A new cellular automata model of traffic flow with negative exponential weighted look-ahead potential*

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With the development of traffic systems, some issues such as traffic jams become more and more serious. Efficient traffic flow theory is needed to guide the overall controlling, organizing and management of traffic systems. On the basis of the cellular automata model and the traffic flow model with look-ahead potential, a new cellular automata traffic flow model with negative exponential weighted look-ahead potential is presented in this paper. By introducing the negative exponential weighting coefficient into the look-ahead potential and endowing the potential of vehicles closer to the driver with a greater coefficient, the modeling process is more suitable for the driver's random decision-making process which is based on the traffic environment that the driver is facing. The fundamental diagrams for different weighting parameters are obtained by using numerical simulations which show that the negative exponential weighting coefficient has an obvious effect on high density traffic flux. The complex high density non-linear traffic behavior is also reproduced by numerical simulations.

Keywords: traffic flow, look-ahead potential, cellular automata, negative exponential weighting

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1. Introduction

With the development of the economy and increasing of populations, vehicular traffic jams are becoming one of the major problems in many cities.[1,2] More efficient traffic flow theory is needed to guide the overall controlling, organizing and managing of traffic systems. Due to the dynamic, stochastic, nonlinear, and multi-behavior subject characteristics of traffic flow, the existing models cannot well describe the complex traffic phenomenon. Research on stochastic behaviors of traffic flow plays an important role in understanding the intrinsic evolution rules of traffic systems.

Since the beginning of the study on traffic flow in 1935,[3] a great number of models have been proposed, the corresponding theoretical systems have been formed, and continuously been applied to real traffic. These models could be classified as several types as follows:[4] (i) macroscopic traffic flow models, (ii) mesoscopic traffic flow models, and (iii) microscopic traffic flow models. In microscopic traffic flow models the Lagrangian method is used to study traffic flow dynamics and describe the interaction between single vehicular trajectories or the interactions among multiple vehicles.[5] Among the microscopic models, cellular automata (CA) is a most powerful tool to describe nonlinear phenomena, which can be used to describe the motion of a particle. The CA model evolves automatically according to stochastic evolution rules. Due to its efficient and fast performance and its ability to reproduce the spontaneous traffic jams like real-life traffic flows, it is widely applied to traffic modeling. With the help of faster computers, the CA model has produced promising results when it was used to describe traffic phenomenon.[6] The first CA model was proposed by Nagel and Schreckenberg in 1992[7] (NS). Since then, a great number of improvements and extensions have been proposed. Chowdhury and Schadschneider[8] studied the interactions between control signal and vehicles in urban traffic. Mou *et al.*[9] considered the influence of the safety probability. Jetto *et al.*[10] takes the disorder of length and the maximal speed of cars into account. Kokubo *et al.*[11] studied the effect of decelerating damping. Bentaleb *et al.*[12] considered the satisfaction rate of desired velocity in the case of a mixture of fast and slow vehicles. In Ref. [13], a CA model with safe driving conditions was proposed, in which the authors analyzed the formation and dissolution of clusters or platoons of vehicles. Chmura *et al.*[14] studied the stable states of synchronized flow by using cellular automata. Wang and Chen[15] studied the various driving behaviors when the vehicles arrived at and passed through the traffic light. More CA traffic flow models can be found in Refs. [16] and [17].

In the CA models mentioned above, the stationary slowdown probability is usually adopted. It is hard to capture the effects of the random behavior above the critical density because of its inability to describe the probability. Thus, many of these models have been condemned.[18] To describe the stochastic phenomenon of high-density traffic flow, Sopasakis and Katsoulakis[19,20] proposed a stochastic traffic flow model

