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Modeling and simulation for microscopic traffic flow based on multiple headway, velocity and acceleration difference

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Abstract A new car-following model termed as multiple headway, velocity, and acceleration difference (MHVAD) is proposed to describe the traffic phenomenon, which is a further extension of the existing model of full velocity difference (FVD) and full velocity and acceleration difference (FVAD). Based on the stability analysis, it is shown that the critical value of the sensitivity in the MHVAD model decreases and the stable region is apparently enlarged, compared with the FVD model and other previous models. At the end, the simulation results demonstrate that the dynamic performance of the proposed MHVAD model is better than that of the FVD and FVAD models.

Keywords Traffic flow · Car-following model · Stability analysis · Dynamic performance

1 Introduction

Traffic problems have been widely investigated in recent years. The hot scope of the traffic includes the vehicle routing problem [1], dynamic assignment problem [2], traffic jams problem [3] and so on. In order to understand the complex traffic behavior, several traffic flow models have been developed. For instance, in case of macroscopic models, the traffic is viewed as a compressible fluid formed by vehicles; while in the microscopic models, each individual vehicle is represented by a particle and the vehicle traffic is treated as a system of interacting particles driven far from equilibrium [3]. The current car-following theory is an effective method to study the microscopic traffic flow. A lot of achievements have been obtained [4–18].

In the car-following theory, the relation between the preceding vehicle and the following vehicle is described that each individual vehicle always decelerates or accelerates as a response of its surrounding stimulus. Thus, the motion equation of the nth vehicle can be presented in the following way [6]:

$$[\text{Response}]_n \propto [\text{Stimulus}]_n \tag{1}$$

Those proposed models vary according to the definitions of the stimulus. Generally speaking, the stimulus may include the speed of the vehicle, the acceleration of the vehicle, the relative speed and spacing between the nth and $n+1$th vehicle (the nth vehicle follows the $n+1$th vehicle).

In 1995, Bando et al. [7] argued that there were two types of theories on regulations of car-following. The first type is based on the assumption that the driver of each vehicle seeks a safe following distance from

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its leading vehicle, which depends on the relative velocity of the two successive vehicles. The second type theory assumes that the driver seeks a safe velocity determined by the distance from the leading vehicle. Based on the latter assumption, they proposed a car-following model, by which an optimal velocity was brought forward. The classical model is known as the optimal velocity (OV) model, which is simple and widely used in car-following modeling.

Later in 1998, Helbing and Tilch [8] carried out a comparison of the OV model simulation results with respect to the empirical follow-the-leader data. The comparison with field data suggests that high acceleration and unrealistic deceleration occur in the OV model. In order to make an improvement of the OV model, the acceleration caused by the relative speed of any two successive cars was taken into consideration. Thus, a generalized force (GF) model was developed which showed a good agreement with the empirical data.

However, neither the OV model nor the GF model could explain the traffic phenomena described by Treiber et al. (1999) [9]. If the preceding cars are much faster than the followers, the following vehicle would not brake, even if its headway is smaller than the safe distance, because the headway between the two vehicles will become larger. Given the observed car-following phenomena, Jiang et al. (2001) [10, 11] argued that the relative speed between the leading and the following vehicles had an impact on the behavior of the following driver and, therefore, this factor should be considered explicitly. Based on the assumption, by taking both positive and negative velocity difference into account, they proposed a full velocity difference (FVD) model. This model considers the effects of both the headway and velocity difference.

Both the GF model and FVD model can avoid an accident if a freely moving car reaches a standing car from a large distance. In this situation, the velocity difference has strong effects on the traffic behavior due to its large value, so that the moving vehicle can quickly respond to the standing vehicle ahead. However, if the successive vehicles have nearly identical speed, there is zero or small velocity difference, the follower can react correctly to the strong decelerating leader to avoid a collision. Given this real traffic phenomena, Zhao et al. (2005) [12, 13] argued that the acceleration difference played an important role in traffic dynamics, and by taking the acceleration difference into account, they developed a new car-following model known as the full velocity and acceleration difference (FVAD) model.

Unfortunately, the above car-following models just consider the two successive vehicles, in the real world, a following driver may respond to the variation of not only the nearest preceding vehicle, multiple preceding vehicles are also in its consideration. Therefore, by applying the Intelligent Transportation System (ITS), drivers can receive information of other vehicles on roads, and then determine the velocity of their own vehicles. In light of this information, an extended car-following model was proposed by Ge et al. (2004) [14]. Then Wang et al. (2006) [15] developed a new car-following model, which considered multiple preceding vehicles' stimulus, called the multiple velocity difference (MVD) model. Through the numerical investigations, it can be found that the critical value of the sensitivity in the MVD model decreases and the stable region is apparently enlarged, compared with the FVD model.

Previous studies have indicated that the headway or velocity difference can stabilize the traffic flow. However, all above models are only subject to one type of the ITS information, either headway or velocity difference of other cars. It is expected that traffic flow can be more stable by simultaneously introducing both two types of the ITS information [16, 17]. Based on this idea, an extended car-following model by incorporating both headway and velocity difference of multiple preceding cars, called the multiple headway and velocity difference (MHVD)model, was proposed by Xie et al. (2008) [18]. While from another system viewpoint, in order to introduce the factors of the different vehicle modes and distinguish the extent of the different preceding vehicles, Sun et al. (2010) [19] put forward another way of multiple ahead and velocity difference (MAVD) model. However, these models also seldom refer to the acceleration difference of multiple preceding vehicles.

