essential for developing strategies and measures for risk reduction. For example, firms operating in an earthquake-prone zone would need to keep abreast of information on real-time seismic patterns complemented with forecasts on expected hazards. This is complemented by the necessary exposure analysis using mapping, modelling, and hazard analysis to assess industry and corporate risk. The evaluations should include calculating a probability profile of occurrence and impacts of hazard events in terms of their characteristics and factoring these elements into the firm's decision-making process. Thus, risk identification and analysis provide for informed decision-making on business investment that will effectively reduce the impacts of potential disaster events and prioritization of risk management efforts.

Second, risk reduction involves measures to avoid, mitigate or prepare against the destructive and disruptive consequences of hazards to minimize the potential financial impact. The mitigation measures are actions aimed at reducing the overall risk exposure associated with disasters. This requires an ex ante business strategy that combines mitigation investments and pre-established financial protection. In this respect, firms can prevent natural disaster losses by avoiding investment in disaster-prone regions (i.e., prevention investments) or they may take actions to locate and structure their business operations to avoid heavy investments in disaster-prone regions. Such actions require short- and long-term strategic business planning and disaster recovery mechanisms, such as those pertaining to supply chain management. Risk mitigation planning is aimed at taking into account the economic impacts of disasters such as earthquakes. Access to relevant information is important for better-informed decision-making and planning. For example, access to hazard information such as frequency, magnitude, and trends are required for disaster risk mitigation for corporate investment decisions.

Finally, risk transfer mechanisms enable the distribution of the risks associated with natural hazard events such as floods and earthquakes to reduce financial and economic impacts. This might not fully eliminate the firm's financial risk exposure but it allows risk to be shared with other parties. The common risk transfer tool is catastrophic insurance, which allows firms to recover some of their disaster losses and thus managing the financial impacts of disasters. Other financial instruments include catastrophic bonds (cat-bonds) and weather risk management products. The issuance of catastrophe risk-linked bonds by insurance or reinsurance companies enables them to obtain coverage for particular risk exposures in case of predefined catastrophic events (e.g., earthquakes). These catastrophe bonds allow the insurance companies to transfer risk and obtain complementary coverage in the capital market and increase their capacity to take on more catastrophe risk coverage.

The use of insurance for mitigating financial losses from natural catastrophes is generally lacking in the private sector in developing countries (Guy Carpenter & Company, 2000). Catastrophe risk is a public shared risk ("covariate" risk) and collective in nature, therefore, making it difficult to find individual and community solutions (Comfort, 1999). An effective insurance market is essential for financing post-disaster recuperation and rehabilitation of firms. In the absence of a sophisticated insurance market, the government normally acts as a financier for disaster recovery efforts. Governments can also influence risk financing arrangements by encouraging the establishment of insurance pools by the local insurance industry and covering higher exposures in the global reinsurance and capital markets.

Property insurance policies for firms in earthquake-prone provinces may not be readily available due to inadequate local regulation of property titles, building codes, and developmental planning. In this respect, the local governments play an important role in ensuring proper public policies are implemented and regulations enforced to lower premiums and achieve higher insurance coverage in these provinces.

There is a bigger range of instruments for risk financing in the markets today. Other than insurance coverage for disaster risk, new instruments such as catastrophe risk swaps and risk-linked securities are also available in the global capital market. In 1994, the original capital market instrument linked to catastrophe risk called a catastrophe bond was introduced. Since then, more risk-linked securities are available including those providing outright funding commitments to recover economic losses from disasters. These contingent capital instruments are based on estimating the amount of risk involved through risk and loss impact estimates to build a disaster risk profile for the client. The implied risk profile is used to identify and define the risk-linked financial instruments.

Natural Disaster Risk and Firm Value (Oh et al., 2009)

The current dynamic business environment embraces the international flow of investment to facilitate success and growth. Firms with sustainable competitiveness and growth are likely to enhance their market value. Business globalization invariably means that firms become more proactive in scouting for opportunities in foreign markets in order to sustain and build corporate value. Other than the social, economic, and political risk factors normally considered in foreign investment evaluations and enterprise risk management processes, firms also need to take into account natural disaster risk. The premiums for catastrophe risk insurance are expensive and there must be a compelling case or economic incentives for firms to establish adequate insurance coverage on their assets. We are interested in the economic impacts of natural catastrophes from a financial management perspective. The primary objective of the firm is to maximize shareholder wealth and an effective corporate risk management program enhances corporate value. The existent literature contains a respectable body of theories and general acceptance in the market that corporate value can be created with the proper understanding and management of risk. There is a perception of risk associated with investments and traditional finance suggests such perceptions imply that there must be a reward in the form of a risk premium for investors to take on this risk. The firm as a corporate investor is no different in that it also requires a risk premium for assuming risk. The magnitude of the firm value depends on how efficiently and effectively it can manage its risk exposure. From a firm value versus risk management perspective, it is possible to construe the firm's value as a function of all relevant risk factors.

While the frequency and severity of natural hazards are dictated by the natural phenomenon itself, the losses caused can be controlled by understanding and managing the business development and population density according to the vulnerability of the geographical location. Business development and population density tend to have a positive correlation and therefore natural catastrophe risk has profound social and economic impacts on the local inhabitants and economy.

Contemporary enterprise risk exposure modelling tends to ignore natural hazards and focuses on estimating the severity and frequency of financial or operational exposures. The global warming phenomenon has brought about a heightened awareness of many environmental risks that may affect business. Hence, there is a need for firms and policy makers to model, monitor, and measure the risk exposure from natural hazards and prepare to manage the potential impacts.

The impacts from a natural catastrophe include the loss of property, life, injury, business interruption, and loss of profit. From a firm's perspective, the financial impact on its market value can be mathematically specified as:

$$Firm\ Value\ at\ Risk = f(hazard, vulnerability) \tag{13.1}$$

From Eq. (13.1), the firm's value at risk from natural phenomena is a function of hazard and vulnerability. Equation (13.1) integrates the impact on the firm's value from natural phenomena and their consequence or exposure. The natural disaster risk management process has to be managed properly from the beginning therefore, it is important that firms improve the evaluation, coordination, efficiency, and control of business development and management process to minimize such risks. The issues in this context are the considerations and measures that are available to firms in the natural disaster risk management process. Vulnerability in turn is a function of three factors:

$$Firm\ vulnerability = f(fragility, resilience, exposure) \tag{13.2}$$

Effective risk management requires attention to three factors—hazards, exposure, and vulnerability. Primary disaster impacts include potential physical damage to production facilities and infrastructure. But there also are often secondary impacts to include business interruption form lack of materials and information, especially in interacting supply chain networks. Risk is a function of hazard and vulnerability, while vulnerability is a function of fragility, resilience, and exposure (Merz et al., 2013).

Coase's theory of the firm stresses that the impetus for the emergence of business corporations is the specialized institutional structure that comes into being to reduce the transaction costs (Coase, 1937). Since the threat of natural disasters, like the volatility of financial prices, implies potential transaction costs to the firm, it is imperative to manage catastrophe risk as it can affect the cost of capital, the cost of production, and revenues. Financial theory suggests that rational firms would hedge their risk exposure to remove the variability in their cash flows. The significance of this view is that by removing variability, firms enhance the predictability in cash flows allowing them to invest in future projects without uncertainty about the negative impact of price fluctuations. The manifestations of variability as a result of a natural catastrophe are disruptions to the firm's supply chain, production, logistics, manpower, and clientele. The management issues to be addressed in relation to catastrophe risk management using risk transfer instruments are moral hazard and adverse selection. Moral hazard occurs when the firm fails to implement preventive measures after the risk transfer has taken place and reports excessive losses. Adverse selection happens if the firms uses inside knowledge about the exposure to obtain more favorable terms in the risk transfer policy from the issuing company.

The firm's overall exposure to natural catastrophes like earthquakes needs to be analyzed based on the region's vulnerability to assess the collective need for risk mitigation arrangements. Therefore, it is necessary to identify and map the major catastrophe risks that affect the region and assess how the business can be organized by adopting a risk neutral structure and/or how to obtain aggregate risk financing arrangements.

The financial impact of natural disasters is determined by the frequency of an event occurring and by the severity of the resulting loss. The vulnerability to natural catastrophes can be reduced significantly through risk mitigation to lessen the impact of disasters. The catastrophe risk exposures in individual investment projects can be mitigated using a project-based approach to manage catastrophe risk through risk transfer such as insurance to reduce specific project exposures. Risk can also be reduced through corporate planning by building earthquake-resistant structures, implementing risk neutral logistics or supply chain, market diversification, and other such actions that minimize the overall asset at risk of the firm.

Financial Issues

Natural disasters can cause serious financial issues for firms as they affect the efficient management and performance of their assets and liabilities. The structural risks associated with natural disasters constitute one of the major sources of risk for most enterprises (Sebstad & Cohen, 2000). Disaster hazards can cause damages and losses to firms in partial or total destruction of assets and disruptions in service delivery. Natural disasters also cause macroeconomic effects in the economy as a whole and can bring significant changes in the macroeconomic environment. The effects of a natural disaster can interact with some of the normal risks faced by firms, including strategic management, operational, financial, and market risks. These effects will reveal corporate vulnerabilities related to poor financial decisions.

The following financial issues in relation to risk management are analyzed in this section:

- Systematic and unsystematic risk exposure.
- Investment evaluation and planning.
- Investment to meet strategic demands.
- Financial risk management and compliance.

Firms are constantly trying to develop more efficient models to evaluate the size and scope of risk exposure consequences using risk modelling approaches such as shareholder value at risk (SVA), value at risk (VAR), and stress testing.

Systematic and Unsystematic Risk

The overall corporate risk can be divided into *alpha* (the competency of the company's management or unsystematic risk) and *beta* (the market or systematic risk). The *alpha* risk is of an idiosyncratic nature can be eliminated by diversifying the investment portfolio, leaving *beta* as the main variable. The risk exposure of a firm can come from the political, economic, or operating environments. The operating environment refers more specifically to the idiosyncratic internal and external environments in which the firm conducts its business and the inherent risks to the firm. In this context, the natural disaster risk posed by earthquakes and floods would fall within the definition of external environment. The implication of disaster risk in the internal environment would be related to the internal processes and resources available to manage this risk.