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(AM model) that is based on the asymmetric single exclusion process (ASEP) and Arrhenius dynamic method. In his model, the state of traffic was described by the results of the random driving system. Vehicles advance based on the interactional potential of its traffic situations in the look-ahead length. Here, the interactional potential is called the look-ahead potential. The statistical properties of the AM model were studied in Ref. [21]. By introducing the interactional potential of vehicles into the randomization step, an improved cellular automata traffic flow model with variable probability of randomization was proposed in Ref. [22] (VP model). However, it is a draw that the look-ahead potential is a constant in the AM, VP model. The different effects of the different distance vehicles on each other are not considered. In an actual traffic system, the effect of different distance before the driver has different effects on the driver's acceleration and deceleration process. New mechanisms need to be constructed to take these differences into account. To describe these differences, by introducing a weighting coefficient into the look-head potential and endowing the potential of vehicles closer to the driver with a greater weight, a traffic flow model with weighted look-ahead potential was proposed in Ref. [23] (WP model). Nevertheless, in the WP model a proportional constant is used as a weighting coefficient. There still exist limitations. However, in our empirical knowledge, the dependent variable decreases with the increase of the independent variable in the negative exponential function in mathematics. So, the negative exponential function could be used to describe the greater effect of closer vehicles on the driver.

In summary, there are few studies directly on the different effects of the different distance vehicles on each other in existing models. But in a real traffic case, the slowdown probability of randomization is randomly changed with the vehicles at different distances before the driver. To improve the limitations of AM, VP, and WP models, based on the characteristics of negative exponential function, a new cellular automata model of traffic flow (NE model) with negative exponential weighted look-ahead potential is proposed in this paper. By introducing the negative exponential weighting function, different weights are given to the vehicles with different distances, the modeling process is more suitable for the driver's random decision-making process based on the traffic environment situations that the driver is facing. From the improved model, the fundamental diagrams (flow–density relationship) are obtained, and the detailed high-density traffic phenomenon is reproduced through numerical simulation.

The remainder of this paper is organized as follows. The modeling process is discussed in Section 2. The influences of different parameters on traffic flow are discussed in Section 3 by numerical simulation, and the primary conclusions are summarized in Section 4.

2. Modeling process

In this section, we will describe the modeling process of the new model from the typical CA models. In the CA model rule set,[7] there are four step movements, i.e., the acceleration, deceleration, randomization with probability p, and vehicle position update. In an actual traffic case, the driver decision-making process is influenced by the different effects of the vehicles at different distances. Referring to the mechanism to describe the probability of randomization in the AM, VP, and WP models, a negative exponential weighting function is introduced into the look-ahead potential in the new model. The dynamic changed transition rate to a new form in the randomization step is adopted. The modeling process is as follows.

Like the modeling process of AM and VP models in Ref. [22], to describe the state of the single lane traffic system, a one-dimensional highway road is divided into N cells, $L = \{1,2,\ldots,N\}, N > 1$. On each of the cell sites $x \in L$, the state of the system is given by an order parameter $\sigma = \{\sigma(x) : x \in L\}$, in which

$$\sigma(x) = \begin{cases} 1, & \text{when cell } x \text{ is occupied;} \\ 0, & \text{when cell } x \text{ is not occupied (no car).} \end{cases} \tag{1}$$

Vehicles are assumed cannot move backward in traffic. Vehicles can move to the next cell from back to front, and only one vehicle is allowed to occupy one cell at a time.

In AM, WP models, similar to the Arrhenius dynamics for Ising systems,[24] the interactional potential function of the target vehicle has the following form:

$$U(x,\sigma) = \sum_{\substack{y\in L \\ y>x}} J_0\sigma(y) = \frac{1}{Q}J_0\sum_{i=1}^{Q}\sigma(x+i). \tag{2}$$

In this function, Q is the number of vehicles on the right side of cell site x, which affects the velocity of the vehicle in cell site x; J_0 is a simple constant parameter of interactional potential strength that is based on its sign describing attraction, or repulsion, or no-interaction.

Clearly, in AM, VP models, the interaction potential of all vehicles is constant J_0, which does not take the different effects of the vehicles at different distances on the driver into account.