Based on the above car-following models, the present paper further considers the action of the multiple acceleration difference of preceding vehicles and proposed the multiple headway, velocity and acceleration difference (MHVAD) model. The organization of this paper is as follows: In Sect. 1, we give a review of car-following models; based on the exiting models, a new model, called the multiple headway, velocity and acceleration difference (MHVAD) model is proposed in Sect. 2; in Sect. 3, the stability analysis of

MHVAD model is conducted, and the comparison among the OV model, FVD model, MVD model, and MAVD model is discussed. The numerical simulation is included in Sect. 4, and then a conclusion is given in the final section.

2 MHVAD model

Previous studies have indicated that the headway, velocity, or acceleration difference can stabilize the traffic flow. However, among all of these models, only one type of the ITS information, either headway, velocity, or acceleration difference of other cars, is used. It is expected that traffic flow can be more stable by simultaneously introducing all the three types of the ITS information. In a practice traffic system, all of the headway, velocity, or acceleration difference information of the multiple preceding vehicles is useful for the following vehicle. Indeed, the relation between the headway and the velocity difference is coupling. Generally speaking, when the headway between the preceding vehicle and the following vehicle is large, the following vehicle will accelerate, and it will result in that the headway become small, but when the headway approximates to the critical safe value, the following vehicle will decelerate until it moves with a safe distance. During the coupling process, the information of acceleration difference is so important that it can not be ignored. Based on the above exiting car-following models, and according to the real traffic phenomenon, it can be seen that the acceleration difference of the multiple preceding vehicles also affects the behavior of the following vehicle just as the headway and the velocity difference. The present paper, with the factor of vehicle mode, proposes a new car-following model-multiple headway, velocity, and acceleration difference (MHVAD). Taking q preceding vehicles into account, its mathematical description is following:

$$a_n(t) = k\left[V\left(\sum_{j=1}^{q}\beta_j \Delta x_{n+j-1}(t)\right) - v_n(t)\right] + \lambda\sum_{j=1}^{q}\varsigma_j \Delta v_{n+j-1}(t) + \kappa\sum_{j=1}^{q}\zeta_j \Delta a_{n+j-1}(t-1) \tag{2}$$

where $x_n(t) > 0, v_n(t) > 0$ and $a_n(t)$ represent position (m), velocity (m/s), and acceleration (m/s^2), respectively, of the nth vehicle. $t \in \mathbf{R}$ is the time(s); $q \in \mathbf{N}$ is the number of preceding vehicles in consideration. $k, \lambda, \kappa \in \mathbf{R}$, and $k > 0, \lambda \geq 0, \kappa \geq 0$ and $\lambda, \kappa \in [0, 1]$ are the different constant sensitivity coefficients. $\Delta x_n(t) = x_{n+1}(t) - x_n(t)$, $\Delta v_n(t) = v_{n+1}(t) - v_n(t)$, and $\Delta a_n(t) = a_{n+1}(t) - a_n(t)$ are the spatial headway distance, the velocity difference and the acceleration difference between the preceding vehicle $n+1$ and the following vehicle n at time t, respectively. $\beta_j, \varsigma_j, \zeta_j \in \mathbf{R}$, and $\beta_j \geq 0, \varsigma_j \geq 0, \zeta_j \geq 0$ are different weighting value coefficients, respectively. For convenience, we suppose $\beta_j = \varsigma_j = \zeta_j$. And $V(\bullet)$ is the optimal velocity function, which is a function of $\Delta x_n(t)$ and its general form is as follows [7]:

$$V\big(\Delta x_n(t)\big) = \big[\tanh(\Delta x_n(t) - h_c) + \tanh(h_c)\big]v_{\max}/2 \tag{3}$$

where $v_{\max}$ is the maximal speed of the vehicle, h_c is the safe distance, and $\tanh(\bullet)$is the hyperbolic tangent function. And (3) is a monotonically increasing function with $\Delta x_n(t)$ and it has an upper bound, while it has a turning point at $\Delta x_n(t) = h_c$: $V''(h_c) = 0$.

In the MHVAD model, β_j satisfies the following two conditions:

(1) β_j is a monotone decreasing function with the j, namely, $\beta_j < \beta_{j-1}$. Because the effect of the preceding vehicle to the current car reduces with the increase of the headway distance.
(2) $\sum_{j=1}^{q}\beta_j = 1$, $\beta_j = 1$ for $q = 1$, so as to ς_j and ζ_j.

And β_j is defined as follows [17]:

$$\beta_j = \begin{cases} \frac{q-1}{q^j} & \text{for } j \neq q \\ \frac{1}{q^{j-1}} & \text{for } j = q \end{cases} \qquad (j = 1, 2, \ldots, q) \tag{4}$$

3 Stability analysis

For all types of the car-following models, stability analysis is definitely an important issue [20, 21]. In the car-following models, the stability means that the vehicle can drive free with the safe velocity and distance; in other words, if the stability region is larger, the opportunity of collision is lower.

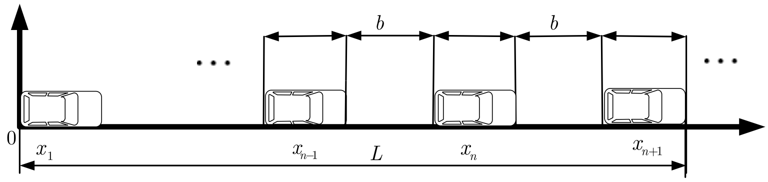

Fig. 1 Sketch of car-following phenomenon

The car-following phenomenon in the car-following theory is briefly described as in Fig. 1:

In Fig. 1b is the space headway distance of two successive vehicles in the initial phase, and L is the length of the considering road.

The following behavior of a platoon of vehicles is similar to that of one vehicle, so the description is also as the (2). Any specific solution of the equation depends on the velocity of the leading vehicle of the platoon, v_0, and the three parameters k, λ , and κ. For any relative spacing, if a disturbance grows in amplitude, then a "collision" would eventually occur somewhere back in the platoon of vehicles.

