Modelling a vehicle's speed fluctuation with a cellular automata model

J. Zheng, K. Suzuki & M. Fujita
Graduate School of Engineering, Nagoya Institute of Technology, Japan

Abstract

As is well known, a vehicle's speed fluctuation has significant impact on traffic capacity, road safety, fuel consumption, and exhaust gas emission. Considerable microscopic traffic models have been developed in past decades, while the ability of describing the realistic speed fluctuation has rarely been examined. With the data from real traffic, in this study we investigate the performance of two typical car-following models on modelling speed fluctuation. Our findings indicate that neither of them can mimic a realistic speed fluctuation with high accuracy. In addition, it is found that the model with the minimum speed error does not necessarily mean it can describe speed fluctuation most realistically. To simulate this phenomenon more accurately, by introducing a reasonable duration of stable speed, we propose one kind of cellular automata model. Simulation results show that the model depicts a vehicle's speed fluctuation with higher fidelity, relative to two typical models.
Keywords: traffic simulation, car-following model, cellular automata model, speed fluctuation.

1 Introduction

Traffic simulation as an effective tool for traffic system analysis and traffic management has become very popular in recent years. One critical problem, however, in traffic simulation is the reality of the used models, which has had a great effect on the validity of analysis results and correct judgment of traffic strategies. Car-following models and lane-changing models, the most significant components in a traffic simulator, attract a lot of attention from traffic researchers. A number of models have been proposed to describe the phenomena from real traffic more accurately [1–8].

WIT Transactions on The Built Environment, Vol 128, © 2012 WIT Press
www.witpress.com, ISSN 1743-3509 (on-line)
doi:10.2495/UT120321

In 1992, Nagel and Schreckenberg [3] proposed a compelling cellular automaton model (NaSch model) by introducing a randomization term into the deterministic cellular automaton (CA) model, which can reproduce some phenomena in real traffic, such as phase transition in traffic flow and the spontaneous formation of jams. Thereafter, more realistic traffic features have been introduced into this model, for example, slow to start rules [9–11], anticipation effects [12, 13] and braking light effects [14, 15]. However, scarce attention is paid to examine the reality of the randomization term in the NaSch model, which is used to reflect natural speed fluctuation due to human behaviour or varying external conditions. Particularly, the randomization term is the most important term different from the deterministic CA model in the NaSch model.

It is a widely-held and true belief that a vehicle's speed fluctuation has a significant impact on traffic capacity, road safety, fuel consumption, and exhaust gas emission [16, 17]. However, the ability to describe the realistic speed fluctuation of microscopic traffic models was rarely examined in previous studies. In this study, we investigate the performance of two typical car-following models on depicting the realistic speed fluctuations. Our findings show that neither the Gipps model [2] nor the NaSch model [3] can describe the realistic speed fluctuation accurately. In addition, we also find that the model with the minimum speed error does not necessarily mean it can describe speed fluctuation most realistically. In order to overcome this shortcoming of previous car-following models and simulate this phenomenon more accurately, by introducing the duration term of stable speed, we propose an improved CA model. Simulation results show that the speed fluctuation in the improved model is more consistent with the real traffic condition, relative to the Gipps and NaSch model.

This paper is composed of five sections. Two typical car-following models, the Gipps and NaSch model, are briefly introduced in the second section, followed by the definition of the improved model. The simulation results are in the fourth section. The last section is devoted to the conclusion of the study.

2 Car-following models

The concept of car-following was first proposed by Reuschel [18] and Pipes [19], which is assumed that the following vehicle controls its behaviour with respect to the preceding one in the same lane. As one of the most important components in a traffic simulator, in past decades a number of car-following models were developed to mimic this process more consistently with real traffic (see [20] and references therein). In this paper, the performance of the following typical models is discussed.

2.1 Gipps model

Taking safety reaction time into account, in 1981, Gipps [2] developed a car-following model consisting of two components: acceleration and deceleration, using variables corresponding to the obvious characteristics of drivers and vehicles. Assuming that if one vehicle is not affected by its leader, acceleration should increase with speed then decrease to zero as the vehicle approaches the desired speed. The desired speed limitation fitted from field data is presented as:

$$v_n^a(t+T) \le v_n(t) + 2.5Ta_n(1-\frac{v_n(t)}{V_n})\sqrt{0.025+\frac{v_n(t)}{V_n}} \qquad (1)$$

where a_n is the maximum acceleration that the driver in vehicle n wishes to apply and V_n is the desired velocity. And, $v_n(t)$ is the speed of vehicle n at time t, T is the reaction time.