In terms of unsystematic effects of natural disasters like an earthquake, losses related to disruptions in service delivery are the result of a combination of the direct damages to the firm's assets institution and its human resource. The better prepared a firm is in risk managing its resources the lesser the impact of damages and losses to its assets and facilitate in post-disaster business recovery. Systematic risk effects on the firms can be illustrated by damages to the overall infrastructure in the region causing major disruptions to its operations even if the firm is reasonable unscathed at the micro level.

Government normally intervenes in disaster risk management to mitigate systemic risk as damage from disasters tends to be large and locally covariate and the remedial actions are targeted at the provision of public goods, such as infrastructure. The World Bank (2000) suggests that governments are more effective in covering covariant risks, while most idiosyncratic or unsystematic risks may be handled better by private providers. (World Bank, 2000)

Investment Evaluation

An investment evaluation is conducted when a firm is considering a major expenditure. The variables taken into consideration are the cash flows, growth potential, and risk associated with the project. The common tools used in investment evaluation are the net present value and internal rate of returns methods. Both these methods incorporate a parameter to measure the risk exposure inherent in the project. As the basic tenet of financial management is one of risk-return optimization. A central feature in modern risk management is the issue of risk and return relationship in investment decisions. The basic link between risk and return says that greater rewards come with greater risk and firms investing in an area highly prone to natural disaster would need to acknowledge this in their investment. This acknowledgment of catastrophe risk in investment evaluation is similar to accounting for political or economic risks of a country.

The price of risk is commonly referred to as the risk premium. A firm as the investor would demand a risk premium commensurate with the risk characteristics of their investment for the higher risk exposure of operating in a region with greater natural disaster risk. The risk premium to compensate for potential disaster risk can be built into the risk equation by factoring in liquidity risk from destabilizing cash fluctuations, and default or credit risk. Moreover, liquidity risk and credit risk interact under disaster conditions escalating risk premium and thus the cost of capital. This will impact on firms after the disaster when they go back into the capital markets to raise credit to rebuild their business.

Natural disasters typically trigger operational risks resulting in disruptions to cash flows and possible default of loan obligations to creditors. However, firms with efficient liquidity management will minimize the disaster effects on cash flows. The nature and magnitude of the disaster and clients' profile are factors that will influence the severity of cash flow disruptions and the ensuing credit risk. The firm can manage a credibility problem and spiraling cost of capital from a disaster if it made prior financial arrangements with creditors. These effects may lead to short term liquidity crises and heightened cost of capital in the medium term for firms. Credit risk is particularly heightened by a disaster due to disruptions to cash flows and serious loss of assets used as collaterals for loans. Unless prior arrangements are in place for creditors to mitigate repayment risks and redress the deterioration in the quality of securities, firms may face delinquency actions and loss of financial facilities.

Strategic Investment

Firms can reduce cash flow variability through business portfolio diversification by engaging in different investments, different locations and activities whose returns are not perfectly correlated. In the context of natural disaster risk management, strategic investment refers to making a financial commitment in a location after considering the risk implications and the available investment alternatives. That is, investment in risky environments must be consistent and sensitive to the risk and return profile of the firm. For instance, making a decision to invest in a new supply chain process in a disaster-prone area may require looking at risk neutral alternatives. The risk neutral option may be more costly but would be appropriate if the new supply chain is to service the entire firm's operations. A Cost Effectiveness Analysis (CEA) technique can be used to compare the monetary costs of different options that provide the same physical outputs.

The commercial challenges after a natural disaster are the resumption and maintenance of client services and the financial viability of the business. Firms are caught unprepared and will struggle during a disaster to provide emergency and recovery services to their clients without adversely affecting its own financial position. The strategic perspective of disaster effects is on the adequacy of organizational and financial planning on the part of management in relation to the firm's business growth and the resultant structural design. Firms that have experienced rapid growth but do not comprehensively plan and design their business model around a disaster contingency plan are likely to be more affected by a disaster. Rapid business expansion without a appropriately well-designed business model, planned investments, and logistics addressing disaster risk will likely experience exacerbated problems during a disaster.

Risk Management and Compliance

To fully address corporate risk exposure with respect to natural disasters, companies need a comprehensive risk management process that identifies and mitigates the major sources of risk. Formulating a detailed risk program with capabilities for risk identification, assessment, measurement, mitigation, and transfer is necessary in a complete risk management strategy. A comprehensive corporate risk management process requires effective techniques that provide a systematic evaluation of risks, which then enables risk managers to make judgments on acceptable risks. Such a process should allow insight into primary areas of uncertainty by identification of the risk factors, highlighting likely outcomes of events and measuring the possible financial impact on the company. The process must also have built-in techniques that can provide a cost-benefit analysis of hedging options as a basis for prioritizing risk strategies. Through the risk management process, a company is able to set its risk tolerance level and any unwanted exposure may be avoided or hedged and the company is left bearing the risk it is willing to assume.

A firm-wide risk management system, using tools like the value-at-risk (VaR) model, which is capable of capturing the aggregate effect of financial risk exposure to financial, is important to enhance the company's overall market value. The VAR model summarizes the value at risk in a worst case scenario of possible loss under normal conditions.

Conclusions

The severe climatic changes brought about by global warming are evident by the freezing temperature which caused damages amounting to billions of dollars in China in February 2008. The rapidly changing built environment in China also means that new risk assessment models need to be developed to accurately reflect and risk assess the real impact. Financial risk modelling and management using computer simulations incorporating probabilistic and statistical models would be valuable for evaluating potential losses from future natural catastrophes for better managing potential losses. Firms operating in high natural disaster risk areas should use risk modelling for investment evaluation, risk mitigation, disaster management, and recovery planning as part of the overall enterprise-wide risk management strategy. They also need to identify new business strategies for operating in disaster-prone regions and financial instruments to manage risk.

Governments play an important role in financial markets in encouraging financial institutions to support borrowers in risk reduction and to mitigate the impacts of natural disasters.

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14 Sustainability and Enterprise Risk Management

The challenge of environmental sustainability is important not only as a moral imperative but also as a managerial responsibility to operate profitably. Environmental sustainability has become a critical factor in business, as the threats to environmental degradation from carbon emissions, chemical pollution, and other sources have repeatedly created liability for firms that do not consider the environment, as well as regulatory attention. Legislators and journalists provide intensive oversight of the operations of any organization. There are many cases of multi-billion dollar corporations brought to or near to bankruptcy by responsibilities for things like asbestos, chemical spills, and oil spills. As the case of the fire and collapse of the Dhaka garment factory in April 2013 attests, global supply chains create complex relationships that place apparently unaware supply chain members such as Nike at great risk, not only legally, but also in terms of market reputation.

Global warming is here, with notable temperature rise exceeding what appears to be sustainable since 1980 (Anderson & Anderson, 2009). This places ecosystem pressure, creating additional risks to property through greater storm magnitude since the 1960s. Natural disasters are increasing in financial magnitude, due to increased population and development. There are many predictions of more intensive rainfall, stronger storms, and increased sea levels along with simultaneous drought.

Other risks arise from:

- Medical risks from diseases, such as Zika virus, West Nile virus, malaria, COVID, and others.
- Boycott risk from supply chain linkages to upstream vendors who utilize child labor (affecting Nike) or unsafe practices (Dhaka, Bangladesh).
- Evolving understanding of scientific risks such as asbestos, once thought a cure for building fire, is now considered a major health risk issue.
- Hazardous waste, such as nuclear disposal.
- Oil and chemical spills.

Risk arises in everything attempted by humans (Olson et al., 2014). Life is worthwhile because of its challenges. Doing business has no profit without risk,

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rewarding those who best understand systems and take what turns out to be the best way to manage these risks. We will discuss risk management as applied to the production of the food we eat, the energy we use to live, and the manifestation of global economy and supply chains.

What We Eat

One of the major issues facing human culture is the need for quality food. Two factors that need to be considered are first, population growth, and second, threats to the environment. We have understood since Malthus that population cannot continue to grow exponentially without severe changes to our ways of life. Some countries, such as China, have been proactive in controlling population growth. Other areas, such as Europe, seem to find a decrease in population growth, probably due to societal consensus. But other areas, including India and Africa, continue to see rapid increases in population. Some think that this will change as these areas become more affluent (see China and Europe). But there is no universally acceptable way to control population growth. Thus, we expect to see a continued increase in demand for food.

Agricultural science has been highly proactive in developing better strains of crops, through a number of methods, including bioengineering and genetic science. This led to what was expected to be a green revolution a generation ago. As with all of mankind's schemes, the best-laid plans of humans involve many complexities and unexpected consequences. North America has developed means to vastly increase the production of food free from many of the problems that existed a century ago. However, Europe and even Africa are concerned about new threats arising from genetic agriculture.

A third factor complicating the food issue is distribution. North America and Ukraine have long been fertile producing centers, generating surpluses of food. This connects to supply chains, to be discussed below. But the issue is the interconnected global human system with surpluses in some locations and dearth in others. Technically, this is a supply chain issue. But more important really is the economic issue of sharing spoils, which ultimately leads to political issues. Contemporary business with heavy reliance on international collaborative supply chains leads to many risks arising from shipping (as well as other factors). Sustainable supply chain management has become an area of heavy interest (Seuring & Műller, 2008).

Water is one of the most widespread assets Earth has (probably next to oxygen, which chemists know is a related entity). Rainwater used to be considered pure. The industrial revolution managed the unintended consequence of acid rain. Water used to be free in many places. In Europe, population density and things like the black plague made beer a necessary health food. In North America, it led to the bottled water industry. Only 30 years ago paying for water would have been considered the height of idiocy. Managing water is recognized as a major issue (Lambooy, 2011). Water management also ultimately becomes an economic issue, leading to the political arena.

The Energy We Use

Generation of energy in its various forms is a major issue leading to the political debate concerning trade-offs among those seeking to expand existing fuel needs, often opposed by those seeking to stress alternative sources of energy. Oil of course is a major source of current energy but involves not only environmental risks (Ng & Goldsmith, 2010) but also related catastrophe risks (Meyler et al., 2007) and market risks (Pulver, 2007). The impact of oil exploration on the Mexican rain forest (Santiago, 2011) has been reported and cost risks in alternative energy resources studied (Zhelev, 2005).