Assumption 1 *Supposing the initial state of the traffic flow is steady, and the space headway distance is b, while the corresponding optimal velocity is $V(b)$.*

Theorem 1 *If the following condition is satisfied*:

$$V'(b) < \frac{k}{1-\kappa}\sum_{j=1}^{q}\frac{\beta_j(2j-1)}{2} + \frac{\lambda}{1-\kappa} \tag{5}$$

then the MHVAD model is stable.

Proof According to the above assumption, the position solution to the stability flow is:

$$x_n^0(t) = bn + V(b)t \tag{6}$$

adding a disturbance $y_n(t)$ to the (6), it will become

$$y_n(t) = x_n(t) - x_n^0(t) \tag{7}$$

And $\Delta x_{n+j-1} = \Delta y_{n+j-1} + b$, $v_n = \dot{y}_n + V(b)$, $a_{n+j-1}(t-1) = \ddot{y}_{n+j-1}(t-1)$, substitute (7) into the (2) and using the Taylor expansion, it will deduce:

$$\ddot{y}_n(t) = k\left[V'(b)\sum_{j=1}^{q}\beta_j\Delta y_{n+j-1} - \dot{y}_n(t)\right] + \lambda\sum_{j=1}^{q}\xi_j\Delta\dot{y}_{n+j-1} + \kappa\sum_{j=1}^{q}\eta_j\Delta\ddot{y}_{n+j-1} \tag{8}$$

Set $y_n(t) = \exp(i\alpha n + zt)$, then, $\Delta y_{n+j-1}(t) = e^{i\alpha(n+j-1)+zt}(e^{i\alpha}-1)$, $\Delta\dot{y}_{n+j-1}(t) = ze^{i\alpha(n+j-1)+zt}\times(e^{i\alpha}-1)\Delta\ddot{y}_{n+j-1}(t-1) = z^2e^{i\alpha(n+j-1)+z(t-1)}(e^{i\alpha}-1)$, substituting it in (8) and according to the Fourier transform:

$$\begin{aligned} z^2 &= kV'(b)\sum_{j=1}^{q}\beta_j\left[i\alpha + \frac{1}{2}(i\alpha)^2(2j-1)\right] \\ &\quad - kz + \lambda z\sum_{j=1}^{q}\xi_j\left[i\alpha + \frac{1}{2}(i\alpha)^2(2j-1)\right] \\ &\quad + \kappa z^2\exp(-z)\sum_{j=1}^{q}\eta_j\left[i\alpha + \frac{1}{2}(i\alpha)^2(2j-1)\right] \end{aligned} \tag{9}$$

let $z = z_1(i\alpha) + z_2(i\alpha)^2 + \cdots$, and expand it to the second term of $(i\alpha)$, we will obtain

$$\begin{aligned} &\left[z_1(i\alpha) + z_2(i\alpha)^2\right]^2 \\ &\quad = kV'(b)\sum_{j=1}^{q}\beta_j\left[(i\alpha) + \frac{1}{2}(i\alpha)^2(2j-1)\right] \\ &\qquad - k\left[z_1(i\alpha) + z_2(i\alpha)^2\right] \\ &\qquad + \lambda\left[z_1(i\alpha) + z_2(i\alpha)^2\right] \\ &\qquad \times\sum_{j=1}^{q}\xi_j\left[(i\alpha) + \frac{1}{2}(i\alpha)^2(2j-1)\right] \\ &\qquad + \kappa\left[z_1(i\alpha) + z_2(i\alpha)^2\right]^2 \\ &\qquad \times\exp\left(-\left[z_1(i\alpha) + z_2(i\alpha)^2\right]\right) \\ &\qquad \times\sum_{j=1}^{q}\eta_j\left[(i\alpha) + \frac{1}{2}(i\alpha)^2(2j-1)\right] \end{aligned} \tag{10}$$

And so we have

$$\begin{cases} kV'(b)\sum_{j=1}^{q}\beta_j - kz_1 = 0 \\ -z_1^2 + kV'(b)\sum_{j=1}^{q}\frac{\beta_j(j-1)}{2} - kz_2 \\ \quad + \lambda z_1\sum_{j=1}^{q}\xi_j + \kappa z_1^2\sum_{j=1}^{q}\eta_j = 0 \end{cases} \tag{11}$$

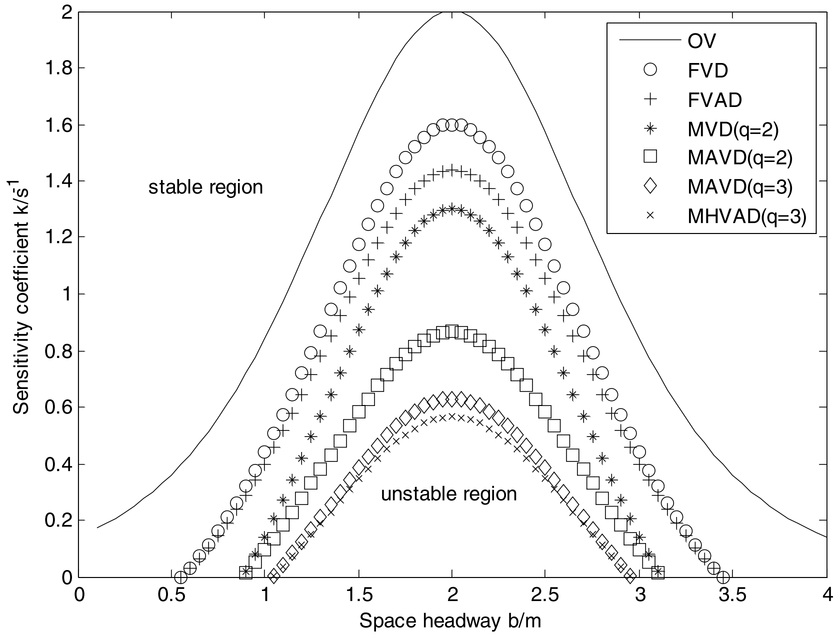

Fig. 2 The critical curves between sensitivity coefficient and the space headway distance