As described in AM and VP models, the state transition of cells in look-ahead length during the time interval $[t, t+\Delta t]$ occurs with probability expressed as

$$\begin{aligned} P &= c_0 \exp(-U(x,\sigma))\Delta t \\ &= c_0 \exp\left(-J_0\frac{1}{Q}\sum_{i=1}^{Q}\sigma(x+i)\right)\Delta t, \end{aligned} \tag{3}$$

where the parameters are $c_0 = 1/\tau_0$, and τ_0 as the characteristic or relaxing time for the process.

As discussed in AM and VP models, in order to derive the link to the well-known Lighthill–Whitham macroscopic

model, the following assumption is needed as described in Ref. [21].

Assumption 1 The probability measure on σ is approximately a product measure.

$$f(\sigma(k)=\delta(k),\sigma(l)=\delta(l))=f(\sigma(k)=\delta(k))f(\sigma(l)=\delta(l)).$$

In an actual traffic case, considering the fact that the driver decision-making process is affected more seriously by the closer vehicles ahead of the driver, the vehicles closer to the driver should have a greater potential. In the paper, a negative exponential weighting function is introduced into the look-ahead potential and a greater weight is endowed to the potential of vehicles closer to the driver with a greater coefficient. Namely, the negative exponential weighting function can be defined as $w_i=\exp(-(M/Q)i)$ $(i\in[1,\ldots,Q])$, where w_i represents the weight of the i-th vehicle ahead, and M is the total number of vehicles within the range of the look-ahead potential. Namely,

$$M=\sum_{i=1}^{Q}\sigma(x+i). \tag{4}$$

Therefore, the potential function in Eq. (2) can be rewritten as

$$\begin{aligned}U(x,\sigma) &= \sum_{\substack{y\in L\\ y>x}} J_0\sigma(y)=\frac{1}{Q}J_0\left[\left(\sum_{i=1}^{Q}w_i\sigma(x+i)\right)\Big/\sum_{i=1}^{Q}w_i\right]\\ &= \sum_{\substack{y\in L\\ y>x}} J_0\sigma(y)=\frac{1}{Q}J_0\left[\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma(x+i)\right)\Big/\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right].\end{aligned} \tag{5}$$

In this way, we obtain the negative exponential weighted potential traffic flow model, in which the state transition probability P is as follows:

$$\begin{aligned}P &= c_0\exp(-U(x,\sigma))=c_0\exp\left(-\frac{1}{Q}J_0\left[\sum_{i=1}^{Q}w_i\sigma(x+i)\Big/\sum_{i=1}^{Q}w_i\right]\right)\Delta t\\ &= c_0\exp\left(-\frac{1}{Q}J_0\left[\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma(x+i)\right)\Big/\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right]\right)\Delta t.\end{aligned} \tag{6}$$

Like the derivation process of the AM model,[20,21,24] we can derive the link between the corresponding random traffic flow model and other traffic flow models.

By the above assumption, we can obtain that $\sigma(x)$ and $\sigma(y)$ are not relevant to each other, in which $x,y(x\neq y)$ are two different cell sites. In other words, for any $x\neq y$, we can obtain $E(\sigma(x,t)\sigma(y,t))\approx E(\sigma(x,t))E(\sigma(y,t))=u_xu_y$, where $u_k=\sigma(k,t))$. Then the approximate formula can be expressed as

$$\begin{aligned}E\exp(-J_0U(k,\sigma)) &= E\left(\prod_{i=1}^{Q}\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma(k+i)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)\right)\\ &\approx \prod_{i=1}^{Q}E\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma(k+i)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)\right),\end{aligned} \tag{7}$$

where $\overline{J_0}=J_0/Q$ when $1\leq i\leq N$, we have $(\sigma_l)^m=\sigma_l(\sigma_l=\sigma(l))$ for any positive integer m, with l denoting the potential radius. So the above equation can be simplified into

$$\begin{aligned}&\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma_l\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)\\ &= \sum_{m=0}^{\infty}\frac{\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma(k+i)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)^m(\sigma_l)^m}{m!}\\ &= 1+\sigma_l\sum_{m=1}^{\infty}\frac{\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma(k+i)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)^m}{m!}\\ &= 1+\sigma_l\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right).\end{aligned} \tag{8}$$

