Experimental Analysis of Car Following Dynamics and Traffic Stability

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ABSTRACT

The study on car following dynamics is useful for capacity analysis, safety research and traffic simulation. Besides, there are growing interests on its applications in Intelligent Transportation Systems such as Advanced Vehicle Control and Safety System (AVCSS) and Autonomous Cruise Control System (ACC). A large number of car following models have been developed in the last five decades. Some of them were investigated and validated against experimental data; nevertheless the results were not that consistent for some models e.g. those for General Motors (GM) model. As a part of problem, the data acquisition and calibration techniques were not much advanced then. The last few decades have seen remarkable advancements in these techniques e.g. differential GPS for position measurement, Doppler's principle for speed measurement, genetic algorithm for optimization etc. It might be useful to reassess some outstanding issues in the car following dynamics in the light of these latest technological advancements. This paper attempts to investigate the dynamics based on the RTK GPS data collected from test track experiments. The GM model was evaluated along with some well-known simulation models including Gipps model and Leutzbach model. A genetic algorithm based optimization technique was adapted for calibration. The sensitivity of drivers towards their speed and spacing from the vehicle ahead were found varying among drivers. The interpersonal variations in the model performance were significant. The GM model parameters were identified with improved reliability. The stability of traffic flow was analyzed experimentally.

Keywords: car following, GM model, traffic stability, differential GPS, genetic algorithm

INTRODUCTION

The early investigation on car following dynamics was pioneered by Pipes (1) and Reuschel (2) almost half century ago to model the interaction between adjacent vehicles in the same lane. Later, Chandler et al. (3) proposed a linear model based on stimulus-response concept that eventually lead to the development of generalized General Motors (GM) model after a series of investigations from Herman et al. (4), Gazis et al.(5), Herman et al. (6), and Gazis et al. (7).

Chandler model:

$$a_n\,(t+T) = \lambda\;\Delta v\,(t) \tag{1}$$

Generalized General Motors model (GGM):

$$a_n\,(t+T) = \alpha\;\frac{v_n\left(t+T\right)^m}{\Delta x\,(t)^{\ell}}\;\Delta v\,(t) \tag{2}$$

In equation (1), $a_n\,(t + T)$ is acceleration at a time delayed by response time T, $\Delta v\,(t)$ is relative speed and λ is sensitivity factor. In equation (2), $v_n\,(t + T)$ is speed, $\Delta x\,(t)$ is spacing with respect to the vehicle ahead and α, m and l are sensitivity parameters. A high correlation between acceleration and relative speed revealed from the experimental investigations then and afterwards strengthened the concept; however the model is often criticized for two reasons. Firstly, a single stimulus term i.e. relative speed (Kikuchi et al. (8)), and secondly for the contradictions on its calibration (Brackstone et al. (9)). Some researchers have proposed modifications in the GM model adding some additional stimuli terms e.g. those proposed by Addison et al (10), Gurushinghe et al. (11) and Sultan et al. (12), while they are yet to be validated.

The stability of traffic flow can be studied from two view points: local and asymptotic, both are concerned with the propagation of disturbances in the motion of vehicles down the traffic steam. It is local if only the immediate following vehicle is considered and asymptotic if a line of following vehicles are considered. Chandler et al. (3) derived the criterion for asymptotic stability numerically, based on their linear model. It was stated that for $\lambda T>0.5$ any initial perturbation to an equilibrium state will grow as it passes down a platoon of vehicles, though it could not be validated for some drivers. Ferrari (13) showed that it might take too long for the instability to grown enough to cause a flow break down. Zhang et al. (14) extended the stability criterion to accommodate interpersonal variations in the response time and sensitivity factor. Most of the previous investigations on traffic stability are based on either theoretical or numerical approaches, while there are only a few that investigated the stability experimentally.

The last few decades have witnessed remarkable advancements in data acquisition and calibration techniques e.g. differential GPS for position measurements, Doppler's principle for speed measurements, genetic algorithm for optimization etc. It is now possible to acquire high resolution car following measurements more precisely and more conveniently than ever before. It might be useful to investigate some previously developed car following concepts in the light of these latest technological advancements. This paper attempts to evaluate the GM model and some well- known simulation models including Gipps model (15) and Leutzbach model (16), based on the data taken from test track experiments.

The specific objectives of this paper can be outlined as follows:

- Investigate car following dynamics based on experimental data
- Evaluate the performance of car following models
- Identify and characterize the GM model parameters
- Analyze traffic stability based on experimental data

The models investigated are described in the next section. A Genetic Algorithm (GA) based optimization method is proposed in section three. The data used in this study is described in section four. The analysis results are presented in section five under the subheadings: model comparison, parameter identification and stability analysis. Finally, the outcomes of this study will be summarized and discussed in the last section.

CAR FOLLOWING MODELS

GM Model

A great deal of investigation works were performed in the past to calibrate and validate the GM model, a summary is presented in Table 1 (Brackstone et al. (9)). The proposed optimal values for the sensitivity parameters m and l vary over a wide range. It might be useful to look into the details of these investigations to interpret those variations. The first two investigations by Chandler et al (3) and Herman et al. (6) were based on the data taken from wire linked vehicles, a primitive data acquisition technique. Such data potentially contains high measurement error. The aerial techniques used by Treiterer et al. (17) and Ozaki et al. (18) also have limitations as the frame size of vehicles decreases with increase in the field of view i.e. distance measurement error also increases. The computation acceleration from such data potentially yields even larger error. It shall be noted that almost half of these investigations are based on microscopic approach i.e. using car following data and the GM model for calibration (as shown in the rightmost column), while others are based on macroscopic approach i.e. using aggregate data and steady state equations derived from the GM model. The calibration methods adapted were also different as some preferred least square method while others used nonlinear methods. The reliability of these methods in the case of GM model is yet to be confirmed, as there are cases where they yield unstable results. Gurushinghe (19) found the least square method producing low R^2 values for the GM model, using the same data sets as used in this study. The traffic conditions represented were also different e.g. Aron (20) used congested urban street data while Ozaki (18) used high speed motorway data. The data were treated differently e.g. Hoef (21), Treiterer et al. (17), Aron (20) and Ozaki (18) analyzed acceleration / deceleration separately while no such consideration were made in others. With such a diversified data, approaches, calibration methods it is not wise to expect consistent results. In this study, the chandler model and generalized GM model presented earlier will be calibrated using the test track data representing a simple driving condition and a genetic algorithm based optimization method.