that is,

$$\begin{cases} z_1 = V'(b) \\ z_2 = V'(b)\sum_{j=1}^{q}\frac{\beta_j(2j-1)}{2} - \frac{V'(b)^2}{k} + \frac{V'(b)\lambda}{k} \\ \qquad + \frac{V'(b)^2\kappa}{k} \end{cases} \tag{12}$$

when $z_2 > 0$, we get

$$V'(b) < \frac{k}{1-\kappa}\sum_{j=1}^{q}\frac{\beta_j(2j-1)}{2} + \frac{\lambda}{1-\kappa} \tag{13}$$

then the stability condition is

$$V'(b) < \frac{k}{1-\kappa}\sum_{j=1}^{q}\frac{\beta_j(2j-1)}{2} + \frac{\lambda}{1-\kappa} \tag{14}$$

so the proof is over. □

Remark 1 According to (14), we can draw a conclusion as follows: when $q = 1, \lambda = \kappa = 0$, that is the OV model, the stable condition is

$$V'(b) < k/2$$

when $q = 1, \lambda \neq 0, \kappa = 0$, that is FVD model, the stable condition is

$$V'(b) < k/2 + \lambda$$

when $q = 1, \lambda \neq 0, \kappa \neq 0$, that is FVAD model, the stable condition is

$$V'(b) < (k + 2\lambda)/2(1-\kappa)$$

when $q \neq 1, \lambda \neq 0, \kappa = 0$, that is MAVD model, the stable condition is

$$V'(b) < k\sum_{j=1}^{q}\beta_j(2j-1)/2 + \lambda$$

Because k, λ are not negative constants and $\kappa \in (0, 1)$, it can be seen that the stable region of MHVAD model is larger than the other models. In Fig. 2, we give the critical stable curves of five models, which are the critical curves between sensitivity coefficient and the headway of the OV model $(q = 1, \lambda = 0)$, FVD model $(q = 1, \lambda = 0.2\ \mathrm{s}^{-1})$, FVAD model $(q = 1, \lambda = 0.2\ \mathrm{s}^{-1}, \kappa = 0.1)$ MVD model $(q = 2, \lambda_1 = 0.2\ \mathrm{s}^{-1}, \lambda_2 = 0.15\ \mathrm{s}^{-1})$, MAVD model $(q = 2, \lambda = 0.2\ \mathrm{s}^{-1}; q = 3, \lambda = 0.2\ \mathrm{s}^{-1})$, and MHVAD model $(q = 3, \lambda = 0.2\ \mathrm{s}^{-1}, \kappa = 0.1)$.

In Fig. 2, the region over the critical curve is the stable region; while the remainder is the unstable region. From Fig. 2, it has been intuitively shown that the stable region of FVD model is larger than that of OV model. In other words, the vehicles can move freely within a certain range. The reason is that the