Therefore, we compute the expectations on both sides of the above equation.

$$\begin{aligned}
&\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma_l\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)\\
&=1+E(\sigma_l)\sum_{m=1}^{\infty}\frac{\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\sigma(k+i)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)^m}{m!}\\
&=1+u_l\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right).
\end{aligned}\tag{9}$$

Substituting Eq. (9) into the term on the right-hand side of Eq. (7), we can obtain the following equation:

$$E\exp(-J_0U(k,\sigma))=\prod_{i=1}^{Q}\left[1+u_{k+i}\times\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right)\right].\tag{10}$$

This expression can be used to derive the negative exponential weighted potential traffic flow model with the vehicle density $u_k(t)$ satisfying the following equation:

$$\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}t}u_k=\;&c_0u_{k-1}(1-u_k)\prod_{i=1}^{Q}\left[1+u_{k+i}\times\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right)\right]\\
&-c_0u_k(1-u_{k+1})\prod_{i=1}^{Q}\left[1+u_{k+i}\times\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right)\right].
\end{aligned}\tag{11}$$

Further, the above formula can be rewritten as:

$$\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}t}u_k=\;&c_0u_{k-1}(1-u_k)\exp\left(\sum_{i=1}^{Q}\ln\left[1+u_{k+i}\times\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right)\right]\right)\\
&-c_0u_k(1-u_{k+1})\exp\left(\sum_{i=1}^{Q}\ln\left[1+u_{k+i}\times\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right)\right]\right).
\end{aligned}\tag{12}$$

We can recover the model in Ref. [22] by expanding the exponential and logarithmic functions in Eq. (12). In fact, through simple Taylor expansion, we can obtain the following equation:

$$\begin{aligned}
&\ln\left[1+u_{k+i}\times\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right)\right]\\
&=-\bar{J}_0u_{k+i}\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)+O(\bar{J}_0^2),\\
&\sum_{i=1}^{Q}\ln\left[1+u_{k+i}\times\left(\exp\left(-\bar{J}_0\exp\left(-\left(\frac{M}{Q}\right)i\right)\Big/\left(\sum_{i=1}^{Q}\exp\left(-\left(\frac{M}{Q}\right)i\right)\right)\right)-1\right)\right]=-J_0U_k+O(Q^{-1}).
\end{aligned}\tag{13}$$

When $N\to\infty$, there is $M^{-1}=O(l/N)$. So the above negative exponential weighted model has the same equation limits as the previous AM model.

From the above consequence, the AM and VP model state transition probability in the randomization step can be replaced by the state transition probability of Eq. (6). Thus, the improved cellular automata model of traffic flow with negative exponential weighted potential is obtained and includes four steps as follows.

Let x_n and v_n denote the position and speed of the n-th vehicle, $V_{\max}$ be the maximum speed that a vehicle can achieve, and $d_i(t)=x_{i+1}(t)-x_i(t)-1$ the distance between the i-th vehicle and the front vehicle.

Step 1 Acceleration process

If $V_i(t)<V_{\max}$ the speed of the n-th vehicle is increased by one. The rule is given as

$$V_i(t+1)=\min(V_i(t)+1,V_{\max}).$$

Step 2 Deceleration process

If $V_i(t)<V_{\max}$ the speed of the n-th vehicle is reduced to $d_i(t)-1$. The rule is given as

$$V_i(t+1)=\min(V_i(t),d_i(t)-1).$$

Step 3 Randomization slowdown process with variable probability

If $x_{i+1}(t) = 0$, and

$$p >= c_0 \exp\left(-\frac{1}{Q} J_0 \left[\sum_{i=1}^{Q} w_i \sigma(x+i) / \sum_{i=1}^{Q} w_i \right] \right) \Delta t,$$

then $V_i(t+1) = \max(V_i(t) - 1, 0)$. Here, p is a randomly generated number between [0,1].