Furthermore, the speed limitation used to avoid collision with the leading vehicle is written as follows:

$$v_n^d(t+T) \le b_nT + \sqrt{b_n^2T^2 - b_n[2(x_{n-1}(t)-s_{n-1}-x_n(t)) - v_n(t)T - \frac{v_{n-1}^2(t)}{\hat{b}}]} \qquad (2)$$

where b_n is the most severe braking that the driver of vehicle n wishes to undertake $(b_n < 0)$, s_{n-1} is the effective size of vehicle n-1 and $\hat{b}$ is the estimation of b_{n-1}.

Combining the limitation (1) and (2), the velocity of vehicle n at time $t+T$ is set as:

$$v_n(t+T) = \min\{v_n^a(t+T), v_n^d(t+T)\} \qquad (3)$$

which can guarantee that drivers achieve the desired speed as far as possible and avoid collision in the meanwhile.

2.2 NaSch model

The CA model is based on a coarse description of driving behaviour by a discrete representation of both time and space. Road lanes are divided into cells of equal size (typically 7.5 meters long). Each cell has two states, occupied or not, depending on the presence of a vehicle. Each time step vehicle's speed and position are updated according to its desired speed and whether there is a vehicle blocking its movement in front. In 1992, Nagel and Schreckenberg [3] introduced stochastic perturbations into updating rules and presented a typical CA model with four rules:

Acceleration, $\tilde{v}_n(t+1) = \min(v_n(t)+1, V_{\max})$ (4)

Deceleration, $\tilde{v}_n(t+1) = \min(\tilde{v}_n(t+1), g_n(t))$ (5)

Randomization, $v_n(t+1) = \begin{cases} \max(\tilde{v}_n(t+1)-1, 0), & if \quad C_{rand} \le P \\ \tilde{v}_n(t+1), & Otherwise \end{cases}$ (6)

Vehicle movement, $x_n(t+1) = x_n(t) + v_n(t+1)$ (7)

where $\tilde{v}_n(t+1)$ is a temporary value and $g_n(t) = x_{n-1}(t) - x_n(t) - 1$. C_{rand} is a random number ranging from [0,1] and P is a given speed reduction probability. $x_n(t)$ is position of vehicle n at time t.

2.3 The improved model

According to driving experiences, it can be keenly evident that drivers always intend to maintain a stable speed during their trips rather than to change speed continuously, in the pursuit of comfortable driving and fuel saving. On the other hand, the emergence of a dangerous gap imposes them to adjust their speed to avoid collision with leading vehicles. And, the increasing gap with the leading vehicle makes the following driver accelerate in order to follow its leader. After such a speed adjustment, stable speed would be retained again and last some time. Obviously, the duration of stable speed has a significant effect on speed fluctuation. The longer the duration of stable speed, the smaller the magnitude of the speed fluctuation. For previous models using a continuous speed variable such as Gipps model, however, stable speed cannot be maintained, since a tiny change in gap can lead to acceleration or deceleration change and then results in speed change. Although the NaSch model uses the randomization term to reflect the speed fluctuation, as shown in the next section, choosing the appropriate randomization probability P is a very tough task, as P does not refer to any obvious drivers' characteristics or traffic flow characteristics. In order to represent such phenomenon in driving behaviour, we introduce the duration term of stable speed to replace the randomization term in the NaSch model. The duration of stable speed here is defined as the time between two successive speed adjustments. Simulation results in the next section confirm the feasibility of this approach at least in terms of modelling speed fluctuation.

