DEVELOPMENT OF CAR FOLLOWING MODELS

CHAPTER – 5

DEVELOPMENT OF CAR FOLLOWING MODELS

5.0 GENERAL

In traffic stream a vehicle may be forced to follow another vehicle for many reasons. At the same time, drivers will be looking for opportunities to overtake the vehicles ahead of them. In order to avoid collision in such kind of overtaking manoeuvres, the vehicles will be forced to follow the lead vehicle. Thus, in order to study traffic flow characteristics it is necessary to model both these car following and acceleration/deceleration characteristics of vehicles. Thus, these two manoeuvres are decided to be studied and these are presented in two separate chapters. The current chapter deals with the development of car following models, while, the chapter to follow is reserved for discussion on modelling acceleration/deceleration characteristics of vehicles in mixed traffic environment.

Car following models, which describe the behaviour of drivers reacting to the behaviour of their leaders, is another important component of traffic flow simulation model. In conventional methods, the driver behaviour is studied as
response in the form of acceleration/deceleration of the following driver using response-stimuli equations. These models are deterministic and thus do not fully represent the imprecise driver reaction. Neural networks, which have a performance close to human behaviour, are likely to represent the process better than purely mechanical systems. This chapter presents the efforts made to study the car-following behaviour of drivers using conventional response-stimuli method and neural network. A comparison of the two methods is also presented along with review of literature, data collection and analysis and modelling.

5.1 CAR FOLLOWING MODELS

The principal goal of a driver is to guide the vehicle from origin to destination in a safe manner, along with additional goals such as arriving at destination at the earliest possible time etc. The task of accomplishing the driver’s goals can be split into different categories of action such as perception, judgment, decision and control. The driver’s control actions are limited to the control of heading (steering) and control of acceleration. To accomplish the steering function, the driver attempts to maintain the vehicle within the error criterion limits assessed based on experience, throughout the duration of the steering job. The acceleration control subtask consists of detecting the differences in velocity or spacing with adjacent vehicles and taking actions that will prevent unsafe conditions and fulfil the driver’s goal of proceeding at a particular speed. The physical action that a driver performs after perceiving and judging the situations is to accelerate, decelerate or move at the same speed. Thus, in driver behaviour studies, the response or the output parameter is considered as acceleration or deceleration.
As the vehicle moves on the roadway, the driver gathers information about the surrounding environment required for performing the different vehicle manoeuvres. These information act as the stimuli for the decision making process of the driver. The driver positions the vehicle in a traffic stream such that safe clearances are maintained with respect to the surrounding vehicles or objects and drives the vehicle at a speed perceived as safe. If the available safe clearances are less than the required safe clearances, then he decelerates. Otherwise, accelerates to the desired speed. In most of those studies, the driver behaviour in a single lane traffic stream was modelled by examining the manner in which the individual vehicles followed one another. The most pertinent car-following theories in the chronological order of their development are briefly discussed in the following articles.

5.2 LITERATURE REVIEW

Pipes (1953) characterised the motion of vehicles in traffic stream, following the rule suggested in the California Motor Vehicle Code, that for following another vehicle at safe distance is allow to yourself at least the length of a car between your vehicle and the vehicle ahead for every 10 miles per hour of speed at which you are travelling. He described the distance headway as a function of speed and derived the car following model. The limitation of the model is that the compatibility between the predicted values and the actual field measurements exists only in the midranges of speeds. However, considering the simplicity of models, the close agreement with real-life observations is astonishing (Pignataro (1973)).

Forbes et al (1958) approached car following behaviour of driver by considering the reaction time needed for the following vehicle to perceive the need to
decelerate and apply the brakes. According to this theory, the minimum time headway is considered to be equal to the reaction time and the time required for the lead vehicle to travel a distance equal to its length. Similar to Pipe's theory, there is close agreement between the values predicted by Forbes' model and the field observations in mid range speeds only.

The General Motors' models were based on the premise that the reaction of the driver of following vehicle at time 't' depends on the sensitivity of the driver of the following vehicle and the strength of the stimulus at time (t-τ). In these models, the strength of the stimulus is measured in terms of the relative velocity between the lead vehicle and the following vehicle and the reaction of the following vehicle is taken as the acceleration or deceleration rate. The time difference τ, is equal to the perception reaction time and the sensitivity term (α₀) maps the unit of a stimulus to a reaction.