Step 4 Vehicle position update process Each vehicle is moved forward according to its new velocity determined in Steps 1–3. The rule is given as

$$x_i(t+1) \to x_i(t) + v_i(t+1).$$

From the above steps, we can obtain the evolution algorithm of our one-lane CA model as follows.

3. Numerical simulation and discussion

The one-lane traffic flow system is simulated by using Matlab. In our simulation, the one-lane road is divided into one thousand cells where each cell is 7.5 m long. Then, the total length of the highway is $1000 \times 7.5 = 7500$ m. The maximal expected safety speed is 135 km/h, i.e., $V_{\max} = 5$ cell/s. The vehicles only move forward or stop. The speed of each vehicle is non-negative.

To build a better simulation of the actual highway, we take the periodic boundary conditions. The initial vehicle distribution and the random initial speed are configured at the beginning, and then vehicles are set to run within a given time. According to the initial distribution of vehicles, the density and speed are calculated by the average of the time and space of the whole circular road. The results and discussion are presented as follows.

3.1. Fundamental diagram changes with interactional potential length

In simulations, the look-ahead potential length Q takes the values of 1, 2, 4, 8 and the look-ahead strength J_0 equals 4. The other parameters are $c_0 = 1$, $V_{\max} = 5$, $\Delta t = 1$ s, and the total run time is 1000 s. The results of the flow–density of NE model and VP models are shown in Fig. 1.

As shown in Fig. 1, in the non-weighted case, under the fixed J_0, maximum flux and critical density decrease with increasing the look-ahead length Q. In the weighted case, from the NE model, the result is quite the contrary. There is an exception case, when $Q = 1$, the results of the weighted and non-weighted models are consistent. Compared with in the VP model, in the negative exponential weighted model, the traffic flux is improved evidently. Especially in the high density traffic case, the effect is more obvious.

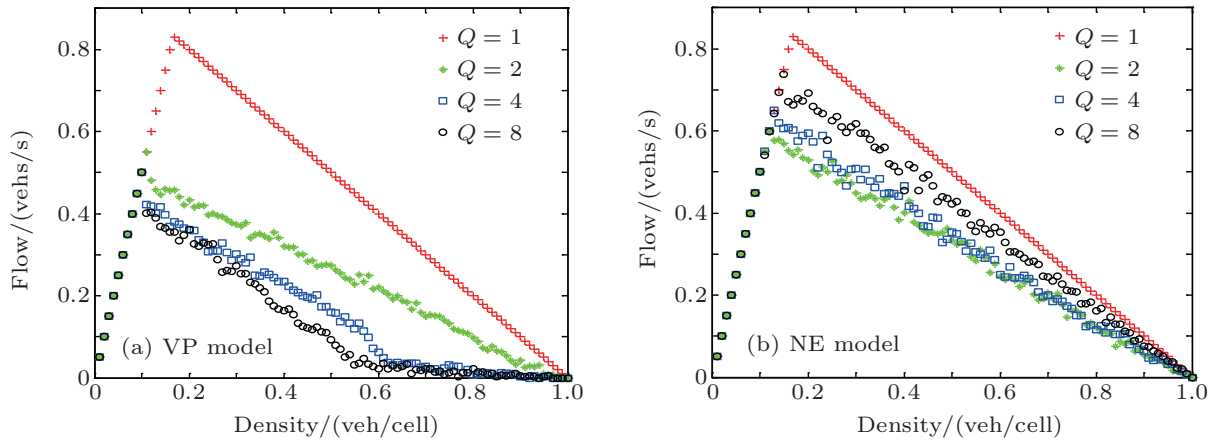


Fig. 1. (color online) Fundamental diagrams of (a) non-weighted VP model and (b) NE model with different values of Q.