The model is defined as follows:

Generating the duration of stable speed, $T_n = Rand(R_1, R_2, R_3, ...)$ (8)

Determining the speed,

$$v_n(t+1) = \begin{cases} \min(v_n(T_n')+1, g_n(t), V_{\max}), & if \quad t = T_n' + T_n \\ \min(v_n(T_n'), g_n(t)), & Otherwise \end{cases} \tag{9}$$

Moving the vehicle, $x_n(t+1) = x_n(t) + v_n(t+1)$ (10)

where T_n' is the time at which the last speed adjustment of the driver in vehicle n occurred. And, if $t = T_n' + T_n$ in this time step, the driver needs to adjust speed, then T_n' is updated to $T_n' + T_n$ in the next time step. In addition, g_n is the same as in the NaSch model. Note that in equation (8) random duration of stable speed for the driver of vehicle n is chosen from several values and the current gap $g_n(t)$ in equation (9) is used to avoid collision with the leading vehicle. When R1, R2, R3 all take the same value, the stochastic model reduces to the deterministic CA model. Moreover, the improved model is as simple as the NaSch model, which implies the model owning a high computational efficiency is also suitable for a larger-scale network simulation and online simulation.

www.witpress.com, ISSN 1743-3509 (on-line)

3 Simulation

3.1 Data set

The trajectory data set used in this study was collected on a segment of interstate freeway I-80 in Emeryville, California, by using several video cameras that were mounted on a nearby high-story building. The data set was provided by the Cambridge Systematic Incorporation for the Federal Highway Administration as a part of the Next Generation Simulation (NGSIM) project. Detailed information of observed vehicles, vehicle class and size, lane identification, two-dimensional position, speed and acceleration, were extracted from video data, as well as the identification of the preceding and following vehicle.

The study site including an on-ramp is 503 m long and has five main lanes and one auxiliary lane and the leftmost lane is a high occupancy vehicle (HOV) lane. Data reflecting the congested traffic condition between the afternoon peak periods were collected from 5:00 p.m. to 5:30 p.m. on April 13, 2005. The video data were transcribed at a resolution of 10 frames per second. The data set contains 3626 vehicles and the proportion of automobile, truck, motorcycle is 95.6%, 3.3% and 1.1%, respectively. Traffic flow parameters for density, speed, flow are 43.3 (veh/km/lane), 27.9 (km/hr) and 7252 (veh/hr). In addition, these data were collected in clear weather, good visibility and dry pavement conditions. There were no incidents or events within the study section during data collection period. To examine the discussed car-following models, six vehicles obviously in a car-following state are selected from the data set. These vehicles are automobiles and the mean speed is 6.8 m/s. Figure 1 exhibits the trajectories and speed profiles of these vehicles.

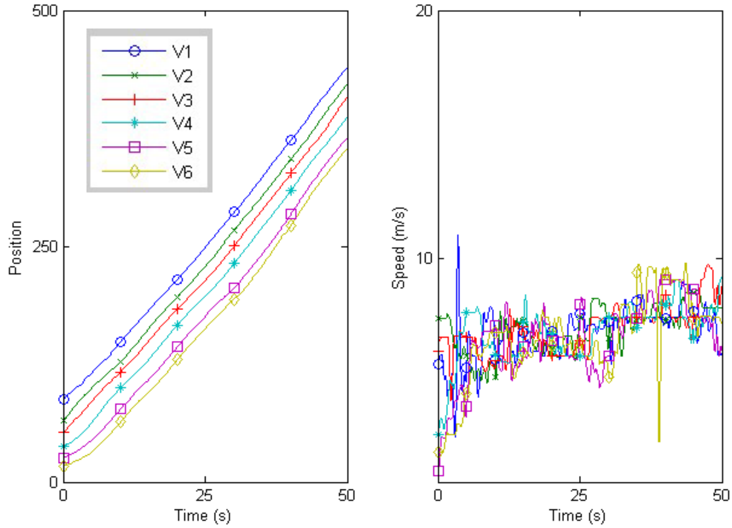

Figure 1: Trajectories and speed profiles of the 6 selected vehicles.

3.2 Vehicle's speed fluctuation

To examine the performance of the Gipps model, NaSch model and the improved model, simulations are carried out to model the real driving behaviour shown in fig. 1.

Table 1: Calibrated parameters for the Gipps model.