The researchers at General Motors developed five models, known as GM Models, that have the same general structure, but differ from one another with respect to the sensitivity term. The third generation model proposed by Gazis et al (1961) is the most widely used as it is simple and more realistic (Gipps, 1981). It is represented as follows:

\[ a_n(t + \tau) = \alpha_0 \frac{v_{n-1}(t) - v_n(t)}{x_{n-1}(t) - x_n(t)} \quad \text{Eqn. 5.1} \]

where

\( a_n(t+\tau) \) - acceleration/deceleration of the following vehicle at time \( t + \tau \)

\( \alpha_0 \) - Sensitivity parameter
\[ v_{n-1}(t) - v_n(t) \] - Relative speed between the two vehicles at time \( t \).

\[ X_{n-1}(t) - X_n(t) \] - Distance between the two vehicles at time \( t \).

The drawbacks of these models are the following:

- The interaction between stimulus and reaction has a one-to-one correspondence.

- The imprecise driver's reaction pattern is not fully represented.

- Representation of a human behavioural pattern may be better explained by an approximate reasoning process than a deterministic model.

- The following vehicle reacts even to minute changes in relative velocity between lead vehicle and the following vehicle in a deterministic manner.

Psycho-physical models describe driving in a way very close to reality. Research into a perceptual psychology has shown that drivers are subjected to certain limits on the stimuli to which they respond [Leutzbach, 1988]. The basis of such models is,

1. at large spacing, the driver of a following vehicle is not influenced by the size of speed difference.

2. at small spacing, there are combinations of relative speeds and distance headway for which there is, as in (1), no response of driver of the following vehicle because the relative motion is too small.

This model thus considers the existence of perceptual thresholds. Only when these thresholds are reached the driver of a following vehicle will be able to perceive the change in the apparent size of the lead vehicle and will be able to react to the changes in the kinematic variables. These models include
substantially more realistic assumptions concerning traffic flow phenomenon. A model for traffic simulation by Fritschze (1994) based on psycho-physical modelling shows that the phase area of relative distance is differentiated into a number of thresholds defined by rules. These rules are directly incorporated in traffic simulation. But these rules can be made only if the information about the psychological evaluation of the drivers of the available spacing is known. Since such form of data is very difficult to collect, the validation of these models is difficult.

Lloyd and Gerlough (1976) attempted to simulate more significant characteristics of a car following driver–vehicle system, using control system theory techniques. The model was implemented by a computer program, which outputs time histories of driver–vehicle response to step perturbations. The major parameters considered were related to response, time perception threshold and sensitivities. But the results showed that more work was needed to make it more realistic. The characteristic of self-adaptability is lacking in this approach.

In recent years, fuzzy logic has been applied to many practical problems involving control and decisions under the environment of the imprecise human reasoning process. Kikuchi and Chakraborty (1992) proposed a fuzzy rule based car following model that assumed that a driver's decision is the result of fuzzy reasoning process and predicted the possibilities of the reaction of the following vehicles. The predicted range was found to be reasonable. Also, it was applied to analyse the traffic stability and speed–density relationship that gave better results when compared with the deterministic models. Chakraborty and Kikuchi (1999) compared the performance of GM models and fuzzy inference logic based models using real world data and concluded that fuzzy model
possessed many desirable properties of car-following models, which were not found in GM models.

A review of the theories developed on the car following behaviour and the studies conducted reveals that, while the deterministic models do not reflect the stochastic nature of driver behaviour, attempts involving fuzzy logic, which approximates the human reasoning process, were more successful in describing the driver behaviour. Artificial Neural Networks is another branch of Artificial intelligence, which tries to mimic the functionality of brain in a fundamental manner. It maps the different relationships by being exposed to a set of examples of the behaviour concerned, by allowing the data to speak for itself.

In reality, the driver continually reviews the driving situation. As the driver moves, his/her brain receives a stream of consecutive images representing a stream of traffic patterns, which is directly processed in the brain. The driver behaviour resulting from the input is based on a learned reaction to a particular situation described by the input and can be represented by a modelling technique that closely follows this process. Hence, the neural network approach is possibly a better solution in modelling the driver behaviour, as the network itself would develop the relationships.