Mining is a field traditionally facing high production risks. Power generation is a major user of mine output. Cyanide management has occurred in gold and silver mining in Turkey (Akcil, 2006), and benzene imposes risks (Nakayama et al., 2009). Life cycle mine management has been addressed through risk management techniques (Kowalska, 2014). The chemical industry also is loaded with inherent risks. Risk management in the chemical industry has been discussed as well (Műller, 2015).

The Supply Chains that Link Us to the World

Supply chain risk management involves a number of frameworks, categorization of risks, processes, and mitigation strategies. Frameworks have been provided by many, some focusing on a context, such as supply chain (Khan & Burnes, 2007; Tang & Tomlin, 2008) or small-to-medium-sized enterprises (Nishat Faisal et al., 2007). Some have focused on context, such as food (Roth et al., 2008) or pharmaceutical recalls, or terrorism (Williams et al., 2008). Five major components to a framework in managing supply chain risk have been suggested (Ritchie & Brindley, 2007):

- Risk context and drivers.
  Risk drivers arising from the external environment will affect all organizations and can include elements such as the potential collapse of the global financial system, or wars. Industry specific supply chains may have different degrees of exposure to risks. A regional grocery will be less impacted by recalls of Chinese products involving lead paint than will those supply chains carrying such items. Supply chain configuration can be the source of risks. Specific organizations can reduce industry risk by the way they make decisions with respect to vendor selection. Partner-specific risks include consideration of financial solvency, product quality capabilities, and compatibility and capabilities of vendor information systems. The last level of risk drivers relates to internal organizational processes in risk assessment and response and can be improved by better equipping and training of staff and improved managerial control through better information systems.
- Risk management influencers.

This level involves actions taken by the organization to improve their risk position. The organization's attitude toward risk will affect its reward system, and mold how individuals within the organization will react to events. This attitude can be dynamic over time, responding to organizational success or decline.

- Decision makers.
  Individuals within the organization have risk profiles. Some humans are more risk averse, others more risk seeking. Different organizations have different degrees of group decision-making. More hierarchical organizations may isolate specific decisions to particular individuals or offices, while flatter organizations may stress greater levels of participation. Individual or group attitudes toward risk can be shaped by their recent experiences, as well as by the reward and penalty structure used by the organization.
- Risk management responses.
  Each organization must respond to risks, but there are many alternative ways in which the process used can be applied. Risk must first be identified. Monitoring and review require measurement of organizational performance. Once risks are identified, responses must be selected. Risks can be mitigated by an implicit tradeoff between insurance and cost reduction. Most actions available to organizations involve knowing what risks the organization can cope with because of their expertise and capabilities, and which risks they should outsource to others at some cost. Some risks can be dealt with, and others avoided. One view of the strategic options available includes the following six broad generalizations (Rosenberg, 2016):
  – Break the law
  – Take the low road
  – Wait and see
  – Show and tell
  – Pay for principle
  – Think ahead

The first option, breaking the law, apart from ethical considerations, poses serious risks in terms of the ability to operate and can lead to jail.

The second implies doing the absolute minimum required to comply with laws and regulations. This approach satisfies legal requirements, but environmental laws and regulations change, so modified behavior will probably be required in the future and will probably be much more expensive than earlier consideration of sustainability factors.

The wait-and-see option would see firms preparing for expected regulatory changes as well as consumer behavior and competitor strategies. Thus, option 3 is more proactive than the prior two options.

Show and tell presumes that the organization is addressing environmental issues but not fully publicizing these activities. Show and tell implies an honest portrayal of environmental performance, as opposed to "greenwashing" where public relations is used to present a misleading report. Show and tell has the deficiency that if problems do arise, or if false accusations are made, firm reputation can suffer.

Pay for principle involves sacrificing some financial performance in order to meet ethical and environmental standards. It implies financial sacrifice.

Thinking ahead involves proceeding based on principle as well as business logic. Benefits include gaining a competitive advantage and protecting against future legislation, seeking to be at the leading edge of sustainability.

Which of these broad general options is appropriate of course depends on firm circumstances, although there is little justifiable support for options 1 and 2.

The Triple Bottom Line

Organizational performance measures can vary widely. Private for-profit organizations are generally measured in terms of profitability, short- and long-run. Public organizations are held accountable in terms of effectiveness in delivering services as well as the cost of providing these services. One effort to consider sustainability and other aspects of risk management is the triple bottom line (TBL) (Elkington, 1997), considering financial performance, environmental performance, and social responsibility.

$$TBL = f(F, E, SR, cost)$$

All three areas need to be considered to maximize firm value. In normal times, there is more of a focus on high returns for private organizations and lower taxes for public institutions. Risk events can make their preparation in dealing with risk exposure much more important, focusing on survival.

Sustainability Risks in Supply Chains

As we covered in Chap. 1, supply chains involve many risks imposing disruptions and delays due to problems of capacity, quality, financial liquidity, changing demand and competitive pressure, and transportation problems. By their nature, supply chains require networks of suppliers leading to the need for reliable sources of materials and products with backup plans for contingencies. Demands are at the whim of customers in most cases. There are endogenous risks somewhat within a firm's control, as well as exogenous risks. These can also be viewed by the triple bottom line. Sustainability aspects arise in both endogenous and exogenous risks, as shown in Table 14.1.

Table 14.2 in turn describes exogenous risks and possible responses with practices to implement them.

Tables 14.1 and 14.2 both highlight the variety of things that can go wrong in a supply chain, as well as some basic responses available. Each particular

Table 14.1 Endogenous risks related to the triple bottom line (Giannakis & Papadopoulos, 2016)

Endogenous	Risk	Response	Practice
Environmental	Accident	Prevent Mitigate Reduce Cooperate Insure	Locate away from heavy population Emergency response plans Quick admission of responsibility Work with suppliers to identify sources Work with insurers to prevent and mitigate
	Pollution	Avoid Mitigate Reduce	Use clean energy, avoid polluting Monitor and reduce emissions Sustainable waste management
	Legal compliance	Assure Control Share	Legal policies, disseminate Monitor compliance Sustainability audits with suppliers
	Product/ package waste	Prevent Mitigate Cooperate	Apply lean management practices Recycle Design products with sustainable packaging
Social	Labor	Avoid Prevent Mitigate	Shun sources using child labor Fair wages/reasonable hours Quick admission of responsibility
	Safety	Prevent Mitigate Insure	Training Adequate medical access Work with insurers to prevent and mitigate
	Discrimination	Prevent Mitigate Transfer	Equal opportunity practices Complaint handling system Legal services and public relations
Economic	Antitrust	Avoid Reduce Mitigate	Avoid investing in unstable regions Build local relationships Create extra capacity
	Bribery Corruption	Prevent Cooperate	Train management Work with legal authorities
	Price fixing Patents	Prevent Mitigate Insure	Follow licensing laws Use whistleblowing Work with supply chain partners
	Tax evasion	Prevent	Follow tax laws

circumstance would of course have more specific appropriate practices available to adequately respond.

The United Nations View of Sustainability

The challenge of environmental sustainability is important not only as a moral imperative, but also as a managerial responsibility to operate profitably. Threats to environmental degradation from carbon emissions, chemical pollution, and other

Table 14.2 Exogenous risks related to sustainability (Giannakis & Papadopoulos, 2016)

Exogenous	Risk	Response	Practice
Environmental	Natural disaster	Reduce Mitigate Insure	Have alternative sources available; Resilient contingency plan Insure when risk is unavoidable
	Weather	Prevent Mitigate Reduce Insure	Built flexible supply chain, forecast; Resilient contingency plan Water recycling Insure when risk is unavoidable
Social	Demographic	Mitigate Reduce	Agile product design; Proactively advertise
	Pandemic	Reduce Mitigate	Strong health procedures in place; Monitor in real time
	Social unrest	Mitigate Insure	Maintain good local relations Have alternative sources, evacuation plans
Economic	Boycotts	Prevent Reduce Retain	Provide quality product; Public relations Accept risk if cost is low
	Litigation	Avoid Prevent Insure	Quality control Responsive public relations; Follow laws and regulations
	Financial crisis	Avoid Insure	Keep informed Have contingency sources
	Energy	Mitigate Transfer	Improve environmental audits; Hedge

sources have repeatedly created liability and regulatory attention for firms that avoid their environmental responsibilities. There are many cases of multi-billion dollar corporations brought to or near bankruptcy due to chemical and oil spills, asbestos mitigation, and other environmental catastrophes.

Sustainability is a crucial challenge in contemporary business. The Earth faces perils from a range of fundamental sustainable threats, in areas such as climate, water, energy, where a growing population lives, and what they need to eat. This book discusses some of these risks we all face and presents some analytic models that have been presented. We review a number of related academic papers for the techniques they used to model sustainability. This chapter discusses the United Nations set of Sustainable Development Goals, elaboration of their targets, and some of the measures used to monitor their attainment.

This is followed by a review of two published applications of different forms of data mining related to their study. The first utilizes text mining, the second a decision tree. We can start by looking at some definitions others have given of sustainability. Bruntland (1987) called sustainable development that which meets the needs of the present without compromising the ability of future generations to meet their own needs.

Table 14.3 Silvius and Schipper sustainability dimensions

Dimension	Elaboration
Value	A normative reflection of ethical considerations of society
Time	Resource extraction should not exceed nature's ability to generate or produce
Geographical	Globalization leads to international stakeholders who need to be coordinated
Performance	Economic efficiency must consider the greenfield aspect of replenishment
Waste reduction	Overproduction, waiting, transporting, inappropriate processing, unnecessary inventory, wasted motion, and defects
Transparency	Openness to organizational policies, decisions, and actions
Accountability	Providing timely, clear, and relevant information to stakeholders
Cultural	Social capital needs to be managed
Risk reduction	We have reached a level of complexity, indeterminacy and irreversibility where it is more efficient to prevent damage rather than amelioration
Political	The rights of all need to be maintained

Dimensions of Sustainability

Thus sustainability has a number of different dimensions. Silvius and Schipper (2014) listed the dimensions given in Table 14.3.

Balancing the triple bottom-line elements of social, environmental, and economic interests in both short- and long-term time dimensions increases the number of stakeholders. The group of stakeholders will include environmental pressure groups, human rights groups, and nongovernmental organizations. The multiple criteria involved in global sustainable development goals are reflected in the United Nations' (https://sdgs.un.org) set of 17 sustainable development goals listed below.