3.2. Fundamental diagram changes with interactional potential strength

In simulations, the look-ahead potential strength J_0 takes the values of 1, 4, 8, 16 separately, and the look-ahead length $Q = 6$. The other parameters remain the same as those in Subsection 3.1. The simulation results of the flow–density are presented in Fig. 2.

From Fig. 2, we can see that the flow–density diagrams show the same regular patterns in the cases of weighted NE and non weighted VP model. We can clearly observe that maximum flux and critical density gradually decrease with the increasing of parameterJ_0, and in a high density area, the curves each show a concave tendency. This result is consistent with that in Fig. 10 of Ref. [19].

3.3. Comparison among NS, VP, WP, and NE models

By further comparison among NS, VP, WP, and NE models, the results are drawn into a diagram as Fig. 3. The basic parameters are $Q = 6$, $J_0 = 4$, $V_{\max} = 5$, $\Delta t = 1$ s, time = 1000 s; the randomization deceleration probability of the NS model is $p = 0.2$. The weighting coefficient of the WP model is $w_1 = 16$.[23]

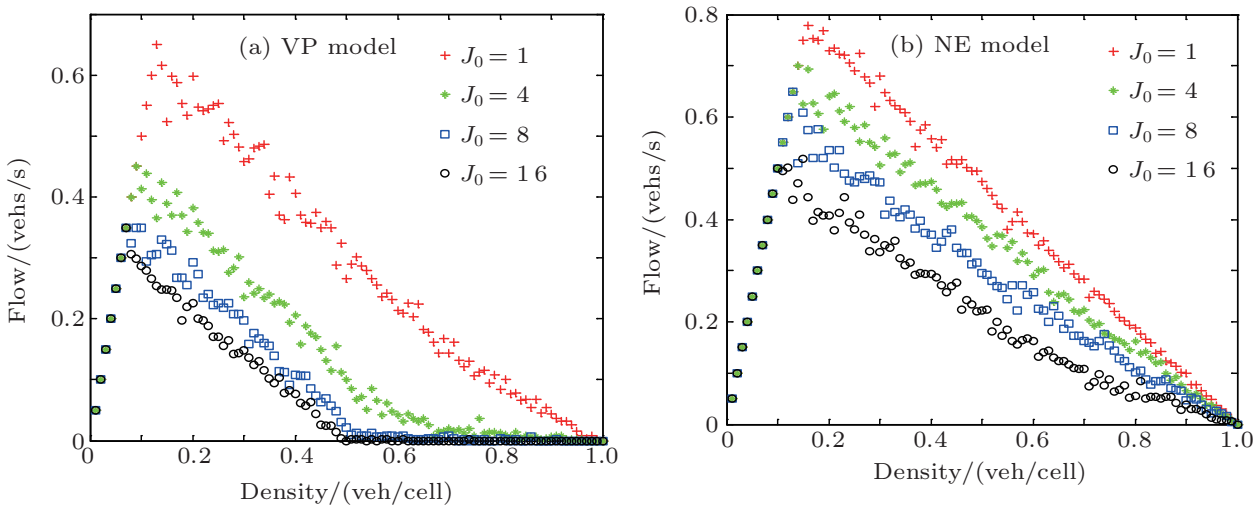


Fig. 2. (color online) Fundamental diagrams of (a) non-weighted VP model and (b) NE model with different values of J_0.

