Evaluating NaSch model from the view of vehicle's speed fluctuations

Jian ZHENG[1], Koji SUZUKI[2] and Motohiro FUJITA[3]

[1]Doctoral student, Graduate School of Engineering, Nagoya Institute of Technology
(Gokiso-cho, Showa-ku, Nagoya, Aichi, 466-8555, Japan)
zhengjian1112@gmail.com
[2]Member of JSCE, Associate Professor, Graduate School of Engineering, Nagoya Institute of Technology
(Gokiso-cho, Showa-ku, Nagoya, Aichi, 466-8555, Japan)
suzuki.koji@nitech.ac.jp
[3]Member of JSCE, Professor, Graduate School of Engineering, Nagoya Institute of Technology
(Gokiso-cho, Showa-ku, Nagoya, Aichi, 466-8555, Japan)
(fujita.motohiro@nitech.ac.jp)

As well known, vehicle's speed fluctuations have significant impact on traffic capacity, road safety, fuel consumption, exhaust gas emissions. In this study with two groups of data from real traffic condition, we examined the randomization term in NaSch model, which is used to reflect the speed fluctuation due to human behavior and varying external conditions. Our findings indicate that the model with the minimum simulation speed error does not necessarily mean it can describe speed fluctuations most realistically. In addition, it is suggested that when NaSch is used at microscopic level, the value of probability P in randomization term should not be bigger than 0.1.

Key Words: *traffic simulation, cellular automaton model, speed deviation*

1. INTRODUCTION

Traffic simulation as an effective tool for traffic system analysis and traffic management has been becoming very popular in recent years. Car-following models and lane-changing models, the most significant components in traffic simulator, attract lots of attentions from traffic researchers. Numbers of models have been proposed to describe the phenomena from real traffic more accurately [1-8].

In this study, we pay our attention to one kind of car-following models. In 1992, Nagel and Schreckenberg [3] proposed a compelling cellular automaton model (NaSch model) by introducing randomization term into deterministic cellular automaton (CA) model, which can reproduce some phenomena in real traffic, such as phase transition in traffic flow and spontaneous formation of jams. Thereafter, more realistic traffic features have been introduced into this model, e.g. slow to start rules [9-11], anticipation effects [12, 13] and braking light effects [14, 15]. However scarce attentions are paid to examine the reality of the randomization term in NaSch model, which is used to reflect natural speed fluctuations due to human behavior or varying external conditions.

It is a widely-held and true belief that vehicle's speed fluctuations have significant impacts on traffic capacity, road safety, fuel consumption, exhaust gas emissions [16, 17]. In this study with two groups of data from real traffic condition, we examine the randomization term in NaSch model. Our findings indicate that the model with the minimum simulation speed error does not necessarily mean it can describe speed fluctuations most realistically. In addition, the findings suggest that when NaSch is used at microscopic level, the value of probability P in randomization term should not be bigger than 0.1.

2. NASCH MODEL

CA models are based on a coarse description of driving behavior 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:

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

Deceleration:

$$\tilde{v}_n(t+1) = \min\{\tilde{v}_n(t+1), g_n(t)\} \tag{2}$$

Randomization:

$$v_n(t+1) = \begin{cases} \max(\tilde{v}_n(t+1)-1, 0), C_{rand} \leq P \\ \tilde{v}_n(t+1), \qquad\qquad otherwise \end{cases} \tag{3}$$

Vehicle movement:

$$x_n(t+1) = x_n(t) + v_n(t+1) \ , \tag{4}$$

where,

$$g_n(t) = x_{n-1}(t) - x_n(t) - 1 \ . \tag{5}$$

In addition, $\tilde{v}_n(t+1)$ is an temporary value and C_{rand} is a random number from [0, 1], P is a given speed reduction probability, and V_{max} is limited maximum speed.

Due to its computational efficiency and simple rules, CA models can be used for large scale traffic simulation and online traffic simulation.

3. SIMULATION

(1) Field data sets

The data used in this study are collected by NGSIM program during the afternoon peak period (4:00-5:30 pm, April 13, 2005) on a segment of six-lane freeway, Interstate 80 in Emeryville (San Francisco), California. Additionally, the detected segment covers one on-ramp and one off-ramp and the first lane is the high-occupancy vehicle lane.