	V2	V3	V4	V5	V6
a_n m/s^2	5.6	5.8	2.0	2.7	4.1
V_n m/s	13.2	34.5	18.6	19.1	31.5
b_n m/s^2	-8.7	-7.5	-10.0	-4.0	-10.0
S_{n-1} m	7.5	5.0	9.8	7.8	5.6
$\hat{b}$ m/s^2	-10.0	-4.9	-5.0	-8.1	-4.0

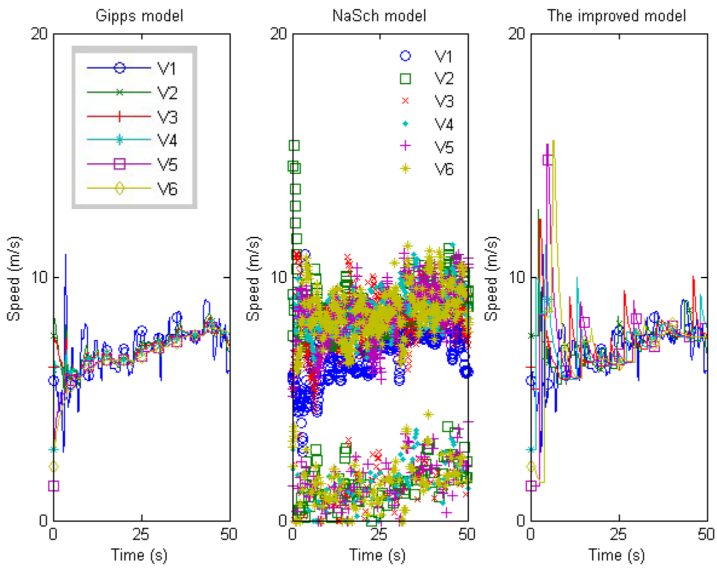

Figure 2: The simulated speed profiles of the 6 selected vehicles.

For the Gipps model, a genetic optimization algorithm is used to calibrate the parameters in the model. The calibrated parameters are listed in table 1 and reaction time T is 0.6 s. For the NaSch model and the improved model, the simulation results are an average of 10 simulation runs due to the randomization term in the model. Furthermore, unlike the value used in equations (4), (6) and (9), one cell per time step, the mean speed of all vehicles is taken as the increase or decrease of speed in one time step, 7 m/s one time step. V_{max} in both models are set as the same, 37.5 m/s and $g_n(t)=x_{n-1}(t)-x_n(t)-L_{n-1}-2.6$, where L_{n-1} is the length of the preceding vehicle and 2.6 is the mean gap of standing vehicles in the data set. Each simulation time step represents 0.1 seconds in order to keep pace with the recording data. Besides, the first vehicle is fed into the simulation run and the following vehicles are updated according to the corresponding models. Simulation results are shown in fig. 2.

From fig. 2, it appears that due to the deterministic mechanism in the Gipps model speed is continuous. Therefore, the speed profiles look much smoother than the other two models. The randomization rule in the NaSch model makes the speed fluctuation over severe; as a result, no stable speed can be retained. While, for the improved model, due to the introduction of the random duration of stable speed, during some period vehicles speeds are constant and at some time they are changed sharply, which looks more consistent with real conditions.

To reflect the differences between these models more clearly, the following statistical variables are used to quantitatively measure the closeness of simulation results and field data. The standard deviation of speed is used to reflect the vehicle's speed fluctuation, which is defined as:

$$\sigma_n = \sqrt{\frac{1}{\Delta T}\sum_{t=1}^{\Delta T}(v_n(t)-\overline{v}_n)^2} , \tag{11}$$

where $\overline{v}_n$ is the mean speed of vehicle n, ΔT is the total simulation time. Further, the speed fluctuation error rate (SFER) is calculated by:

$$SFER = \frac{|\sigma_n^{sim} - \sigma_n^{obs}|}{\sigma_n^{obs}} \times 100\% . \tag{12}$$

In addition, the root mean square error (RMSE) is used to show speed error in simulation results relative to the real value:

$$RMSE = \sqrt{\frac{1}{\Delta T}\sum_{t=1}^{\Delta T}(v_n^{sim}(t)-v_n^{obs}(t))^2} \tag{13}$$

Here, in equations (12) and (13) $\sigma_n^{sim}, v_n^{sim}$ and $\sigma_n^{obs}, v_n^{obs}$ are the simulated and observed value of vehicle n, respectively. From the definition, it is clear that the smaller the value of SFER and RMSE, the more desirable the simulation results. The calculation results are listed in table 2.