5.3 DATA COLLECTION

The information required to be collected for development of car following models include type and speed of the subject vehicle, type and speed of the lead vehicle and distance between the two vehicles at successive time intervals. Video graphic method was adopted for collection of data as it offers many advantages. A road section free from interruptions such as cross roads, bus stops, etc, was
selected. The video camera was set up on the top of an adjacent seven storey building and was adjusted to get a clear view for about 50 m length of the road. To facilitate easy retrieval of accurate information regarding speed, linear and lateral clearances, paint markings were made at intervals of 5 m in the longitudinal direction for 50 m length and 1 m in the lateral direction on the chosen road surface. For the purpose of retrieval of required data, the video input was fed to a computer provided with a frame grabber card and software that enables to capture and digitise the frames of taped video. The sequences of captured images were then stored as AVI (Audio Video Interweaved) files. The following details were noted from each frame, making use of the grids marked on transparent sheet, which was pasted on the monitor.

i. Longitudinal position of subject vehicle and its type.

ii. Longitudinal position of the vehicle in the front and its type.

The speeds of vehicles in metres per second were determined by finding the difference in respective positions of vehicles in the subsequent frames. The determined speeds were then converted to kilometres per hour.

5.4 RESPONSE – STIMULUS MODELS

Car-following models, which are of the form of stimulus-response equation, are generally used to describe the behaviour of drivers in a traffic stream. These models give the acceleration of the vehicle depending on its relative position with respect to the lead vehicle. These models are of the form:

\[ \text{Response} (t + \tau) = \text{sensitivity} \times \text{stimulus} \quad \text{Eqn. 5.2} \]
The third generation model among the models proposed by General Motor's research team was used in this study for the comparative evaluation of the performance of neural network models. Equation 5.1 gives this model.

The model was developed by the regression analysis of the observed data for which the dependent variable was the acceleration of the following vehicle in the present interval and the independent variables were the relative speed and the relative headway between the lead and the following vehicles. The values of the sensitivity parameter estimated during calibration were used along with explanatory data to predict the acceleration values. These acceleration values were then used to determine the corresponding speeds for comparing the same with that of the outputs of neural network model.

5.5 NEURAL NETWORK MODEL

The neural network models of driver behaviour with regard to speed changes were developed using the software package called MATLAB (Matrix laboratory), of Mathworks Inc. For this purpose, a partially recurrent neural network proposed by Elman (1990) was used. Elman Recurrent Networks (ERN) are two layer back propagation networks with the addition of a feedback connection from the output of hidden layer to its input. This feedback path allows Elman networks to learn, to recognise and generate temporal patterns as well as spatial patterns. Using Neural Net toolbox of MATLAB, the ERNs can be trained with momentum and adaptive learning rate.

To arrive at the appropriate network architecture, trial models were developed by varying the number of neurons in the hidden layer. It was observed, as shown in Fig. 5.1, that the performance of the neural networks improved with the increase
in number of neurons up to certain level and then deceased. It was also observed that when the number of hidden neurons exceeded 100, the network showed a tendency to get trapped in local minima and to reach premature saturation. Hence, for large sized data sets, the number of hidden neurons was limited to 50.

![Graph](image)

**Fig 5.1 Performance Curve for Various Number of Hidden Neurons**

### 5.5.1 Representation of Vehicles in Neural Model

Experiments were also done by representing the vehicles by simple numbers, by PCU values or by binary representation. When the type was represented in the binary form, each type representation required 1 input node, i.e. if eight modes are considered then eight nodes will be required. The network was thus unable to understand the function as the number of input nodes increased considerably.
and the performance was very poor. As presented in Table 5.1, when the vehicle type was represented by a simple number, the performance of models both at the time of training and testing was better than that of other representations.

<table>
<thead>
<tr>
<th>Description</th>
<th>Training</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Size</td>
<td>85</td>
<td>25</td>
</tr>
<tr>
<td>All variables excluding vehicle type</td>
<td>0.44</td>
<td>75.69</td>
</tr>
<tr>
<td>All variables (Vehicle type represented by simple numbers)</td>
<td>0.44</td>
<td>28.35</td>
</tr>
<tr>
<td>All variables (Vehicle type represented by PCU values (Nagaraj et al, 1990))</td>
<td>0.44</td>
<td>32.37</td>
</tr>
<tr>
<td>All variables (Vehicle type by binary representation)</td>
<td>0.44</td>
<td>56.96</td>
</tr>
</tbody>
</table>

Models were developed by both neural networks and conventional car following method (GM Model), using the data for all types of vehicles. The input vector for neural models consisted of data regarding all variables in previous interval and the output was the speed of the selected vehicle in the present interval. The performance curve given in Fig. 5.2 shows the change in error with respect to the number of iterations (epochs) during training.

Fig. 5.2 Performance curve considering all types of vehicles during
5.6 COMPARISON OF NEURAL AND CAR FOLLOWING MODELS

The models thus developed were used to predict the speed values for the validation data set. The percentage RMS error for predicted speeds of vehicles were computed and comparison was made for the performance of both the models.