In Figure 1 and Figure 2, two groups of data exhibit the trajectories and speed profiles of six and four passenger respectively, which are from the fifth lane and fourth lane during 4:00 to 4:15 pm and 5:00 to 5:15 pm. The vehicles' mean speed during 4:00 to 4:15 pm and 5:00 to 5:15 under the recorded segment are 27.8 km/h and 20 km/m, respectively. So we can see both group of data are in congested state, but the second group of data are under the stop and go condition.

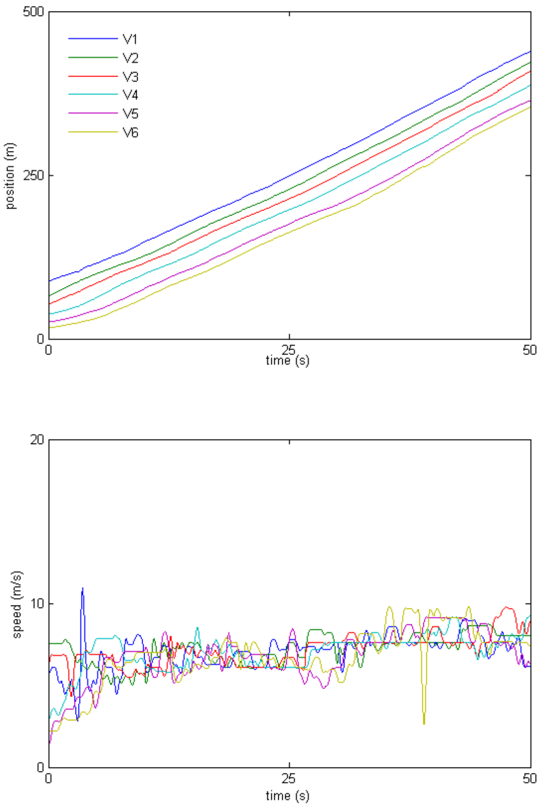

Fig. 1 Trajectories and speed profiles of 6 vehicles

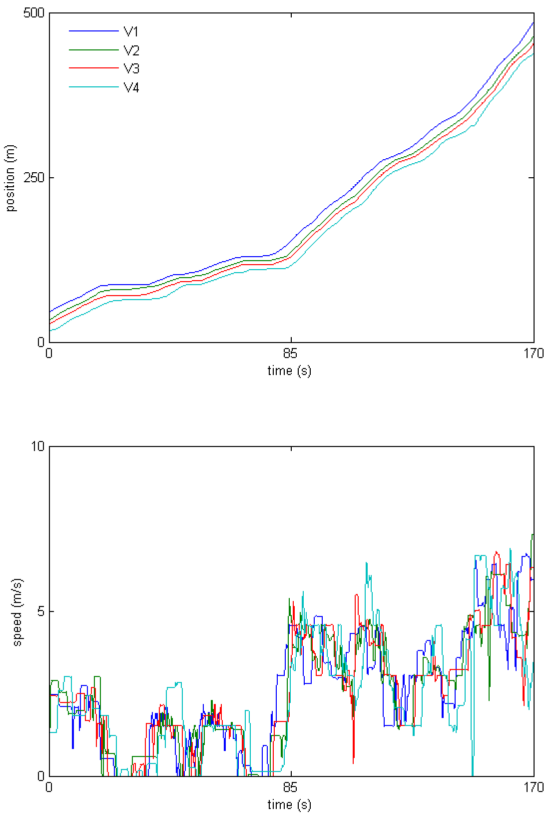

Fig. 2 Trajectories and speed profiles of 4 vehicles

From vehicle's speed profiles one can see clearly that drivers do not always change their speed continually. Stationary values during a relative long time interval are retained, regardless at low or high speed, and at some points of time obvious speed variations appear. According to driving experiences, we are keenly aware that drivers are always intending to maintain a stable speed due to the pursuit of comfortable driving and fuel saving in driving behavior. On the another hand, the emergence of dangerous gap imposes them to adjust their speed to suit the current situation. After the adjustment, stable speed are retained again. Obviously, such driving tendency is accordance with what the figures exhibit.

(2) Evaluation formulas

To reflect the differences between simulation results and field data more clearly, the following formulas are used to quantitatively measure the closeness of them.

The root mean square error (RMSE) is used to show speed error in simulation results,

$$\rho_n = \sqrt{\frac{1}{\Delta T}\sum_{t=1}^{\Delta T}(v_n^{sim}(t) - v_n^{data}(t))^2} \qquad (6)$$

where $v_n^{sim}(t), v_n^{data}(t)$ are the simulated and recorded speed of vehicle n at time T.