Most of the previous investigations ignored the possibility of intrapersonal variations in the response time, while Gurusinghe et al. (11) have recently proposed a graphical method to estimate time variant response time. The concept of this method is illustrated in Figure 1. The time difference between a peak point in relative speed time series (stimulus) and the consecutive peak point in acceleration time series (response) gives the value of response time at that time. Ranjitkar et al. (22) estimated a large number of instantaneous response time data based on this method using a computer program. The same data sets will be used to calibrate the GM model using instantaneous response time, termed here as GMIT.

Additionally, a modified GM model proposed by Sultan et al. (12) will also be evaluated. This alternative is termed here as MGM, modified GM model. The model formulation was given as follows,

$$a_n(t+T) = \alpha \frac{v_n(t+T)^m}{\Delta x(t)^{\ell}} \Delta v(t) + k_1 * a_{n-1}(t) + k_2 * a_n(t) \tag{3}$$

Where, a_n (t) and a_{n-1} (t) are the accelerations of the following vehicle and the vehicle ahead.

Gipps Model

The Gipps model (15) is a safe distance based car following model, widely used for simulation. Ranjitkar et al. (23) and Brockfeld et al. (24) found this model performing well compared with some other models tested. The model formulation was equivalent to,

$$v_n(t+T) = \min\left\{ \begin{array}{l} v_n(t) + 2.5aT(1 - v_n(t)/V_n)\sqrt{0.025 + v_n(t)/V_n}, \\ bT + \sqrt{b^2T^2 - b\{2[x_{n-1}(t) - x_n(t) - s]v_n(t)T - v_{n-1}(t)^2/b^*\}} \end{array} \right\} \tag{4}$$

Where, T is following driver's response time, a is maximum acceleration rate, b is maximum braking rate, V_n is desired speed, s is jam headway, and b^* is assumed braking rate of vehicle ahead.

Leutzbach Model

Leutzbach et al. (16) proposed this model, which is based on psychological concept. This model is also popular for simulation. The model formulation was equivalent to,

$$a_n(t+T) = \frac{\Delta v(t)^2}{2[S - \Delta x(t)]} + a_{n-1}(t) \tag{5}$$

Here S is the minimum desired following distance and $a_{n-1}(t)$ is the acceleration or deceleration of the vehicle ahead.

CALIBRATION METHOD

Calibration is the optimization of model parameters against a given data set so that the model can make better predictions. There are several optimization methods available for this purpose e.g. least square method, non-linear methods, random search methods etc. A common problem with many optimization methods is that they get trapped in local minima. Genetic algorithm (GA), a random search based optimization technique is well recognized for being effective in escaping local minima particularly when the objective function have a lot of peaks. GENECOP III, a GA based optimization program proposed by Z. Michalewicz (25) is adapted in this study to optimize the car following models using acceleration as the objective variable. A percentile error function is used as the objective function to be minimized.

$$J(e) = \mathrm{Min}\frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{\sum_{i=1}^{n}|y_i|} \tag{6}$$

Here, y_i and $\hat{y}_i$ are the measured and estimated values for the objective variable and n is the total number of data points in a given data set. The estimated values $\hat{y}_i$ are computed using the respective model formulation providing position, speed, and acceleration time series data of the vehicle ahead as input. The value of percentile error computed after optimizing the model parameters will be used to evaluate the performances of the models under consideration.

The following boundary conditions are used for optimization,

- Response time (T) = 0.5 to 3 sec
- Maximum acceleration (a) =1.5 m/sec^2
- Maximum deceleration (b and b*) = - 4.5 m/sec^2
- Desired speed (V_n) = 20 to 25 m/sec
- Jam headway (s) = 7.5 m
- Minimum desired spacing (S) = 10 to 50 m

The constraint used to avoid collision is:

$x_{n-1} \geq x_n$ + minimum gap

It shall be noted that some models have additional free parameters e.g. 2.5 and 0.025 in the Gipps model, and 2 in Leutzbach model. These are rather arbitrarily chosen as proposed by their developers.

GPS DATA

The data used in this study was taken from car following experiments conducted in a test track. Test track was chosen mainly to ensure a simple driving condition so as to extract the essence of car following behavior. Figure

2 (a) depicts the schematic layout of the test track that consists of two 1.2 km long straight sections connected by two semicircular curves 150 m each. Ten passenger cars were participated in these experiments each equipped with Real Time Kinematic (RTK) GPS receivers. Several speed patterns were tested for the lead driver emulating uninterrupted driving conditions of real world. Figure 2 (b) depicts those patterns among which , the first four are sine wave speed patterns with the wave lengths varying from 267 m to 1600 m, while the last two are random and constant speed patterns. The lead driver was an experienced driver at his 50's, while the followers were young college students aged between 22 to 30. The drivers were arranged in platoon in two different order patterns A and B. For patterns A, the drivers were arranged in an order with D1 as the leader followed by D2, D3, D4, D5, D6, D7, D8, D9 and D10. For pattern B, they were arranged as D1 followed by D8, D7, D6, D5, D4, D3, D2, D9 and D10.

The RTK GPS receivers output position and speed data at every 0.1 second interval. It has a position accuracy of 10 mm + 2ppm and speed accuracy of less than 0.2 km/h. Gurushinghe et al. (26) have confirmed the accuracy of spacing, speed and acceleration data computed from RTK GPS measurements, after comparing them with those taken by distance meter, speedometer and accelerometer. The acceleration data was computed from speed measurements by polynomial fitting technique (Suzuki et al. (27)). These data represents a wide range of uninterrupted driving conditions with speed typically ranging from 20 km/h to 100 km/h and spacing ranging from 10 m to 70 m. Table 2 presents the number of data sets used in this study from each speed patterns. In total 47 data sets are used 20 from pattern A and 27 from pattern B. Each data set represents a single run in a straight section of the test track. For further details on these experiments and data sets please refer Gurusinghe et al. (26), Ranjitkar et al. (28).

ANALYSIS RESULTS

Figure 3 presents the scatter plots of average sensitivity versus average spacing, separately for individual drivers averaged based on speed patterns. In these figures, only the driver D8 have better R^2 values that stands at 0.73, while for the rest of drivers this value is much lower. The regression line shows slightly decreasing trend in the most of the cases indicating that the drivers' sensitivity decreases with increase in the spacing between vehicles. The drivers D3 and D4 are exception to this trend, though the R^2 values remained as lower as below 0.1 in these two cases.

Figure 4 presents the scatter plots of average sensitivity versus average speed, separately for individual drivers averaged based on speed patterns. In these figures, the drivers D4, D6 and D8 have better R^2 values ranging from 0.5 to 0.8, while for the other drivers this value is lower than 0.5. The regression line shows slightly increasing trend for the drivers D3, D4, D5 and D6, while the trend is just opposite for the other four drivers.