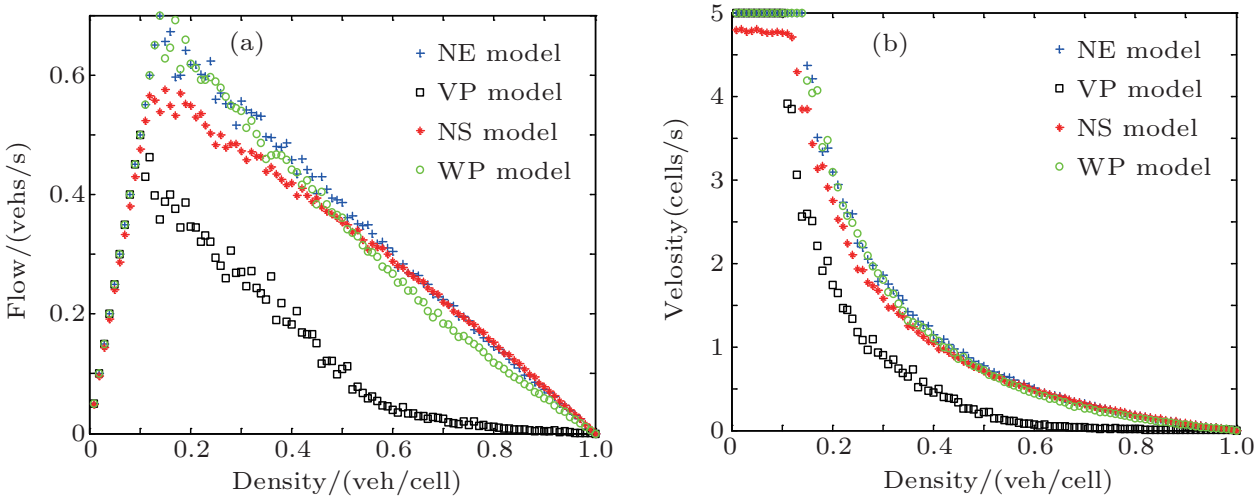


Fig. 3. (color online) Comparisons of (a) flow–density diagram and (b) velocity–density diagram among NS, VP, WP, and NE models.

From Fig. 3(a), we can see that the maximal average flow of the NS model is 0.58, while the maximal flow rate of the NE model is 0.7, which is significantly higher than that from the NS model. In the whole process, the vehicle flux from the VP model is less than that from the NE model. Furthermore, in the high-density region ($\rho > 0.5$), the vehicle flux from the NE model is higher than that from the WP model. Figure 3(b) shows that the speed from the NE model is higher than those from NS, VP, and WP models.

3.4. Comparison of three model's space–time evolvement diagrams

In simulations, the initial distribution density is $\rho = 0.2$. The other parameters are $Q = 6$, $J_0 = 4$, $V_{\max} = 5$, $\Delta t = 1$ s, and time = 1000 s. The randomization deceleration probability from the NS model is $p = 0.2$. The weighting coefficient from the WP model is $w_1 = 16$.[23] The simulation results of space-time evolvement diagrams from four models are presented in Fig. 4.

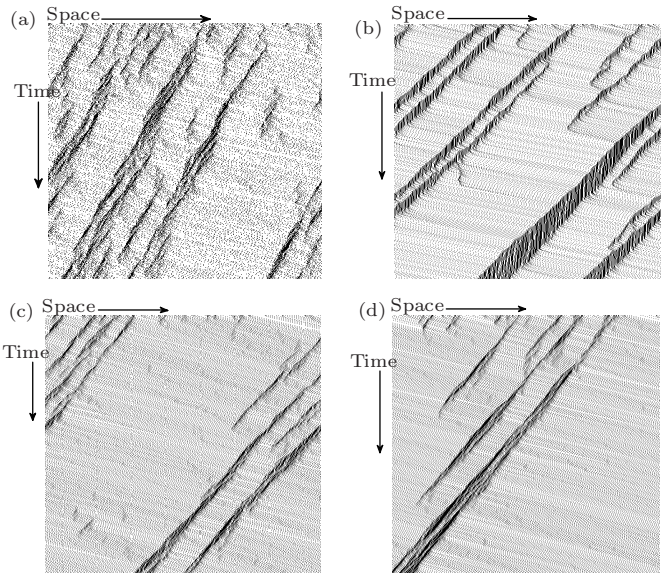


Fig. 4. Space–time diagrams from (a) NS model, (b) VP model, (c) WP model, and (d) NE model.