UN Sustainable Development Goals

In 2015, all United Nations Member States adopted the 2030 Agenda for Sustainable Development. The 17 goals are divided into the six macro areas of dignity, people, planet, partnership, justice, and prosperity. The intent was a shared blueprint for peace and prosperity now and into the future. The focus is on 17 sustainable development goals (SDGs). It recognizes that in order to end poverty and other depredations there is a need to adopt strategies improving health and education, reduce inequality, and spur economic growth while dealing with climate change and preservation of oceans for forests. While commendable, the list is limited by the omission of some critical issues such as migration, terrorism, capital flight, and democracy.

The 17 Sustainable Development Goals and measures (labeled SDG) are listed as given by the 2023 report. Additionally, measures used by the Sustainable Development Solutions Network are also given with prefix SDR.

Goal 1: End poverty in all its forms everywhere

Variables:
SDG1.1 Proportion of population using basic drinking water services (%)
SDG1.2 Proportion of population below international poverty line (%)
SDR1.1 Poverty headcount ratio at $1.90/day
SDR1.2 Poverty headcount ratio at $3.20/day
SDR1.3 Poverty rate after taxes and transfers

Goal 2: End hunger, achieve food security and improved nutrition, and promote sustainable agriculture.

Variable:
SDG02Prevalence of undernourishment (%) (SDR2.1)
SDR2.2 Prevalence of stunting in children under 5 years of age
SDR2.3 Prevalence of wasting in children under 5 years of age
SDR2.4 Prevalence of obesity, BMI $\geq$ 30
SDR2.5 Human trophic level
SDR2.6 Cereal yield
SDR2.7 Sustainable nitrogen management index
SDR2.8 Yield gap closure
SDR2.9 Exports of hazardous pesticides

Goal 3: Ensure healthy lives and promote well-being for all at all ages

Variable:

SDG03 Life expectancy at birth (years) (SDR3.8)

SDR3.1 Material mortality rate

SDR3.2 Neonatal mortality rate

SDR3.3 Mortality rate, under-5

SDR3.4 Incidence of tuberculosis

SDR3.5 New HIV infections

SDR3.6 Age-standardized death rate from heart, cancer, diabetes of 30–70 year olds

SDR3.7 Traffic deaths

SDR3.9 Adolescent fertility rate

SDR3.10 Births attended by skilled health personnel

SDR3.11 Surviving infants who received 2 WHO-recommended vaccines

SDR3.12 Universal health coverage index of service coverage

SDR3.13 Subjective well-being

SDR3.14 Gap in life expectancy at birth among regions

SDR3.15 Gap in self-reported health status by income

SDR3.16 Daily smokers

Goal 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all

Variables
SDG04.1 Compulsory education (% of primary school age)
SDG04.2 Compulsory education, duration (years)
SDG04.3 Primary completion rate (% of relevant age group)
SDG04.4 School enrollment, preprimary (% gross) (SDR 4.1)
SDG04.5 School enrollment, primary (% gross) (SDR 4.2)
SDG04.6 School enrollment, secondary (% gross)
SDG04.8 Pupil-teacher ratio, primary
SDR 4.3 Lower secondary completion rate
SDR 4.4 Literacy rate
SDR4.5 Tertiary educational attainment
SDR4.6 PISA score
SDR4.7 Variation in science performance by socio-economic status
SDR4.8 Underachievers in science
Goal 5: Achieve gender equality and empower all women and girls

Variable
SDG05.1 Proportion of seats held by women in national parliaments (%) (SDR 5.4)
SDG05.2 Women Business and the Law Index Score (scale 1–100)
SDR5.1 Demand for family planning satisfied by modern methods
SDR5.2 Ratio of female-to-male mean years of education received
SDR5.3 Ratio of female-to-male labor force participation rate
SDR5.5 Gender wage gap
Goal 6: Ensure availability and sustainable management of water and sanitation for all

SDR 6.1 Population using at least basic drinking water services

SDR 6.2 Population using at least basic sanitation services

SDR 6.3 CO_2 emissions from fuel combustion per total electricity output

SDR 6.4 Share of renewable energy in total primary energy supply (SDG07.1)

Goal 7: Ensure access to affordable, reliable, sustainable and modern energy for all

Variables.

SDG07.1 Renewable energy consumption (% of total final energy consumption)

SDG07.2 Renewable electricity output (% of total electricity output)

SDR7.1 Population with access to electricity

SDR7.2 Population with access to clean fuels and technology for cooking

SDR7.3 CO_2 emissions from fuel combustion per total electricity output

SDR7.4 Share of renewable energy in total primary energy supply (SDR6.4)

Goal 8: Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all

Variables.

SDG08.1 Unemployment rate, male (%)

SDG08.2 Unemployment rate, women (%)

SDR8.1 Adjusted GDP growth

SDR8.2 Victims of modern slavery

SDR8.3 Adults with a bank, financial institution, or mobile-money-service account

SDR8.4 Fundamental labor rights effectively guaranteed

SDR8.5 Fatal work-related accidents embodies in imports

SDR8.6 Employment-to-population ratio

SDR8.7 Youth not in employment education or training

Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation

Variables.

SDG09.1 Proportion of population covered by at least a 2G mobile network (%)

SDG09.2 Proportion of population covered by at least a 3G mobile network (%)

SDG09.3 Access to electricity (% of population)

SDG09.4 Automated teller machines (per 100,000 adults)

SDG09.5 Cost of business start-up procedures, female (% of GNI per capita)*

SDG09.6 Cost of business start-up procedures, male (% of GNI per capita)

SDR9.1 Population using the Internet
SDR9.2 Mobile broadband subscriptions
SDR9.3 Logistics performance index: quality of trade and transport-related infrastructure
SDR9.4 The Times Higher Education Universities training average score of top 3 universities
SDR9.5 Articles published in academic journals
SDR9.6 Expenditure on research and development
SDR9.7 Researchers
SDR9.8 Triadic patent families filed
SDR9.9 Gap in internet access by income
SDR9.10 Female share of graduates from STEM fields at the tertiary level
Goal 10: Reduce inequality within and among countries

Variables
SDG10.1 GINI index (SDR10.1)
SDG10.2 Adjusted et national income per capita (annual % growth)
SDR10.2 Palma ratio
SDR10.3 Elderly poverty rate
Goal 11: Make cities and human settlements inclusive, safe, resilient and sustainable

SDR11.1 Proportion of urban population living in slums

SDR11.2 Annual mean concentration of particulate matter of less than 2.5 microns in diameter

SDR11.3 Access to improved water source, piped

SDR11.4 Satisfaction with public transport

SDR11.5 Population with rent overburden

Goal 12: Ensure sustainable consumption and production patterns

SDR12.1 Electronic waste

SDR12.2 Production-based SO_2 emissions

SDR12.3 SO_2 emissions embodied in imports

SDR12.4 Production-based nitrogen emissions

SDR12.5 Nitrogen emissions embodied in imports

SDR12.6 Non-recycled municipal solid waste

SDR12.7 Exports of plastic waste

Goal 13: Take urgent action to combat climate change and its impacts

Variables.

SDG13.1 Adjusted net savings, excluding particular emission damage (% of GNI)

SDG13.2 Adjusted savings: carbon dioxide damage (% of GNI)

SDG13.3 Adjusted savings: natural resources depletion (% of GNI)

SDG13.4 Adjusted savings: particulate emission damage (% of GNI)

SDG13.5 Adjusted savings: net forest depletion (% of GNI)

SDR13.1 CO_2 emissions from fossil fuel combustion and cement production

SDR13.2 CO_2 emissions embodied in imports

SDR13.3 CO_2 emissions embodied in fossil fuel exports

SDR13.4 Carbon Pricing Score at EUR60/ICO_2

Goal 14: Conserve and sustainably use the oceans, seas, and marine resources for sustainable development

SDR14.1 Mean area that is protected in marine sites important to biodiversity

SDR14.2 Ocean Health Index: clean waters score

SDR14.3 Fish caught from overexploited or collapsed stocks

SDR14.4 Fish caught by trawling or dredging

SDR14.5 Fish caught that are then discarded

SDR14.6 Marine biodiversity threats embodied in imports

Goal 15: Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss

SDR15.1 Mean area protected in terrestrial sites important to biodiversity
SDR15.2 Mean area protected in freshwater sites important to biodiversity
SDR15.3 Red List Index of species survival
SDR15.4 Permanent deforestation
SDR15.5 Terrestrial and freshwater biodiversity threats embodied in imports

Goal 16: Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels

SDR16.1 Homicides
SDR16.2 Unsentenced detainees
SDR16.3 Population who feel safe walking alone at night
SDR16.4 Property rights
SDR16.5 Birth registrations with civil authority
SDR16.6 Corruption Perceptions Index
SDR16.7 Children involved in child labor

SDR16.8 Exports of major conventional weapons

SDR16.9 Press Freedom Index

SDR16.10 Access to and affordability of justice

SDR16.11 Persons held in prison

Goal 17: Strengthen the means of implementation and revitalize the global partnership for sustainable development

SDR17.1 Government spending on health and education

SDR17.2 For high-income and OECD DAC countries: International concessional public finance

SDR17.3 Other countries: Government revenue excluding grants

SDR17.4 Corporate Tax Haven Score

SDR17.5 Financial Secrecy Score

SDR17.6 Shifted profits of multinationals

SDR17.7 Statistical Performance Index

Studies of Sustainable Development Goals Applying Data Mining

We now look at academic studies using this UN data.

Use of SDGs in Carbon Emission Evaluation

Janikowska and Kulczycka (2021) reported the use of word content analysis (a form of text mining) to evaluate the European response to carbon emission reduction, using the UN's SDG framework. SDG 12 is to ensure sustainable consumption and production patterns, while SDG 13 is to take urgent action to combat climate change and its impacts. The mining industry is a key means to generate economic activity in Europe by boosting domestic supply of raw materials, shifting toward resource efficiency, and attaining a low-carbon economy. Janikowska and Kulczycka were interested in studying the relationship between mineral policy and achieving SDG goals. They obtained data about carbon dioxide emissions, mineral production, and resource productivity in Germany, Finland, the UK, Greece, and Portugal over the period 2009 through 2017. The data was text mining Web of Science and Scopus databases using keywords "sustainable goals," "mineral policy," and "Europe."

