Race Car Chassis Tuning Using Artificial Neural Networks

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Abstract. Proficient chassis tuning is critical to the overall performance of any race car. Determination of the optimum arrangement for specific track conditions can require a large amount of practical testing and, as such, any tools that reduce this expenditure will be of great value to the racing industry. Traditional computer modeling based on simplified vehicle dynamics has had a growing use in this field, but due to the extremely complex nature of the vehicle / driver / environment entity it has a number of practical limitations. Intelligent models, such as Artificial Neural Networks, on the other hand are not limited in this way and show a number of potential benefits. This study presents a simplified application of ANN to predict the optimum chassis arrangement for a steady state cornering condition for a Formula SAE race car to see if these benefits can be realised. The race car was equipped with a large sensor array, including engine speed, throttle angle, wheel speed, suspension position, steering angle, longitudinal and lateral acceleration and yaw rate, and chassis tuning was accomplished by varying caster, toe and front and rear tyre pressures. Data was collected for a total of six different chassis tuning combinations for the steady state cornering condition and a feed-forward back-propagation ANN model capable of predicting the lateral (centrifugal) acceleration of the vehicle for any given chassis tuning was produced. A numerical investigation was then completed with the ANN model to find the maximum lateral acceleration, and therefore speed, of the vehicle for each different possible chassis tuning combination. Each of the resulting 480 combinations were then ranked and compared against the optimal combination found from extensive practical vehicle testing. Despite a few problems encountered throughout the investigation that deteriorated ANN model accuracy, a high degree of correlation was found.

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1 Introduction

It is obvious that the chassis properties have a large impact on the performance of most vehicles, racing cars especially. The suspension system defines how effectively the tyres can be utilised to obtain traction with the pavement, and also goes a long way in determining driver comfort and control. To be competitive, race car suspension must be designed and tuned to meet the demands of each track, each vehicle, and each driver [1..5].

The driver / vehicle / environment system is extremely complex, and an optimum suspension arrangement can be very difficult to develop, as Milliken [1] demonstrates. This is compounded by the fact that suspension design involves a number of compromises, and suspension requirements continuously change. Between races, between track conditions, between vehicle arrangements and between drivers the optimum suspension arrangement must be constantly redeveloped and refined. Short of installing a completely new suspension system for each change, these modifications are best done through chassis tuning.

Tuning allows the fine adjustment of many of the chassis parameters in an attempt to provide the most effective set up for the specific race conditions. Typically, these include camber angle, caster angle, toe, tyre choice and pressure, spring rate, damper resistance and stabiliser bar stiffness, or more depending on the application. Each of these parameters are interrelated, and their effects on vehicle dynamics are intricate and difficult to predict. A small change to one parameter may improve performance in one aspect, but impede it in many others. It is the goal of chassis tuning to provide an arrangement that gives optimal performance in critical situations (such as hard cornering), while still providing adequate performance in all other conditions, with the intent of providing the fastest consistent race times possible, as explained by Adams [2].

Because of the complexities of vehicle dynamics, and the fact that in most categories every vehicle is different to a large degree, there are no specific rules for chassis tuning. Instead, each vehicle must undergo extensive testing on the racetrack until an optimum arrangement is found through iteration and experience.

Obviously, this amount of track time can be expensive, in terms of both time and money. The amount of testing required to find the optimal solution can, however, be reduced with increased experience and the adoption of appropriate tools. Computer modeling has had a growing use in this field, and provides a powerful tool for testing tuning arrangements off-track. In this manner, different arrangements can be evaluated quickly, and without track testing. This means that when track testing is conducted, a high level of chassis tuning can be reached comparably quickly, with minimal expense.

The accuracy of the computer model then, clearly, has a large impact on how quickly the best arrangement can be found. The more parameters that the model takes into account, the better it will generally be. But the dynamics of a vehicle are very complex. Not only must the suspension geometries be considered, but also chassis movement and deflection, as well as tyre grip, deformation and slip - to name only a few. Since the development of mathematical models required for traditional computer modeling grows exponentially more difficult as additional parameters are considered (tyre dynamics alone are extremely complex [6,7]), it can be seen that there are a number of limitations in its use [8].