These observations suggest that the sensitivity of drivers toward their own speed and spacing with respect to the vehicle ahead varies from drivers to driver for the range of driving conditions analyzed in this study.

Model Comparison

Table 3 presents the mean, standard deviation and coefficient of variation of the optimal values computed for the model parameters using the respective models' formulations. For, the Chandler model, Gipps model and Leutzbach model, the optimum values varies within 50% of the mean optimum value, while for other model these variations are relatively higher. Among the different alternatives for the GM model, the optimum values for the sensitivity parameters m and l is distributed with in a narrow range in the case of GMIT compared with those for the other alternatives.

Figure 5 presents the percentile error in acceleration prediction for each model. The first figure 5 (a) shows the bar charts of the percentile errors computed, separately for each model and individual drivers. The model performance differs from driver to driver. The percentile errors computed for the drivers D8 and D9 are relatively lower for all models, while the same computed for the driver D4 is relatively higher. This indicates the individual influence of drivers. The different alternatives for the GM models perform well and closely, while GMIT produces relatively lower percentile error than other models in all cases. In the later figure 5 (b), which presents cumulative distribution of the percentile error for each model, similar results can be observed. The different alternative for the GM models have performed better here also. The chandler model, GGM and MGM have performed closely, while GMIT have produced the lowest percentile error in overall analysis. The Gipps model and Leutzbach model have produced relatively higher percentile error.

Figure 6 presents a typical case of acceleration time series along with the predicted time series using the Chandler model, GGM and Gipps model. The three predicted time series lines are running close to the actual time series except near the peaks, while there are some small fluctuations in the case of Gipps model. This might be the reason for the higher percentile error computed for the model.

Parameter Identification

Figure 7 (a) depicts the cumulative distribution of R^2 values presented by Gurushinghe (19) for the GM model based on least square method. The R^2 values remained under 0.2 for nearly 80% of the cases. Figure 7 (b) presents the cumulative distribution of R^2 values using GMIT and GA based optimization method. In this case, only 20% of the cases have R^2 values under 0.8. This is a significant improvement in the calibration results compared with the former case using least square method. This approves the efficiency of GA in the case of GM model.

Figure 8 presents the frequency distribution of the optimal values computed for the sensitivity parameters m and l in the case of GMIT. The actual distribution is compared with some theoretical distribution patterns. The lognormal distribution looks closer to the actual distribution in these figures. Table 4 presents the results of chi-square goodness of fit test for both the parameters. The estimated chi-square values are much higher than the critical one in the case of normal distribution. While in the case of lognormal distribution, the estimated chi-square value is lower than the critical value for the parameter l and just over the critical value for the parameter m.

Stability Analysis

Figure 9 presents a typical example of acceleration time series plots for the first four vehicles taken from the three wave speed pattern. It includes also the values computed for the sensitivity factor, average response time and stability factor ($C=\lambda T$) for all following vehicles. From the first two figures, the amplitude of acceleration fluctuations has increased as the dynamics passes down from D1 to D2. This indicates that the response of the following driver D2 is unstable. The stability factor computed for the driver D2 stands at 0.88 that exceeds the boundary value 0.5, indicating the unstable response of the driver D2 both locally and asymptotically. The results based on time series analysis have matched with those based on numerical criterion in this case and other cases also as seen in these figures. In overall analysis also the time series results were closely matching with those based on numerical criterion, this approves the validity of the numerical criterion derived from the GM model. The majority of drivers were found to have unstable responses. This might be due to the closer spacing the preferred to maintain.

SUMMARY AND DISCUSSION

The microscopic approach has given more importance in traffic and safety engineering in recent years. Federal Highway Administration has proposed a Next Generation Simulation (NGSIM) program (29) in an effort to develop core research in behavioral algorithms to support traffic simulation with a primary focus on microscopic model. The car following data has been emphasized for the calibration and validation of such algorithms. This paper has investigated the car following dynamics based on the GPS data collected from test track experiments. Some well-known car following models are evaluated based on how well they can predict the accelerating / decelerating behavior of the following drivers. A genetic algorithm based calibration method is adapted for calibration. It shall be noted that all the results obtained in this study are based on a simple driving condition and they can not be generalized for real world cases, where the traffic conditions are much more complicated than the one analyzed.

The sensitivity of drivers towards their speed and spacing from the vehicle ahead were found varying among drivers. The interpersonal variations in the model performance were significant in the most of cases. The chandler model performed better than some more sophisticated models. The use of instantaneous response time instead of the constant one improved the performance of the GM model to a great extent.

The GM model is calibrated with improved reliability. The genetic algorithm has proved effective for the calibration of the models under consideration. The sensitivity parameters m and l were found distributed in lognormal function. The stability criterion derived from the GM model found closely approximating the actual traffic conditions. Most of the drivers had unstable response both locally and asymptotically. It might be due to the closer spacing they preferred to maintain.

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TABLE 1 Summary of optimal values for sensitivity parameters m and l proposed by previous researchers

Source	m	l	Approach
Chandler et al. (3)	0	0	Micro
Herman et al. (6)	0	1	Micro
Helly (17)	1	1	Macro
Gazis et al. (7)	0-2	1-2	Macro
May et al. (18)	0.8	2.8	Macro
Heyes et al. (19)	-0.8	1.2	Macro
Hoefs (23) (dcn no brk/dcn brk/acn)	1.5/0.2/0.6	0.9/0.9/3.2	Micro
Treiterer et al. (15) (dcn/acn)	0.7/0.2	2.5/1.6	Micro
Cedar et al. (20)	0.6	2.4	Macro
Cedar et al. (22) (uncgd/cgd)	0/0	3/0-1	Macro
Aron (21) (dcn/ss/acn)	2.5/2.7/2.5	0.7/0.3/0.1	Micro
Ozaki (16) (dcn/acn)	0.9/-0.2	1/0.2	Micro

Key: dcn/acn: deceleration/acceleration; brk/no brk: deceleration with and without the use of brakes; uncgd/cgd: uncongested/congested; ss: steady state (Source: Brackstone et al. (8))

TABLE 2 Number of data sets used in this study

P.N.	Speed patterns	Drivers' order pattern	
		A	B
1	Half wave	4	6
2	One wave	4	4
3	Two wave	2	6
4	Three wave	4	5
5	Random	4	4
6	Constant speed	2	2
Total		20	27

Table 3 Mean, standard deviation and coefficient of variation of the optimum values for model parameters