From table 2, it can be seen that the Gipps model achieves the smallest speed RMS error. This may result from the rather more parameters in the model and the genetic optimization algorithm based calibration method. The improved model also obtains an acceptable speed RMS error, although a bit larger than the Gipps model. As for the NaSch model, it produces the biggest speed RMS error. However, in terms of the speed fluctuation error rate, the mean value in the Gipps model and the NaSch model are 39.72% and 27.66%, respectively. While the mean SFER in the improved model are only 2.13%. It is important to note that standard deviation in the Gipps model for each vehicle is always less than field data and in the NaSch model the value is always more than field data. However, the standard deviation in the improved model for some vehicles is more than field data and for some vehicle is less than the field data, leading to a rather small mean SFER value.

Table 2: The simulation results of 6 vehicles.

		V2	V3	V4	V5	V6	Mean value
Field data	Mean speed (m/s)	6.83	6.95	6.87	6.81	6.77	6.84
	Speed deviation	1.35	1.23	1.37	1.46	1.64	1.41
Gipps model	Mean speed (m/s)	6.88	6.89	6.86	6.75	6.70	6.82
	Standard deviation	0.90	0.78	0.74	0.88	0.95	0.85
	SFER (%)	33.33	36.59	45.99	39.73	42.07	39.72
	RMSE	0.75	0.86	1.02	0.98	1.10	0.94
NaSch model P=0.05	Mean speed (m/s)	6.94	6.93	6.98	6.97	6.92	6.95
	Standard deviation	1.94	1.85	1.75	1.72	1.74	1.80
	SFER (%)	43.70	50.41	27.74	17.81	6.10	27.66
	RMS error	1.79	1.86	1.96	2.06	2.08	1.95
The improved model T=Rand(1.5s, 2s, 2.5s)	Mean speed	6.94	6.93	6.98	6.98	6.94	6.95
	Standard deviation	1.07	1.21	1.44	1.60	1.89	1.44
	SFER (%)	20.74	1.63	5.11	9.59	15.24	2.13
	RMSE	0.85	1.07	1.16	1.68	1.76	1.30

www.witpress.com, ISSN 1743-3509 (on-line)

Furthermore, according to such results, one can see that although the Gipps model produces the smallest speed RMS error, it cannot make the speed fluctuation most consistent with real conditions. The improved model describes the speed fluctuations with highest fidelity among the investigated models, even though the speed RMS error is a little higher than the Gipps model.

3.3 Relationship between randomization term and speed fluctuation

In previous studies [13, 21–23], the various value of probability P in the kinds of NaSch-related models were adopted to research the realistic traffic phenomena. However, scarce attention is paid to examine the reality of the randomization term in the NaSch model, which is used to reflect natural speed fluctuations due to human behavior or varying external conditions, by using the field data. In fact, choosing appropriate values for probability P for certain study is a very tough task, since it does not relate to any characteristic of traffic behaviour. In this subsection, we study the relationship between probability P in NaSch model and speed fluctuation, as well as the relationship between duration time T in the improved model and speed fluctuation, by using the data of the 6 selected vehicles. It is believed that the identified relationship can provide some guidance for researchers using the NaSch model or the improved model in their study. The simulation results are exhibited by figs. 3 and 4, respectively.

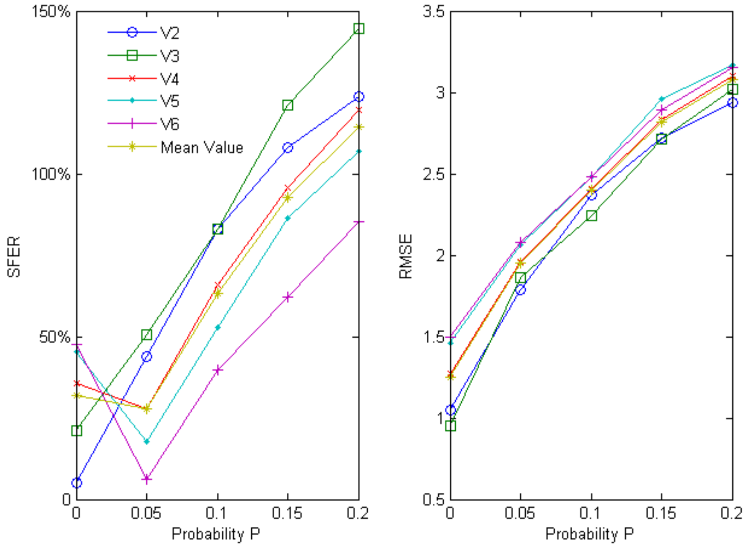

Figure 3: The performance of the NaSch model at different probability P.