Artificial Neural Networks (ANN), on the other hand, offer an alternative to traditional computer modeling, and bring a number of potential benefits [9].

It is the goal of this study to conduct a simplified investigation into the use of ANNs in chassis tuning to discover if these benefits can be realised. As such, the investigation has been restricted to optimising caster, toe and front and rear tyre pressures for an approximately steady state cornering condition.

2 ANN Architecture

Artificial Neural Networks attempt to mimic the operation of the brain at a neural level [10]. As such, they exhibit some similar features, including the ability to learn and model process behaviour where *a priori* knowledge of the associated scientific principles is not available, or extremely difficult to obtain. This means that an ANN model can be programmed using just the input / output data (called training data) of a system, without the need to develop the complex mathematical representations that would otherwise be necessary to characterise the inner workings of the system. A by-product of this property is also that ANNs can include data from a large number of inputs. Therefore, because the ANN statistical model is more complex than conventional models, it can handle a wider variety of operating conditions [11].

The ability of an ANN to model process behaviour depends to a large extent on the network architecture. There are many proven architectures, in a range of applications, and new ones are continuously being developed. Among the most common is the multi-layed feedforward backpropagation (BP) ANN, which has been in use by the manufacturing industry for some time for systems control. This architecture is well known and well documented [15, 16]. It is very simple to construct, is robust and often provides reasonable accuracy - but can take a comparatively long time to train through error backpropagation, as discussed by Zeidenberg et al [12..15].

BP ANNs are structured as shown on Figure 1, with an input layer, one or more hidden layers and an output layer, with *i*, *j* & *k* processing units (called neurons, or nodes) in each respectively. The role of the input neurons is to simply pass forward the model input data to the hidden layer, and so the number of input neurons is equal to the number of model inputs. The hidden and output layers then perform all of the network processing, with each neuron performing an input (summation) function of the weighted inputs, an activation function and an output function, shown in Figure 2.

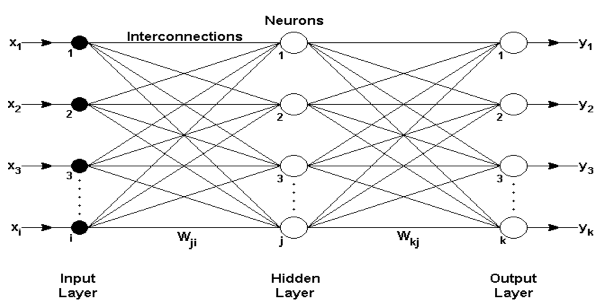

Fig. 1. Feedforward Architecture of a Basic BP ANN

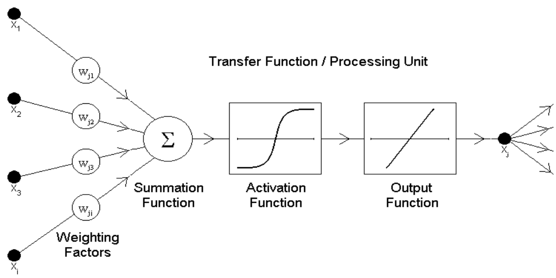

Fig. 2. Structure of the Artificial Neuron

The input function can thus be written as:

$$net_j = \sum_i x_i w_{ji} \tag{1}$$

Where; net_j=summation function result for neuron j, x_i=output from neuron i, w_{ji}=weight factor applied to x_i at neuron j

The goal of the activation function is then to perform a non-linear operation to the summation result. The most common is the sigmoidal function, which has the form:

$$f(net_j) = \frac{1}{1+\exp(-net_j)} . \tag{2}$$

The purpose of the output function is to condition the activation function result before it is passed to other neurons. Generally, this is not required, so the output function normally does not perform any operation.