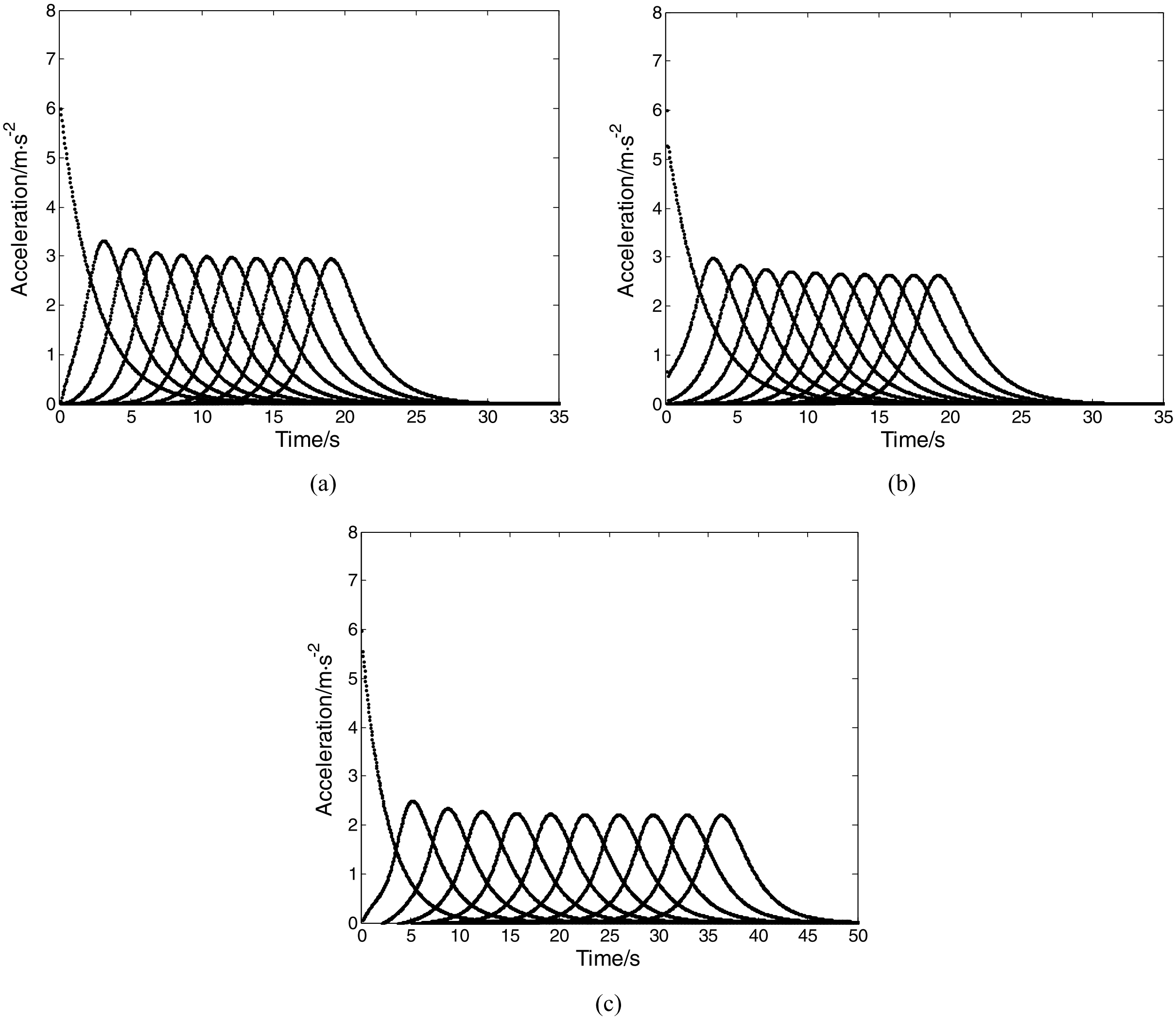

Fig. 3 The acceleration distribution of vehicles starting from a green traffic signal (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

FVD model has taken the velocity difference into account to overcome the drawbacks of the OV model; the stable region of FVAD model is tiny larger than FVD model, that is because the former model considers the effect of the acceleration difference; and the stable region of MVD model ($q = 2$) is larger than FVAD model and FVD model, owing to the velocity difference information of more preceding vehicles being taken into account; and the stable region of the MAVD model ($q = 2$) is larger than the MVD model ($q = 2$), because of both the headway information and the velocity difference information of more preceding vehicles being taken into account; and the stable region of the MHVAD model ($q = 3$) is larger than the MAVD model ($q = 3$), as a result of both the headway information, the velocity difference information and the acceleration difference information of more preceding vehicles being considered. And further considering the more preceding vehicles' information, the stable region will be enlarged, and up to tend to a fixed area. The increase of stable region of traffic flow indicates that vehicles can move freely in a wide range (no congestion), that is meant to suppress traffic jams effectively.

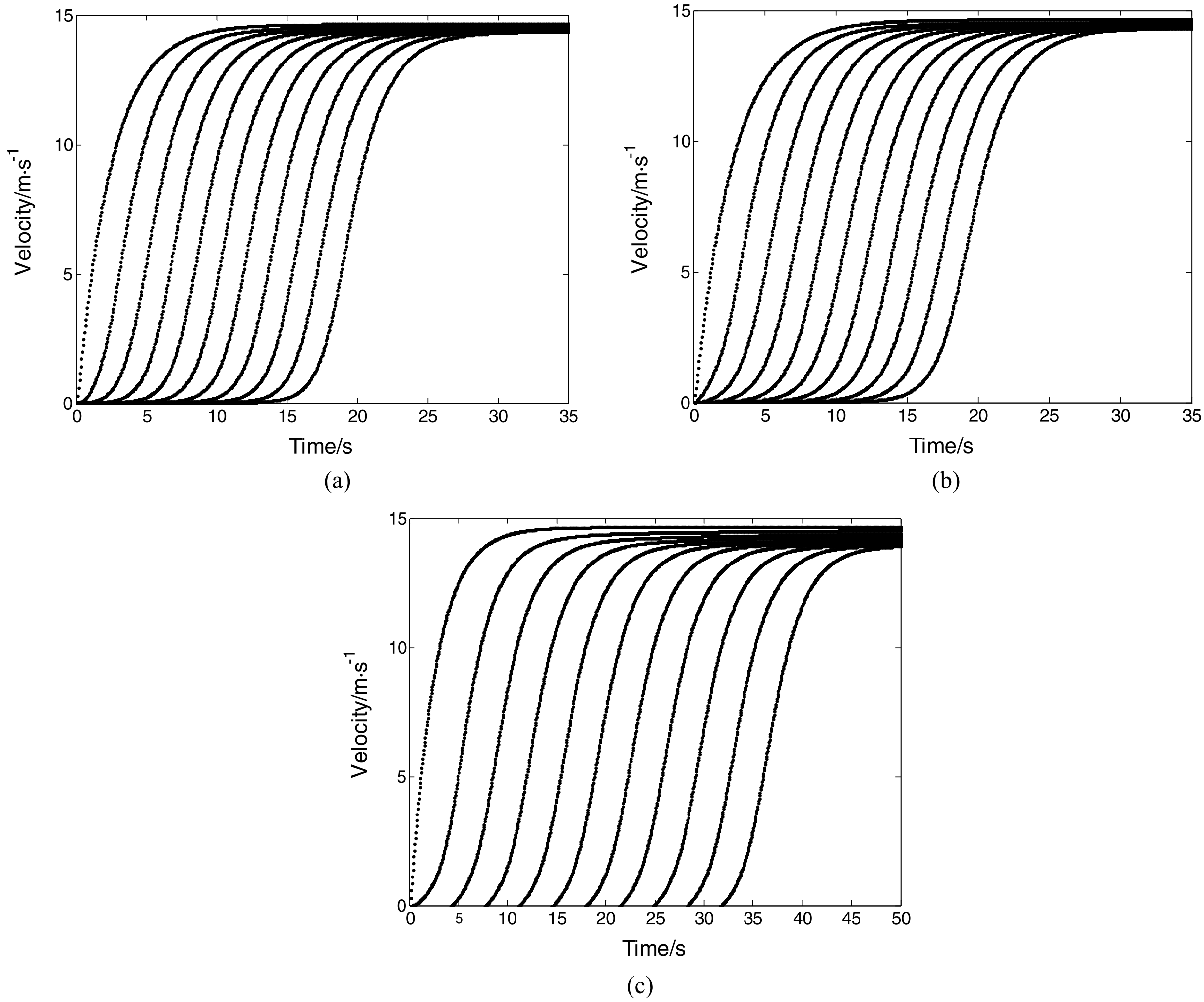

Fig. 4 The velocity distribution of vehicles starting from a green traffic signal (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