From Fig. 4, we note that the phenomena of stop-and-go are clearly displayed in four models. The maintenance time and length of the traffic jam from the NE model are smaller than those from the NS, VP, and WP models, and the jam areas from the NE model are easier to dissipate.

3.5. Comparison among 3D evolvement diagrams from NS, VP, WP, and NE models.

In simulations, the basic parameters remain the same as those in Subsection 3.4. The simulation results of 3D evolvement diagrams from four models are presented in Fig. 5.

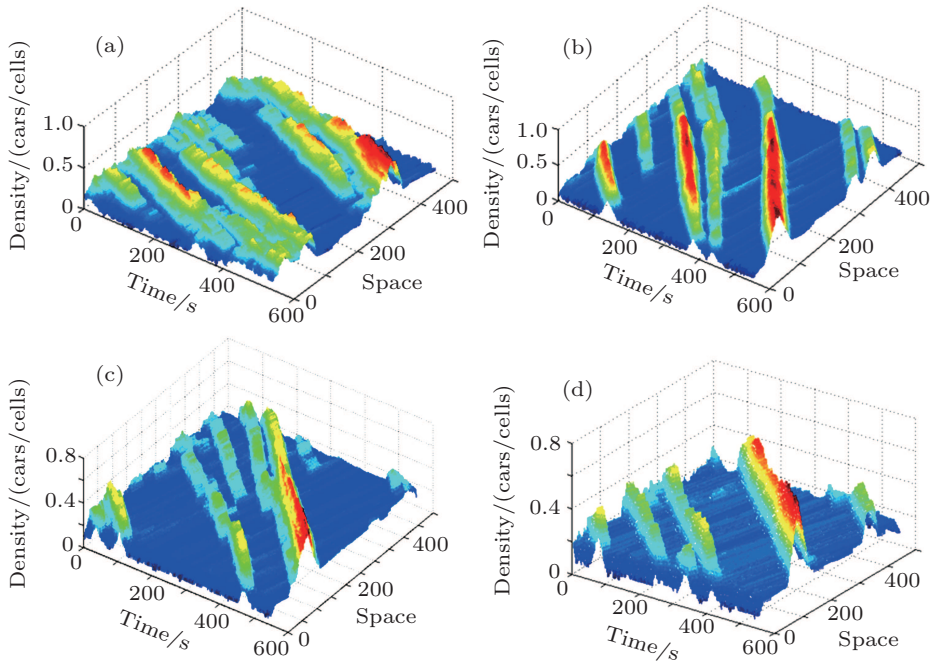


Fig. 5. (color online) 3D evolutions obtained from (a) NS model, (b) VP model, (c) WP model, and (d) NE model.

From Figs. 5(a)–5(d), we can observe the expected rarefaction waves in the four models, which clearly displays the phenomenon of stop-and-go. Furthermore, the characters of the wave movements in the NE model are clearer than those in NS, VP, and WP models. The results are in good agreement with those in Ref. [23].

4. Conclusions

In this paper, we present a new cellular automata traffic flow model with negative exponential weighted look-ahead potential. By introducing the negative exponential weighting coefficient into the look-ahead potential and endowing the potential of vehicles closer to the driver with a greater coefficient, the modeling process is more suitable for the driver random decision-making process based on the traffic environment situations before the driver.

Subsequently, we compare the results from our new model with those from the NS, WP, and non-weighted VP models by numerical simulation. From these simulations, the fundamental diagram and density–speed curves displaying many of the observed traffic phenomena including stop-and-go are obtained. Furthermore, the effects of different parameters of negative exponential weighted function on traffic flow are investigated in this paper. Some 3D evolution diagrams and space–time diagrams of NS, VP, WP, and NE models are compared.

However, there are two primary avenues of research that can be extended from this paper. First, a more suitable interactional potential function could be constructed to describe more detailed stochastic behavior of traffic flow. The proposed negative exponential weighted potential function in this paper is not related to the other random factors such as speed, etc. It can be improved in the future. The second is that we could extend the NE model of one-lane traffic to multi-lane traffic systems.

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