In addition, the standard speed deviation is adopted to reflect the vehicle's speed fluctuations,

$$\sigma_n = \sqrt{\frac{1}{\Delta T}\sum_{t=1}^{\Delta T}(v_n(t) - \bar{v}_n)^2} \qquad (7)$$

where $\bar{v}_n$ is the mean speed of vehicle n. And, the speed deviation error rate (SDER) is calculated by,

$$\delta_n = \frac{|\sigma_n^{sim} - \sigma_n^{data}|}{\sigma_n^{data}} \times 100\% \qquad (8)$$

where $\sigma_n^{sim}, \sigma_n^{data}$ are the simulated and recorded value of vehicle n .

From the definitions, it is clear that the smaller the value of RMSE and SDER, the more desirable the simulation result.

(3) Simulation results

In the simulation run, continuous speed and space variables are adopted and the simulation results are the average of 10 simulation runs due to the randomization term in NaSch model. Furthermore, unlike the value used in equation (1) and (3), one cell per time step, the mean speed of all vehicles in each group of data are taken as the increase or decrease of speed, 7 m/s and 3 m/s, respectively. $V_{\max}$ and g_n 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 preceding vehicle and 2.6 m is the mean gap of all standing vehicles. Each simulation time step represents 0.1 seconds in order to keep pace with the recorded data. The first vehicle is updated according to the recorded data and the following vehicles are updated based on the corresponding models. Simulation results are shown in Figure 3-6.

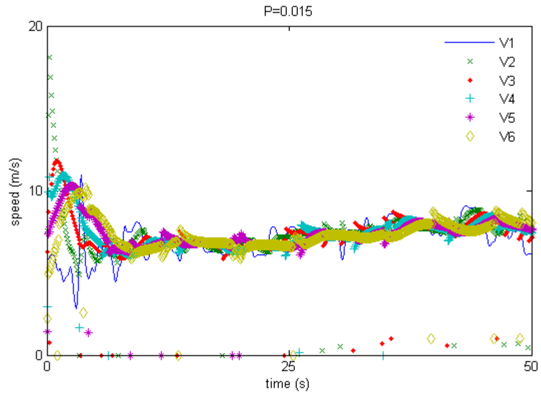

Fig.3 Simulated speed profiles of 6 vehicles at P=0.015

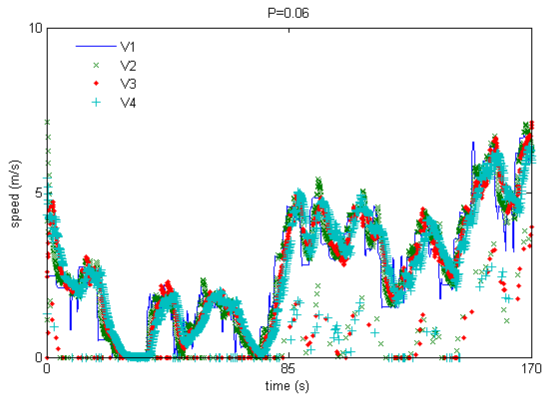

Fig.4 Simulated speed profiles of 4 vehicles at P=0.06

From Figure 3 and Figure 4, it can be seen that due to the relative small value of P used in randomization term, on the whole the simulated speed profiles in NaSch model look much compact, and only at certain points of time discrete speed appear. Additionally, it should be noted that the value of P used here are the most desirable ones with respect to mean value of