Model No.	Models parameters	Mean	Standard deviation	Coefficient of variation
1	**Chandler Model**			
	Response time T, sec	1.13	0.52	46%
	Sensitivity Factor λ, /sec	0.34	0.12	36%
2	**Generalized GM (GGM) Model**			
	Response time T, sec	1.07	0.48	45%
	Parameter α	0.50	0.26	52%
	Parameter m	2.35	2.01	85%
	Parameter l	1.96	1.61	82%
3	**Modified GM (MGM) Model**			
	Response time T, sec	1.81	0.53	29%
	Parameter α	0.48	0.25	53%
	Parameter m	3.32	2.25	68%
	Parameter l	6.08	2.23	37%
	Parameter k1	0.57	0.19	33%
	Parameter k2	0.42	0.19	44%
4	**GM Model with Instantaneous T (GMIT)**			
	Parameter α	0.62	0.30	48%
	Parameter m	1.11	1.47	132%
	Parameter l	1.01	1.23	121%
5	**Gipps Model**			
	Response time T, sec	1.88	0.64	34%
	Braking rate b, m/sec^2	-3.47	0.49	14%
	Maximum speed, V_n, m/sec	22.46	1.85	8%
	Assumed braking rate b^*, m/sec^2	-4.04	0.54	13%
6	**Leutzbach Model**			
	Response time T, sec	2.46	0.47	19%
	Desired headway, m	39.48	18.41	47%

Table 4 Chi-square distribution test results for sensitivity parameters in the case of GM model with instantaneous response time

Model Parameters	Sample	Mean	SD	Normal		Log-Normal	
				χ^2 Estimated	χ^2 5% S.L.	χ^2 Estimated	χ^2 5% S.L.
m	415	1.11	1.47	264.4	22.4	33.1	32.7
l	415	1.01	1.23	245.7	20.1	25.4	32.7

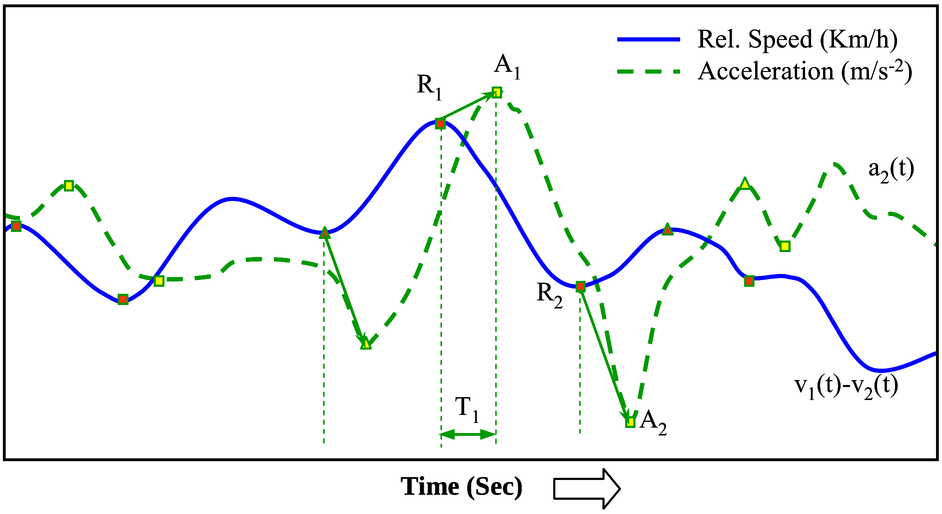
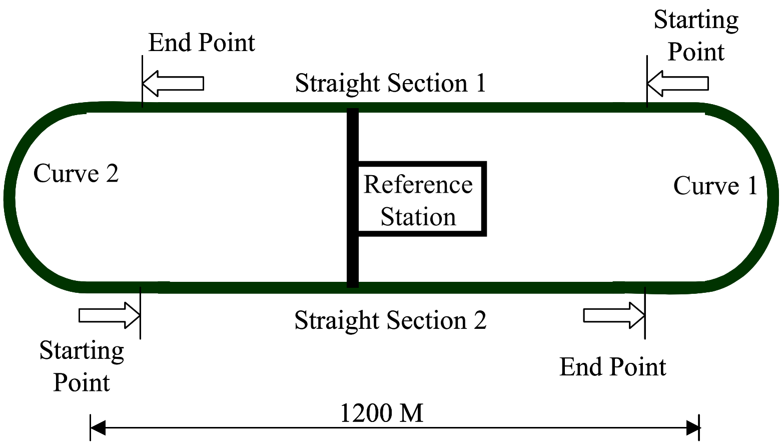
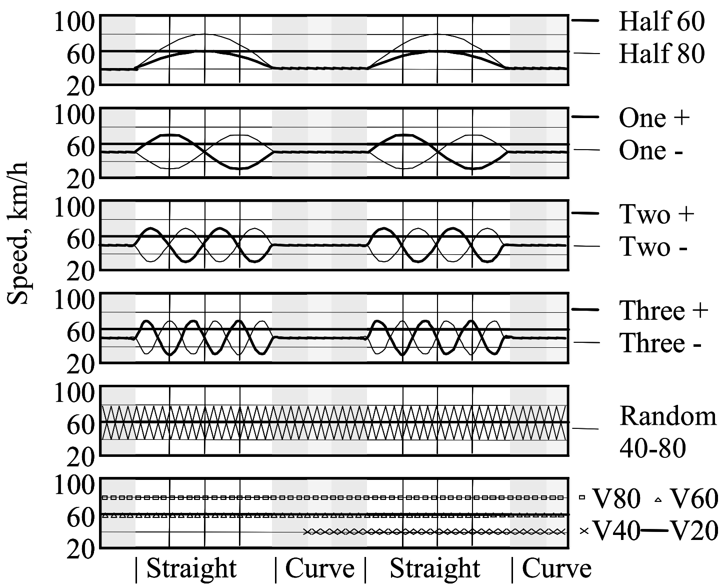