4 Numerical simulation

In order to analyze the dynamic performance of the MHVAD model, three situations are analyzed as follows:

4.1 Start process

Considering the situation that when the red light turns to green light, how do the vehicles perform dynamically? First, we apply the MHVAD model to simulate car motion under a traffic signal and examine certain properties of the MHVAD model. The same simulation is carried out as that in [10]. First, the traffic signal is yellow and all vehicles are waiting with the headway of 7.4 m, where the optimal velocity is zero. Then at time $t = 0$ s, the signal changes to green and the vehicles start. For comparison, we use the same parameters as those in the FVD model and FVAD model. The variations of all vehicles' acceleration for the three models are shown in Fig. 3. From Fig. 3, we can see the maximum value of acceleration in the MHVAD model is much less than that of the FVD model and the FVAD model, which is under the limitation of 3 m/s^2. This advantage can effectively prevent the go-and-stop phenomenon of the vehicles, which exists in the OV model.

Moreover, Figs. 4 and 5 give the velocity and position distribution of vehicles starting from a green traffic signal, respectively. From Fig. 4, we can see

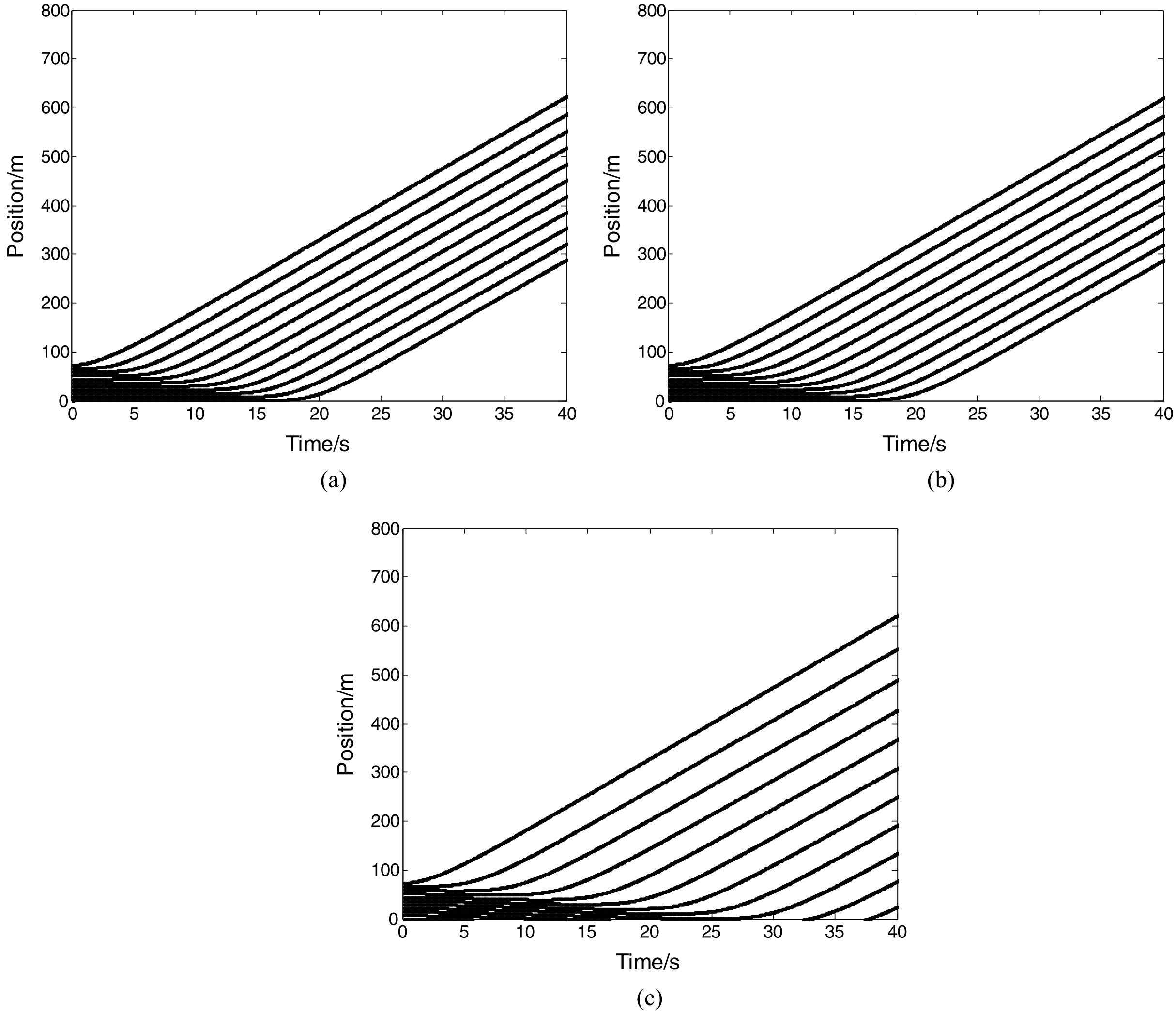

Fig. 5 The position distribution of vehicles starting from a green traffic signal (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

that the velocity distribution in the MHVAD model quickly tends to the maximum value, compared with the FVD model and the FVAD model. It means that the followers of the MHVAD model at the initial stage have a faster start than that of the FVD model and the FVAD model. This coincides completely with the real driving behaviors: the following drivers initially have strong desires to start moving forward, and then calm down until a steady speed is obtained. From Fig. 5, we also can see that the position distribution in the MHVAD model lasts longer than that of the FVD model and the FVAD model, which indicates that the vehicles can move far with the steady velocity.