Looking at the architecture, it can then be seen that the ANN characteristics can be altered by changing the neural weights it contains. Iteratively modifying these neural weights until a state of minimum error is achieved gives the ANN the ability to ‘learn' a process, called Network Training. As the name ‘backpropagation' suggests, this is done by comparing model predicted outputs (at the output layer) with the training data, and propagating this error value back through the network to the input layer, updating weight magnitudes on the way.

Therefore, the error values for the output layer neurons are given by:

$$\delta_k = (t_k - a_k) \cdot f'(net_k). \tag{3}$$

Where; δ_k=error value for neuron k, t_k=target training value for neuron k, a_k=output value of neuron k

And the error values for the hidden layer neurons are determined using:

$$\delta_j = \left[\sum_k \delta_k W_{kj}\right] \cdot f'(net_j). \tag{4}$$

Where; W_{kj}=weight factor to neuron k from neuron j

These error values can then be used to calculate the required weighting factor adjustments for the next training iteration, as shown:

$$\Delta W_{ji}{}^{h} = \eta \cdot \delta_j \cdot a_i + \alpha \cdot \Delta W_{ji}{}^{h-1} . \quad (5)$$

Where; η=learning rate, $0<\eta<1$, α=momentum constant, $0<\alpha<1$, $\Delta W_{ji}{}^{h}$=weight adjustment at iteration *h*, $\Delta W_{ji}{}^{h-1}$=previous iteration weight adjustment

Through this process the networks weights can be continuously adjusted during the training process, with the aim of converging on the arrangement that will give minimum RMS error for the given ANN architecture, as shown by Frost [16].

Typical leaning values used in training are $0.05<\eta<0.9$ and $0.05<\alpha<1$, with higher values improving convergence speed, and lower values enabling network 'fine tuning'. Values should be chosen to produce reasonable convergence speed while maintaining the ability to converge to a specific solution, avoiding false minima.

3 Parameter Selection and Data Acquisition

It was decided at an early stage to keep this initial investigation into the practically of ANNs as an aid in chassis tuning as simple a possible. As such, the testing conditions were limited to a flat uniform asphalt surface, and the test tack was constructed in a 'figure of 8' shape to the specifications of the Formula SAE skid pad [17]. Since the goal on this track is to achieve best performance in steady state cornering (in both directions), and transient responses are unimportant, it significantly simplifies the problem. Also, by assuming the vehicle (built to Formula SAE specifications) will corner in one direction in the same manner as the other, the ANN training data can be shortened to cover only the steady state cornering in one direction. The goal of the model, therefore, is simplified to the prediction of lateral acceleration (and velocity using the relationship $a_s = v^2 / r$) under steady conditions using a selection of measured parameters describing the vehicle/driver dynamics and chassis tuning.