FIGURE 1 Graphical method for the estimation of instantaneous response time



a) Schematic layout of the test track



b) Speed patterns tested for the leader vehicle

FIGURE 2 Details of car following experiments conducted in a test track

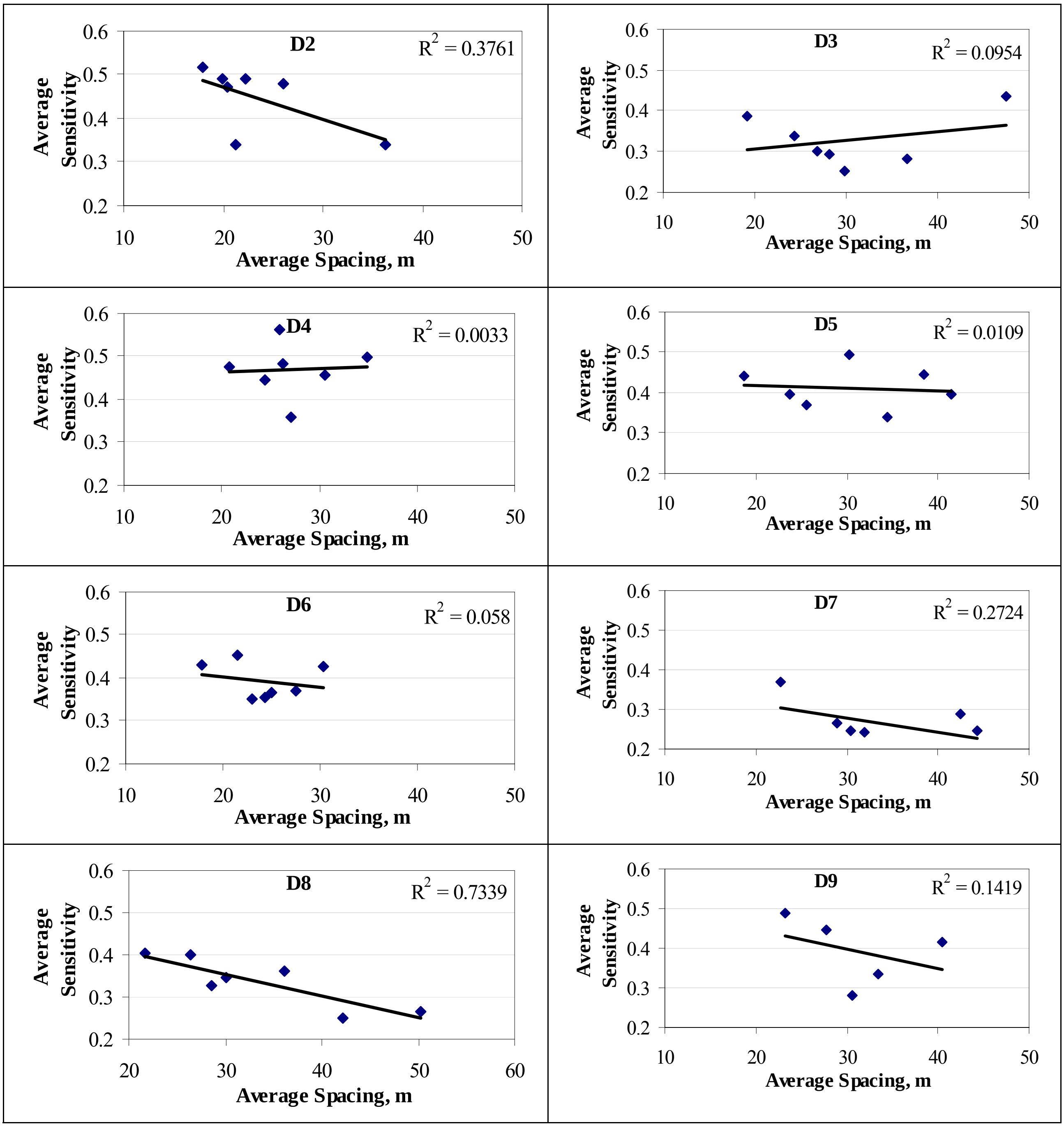


FIGURE 3 Sensitivity factor versus spacing plot

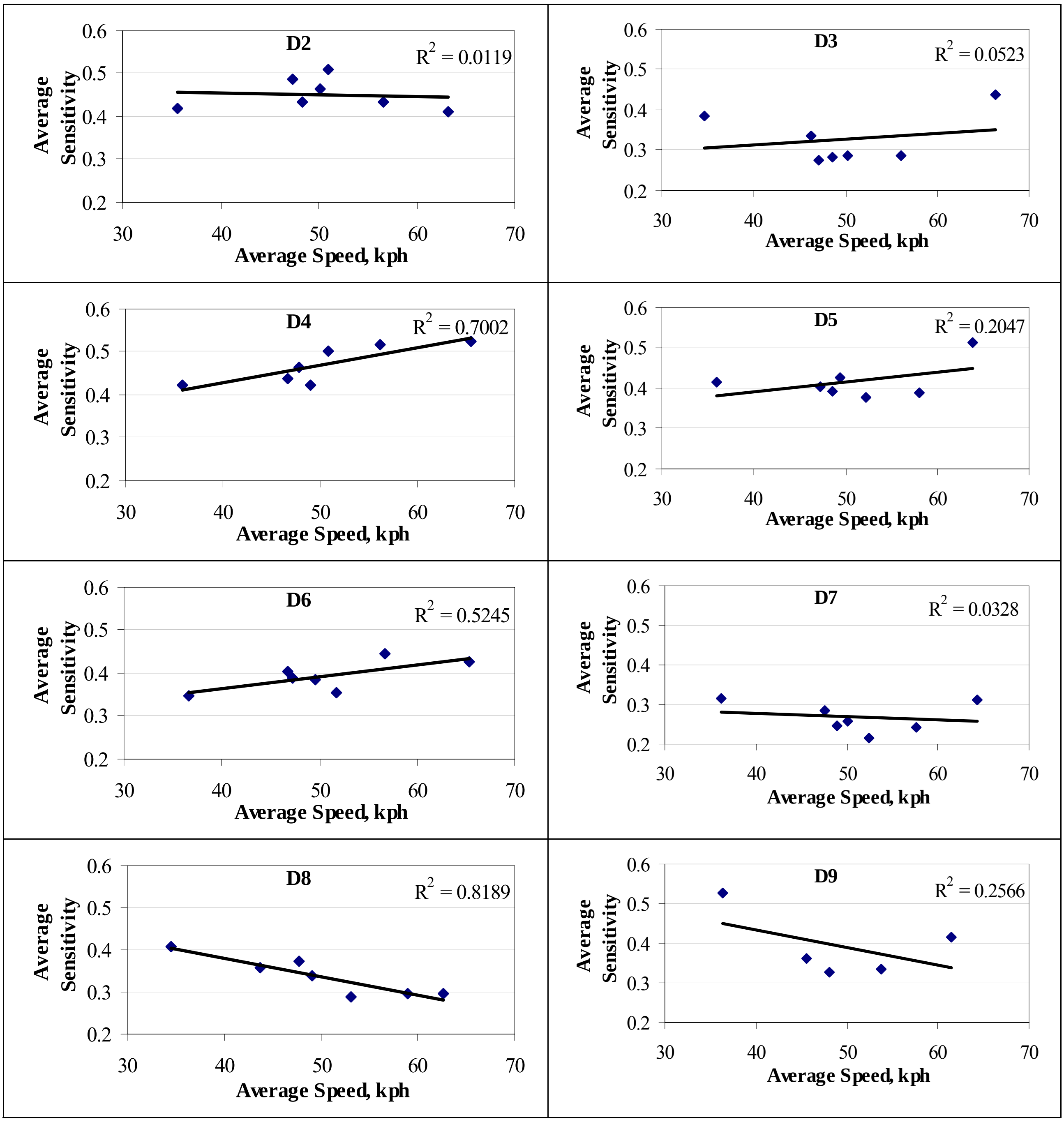
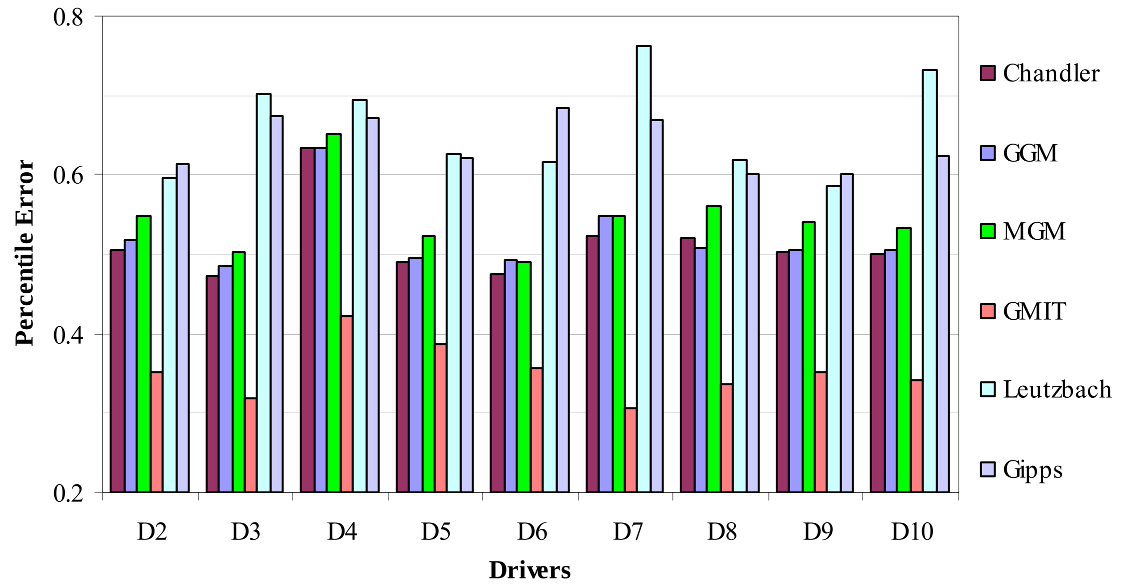
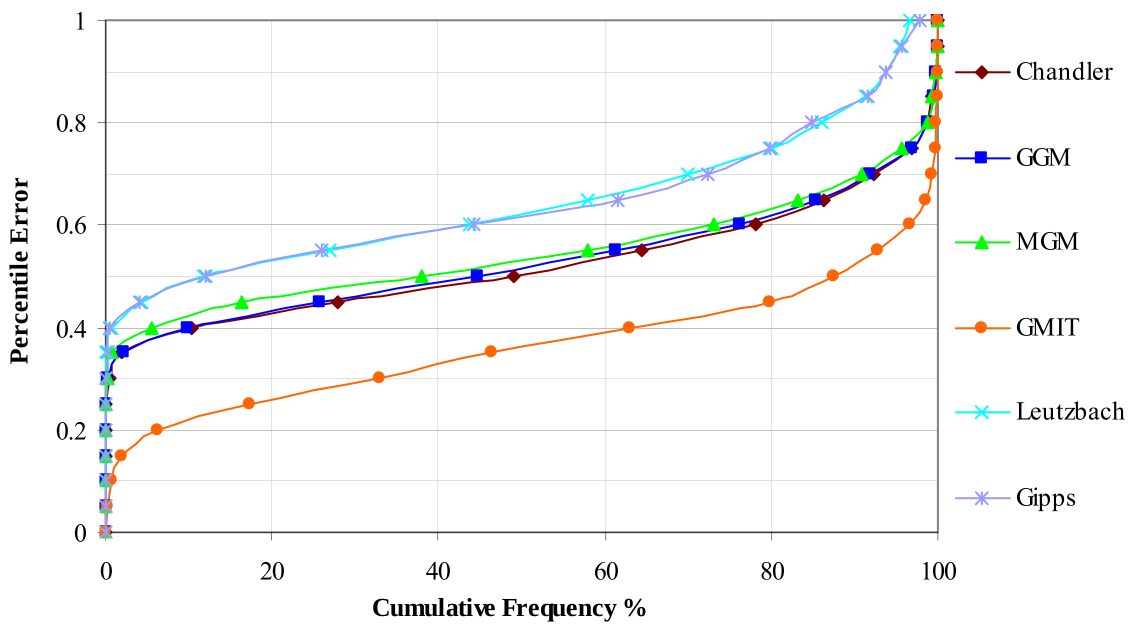