Based on the above analysis, it has been shown that the start performance of the MHVAD model is better than the FVD model and the FVAD model, in terms of the acceleration, velocity and position distribution of the vehicles.

4.2 Stop process

Considering the situation that when the green light turns to red light, how do the vehicles perform dynamically? First, the traffic signal is yellow and all vehicles are moving with the same velocity. Then at the

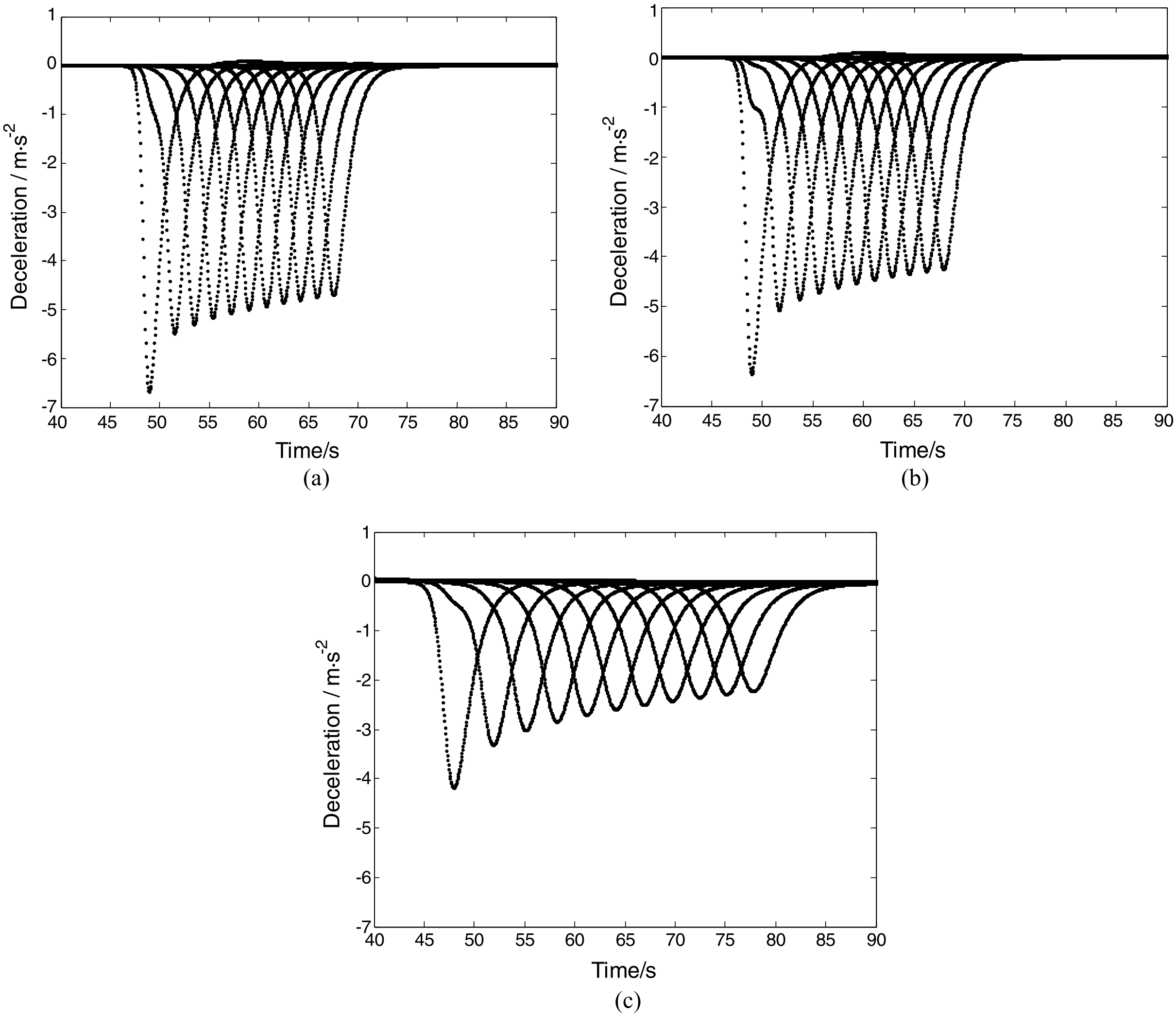

Fig. 6 The deceleration distribution of vehicles stopping at a red traffic signal (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

time $t = 0$ s, the signal changes to red and the vehicles stop. For comparison, we use the same parameters as those in the FVD model and FVAD model. The variations of all vehicles' deceleration for the three models are shown in Fig. 6. From Fig. 6, we can see the maximum value of deceleration in the MHVAD model is much less than that of FVD model and FVAD model, which is about -4 m/s^2. In addition, the velocity and position distribution of vehicles stopping at a red traffic signal are given in Figs. 7 and 8, respectively. By observing Fig. 7c, the velocity in the MHVAD model is nonnegative. However, in Figs. 7a and 7b, there are negative velocities in the FVD model and the FVAD model, which is not realistic. While from Fig. 8, we can see that the position distribution in the MHVAD model lasts shorter than the FVD model and FVAD model, and it means that the vehicles can easily stop at the red light.