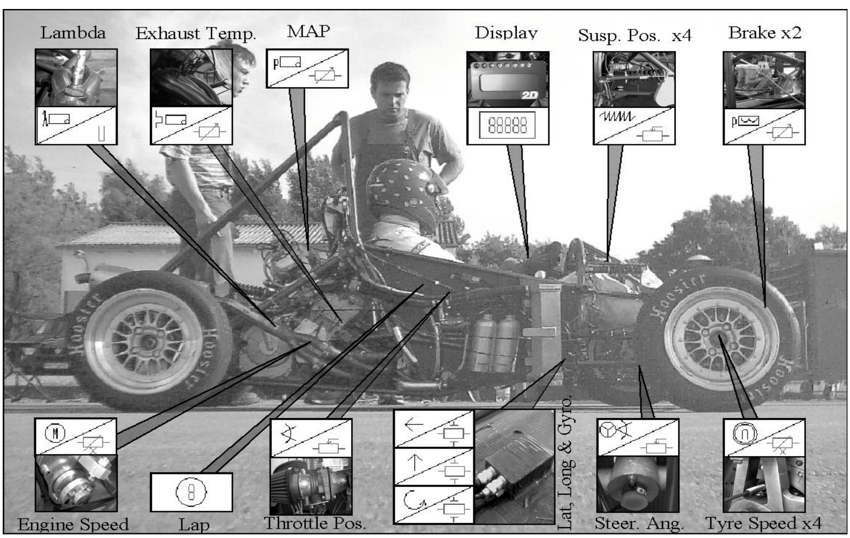

Fig. 3. Data Acquisition System on Test Vehicle

Table 1. Training chassis arrangements

Caster (o)	Toe (')	Front Tyre Press. (bar)	Rear Tyre Press. (bar)
5	-1.2	1	1
5	-1.2	0.8	0.6
5	-1.2	0.6	0.6
5	-1.2	0.4	0.6
5	2.5	0.8	0.6
0	2.5	0.8	0.6

The Formula SAE class race car built at the University of Applied Sciences, Stralsund, Germany for the 2002 Formula Student competition was used as the test vehicle. This racing car is equipped with a comprehensive data acquisition system, and can measure a variety of engine and chassis parameters as shown in Figure 3.

All of the parameters were measured during the data acquisition phase, with a mind to discard parameters that were found to have little or no effect on steady state cornering ability. Data was acquired for six different chassis arrangements, varying caster, front toe and front and rear tyre pressures, as shown in Table 1. It should also be noted that the data for the rear left wheel speed was later found to be erroneous, and so was omitted from the analysis.

4 Model Development

A number of different ANN arrangements were experimented with, and different architectures used, in the hope of finding a suitable model. The ANN programs were first written in LabVIEW [18], and a parameter importance analysis was conducted to see which of the vehicle parameters had significant effects. As anticipated from a previous study [9], the parameters associated with the engine and brakes were found to have negligible effects. As a result, the ANN inputs used to produce a prediction of lateral acceleration were chosen as:

- Caster,
- Front Toe Angle,
- Tyre Pressure (front and rear),
- Wheel Speed & Accel. (x3),
- Suspension Travel & Speed (x4),
- Steering Wheel Angle & Angular Velocity,
- Yaw Rate & Yaw Acceleration,
- Longitudinal Acceleration & Rate of Change.

Network training then went ahead, testing many different network architectures by varying the number of hidden layers and hidden layer neurons. In total over 20 000 lines of data (called patterns) were used to train each network, with about 2000 patterns randomly set aside for network testing and RMS error evaluation.

The 24 input, 16 first hidden layer, 0 second hidden layer and 1 output neuron architecture (Figure 4) proved the best arrangement for this case (using the method suggested by Frost et al [15]), exhibiting a full scale RMS error of only 4.0%.