From fig. 3, one can see that the speed RMS error for all vehicles, along with the SFER for V2 and V3, increases sharply with a small increase of P. SFER for V4, V5, V6 and the mean value decreases to the minimum value at P=0.05, then increases fast with the enhancement of P. Therefore, through such results it can be suggested that when the mean standard deviation of speed is less than 1.4 m/s, the value of P in randomization terms should not be bigger than 0.05 at a microscopic level.

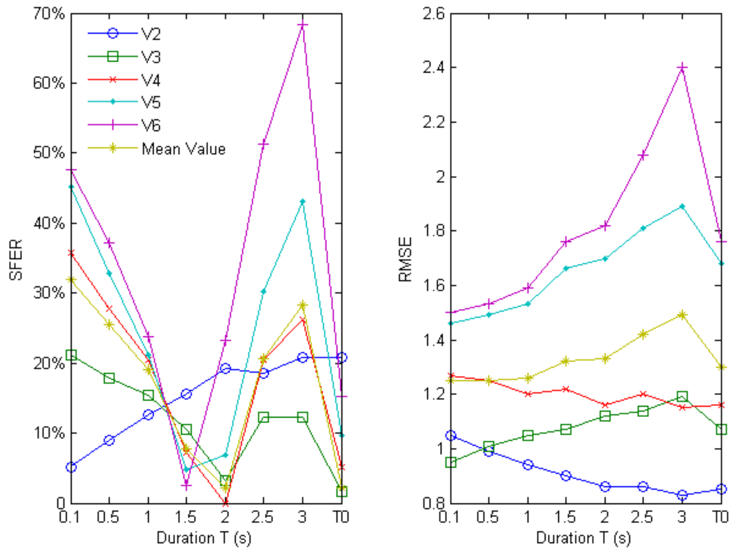

Figure 4: The performance of the improved model at different duration T.

While, the simulation results in fig. 4 show that when T is less than 3 s, speed RMS error for V3, V5 and V6 slowly increases with the enhancement of T. For other vehicles and the mean value, speed RMS error decreases with the increase of T. Except for V2, all the values of SFER first decreases fast when T is less than 1.5 s then increases with the enhancement of T. In addition, it is worth noting that at T_0=Rand(1.5, 2, 2.5), all the vehicles along with the mean value can obtain desirable values both for RMSE and SFER, which means that the introduction of randomization improves the reality of the model.

4 Conclusion

It is well known that a vehicle's speed fluctuation has significant impact on traffic capacity, road safety, fuel consumption, and exhaust gas emission. We can say that the ability of depicting the realistic speed fluctuation is also one of the critical benchmarks for microscopic traffic models. In this study, we examined two typical car-following models, the Gipps model and the NaSch model. With the data from real traffic, our findings show that neither the mentioned models can describe the realistic speed fluctuation. By introducing a duration of stable speed which directly relates to the characteristics of drivers, we proposed one kind of CA model. Simulation results show that the model is capable of mimicking the speed fluctuation in real traffic more accurately. In addition, the relationship between random term and speed fluctuation is investigated. It shows that the probability P in the NaSch model can make the speed fluctuation over severe; even a small change in P can lead to very big error rate in speed fluctuation. It suggests that researchers should use caution in choosing probability P in their study. The duration of a stable speed term in the improved model can be assigned according common driver experience and the appropriate adjustment of T can make the speed fluctuation more realistic.

Although the performance of the improved model is validated at a microscopic level, examining it at a macroscopic level with some real application, such as fuel consumption, and exhaust gas emission, is more persuasive and compelling, which comprises our further study.