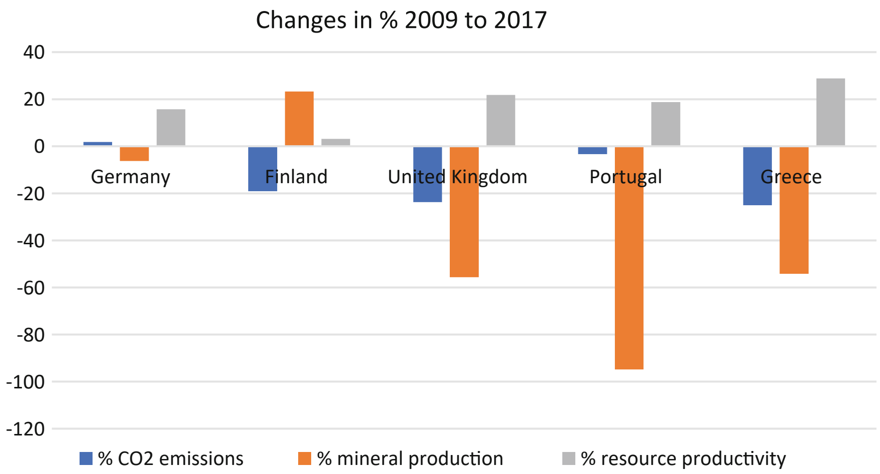

Fig. 14.1 Relationship between mineral production and CO_2 output

They used a word cloud software to identify the relative frequency of these terms, and then correlation between mineral policy and SDGs. This yielded the identification of the relationship between changes in resource productivity and mineral production with CO_2 output.

The mineral policies of each of the five countries were reviewed. The German Government's strategy, seeking a sustainable supply of non-energy mineral resources, considers that social and economic progress is impossible without good governance, respect for human rights, and compliance with environmental and social standards. Finland's Minerals Strategy assumes that Finland should be proactive in implementing sustainable development in the mining sector. The United Kingdom Resource Security Action Plan seeks more efficient use of resources emphasizing reuse, remanufacture, and recycling. The UK minerals strategy seeks sustainable usage of minerals while securing adequate supplies and ensuring environmental impacts of mining and transport are minimized. The Greek National Policy acknowledges the importance of mineral raw materials to their progress and development and has a goal of ensuring supply in a sustainable manner. The National Strategy of Portugal seeks a dynamic mining sector sustainable at social, economic, and territorial levels, promoting economic growth and regional development along with economic return and employment. Results are displayed in Fig. 14.1.

Greece faced a long-term economic crisis, decreasing national GDP per capita which can explain much of their decrease in CO_2 and mineral production output. Resource productivity rose substantially.

The UK saw a similar result. The UK initially reduced the production of minerals with a stable increasing trend in resource productivity. Overall, the UK reduced CO_2 emissions, but not from their mining sector, reflecting a decoupling of mineral production from resource productivity.

Finland saw increases in mineral production along with reduced CO_2 emissions, due to a significant increase in mining production. They face a highly variable result in greenhouse gas emissions due to reliance on hydrological energy sources.

In Portugal, there was a large reduction in mining. They achieved large gains in energy and resource use efficiency.

In Germany, there was a significant increase in total productivity along with a moderate decrease in mining production. CO_2 emissions were up slightly. Germany began reducing greenhouse gas emissions in the early 1990s. In 2011, they adopted a policy of expanding renewable energy sources while resigning from nuclear and fossil fuels as energy sources.

Overall, the Janikowska and Kulczycka study demonstrates visualization as a descriptive data mining tool based on statistical analysis and text mining. It was applied to measure relative effectiveness in attaining UN sustainable development goals.

Clustering of Development Trajectories

Agusdinata et al. (2021) used the sustainable development goals to study the interactions between economic growth (measured by SDG8), inequality (SDG10), and climate action (SDG13), reflecting a view of the triple bottom line. Economic studies have often identified an inverted U-shaped relationship (Kuznets curve) between income per capita and inequality, as well as between income per capita and environmental degradation. The Kuznets curve viewed pollution initially rising as income increased, then decreasing. Before 1980, the orthodox view was that rising income was the key to the long-term reduction of inequality. The inverted U-shaped curve occurred in that as incomes grew, inequality would grow, but with time the money would trickle down to poorer groups. However, after about 2000, rising levels of inequality have become a major issue, leading to phenomena such as the Occupy movement protests.

The Agusdinata et al. study sought to identify development pathways in light of the three criteria given. They applied a regression tree data mining model to identify different clusters of countries and patterns of interactions, followed by cluster analysis to identify development pathway archetypes (defined as recurrent patterns). This was expected to answer policy-relevant questions such as what pathways were sustainable or not, and which countries were using them.

The relationship between pollution and economic growth varies widely. Carbon intensity was defined as the ratio of CO_2 to gross domestic product. They used the formulation of Carbon intensity equal to the product of energy intensity (energy/GDP) and fuel mix (CO_2/energy). Energy intensities in developing countries tend to be higher because industrialized countries have a higher share of GDP coming from services and more importation of carbon-intensive goods from developing countries. Source of energy also makes a major difference as coal generates large amounts of carbon dioxide, nuclear hardly any, and oil and natural gas in between. Different trajectories have been adopted. In the European Union, carbon intensity has declined since the 1990s due to reductions in energy intensity and carbon content. In the USA, carbon intensity since 1990 has come almost exclusively from reduced energy intensity. In India, increased carbon content from high-carbon fuels has offset gains from reduced energy intensity. In South Korea, the reverse is true, as they switched to lower carbon fuels but increased energy intensity.

Agusdinata et al. used the significant structural disruptions of 2008 to divide their data into pre-recession (1980–2008) and post-recession (2009–2014) periods. They used five variables:

1. Slope of per capita carbon dioxide emissions (pre-recession as an IV, post-recession as DV).
2. Average carbon intensity of GDP from energy consumption.
3. Slope of GDP growth rate.
4. Variability of GDP growth (standard deviation).
5. Slope of the Gini index to represent income inequality.

The dependent variable used was the trajectory of emissions level measures as the slope of per capita carbon emissions in the post-recession period. The relationships between variables were estimated by use of the CART form of regression tree. This yielded 12 clusters, displayed in the following set of rules (Table 14.4).

Among developed countries, the model split on the slope of Gini (Japan having stabilized Gini and increasing emissions other rich countries such as Austria, Denmark, Finland, France, and New Zealand with declining Gini and declining emissions). The next level split was on pre-recession GDP slope splitting Costa Rica (higher GDP growth and stabilizing emissions) from a cluster with a lower positive GDP growth slope and decreasing emissions. The determining factor affecting the emissions pathway was found to be economic growth and its variability—too much volatility can negate long-term investments in energy efficiency and renewable energy. Table 14.5 displays these pathway trajectories.

The study led its authors to conclude that a variety of policy options were available to attain declining carbon emissions:

1. Reduce carbon intensity through technology transfer or tax incentives.
2. Adjust fuel mix through the removal of fossil fuel subsidies and promotion of renewable energy.
3. Reduce share of pollution-intensive manufacturing by shifting to services.
4. Slowdown in GDP growth.

Models in Sustainability Risk Management

Sustainability Selection Model

We can consider, the triple bottom-line factors of environmental, social, and economic as a framework of criteria. Calabrese et al. (Calabrese et al., 2016). gave an extensive set of criteria for an analytic hierarchy process framework meant to assess a company's sustainability performance. We simplify their framework and

Table 14.4 Agusdinta et al. (2021) decision tree rules

								RULES
CO2/GDPPost<40.58								
	GiniPost<−0.1							
		GDPPre<0.14						Cluster3(−) $n = 15$
		GDPPre>0.14						Cluster4 (0) $n = 1$
	GiniPost<0.1							Cluster1(+) $n = 1$
CO2/GDPPost>40.58								
	GDPPost<2.55							
		GDPPost<−0.33						Cluster5(+) $n = 6$
		GDPPost> −0.33						
			GDPPre<0.01					Cluster6(+) $n = 9$
			GDPPre>0.01					
				GDPSD<3.97				
					CO2Pre < −0.01			
						CO2/GDPPost<663		Cluster8(−) $n = 9$
						CO2/GDPPost>663		Cluster9 (0) $n = 1$
					CO2Pre > −0.01			
						GiniPre<0.07		Cluster10(−) $n = 4$
						GIniPre>0.07		
							GDPSD<2.05	Cluster11(−) $n = 6$
							GDPSD>2.05	Cluster12(+) $n = 9$
				GDPSD>3.97				Cluster7(+) $n = 6$
	GDPPost>2.55							Cluster2 (0) $n = 3$

demonstrate with hypothetical assessments. We follow the SMART methodology presented in Chap. 3.

Table 14.5 Pathway trajectories identified by decision tree

Cluster	CO_2/GDP	GDP SD	GDP Growth	Gini	CO_2	Representative countries
1	Flat	Rising	Rising	Decline	Slight rise	Japan
2	Rising	Decline	Rising	Decline	Slight rise	Armenia, Latvia, Lithuania
3	Flat	Rising	Rising	Decline	Decline	Denmark, Finland, France, Italy, Norway, Spain, UK
4	Flat	Decline	Rising	Decline	Slight fall	Costa Rica
5	Decline	Decline	Decline	Decline	Sight rise	Argentina, Belarus, Brazil, China, India, Uruguay
6	Flat	Decline	Rising	Decline	Sight rise	Germany, Korea, Malaysia, Singapore, Thailand
7	Decline	Decline	Rising	Decline	Rise	Georgia, Kyrgyzstan, Moldova, Russia, Turkey
8	Decline	Decline	Rising	Decline	Slight fall	Belgium, Hungary, Poland, Venezuela, Romania
9	Rising	Decline	Decline	Decline	Sight rise	Tajikistan
10	Flat	Flat	Rising	Flat	Decline	Greece, the USA, Jordan, Slovenia
11	Flat	Decline	Rising	Decline	Decline	Australia, Israel, South Africa
12	Flat	Flat	Rising	Decline	Sight rise	Canada, Chile, Ecuador, Panama, Sri Lanka

Criteria

Each of the triple bottom line categories has a number of potential sub-criteria. In the environmental category, these might include factors related to inputs (materials, energy, water), pollution generation (impact on biodiversity, emissions, wastes), compliance with regulations, transportation burden, assessment of upstream supplier environmental performance, and presence of a grievance mechanism. This yields six broad categories, each of which might have another level of specific metrics.