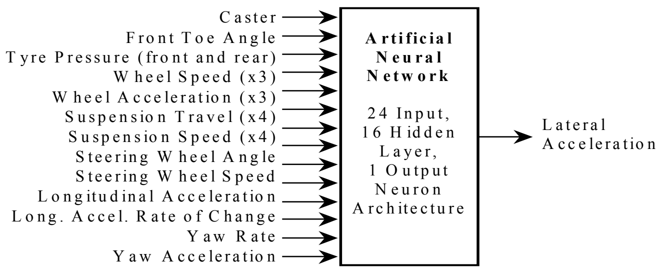

Fig. 4. ANN Model Used for Analysis

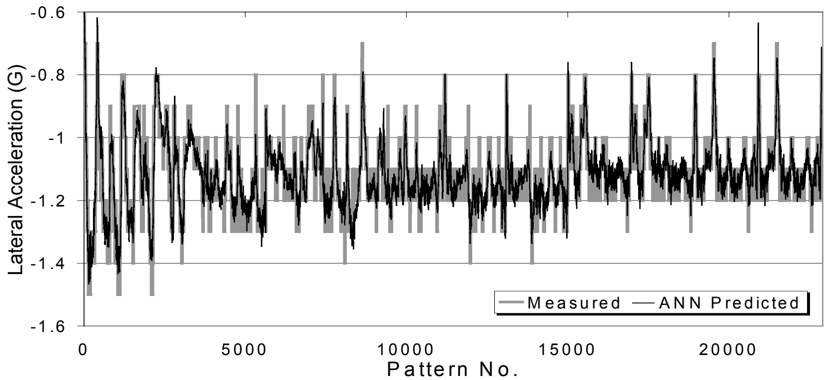

Fig. 5. Training ANN Prediction Results

Figure 5 shows the comparison between the actual measured values (grey) and the ANN predicted values. It can be seen that the measured values have been rounded to one decimal place when logged, which makes error comparison difficult. However, the ANN prediction results seem to follow the trend well and make very few, if any, large deviations from the original data. This is also reflected in the error distribution in Figure 6. Instances of large random errors are non-existent, and the curve follows a general bell shape. This also tends to support the theory that a large part of the error is the result of data rounding, and in reality is much lower.

Figure 7 and 8 follow the same format as above, except in this case just the testing data is displayed. The testing data was excluded from training and as a result remains an excellent tool to establish how well the ANN has ‘learnt' the process. It can be seen that the results are almost identical to the training data. This not only shows that the ANN has learnt the vehicle dynamics very well, but also supports the theory that a significant contributor to the model error comes from data rounding.

Further investigation into this model then revealed the percent importance it placed on the input variables. Parameters that the model finds to have a large impact on the output are given high importance values, while unimportant ones are given low values. The results are shown in Figure 9.