References

[1] Gazis, D., Herman R., & Rothery, R., Nonlinear follow-the-leader models of traffic flow. *Operation Research*, Vol. 9, pp. 545–567, 1961.

[2] Gipps, P. G., A behavioural car-following model for computer simulation. *Transportation Research Part B*, Vol. 15, pp. 105–111, 1981.

[3] Nagel, K., & Schreckenberg, M., A cellular automaton model for freeway traffic. *Journal de Physique I*, France, Vol. 2, pp. 2221–2229, 1992.

[4] Newell, G., A simplified car-following theory: a lower order model. *Transportation Research Part B*, Vol. 36, pp. 195–205, 2002.

[5] Bham, G. H., & Benekohal, R. F., A high fidelity traffic simulation model based on cellular automata and car-following Concepts. *Transportation Research Part C,* vol. 12, pp. 1–32, 2004.

[6] Gunay, B., Car following theory with lateral discomfort. *Transportation Research Part B*, Vol. 41, pp. 722–735, 2007.

[7] Gipps, P. G., A model for the structure of lane-changing decisions. *Transportation Research Part B*, Vol. 20, pp. 403–414, 1986.

[8] Hidas, P., Modelling lane changing and merging in microscopic traffic simulation. *Transportation Research Part C*, Vol. 10, pp. 351–371, 2002.

[9] Barlovic, R., Santen, L., Schadschneider, A. & Schreckenberg, M., Metastable states in cellular automata for traffic flow. *The European Physical Journal B*, Vol. 5, pp. 793–800, 1998.

[10] Benjamin, S. C., Johnson, N. F. & Hui, P. M., Cellular automata models of traffic flow along a highway containing a Junction. *Journal of Physics A,* Vol. 29, pp. 3119–3127, 1996.

[11] Takayasu M. and Takayasu, H., 1/f noise in a traffic model. *Fractals,* Vol. 1, pp. 860–866, 1993.

[12] Lárraga, M. E., del Río, J. A. & Schadschneider, A., New kind of phase separation in a CA traffic model with anticipation. Journal of Physics A: Mathematical and General, Vol. 37, pp. 3769–3781, 2004.

[13] Lárraga, M. E., del Río, J. A. & Alvarez-lcaza, L., Cellular automata for one-lane traffic flow modelling. *Transportation Research Part C*, Vol. 13, pp. 63–74, 2006.

[14] Jiang, R. & Wu, Q. Cellular automata models for synchronized traffic flow. *Journal of Physics A*, Vol. 36, pp. 381–390, 2003.

[15] Knospe, W., Santen, L., Schadschneider, A., & Schreckenberg, M., Towards a realistic microscopic description of highway traffic. *Journal of Physics A*, Vol. 33, pp. L477–L485, 2000.

[16] Joksch, H., Velocity change and fatality risk in a crash–a rule of thumb. *Accident, Analysis and Prevention*, Vol. 25, pp. 103–104, 1993.

[17] Oneyama, H., Oguchi, T. & Kuwahara, M., Estimation model of vehicle emission considering variation of running speed. *Journal of the Eastern Asia Society for Transportation Studies*, Vol. 4, 2001, pp. 105–117.

[18] Reuschel, A., Vehicle movements in a platoon. *Oesterreichisches Ingenieur-Archir*, Vol. 4, pp. 193–215, 1950.

[19] Pipes, L., An operational analysis of traffic dynamics. *J. Appl. Phys,* Vol. 24, pp. 274–287, 1953.

[20] Brackstone, M. & McDonald, M., Car-following: a historical review. Transportation Research Part F, Vol. 2, pp. 181–196, 1999.

[21] Blue, V. J. & Adler, J. L, Cellular automata microsimulation for modelling bi-directional pedestrian walkways. *Transportation Research Part B*, Vol. 35, pp. 293–312, 2001.

[22] Brockfeld, E., Barlovic, R., Schadschneider, A. & Schreckenberg, M., Optimizing traffic lights in a cellular automaton model for city Traffic. *Phys. Rev. E*, Vol. 64, pp. 056132, 2001.

[23] Spyropoulou, I., Modelling a signal controlled traffic stream using cellular automata. *Transportation Research Part C*, Vol. 15, pp. 175–190, 2007.