In the social category, there could be four broad sub-criteria to include labor practices (employment, training, diversity, supplier performance, and grievance mechanism), human rights impact (child labor issues, union relations, security), responsibility to society (anti-corruption, anti-competitive behavior, legal compliance), and product responsibility (customer health and safety, service, marketing, customer privacy protection). This yields four social criteria. Some of the specific metrics at a lower level are in parentheses.

The economic category could include economic performance indicators (profitability), market presence (market share, product diversity), and procurement reliability (three economic criteria).

Weight Development

Weights need to be developed. AHP operates within each category and then relatively weighting each category, but a bit more accurate assessment would be obtained by treating all criteria together. We thus have 13 criteria to weigh. This is a bit large, but this application was intended by Calabrese et al. as a general sustainability assessment tool (and they had 91 overall specific metrics). We demonstrate the following weight development using swing weighting in Table 14.6.

The total of the swing weighting assessments in column 3 is 730. Dividing each entry in column 3 by this 730 yields weights in column 4.

Scores

We can now hypothesize some supply chain firms, and assume relative performances as given in Table 14.7 in verbal form. Firm 1 might emphasize environmental concerns. Firm 2 might emphasize social responsibility. Firm 3 might be one that stresses economic efficiency with relatively less emphasis on environmental or social responsibility.

We can convert these to numbers to obtain overall ratings of the three firms. We do this with the following scale:

Excellent	1.0
Very good	0.9
Good	0.7
Average	0.5
Low	0.2

Table 14.6 Swing weighting for sustainability selection model

Criterion	Rank	Compared to 1st	Weight
Env1—Input sustainability	1	100	0.137
Soc2—Human rights impact	2	90	0.123
Econ2—Market presence	3	85	0.116
Env2—Pollution control	4	80	0.110
Soc3—Responsibility to society	5	70	0.096
Soc1—Labor practices	6	60	0.082
Env3—Compliance with regulations	7	50	0.068
Econ1—Profit	8	45	0.062
Econ3—Procurement reliability	9	40	0.055
Soc4—Product responsibility	10–11	30	0.041
Env4—Transportation sustainability	10–11	30	0.041
Env5—Upstream supplier performance	12–13	25	0.034
Env6—Grievance mechanism	12–13	25	0.034

Table 14.7 Firm assessment of performance by criteria

Criterion	Firm 1	Firm 2	Firm 3
Env1—Input sustainability	Very good	Average	Low
Soc2—Human rights impact	Good	Excellent	Low
Econ2—Market presence	Average	Average	Very good
Env2—Pollution control	Excellent	Good	Low
Soc3—Responsibility to society	Good	Excellent	Low
Soc1—Labor practices	Good	Excellent	Good
Env3—Compliance with regulations	Good	Good	Good
Econ1—Profit	Average	Low	Very good
Econ3—Procurement reliability	Good	Average	Excellent
Soc4—Product responsibility	Very good	Excellent	Good
Env4—Transportation sustainability	Excellent	Very good	Good
Env5—Upstream supplier performance	Very good	Good	Good
Env6—Grievance mechanism	Excellent	Very good	Low

Table 14.8 Performance index calculation

Criterion	Weight	Firm 1	Firm 2	Firm 3
Env1—Input sustainability	0.137	0.9	0.5	0.2
Soc2—Human rights impact	0.123	0.7	1.0	0.2
Econ2—Market presence	0.116	0.5	0.5	0.9
Env2—Pollution control	0.110	1.0	0.7	0.2
Soc3—Responsibility to society	0.096	0.7	1.0	0.2
Soc1—Labor practices	0.082	0.7	1.0	0.7
Env3—Compliance with regulations	0.068	0.7	0.7	0.7
Econ1—Profit	0.062	0.5	0.2	0.9
Econ3—Procurement reliability	0.055	0.7	0.5	1.0
Soc4—Product responsibility	0.041	0.9	1.0	0.7
Env4—Transportation sustainability	0.041	1.0	0.9	0.7
Env5—Upstream supplier performance	0.034	0.9	0.7	0.7
Env6—Grievance mechanism	0.034	1.0	0.9	0.2
Firm score		0.762	0.724	0.501

These numbers yield scores for each firm that can be multiplied by weights as in Table 14.8.

Value Analysis

In this case, Firms 1 and 2 perform relatively much better than Firm 3, but of course that reflects the assumed values assigned. Note that one limitation of the method is that the more criteria, the tendency is to have higher emphasis. There were only three economic factors, as opposed to six environmental factors. Even though the weights could reflect higher rankings for a particular category (here the last four ranked factors were environmental), there is a bias introduced. The six factors for environmental issues here may account for Firm 1 slightly outperforming Firm 2. The overall bottom line is that one should pay attention to all three triple bottom-line categories. The performance index demonstrated here might be used by each firm to draw their attention to criteria where they should expend effort to improve performance.

Conclusions

There is an obvious growing move toward recognition of the importance of sustainability. This is true in all aspects of business. We reviewed some of the risks involved in the supply chain context and considered risk management in a framework including context and drivers, influences, decision maker profiles, and general categories of response.

The triple bottom line is a useful way to focus on the role of sustainability in business management. This chapter included a review of enterprise risk categories along with common responses. We also demonstrated a SMART model and suggested value analysis considerations. Earlier in the book we provided modeling examples where we emphasize the trade-offs among choices available to contemporary decision makers. But it must be realized that sustainability is not necessarily counter to profitability. Wise contemporary decision-making should seek to emphasize the attainment of sustainability, social welfare, and profitability. Admittedly it is a challenge, but it is important for the success of society that this be accomplished.

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15 Environmental Damage and Risk Assessment

Some natural disasters occur on a regular basis, such as earthquakes (and ensuing tsunamis), storms (sometimes generating floods), and wildfires. Among the many catastrophic damages inflicted on our environment, recent events include the 2010 Deepwater Horizon oil spill in the Gulf of Mexico, and the 2011 earthquake and tsunami that destroyed the Fukushima Daiichi nuclear power plant. The Macondo well operated by British Petroleum, aided by driller Transocean Ltd. and receiving cement support from Halliburton Co. blew out on April 20, 2010, leading to 11 deaths. The subsequent 87-day flow of oil into the Gulf of Mexico dominated the news in the United States for an extensive period of time, polluted fisheries in the Gulf as well as coastal areas of Louisiana, Mississippi, Alabama, Florida, and Texas. The cause was attributed to defective cement in the well. The Fukushima nuclear plant disaster led to massive radioactive decontamination, impacting 30,000 km^2 of Japan. All land within 20 km of the plant plus an additional 2090 km^2 northwest was declared too radioactive for habitation, and all humans were evacuated. The Deepwater Horizon spill was estimated to have costs of $11.2 billion in actual containment expense, another $20 billion in trust funds pledged to cover damages, $1 billion to British Petroleum for other expenses, and a risk of $4.7 billion in fines, for a total estimated $36.9 billion (Smith Jr. et al., 2011). The value of the total economic loss at Fukushima ranges widely, from $250 billion to $500 billion. About 160,000 people have been evacuated from their homes, losing almost off of their possessions (http://www.fairewinds.org/nuclear-energy-education/arnie-gundersen-and-, n.d.).

The world is getting warmer, changing the environment substantially. Oil spills have inflicted damage on the environment in a number of instances. While oil spills have occurred for a long time, we are becoming more interested in stopping and remediating them. In the USA, efforts are underway to reduce coal emissions. US policies have tended to focus on economic impact. Europe has had a long-standing interest in additional considerations, although these two entities seem to be converging relative to policy views. In China and Russia, there are newer efforts to control environmental damage, further demonstrating the convergence of world interest in environmental damage and control.

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We have developed the ability to create waste of lethal toxicity. Some of this waste is on a small but potentially terrifying scale, such as plutonium. Other forms of waste (or accident) involve massive quantities that can convert entire regions into wastelands and turn entire seas into man-made bodies of dead water. Siting facilities and controlling the transmission of commodities lead to efforts to deal with environmental damage led to some of the most difficult decisions we face as a society.

Recent US issues have arisen from energy waste disposal. Nuclear waste is a major issue from both nuclear power plants as well as from weapons dismantling (Butler & Olson, 1999). Waste from coal plants, in the form of coal ash slurry, has proven to be a problem as well. The first noted wildlife damage from such waste disposal occurred in 1967 when a containment dam broke and spilled ash into the Clinch River in Virginia (Lemly & Skorupa, 2012). Subsequently, noted spills include Belews Lake, North Carolina in 1976, and the Kingston Fossil Plant in Tennessee in 2008. Lemly noted 21 surface impoundment damage cases from coal waste disposal, 5 due to disposal pond structural failure, 2 from unpermitted ash pond discharge, 2 from unregulated impoundments, and 12 from legally permitted releases.

Some waste is generated as part of someone's plan. Other forms arise due to accidents such as oil spills or chemical plant catastrophes. Location decisions for waste-related facilities are very important. Dangerous facilities have been constructed in isolated places for the most part in the past. However, with time, fewer places in the world are all that isolated. Furthermore, moving toxic material safely to or from wherever these sites are compounds the problem.

Many more qualitative criteria need to be considered, such as the impact on the environment, the possibility of accidents and spills, the consequences of such accidents, and so forth. An accurate means of transforming accident consequences into concrete cost results is challenging. The construction of facilities and/or the processes of producing end products involve high levels of uncertainty. Enterprise activities involve exposure to possible disasters. Each new accident is the coincidence of several causes, each having a low probability taken separately. There is insufficient reliable statistical data to accurately predict possible accidents and their consequences.

Specific Features of Managing Natural Disasters

Problems can have the following features:

1. Multicriteria nature
   Usually, there is a need for decision makers to consider more than mere cost impact. Some criteria are easily measured. Many, however, are qualitative, defying accurate measurements. For those criteria that are measurable, measures are in different units that are difficult to balance. The general value of each alternative must integrate each of these different estimates. This requires some means of integrating different measures based on sound data.