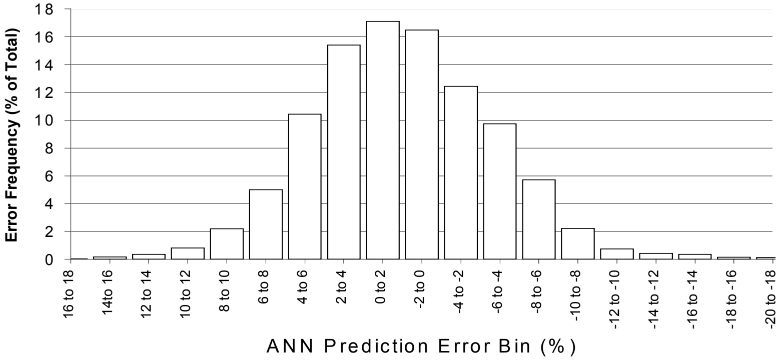

Fig. 6. Training Error Distribution

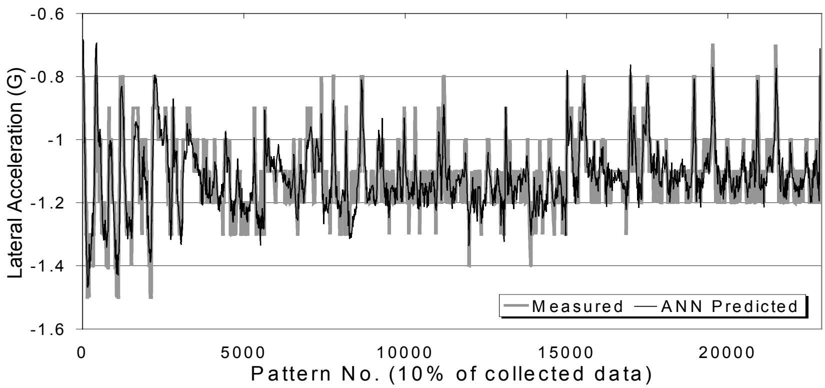

Fig. 7. Testing ANN Prediction Results

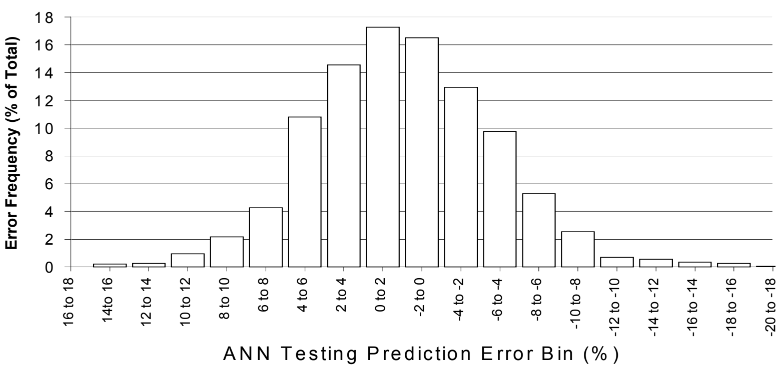

Fig. 8. Testing Error Distribution

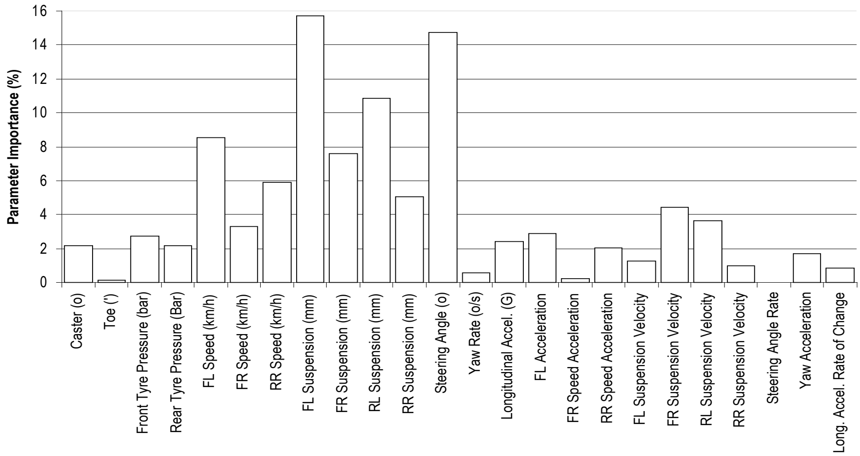

Fig. 9. Importance Analysis for ANN

Firstly, it can be seen that the parameters with high importance seem to follow what would intrinsically be expected for lateral acceleration prediction. This further supports the argument that the ANN has learnt the process very well.

Looking closer we can see that caster has an importance of just 2.16%, toe 0.13%, front tyre pressure 2.74% and rear tyre pressure 2.18% - just over 7% of the total importance. This makes sense though, obviously if a wheel suddenly stops rotating this will have much greater effect on lateral acceleration than, say, the amount of caster. It can also be seen that the importance of toe is extremely small. It is expected that this is due to the presence of Ackerman steering geometry which would produce large amounts of toe-out during cornering, marginalising the small adjustments made here.

5 Chassis Performance Prediction

The goal of the race car is to get from one point to another in the shortest possible time. This means designing and tuning it to provide high acceleration in particular conditions when needed, at the expense of acceleration in non-critical areas. The chassis should be tuned to give maximum performance (i.e. maximum acceleration) during critical maneuvers, while maintaining an adequate compromise of performance for the remainder of the race track.

The highly simplified nature of the track in question here, however, negates this problem. The uncomplicated steady state cornering condition imposed in this study means that there is no compromise in chassis tuning for different conditions. The problem then becomes that of maximising steady state acceleration for one condition only, that of cornering at the specified corner radius.

All things being equal, it is the chassis tuning arrangement that defines this maximum acceleration. Each arrangement of every tuning parameter produces a very large amount of possible combinations, each with their own effect on vehicle performance. In theory then, it should be possible to rank each of these combinations in order of performance for specific maneuvers, such as the steady state cornering condition discussed here.