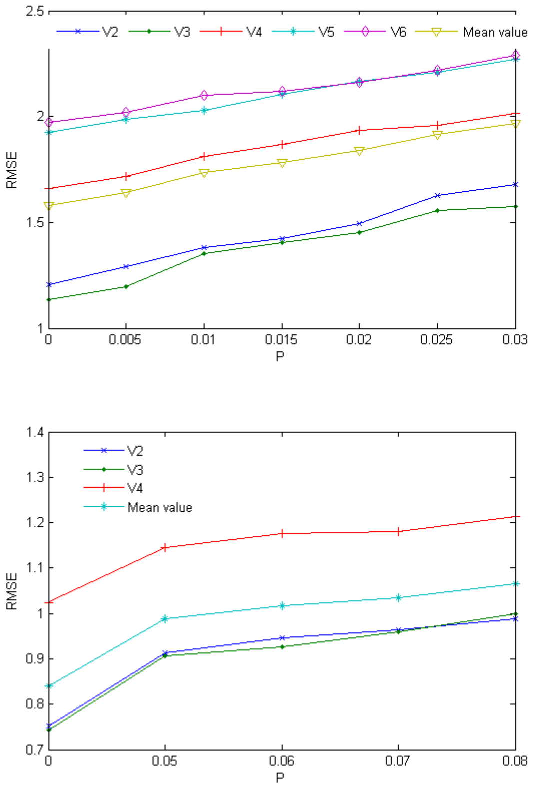

Fig. 5 The root mean square error of speed at different P

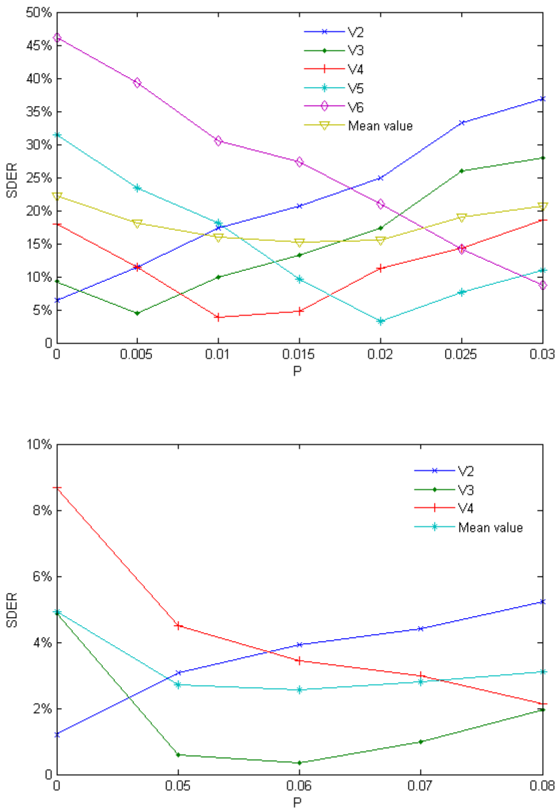

Fig. 6 The speed deviation error rate at different P

speed deviation error rate shown in Figure 6. In fact these figures are similar to those of P=0. From this point of view, one can see that the introduction of randomization term fails to describe the realistic speed fluctuations accurately.

Figure 5 and Figure 6 exhibit the performance of NaSch model at different P. One can see that the root mean square error of speed increase with the enhancement of the value of P. And, for the second group of data the root mean square error increase faster than the second group of data. This is due to that the number of vehicles is more and the mean speed is bigger than those under stop and go condition. On the other hand, it can be seen that for different vehicles, the speed deviation error rate change in different mode. The speed deviation error rate of some vehicles decrease, such as the sixth vehicle in first group of data and the fourth vehicle in second group of data , and some increase, e.g. the second vehicle in both group of data, with the increase of P. However, for most vehicles the speed deviation error rate first decrease and after reaching the minimum value increase with the increase of P, as well as the mean value of speed deviation error rate. It is important to note that the root mean square error for all vehicles at P=0 are the minimum ones, while in terms of the speed deviation error rate, the value at P=0 are not so desirable. Consequently, from such results, it is clear that the model with the minimum simulation speed error does not necessarily mean it can describe speed fluctuations most realistically. In addition, the most desirable value of mean speed deviation error rate in the first and second group of data are 0.015 and 0.06, respectively. This is suggested that when NaSch is used at microscopic level, the value of P in randomization term should not be bigger than 0.1 at least in terms of speed error and speed deviation.

CONCLUSIONS

It is well known that vehicle's speed fluctuations have significant impact on traffic capacity, road safety, fuel consumption, exhaust gas emissions. So we can say the ability of depicting the realistic speed fluctuations is also one of critical benchmarks for microscopic traffic models. With two groups of data from real traffic condition we investigated the randomization term in NaSch model which is used to reflect natural speed fluctuations due to human behavior or varying external conditions. Our findings show that the model with the minimum simulation speed error does not necessarily mean it can describe speed fluctuations most realistically. It also indicates that evaluating microscopic traffic models only from the speed error is not comprehensive. In addition, it is suggested that when NaSch is used at microscopic level, the value of probability P in randomization term should not be bigger than 0.1.

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