Table 5.2 gives the results obtained from neural and car-following models. It could be observed that the overall performance of neural models was better than that of car-following models. The performance of both models in predicting the speeds of each vehicle type was also compared. It was found that neural models performed better than car-following models during both training and validation stages. Thus the neural network models were found to be superior to the conventional car-following models.

<table>
<thead>
<tr>
<th>Description</th>
<th>Neural Models</th>
<th>Car-Following Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training sample size</td>
<td>1166</td>
<td>883</td>
</tr>
<tr>
<td>Test sample size</td>
<td>350</td>
<td>289</td>
</tr>
<tr>
<td>No. of training epochs</td>
<td>2300</td>
<td></td>
</tr>
<tr>
<td>Sensitivity of car-following model</td>
<td>-</td>
<td>0.4018</td>
</tr>
<tr>
<td>% RMS error for training data</td>
<td>15.57</td>
<td>21.55</td>
</tr>
<tr>
<td>% RMS error for test data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All types of vehicles combined</td>
<td>18.11</td>
<td>23.63</td>
</tr>
<tr>
<td>Auto-rickshaw</td>
<td>19.31</td>
<td>21.05</td>
</tr>
<tr>
<td>Two-wheelers</td>
<td>13.73</td>
<td>14.58</td>
</tr>
<tr>
<td>Car</td>
<td>16.78</td>
<td>15.99</td>
</tr>
<tr>
<td>Jeep</td>
<td>23.60</td>
<td>31.99</td>
</tr>
<tr>
<td>Van</td>
<td>23.70</td>
<td>28.32</td>
</tr>
<tr>
<td>Bus</td>
<td>23.61</td>
<td>32.11</td>
</tr>
<tr>
<td>Trucks</td>
<td>17.55</td>
<td>20.08</td>
</tr>
</tbody>
</table>
Validation of the models was also carried out by comparing the frequency distribution diagrams of predicted and observed speeds for test data. The predicted speeds obtained from neural models came, almost, in the same range as the actual speeds, whereas for car-following models, the variations were more pronounced for each category.

The experiments conducted to understand the speed changing decisions of the vehicle drivers indicated that the speed of the subject vehicle in the previous interval is the most influencing variable. However, in order to model the acceleration/deceleration characteristics, it was thought necessary to give the speed of subject vehicle for one more than previous time periods, so that the effect of previous time history could be taken care of. It is because of this experiments were repeated by giving information pertaining to the subject vehicle for previous three time intervals (interval of one second each).

Corresponding to the number of previous time period data which were supplied for modelling three models could be built. In Model 1, apart from information on other influencing variables, only the speed in the previous one second of the subject vehicle was provided. In Model 2, the speeds of the subject vehicle in the two previous time intervals were also given. Similarly, in Model 3 the speeds of the subject vehicle in the previous 3 second intervals were also supplied. Table 5.3 shows the percent RMS errors of the three models.
Table 5.3 Comparison of the three models

<table>
<thead>
<tr>
<th>Description</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Data Sample</td>
<td>420</td>
<td>420</td>
<td>420</td>
</tr>
<tr>
<td>Test Data Sample</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td>% RMS error for training data</td>
<td>17.91</td>
<td>17.91</td>
<td>17.91</td>
</tr>
<tr>
<td>% RMS error for test data</td>
<td>28.3</td>
<td>23.67</td>
<td>19.85</td>
</tr>
</tbody>
</table>

It could be clearly seen that model 3, which has the information on the speeds of the subject vehicle in the three previous intervals, had a lesser percent RMS error, confirming that improved driver behaviour models could be built with better information support from the past travel history. Comparison of frequency distribution diagrams of predicted and observed speeds further reinforced this idea. From Fig. 5.3 it can be observed that when the speed data of the previous three intervals are included in the input, the predictive ability of the model has improved remarkably.

However, this inference could not be generalised, because it was noticed that the models became more and more disturbed with information other than speeds in the previous few time intervals were also supplied. Perhaps, this is what could be expected from a human mind which is bombarded with lot of information, but at the same time because of its limitation it is unable to assimilate the complete information.
Fig 5.3a Speeds of a car at successive intervals

Fig 5.3b Speeds of a car at successive intervals
5.7 CONCLUSIONS

Development of car following models based on real life data and using the response-stimuli approach and the neural network technique is presented in this chapter. The neural models have proven to give more realistic results than car-following models in describing the driver behaviour while following another vehicle. The performance of neural network model improved when presented with history of speeds in previous intervals.