2. Strategic nature
   The time between the making of a decision and its implementation can be great. This leads to detailed studies of possible alternative plans in order to implement a rational decision process.
3. Uncertain and unknown factors
   Typically, some of the information required for a natural disaster is missing due to incomplete understanding of the technical and scientific aspects of a problem.
4. Public participation in decision-making
   At one time, individual leaders of countries and industries could make individual decisions. That is not the case in the twenty-first century.

   While we realize that wastes need to be disposed of, none of us want to expose our families or ourselves to a toxic environment.

Framework

Assessing the value of recovery efforts in response to environmental accidents involves highly variable dynamics of populations, species, and interest groups, making it impossible to settle on one universal method of analysis. There are a number of environmental valuation methods that have been developed. Navrud and Pruckner (Navrud & Pruckner, 1997) and Damigos (Damigos, 2006) provided frameworks of methods. Table 15.1 outlines market evaluation approaches.

There are many techniques that have been used. Table 15.1 has three categories of methods. Household production function methods are based on relative demand between complements and substitutes, widely used for economic evaluation of projects including benefits such as recreational activities.

The Travel Cost Method assumes that the time and travel cost expenses incurred by visitors represent the recreational value of the site. This is an example of a method based on revealed preference.

Hedonic price analysis decomposes prices for market goods based on analysis of willingness to pay, often applied to price health and aesthetic values. Hedonic price analysis assumes that environmental attributes influence decisions to consume. Thus market realty values are compared across areas with different environmental factors to estimate the impact of environmental characteristics. Differences are assumed to appear as willingness to pay as measured by the market. An example of hedonic price analysis was given of work-related risk of death and worker characteristics

Table 15.1 Methods of environmental evaluation

Household production function methods	Revealed preference	Travel cost method
Hedonic price analysis	Revealed preference of willingness to pay	Benefit transfer method
Elicitation of preferences	Stated preference	Contingent valuation

Table 15.2 Environmental evaluation methods

Project evaluation	Extended cost-benefit analysis—normative
Regulatory review	Metric other than currency—Normative
Natural resource damage assessment	Stakeholder consideration—Compensatory
Environmental costing	Licensing analysis
Environmental accounting	Ecology oriented

(Scotton & Taylor, 2011). That study used US Federal statistics on worker fatalities and

worker characteristics obtained from sampling 43,261 workers to obtain worker and job characteristics, and then ran logistic regression models to identify job characteristic relations to the risk of work fatality.

Both household production function methods and hedonic price analysis utilize revealed preferences, induced without direct questioning. Elicitation of preferences conversely is based on stated preference, using hypothetical settings in contingent valuation, or auctions or other simulated market scenarios. The benefit transfer method takes results from one case to a similar case. Because household production function and hedonic price analysis might not be able to capture the holistic value of natural resource damage risk, contingent valuation seeks the total economic value of environmental goods and services based on elicited preferences. Elicitation of preferences seeks to directly assess utility, including economic, through lottery trade-off analysis or other means of direct preference elicitation.

Cost-benefit analysis is an economic approach to pricing every scale to express value in terms of currency units (such as dollars). The term usually refers to the social appraisal of projects involving investment, taking the perspective of society as a whole as opposed to particular commercial interests. It relies on opportunity costs to society, and indirect measures. There have been many applications of cost-benefit analysis around the globe. It is widely used for five environmentally related applications (Navrud and Pruckner, 1997), given in Table 15.2.

The basic method of analysis is cost-benefit analysis outlined above. Regulatory review reflects the need to expand beyond financial-only considerations to reflect other societal values. Natural Resource Damage Assessment applies cost-benefit analysis along with consideration of the impact on various stakeholders (in terms of compensation). Environmental costing applies cost-benefit analysis, with requirements to include the expected cost of complying with stipulated regulations. Distinguishing features are that the focus of environmental costing is expected to reflect a marginal value and that marginal values of environmental services are viewed in terms of shadow prices. Thus when factors influencing decisions change, the value given to environmental services may also change. Environmental accounting focuses on shadow pricing models to seek some metric of value.

Cost-benefit analysis seeks to identify accurate measures of benefits and costs in monetary terms and uses the ratio of benefits/costs (the term benefit-cost ratio seems more appropriate, and is sometimes used, but most people refer to cost-benefit

Table 15.3 Raw numbers for marine environmental damage

Event	Direct loss ($million)	Fishery loss ($million)	Polluted ocean area hectares	Polluted fishery area (hectares)	Population affected (millions)
1	60	12	216	77	20.47
2	11	14	53	10	2.20
3	31	14	217	48	14.65
4	36	11	105	40	11.48
5	14	17	69	12	4.65
6	16	16	17	3	1.96
7	15	15	164	25	13.77
8	38	13	286	90	23.94
9	8	15	24	0	3.88
10	26	13	154	41	16.40
11	9	16	59	15	6.40
12	19	12	162	55	18.82
13	27	11	68	11	8.15
14	18	16	38	4	6.44
15	14	15	108	13	12.89
16	11	17	6	3	5.39
17	5	20	32	0	3.99

analysis). Because projects often involve long time frames (for benefits if not for costs as well), considering the net present value of benefits and costs is important.

We offer the following example to seek to demonstrate these concepts. Yang (2015) provided an analysis of 17 oil spills related to marine ecological environments. That study applied clustering analysis with the intent of sorting out events by magnitude of damage, which is a worthwhile exercise. We will modify that set of data as a basis for demonstrating methods. The data is displayed in Table 15.3.

This provides five criteria. Two of these are measured in dollars. While there might be other reasons why a dollar in direct loss might be more or less important than a dollar lost by fisheries, we will treat these on the same scale. Hectares of the general ocean, however, might be less important than hectares of fishery area, as the ocean might have greater natural recovery ability. We have thus at least four criteria, measured on different scales that need to be combined in some way.

Cost-Benefit Analysis

Cost-benefit analysis requires converting hectares of ocean and hectares of fishery as well as affected population into dollar terms. Means to do that rely on various economic philosophies, including the three market evaluation methods listed in Table 15.1. These pricing systems are problematic, in that different citizens might well have different views of relative importance, and scales may in reality involve

Table 15.4 Cost-benefit calculations of marine environmental damage demonstration

Event	Direct loss ($million)	Fishery loss ($million)	Polluted ocean ($million)	Polluted fishery ($million)	Population affected ($million)	Total ($million)
1	60	12	64.8	38.5	122.82	298.12
2	11	14	15.9	5	13.2	59.1
3	31	14	65.1	24	87.9	222
4	36	11	31.5	20	68.88	167.38
5	14	17	20.7	6	27.9	85.6
6	16	16	5.1	1.5	11.76	50.36
7	15	15	49.2	12.5	82.62	174.32
8	38	13	85.8	45	143.64	325.44
9	8	15	7.2	0	23.28	53.48
10	26	13	46.2	20.5	98.4	204.1
11	9	16	17.7	7.5	38.4	88.6
12	19	12	48.6	27.5	112.92	220.02
13	27	11	20.4	5.5	48.9	112.8
14	18	16	11.4	2	38.64	86.04
15	14	15	32.4	6.5	77.34	145.24
16	11	17	1.8	1.5	32.34	63.64
17	5	20	9.6	0	23.94	58.54

significant nonlinearities reflecting different utilities. But to demonstrate in a simple form, we somehow need to come up with a way to convert hectares of both types and affected populations into dollar terms.

We could apply trade-off analysis to compare the relative willingness of some subject pools to avoid polluting a hectare of the ocean, a hectare of fishery, and avoid affecting one million people. One approach is to use marginal values, or shadow prices to optimization models. Another approach is to use lottery tradeoffs, where subjects might agree upon the following ratios:

Avoiding 1 ha of ocean pollution equivalent to $0.3 million; Avoiding 1 ha of fishery pollution equivalent to $0.5 million; Avoiding impact on one million people is equivalent to $six million.

Admittedly, obtaining agreement on such numbers is highly problematic. But if it were able to be done, the cost of each incident is now obtained by adding the second and third columns of Table 15.2 to the fourth column multiplied by 0.3, the fifth column by 0.5, and the sixth column by 6. This would yield Table 15.4.

This provides a simple (probably misleadingly simple) means to assess the relative damage of these 17 events. By these scales, event 8 and event 1 were the most damaging.

Wen and Chen (Wen & Chen, 2008) gave a report of cost-benefit analysis to balance economic, ecological, and social aspects of pollution with the intent of aiding sustainable development, National welfare, and living quality in China. They used GDP as the measure of benefit, allowing them to use the conventional approach of obtaining a ratio of benefits over costs. Cost-benefit analysis can be refined to include added features, such as net present value if data is appropriate over different time periods.

Contingent Valuation

Contingent valuation uses direct questioning of a sample of individuals to state the maximum they would be willing to pay to preserve an environmental asset or the minimum they would accept to lose that asset. It has been widely used in air and water quality studies as well as assessment of the value of outdoor recreation, wetland, and wilderness area protection, protection of endangered species and cultural heritage sites.

Petrolia and Kim (Petrolia & Kim, 2011) gave an example of applying contingent valuation to estimate public willingness to pay for barrier-island restoration in Mississippi. Five islands in the Mississippi Sound were involved, each undergoing land loss and translocation from storms, sea level rise, and sediment. A survey instrument was used to present subjects with three hypothetical restoration options, each restoring a given number of acres of land and maintaining them for 30 years. Scales had three points: status quo (small-scale restoration), pre-hurricane Camille (medium restoration), and pre-1900 (large-scale restoration). Dichotomous questions were presented to subjects asking for bids set at no action, 50% baseline cost, 100%, 150%, 200%, and 250%. These were all expressed in one-time payments to compare with the level of restoration, asking for the preferred bid and thus indicating a willingness to pay.

Carson (Carson, 2012) reported on the use of contingent valuation in the Exxon Valdez spill of March 1989. The State of Alaska funded such as study based on the results of a 39-page survey, yielding an estimate of the American public's willingness to pay about $3 billion to avoid a similar oil spill. This is compared to a different estimate based on direct economic losses from lost recreation days (hedonic pricing) of only $four million dollars. Exxon spent about $2 billion on response and restoration and paid $1 billion in natural resource damages.