FIGURE 4 Sensitivity factor versus speed plot



a) Bar chart of percentile errors



b) Cumulative distribution of percentile errors

FIGURE 5 Percentile errors in acceleration estimation using car following models

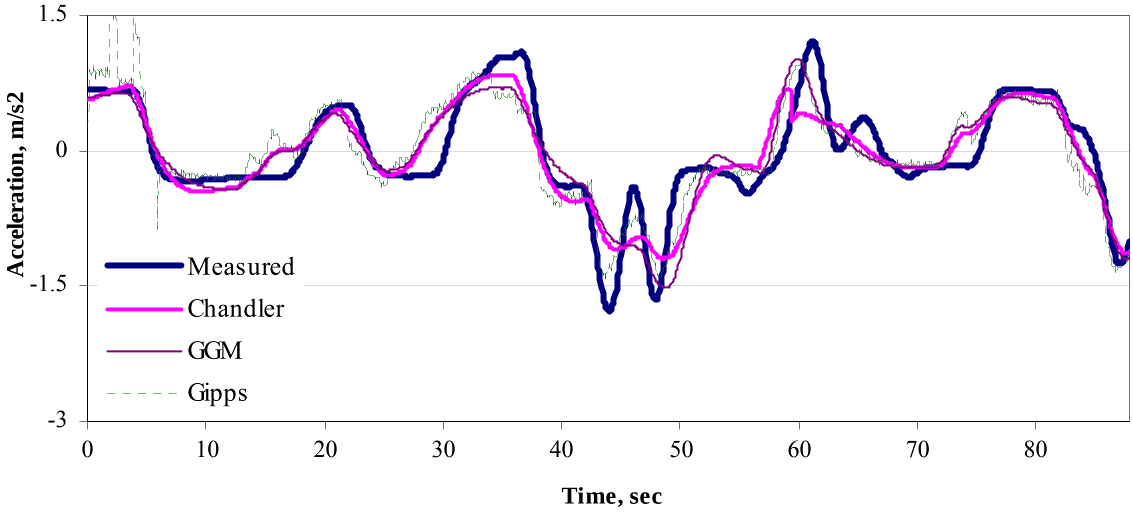
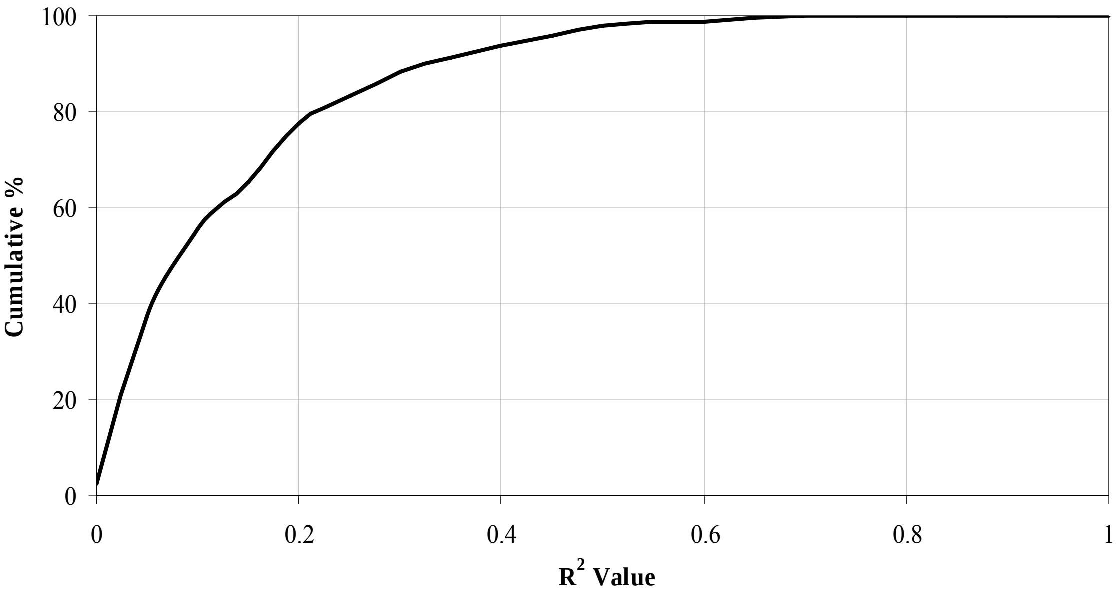
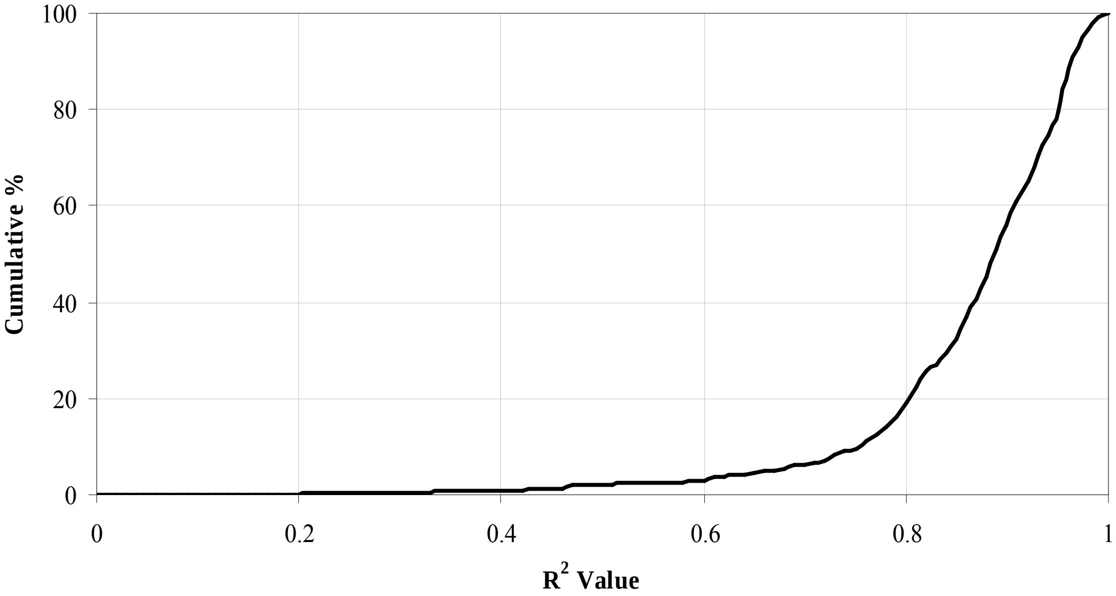


FIGURE 6 A typical acceleration time series using GPS measurement data and those predicted by car following models



a) Using least square method (Source: Gurusinghe (19))



b) Using genetic algorithm

FIGURE 7 Cumulative distribution of R^2 values for the calibration of the GM model