With this in mind, the next stage of the investigation was to use the trained ANN model discussed above to predict the maximum obtainable lateral acceleration for any given combination of caster, toe and front and rear tyre pressure. It was decided that the simplest way to do this was to enter the desired tuning arrangement, set all of the ‘rate of change' parameters defining steady state to zero and let a program (written in LabVIEW again) continuously enter random numbers into the remaining network inputs. This numerical investigation would then, therefore, explore all of the possible running conditions of the car, in the hope of finding the condition that produced the maximum lateral acceleration for the given chassis tuning arrangement. The program would then record the conditions that produced the highest lateral acceleration, and rank it against other chassis tuning arrangements.

Of note, however, is that while the method above should give steady state results, it has the potential of predicting a condition that would be very hard for a driver to control. An additional condition was also included to make sure that the vehicle and wheel velocities reflected a realistic driving condition and correlated with the predicted lateral acceleration. Variations due to slip were included to a degree however, with the introduction of a constant slip error term (1% slip) within the test.

Using this process it was possible to input any chassis arrangement (within the minimum and maximum bounds of the training data) into the ANN and obtain the maximum achievable velocity of the vehicle in steady state cornering at the designated corner radius. Finding the optimum chassis arrangement was then just a process of repeating this procedure for an array of arrangements and identifying the fastest. The different chassis arrangements used in this process were comprised of every combination (480 total) of the following:

- Caster = 0, 2, 3, 4 & 5°
- Toe = -1.2, 0, 1.2 & 2.5'
- Front and rear tyre pressure = 0.6, 0.7, 0.8, 0.9 & 1.0bar.

The fastest final results are given in Table 2, and show an optimum arrangement of 0° caster, -1.2' toe, 1.0bar front tyre pressure and 0.9bar rear tyre pressure.

Table 2. Top ten ANN chassis arrangements

Caster (o)	Toe (')	Front Tyre Press. (bar)	Rear Tyre Press. (bar)	FL Wheel Speed (km/h)
0	-1.2	1.0	0.9	43.414
0	-1.2	1.0	1.0	43.413
0	-1.2	0.8	0.9	43.402
0	-1.2	0.6	1.0	43.400
0	-1.2	0.8	1.0	43.390
0	-1.2	1.0	0.8	43.390
0	-1.2	1.0	0.7	43.385
0	-1.2	0.4	1.0	43.382
0	0	1.0	1.0	43.379
0	-1.2	0.6	0.9	43.376

6 Testing and Appraisal of ANN Model

The data acquisition required for this research was acquired over an eight hour period, with most of this time going into changing the chassis arrangements and re-tuning to suit. This was done in conjunction with the normal chassis tuning regiment that the Stralsund University of Applied Sciences was conducting to prepare for an upcoming competition. All of the data used to train and test the ANN model was recorded on the first day of testing. This was followed by continued chassis tuning for the same steady state cornering condition for a further two days to provide a comparison between practical experimentation and the ANN model.

The optimum arrangement found through practical experimentation was found to be 0° caster, -1.2' toe, 1.0bar front tyre pressure and 1.0bar rear tyre pressure. It can be seen that this arrangement was ranked second in the ANN model, by only 0.001km/hr, which suggests exceptional correlation between the two methods.

The degree of correlation is also even more impressive when considering the quality of the data used to train the ANN. The chassis arrangements used in the training data were taken when the University of Applied Sciences was predominantly investigating the effects of tyre pressure variation, and as a result did not cover a broad range of conditions. Comparing Table 1 and Table 2 shows that there is very little relationship between the training data and the ANN predicted optimum arrangements. In fact, the best training arrangement is ranked at 216th of the 480 ANN predictions. This meant that the ANN model had to extrapolate much of its information from obscure and largely unhelpful data to provide this highly accurate solution.

7 Conclusions

The conditions used in this research are obviously highly simplified when considering the complexities involved in race car chassis tuning. Nonetheless, in this case three days of rigorous track testing was effectively and accurately modeled using an ANN model based on only one day of testing. This was despite model errors induced by coarse measured data rounding and the large deviation between the chassis arrangements used in training and the final, optimal solution. This, strongly suggests a real benefit may exist in the use of ANN in chassis tuning.

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