Conjoint Analysis

Conjoint analysis has been used extensively in marketing research to establish the factors that influence the demand for different commodities and the combinations of attributes that would maximize sales (Green & Srinivasan, 1990).

There are three broad forms of conjoint analysis. Full-profile analysis presents subjects with product descriptions with all attributes represented. This is the most complete form but involves many responses from subjects. The subject provides a score for each of the samples provided, which are usually selected to be efficient representatives of the sample space, to reduce the cognitive burden on subjects. When a large number of attributes are to be investigated, the total number of concepts can be in the thousands and impose an impossible burden for the subject to rate, unless the number is reduced by the adoption of a fractional factorial. The use of a fractional design, however, involves a loss of information about higher-order interactions among the attributes. Full profile ratings-based conjoint analysis, while setting a standard for accuracy, therefore remains difficult to implement if there are many attributes or levels and if interactions among them are suspected. Regression models with attribute levels treated with dummy variables are used to identify the preference function, which can then be applied to products with any combination of attributes.

Hybrid conjoint models have been developed to reduce the cognitive burden. An example is Adaptive Conjoint Analysis (ACA), which reduces the number of attributes presented to subjects, and interactively selects combinations to present until sufficient data was obtained to classify full product profiles.

A third approach is to decompose preference by attribute importance and value of each attribute level. This approach is often referred to as trade-off analysis, or self-explicated preference identification, accomplished in five steps:

1. Identify unacceptable levels on each attribute.
2. Among acceptable levels, determine the most preferred and least preferred levels.
3. Identify the critical attribute, setting its importance rating at 100.
4. Rate each attribute for each remaining acceptable level.
5. Obtain part-worths for acceptable rating levels by multiplying the importance from step 3 by the desirability rating from step 4.

This approach is essentially that of the simple multiattribute rating theory (Olson, 1996). The limitations of conjoint analysis include profile incompleteness, the difference between the artificial experimental environment and reality. Model specification incompleteness recognizes the nonlinearity in real choice introduced by interactions among attributes. Situation incompleteness considers the impact of the assumption of competitive parity. Artificiality refers to the experimental subject weighing more attributes than real customers consider in their purchases. Instability of tastes and beliefs reflects changes in consumer preference.

For studies involving six or fewer attributes, full-profile conjoint methods would be best. Hybrid methods such as Adaptive Conjoint Analysis (ACA) would be better for over six attributes but less than 20 or 30, with up to 100 attribute levels total; and self-explicated methods (trade-off analysis of decomposed utility models) would be better for larger problems. The trade-off method is most attractive when there are a large number of attributes, and implementation, in that case, makes it imperative to use a small subset of trade-off tables.

Conjoint analysis usually provides a linear function fitting the data. This has been established as problematic when consumer preference involves complex interactions. In such contingent preference, what might be valuable to a consumer in one context may be much less attractive in another context. Interactions may be modeled directly in conjoint analysis, but doing so requires (a) knowing which interactions need to be modeled, (b) building in terms to model the interaction (thereby using up degrees of freedom), and (c) correctly specifying the alias terms

Table 15.5 Conjoint structure for Korean carbon emission willingness to pay

Attribute	Low level	Intermediate level	High level
Electricity price	2% increase	6% increase	10% increase
CO_2 reduction	3% decrease/year	5% decrease/year	7% decrease/year
Reduction in unemployment	10,000 new jobs/ year	20,000 new jobs/ year	30,000 new jobs/ year
Power outage	10 min/year	30 min/year	50 min/year
Forest damage	530 km^2/year	660 km^2/year	790 km^2/year

Table 15.6 Sample questionnaire policy choice set

Attribute	Policy 1	Policy 2	Policy 3	Do nothing
Electricity price	2% increase	6% increase	6% increase	0 increase
CO_2 reduction	7% decrease	5% decrease	7% decrease	0 increase
Reduction in unemployment	30,000 new jobs	20,000 new jobs	30,000 new jobs	No new jobs
Power outage	50 min/year	10 min/year	30 min/year	No decrease
Forest damage	660 km^2/year	660 km^2/year	530 km^2/year	No reduction

if one is using a fractional factorial design. With a full-profile conjoint analysis with even a moderate number of attributes and levels, the task of dealing with interactions expands the number of judgments required by subjects to impossible levels, and it is not surprising that conjoint studies default to main effects models in general. Aggregate-level models can model interactions more easily, but again, the number of terms in a moderate-sized design with a fair number of suspected contingencies can become unmanageable. Nonlinear consumer preference functions could arise due to interactions among attributes, as well as from pooling data to estimate overall market response or contextual preference.

Shin et al (Shin et al., 2014). applied conjoint analysis to estimate consumer willingness to pay for the Korean Renewable Portfolio Standard. This standard aims at reducing carbon emissions in various systems, including electrical power generation, transportation, waste management, and agriculture. Korean consumer subjects were asked to trade off five attributes, as shown in Table 15.5.

There are $3^5 = 243$ combinations, clearly too many to meaningfully present to subjects in a reasonable time. Conjoint analysis provides means to intelligently reduce the number of combinations to present to subjects in order to obtain well-considered choices that can identify relative preference. One sample choice set is shown in Table 15.6.

Attributes were presented in specific measures as well as the stated percentages given in Table 15.6. The fractional factorial design used 18 alternatives out of the 243 possible, divided into six choice sets, including no change. None of these had a dominating alternative, thus forcing subjects to trade off among attributes. There were 500 subjects. Selections were fed into a Bayesian mixed logit model to provide estimated consumer preference.

When preference independence is not present, Clemen and Reilly (Clemen & Reilly, 2001) discuss options for utility functions over attributes. The first approach is to perform a direct assessment. However, too many combinations lead to too many subject responses, as with conjoint analysis. The second approach is to transform attributes, using measurable attributes capturing critical problem aspects. Another potential problem is variance in consumer statements of preference. The tedium and abstractness of preference questions can lead to inaccuracy on the part of subject inputs (Larichev, 1992). In addition, human subjects have been noted to respond differently depending on how questions are framed (Kahneman & Tversky, 1979).

Habitat Equivalency Analysis

Habitat equivalency analysis (HEA) quantifies natural resource service losses. The effect is to focus on restoration rather than restitution in terms of currency. It has been developed to aid governmental agencies in the USA to assess natural resource damage to public habitats from accidental events. It calculates natural resource service loss in discounted terms and determines the scale of restoration projects needed to provide equal natural resource service gains in discounted terms in order to fully compensate the public for natural resource injuries.

Computation of HEA takes inputs in terms of measures of injured habitat, such as acres damaged, level of baseline value of what those acres provided, and losses inferred, all of which are discounted over time. It has been applied to studies of oil spill damage to miles of stream, acres of woody vegetation, and acres of crop vegetation (Dunford et al., 2004). The underlying idea is to estimate what it would cost to restore the level of service that is jeopardized by a damaging event.

Resource equivalency analysis (REA) is a refinement of habitat equivalency analysis in that the units measured differ. It compares resources lost due to a pollution incident to benefits obtainable from a restoration project. Compensation is assessed in terms of resource services as opposed to currency (Zafonte & Hamptom, 2007). Components of damage are expressed in Table 15.7.

Defensive costs are those needed for response measures to prevent or minimize damage. Along with monitoring and assessment costs, these occur in all scenarios. If resources are remediable, there are costs for remedying the injured environment as

Table 15.7 Resource equivalency analysis damage components (Defancesco et al., 2014)

Condition	Remedial	Irremediable
Reversible	Defensive costs Costs of monitoring and assessment; Remediation costs Interim welfare costs	Defensive costs Costs of monitoring and assessment; Interim welfare costs
Irreversible	Defensive costs Costs of monitoring and assessment; Remediation costs Interim welfare costs	Defensive costs Costs of monitoring and assessment; Permanent welfare losses

well as temporary welfare loss. For cases where resources are not remediable, damage may be reversible (possibly through spontaneous recovery), in which case welfare costs are temporary. For irreversible situations, welfare loss is permanent.

HEA and REA both imply the adoption of compensatory or complementary remedial action, and generation of substitution costs.

Yet a third variant is the value-based equivalency method, which uses the frame of monetary value. Natural resource damage assessment cases often call for compensation in non-monetary, or restoration equivalent, terms. This was the basic idea behind HEA and REA above. Such scaling can be in terms of service-to-service, seeking restoration of equivalent value resources through restoration. This approach does not include individual preference. Value-to-value scaling converts restoration projects into equivalent discounted present value. It requires individual preference to enable pricing. This can be done with a number of techniques, including the travel cost method of economic valuation (Parsons & Kang, 2010). Essentially, pricing restoration applies conventional economic evaluation through utility assessment.

Summary

The problem of environmental damage and risk assessment has grown to be recognized as critically important, reflecting the emphasis of governments and political bodies on the urgency of need to control environmental degradation. This chapter has reviewed a number of approaches that have been applied to support decision-making relative to project impact on the environment. The traditional approach has been to apply cost-benefit analysis, which has long been recognized to have issues. Most of the variant techniques discussed in this chapter are modifications of CBA in various ways. Contingent valuation focuses on integrating citizen input, accomplished through surveys. Other techniques focus on more accurate inputs of value trade-offs, given in Table 15.1. Conjoint analysis is a means to more accurately obtain such trade-offs but at a high cost of subject input. Habitat equivalency analysis modifies the analysis by viewing environmental damage in terms of natural resource service loss.

Burlington (Burlington, 2002) reviewed the natural resource damage assessment in 2002, reflecting the requirements of the US Oil Pollution Act of 1990. The prior approach to determining environmental liability following oil spills was found too time consuming. Thus, instead of collecting damages and then determining how to spend these funds for restoration, the focus was on timely, cost-effective restoration of damaged natural resources. An initial injury assessment is conducted to determine the nature and extent of damage. Upon completion of this injury assessment, a plan for restoration is generated, seeking restoration to a baseline reflecting natural resources and services that would have existed but for the incident in question. Compensatory restoration assessed reflects actions to compensate for interim losses. A range of possible restoration actions are generated, and costs are estimated for each. Focus is thus on cost of actual restoration. Rather than abstract estimates of the monetary value of injured resources, the focus is on actual cost of restoration to baseline.

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