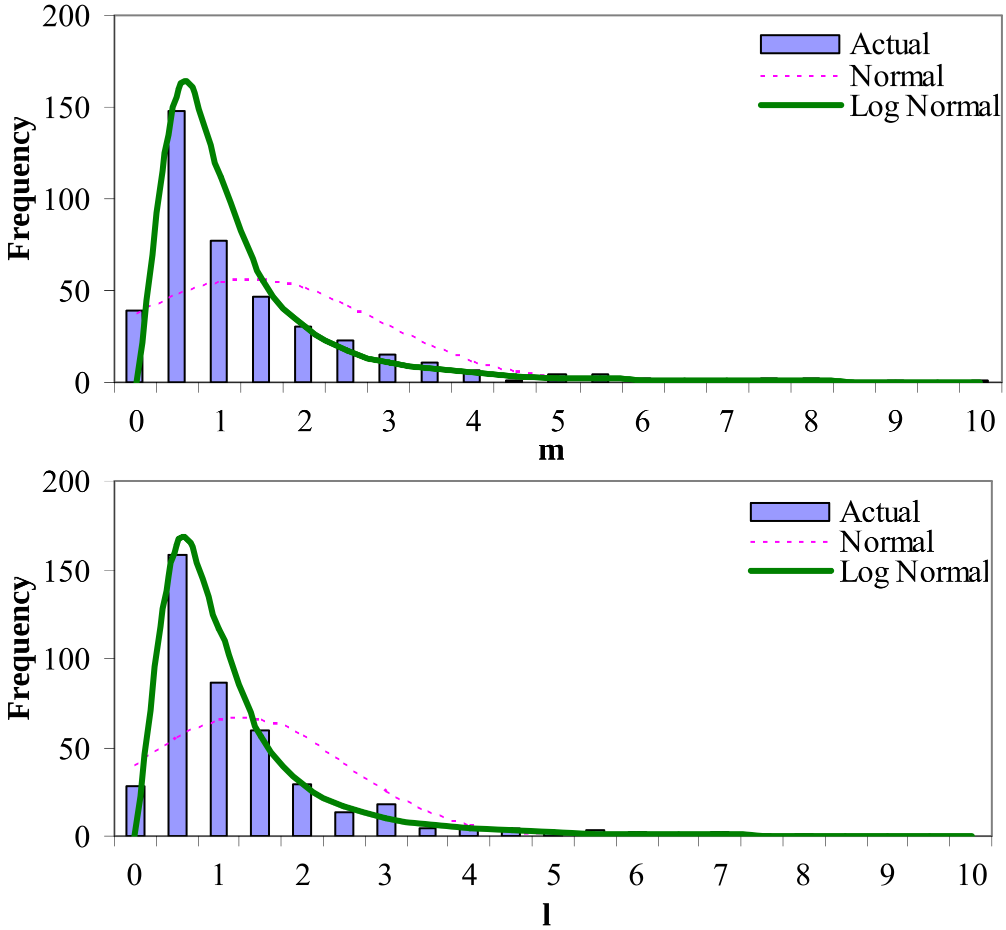


FIGURE 8 Distribution of sensitivity parameters m and l in the case of GM model with instantaneous response time

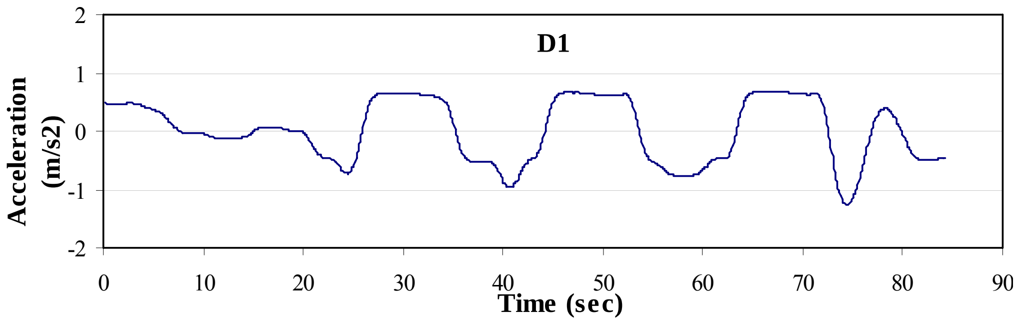
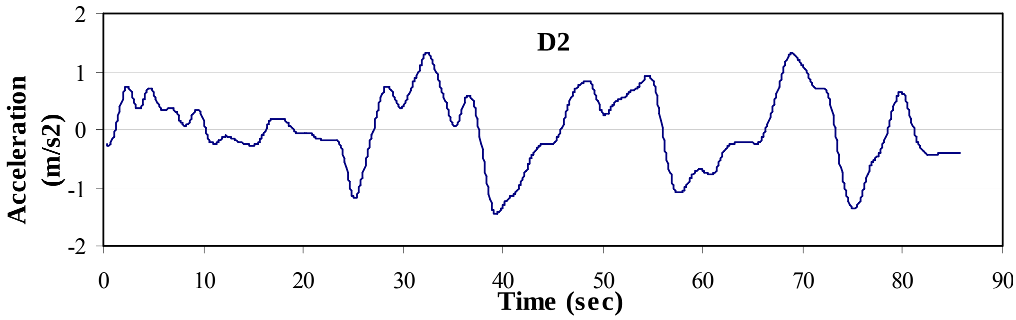
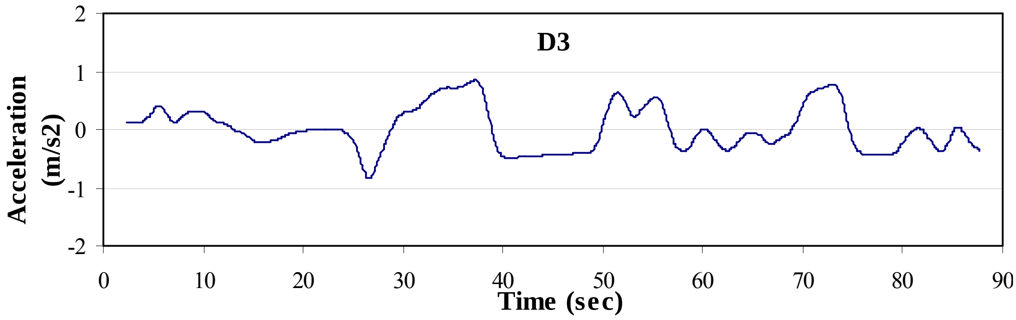
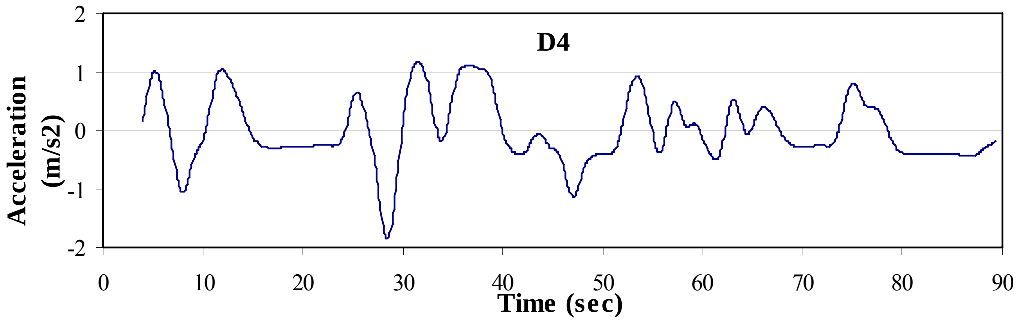
λ	T	λT	Acceleration Time Series
			
0.67	1.31	0.88	
0.27	1.30	0.35	
0.48	1.44	0.70	

FIGURE 9 Validation of stability criteria derived from the Chandler model using acceleration time series