Based on the above analysis, it has been shown that the stop performance of the MHVAD model is better than FVD model and FVAD model, in terms of the deceleration, velocity, and position distribution of the vehicles.

4.3 Evolution process

A numerical simulation is carried out to observe the traffic dynamics in the MHVAD model. For compar-

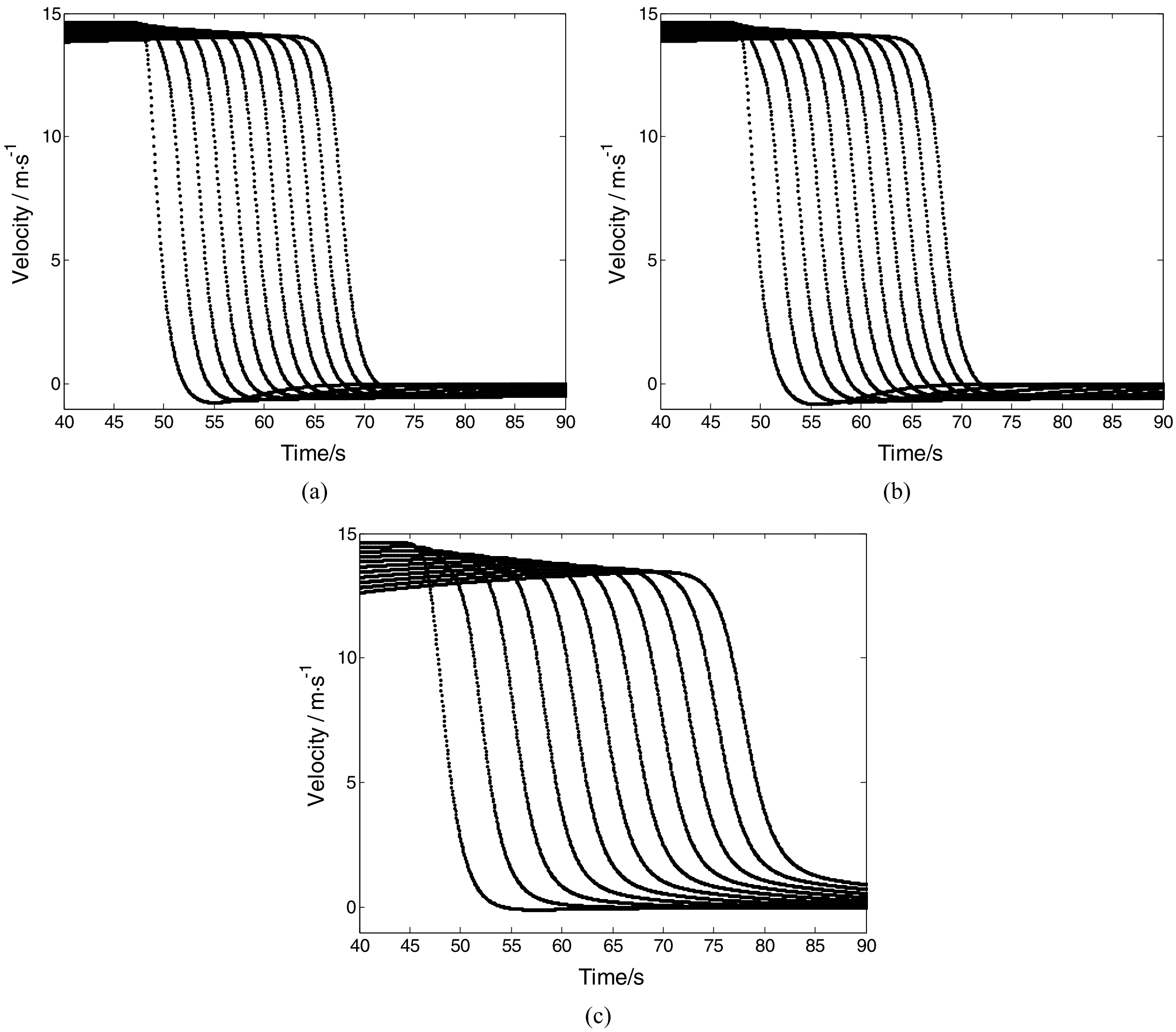

Fig. 7 The velocity distribution of vehicles stopping at a red traffic signal (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

ison, we take the same parameters as in the FVD model and FVAD model into consideration. There are $N = 100$ vehicles running on a road with the length of $L = 1500$ m, under a periodic boundary condition. The parameters are set as $k = 1.0\ \text{m}^{-1}$, $x_c = 2.0$ m, $v_{\max} = 2$ m/s, $v_0 = 0.964$ m/s. For all results, we use Runge–Kutta algorithm for numerical integration with the time-step $\Delta t = 0.01$ s. The uniform random noise with the maximum amplitude 10^{-3} is added to (2) for all the vehicles. The initial conditions are chosen as $\Delta x_i(0) = x_c$, $i = 2, \ldots, N$, $x_i(0) = V^{-1}(x_c) = v_0$. We set the same initial disturbance as that in [10]

$$x_1(0) = 1\ \text{m}; \qquad x_i(0) = (i-1)L/N\text{m}, \quad \text{for } i \neq 1 \tag{15}$$

$$v_i(0) = V(L/N) \tag{16}$$

In order to get the information of the spatial organization of the vehicles, the variations of corresponding velocities for different vehicles at $t = 100$ s are plotted in Figs. 9a, 9b, and 9c, respectively. From Figs. 9a and 9b, it can be seen that the upstream group vehicles oscillate around the constant velocity v_0, while the downstream group vehicles move with constant veloc-

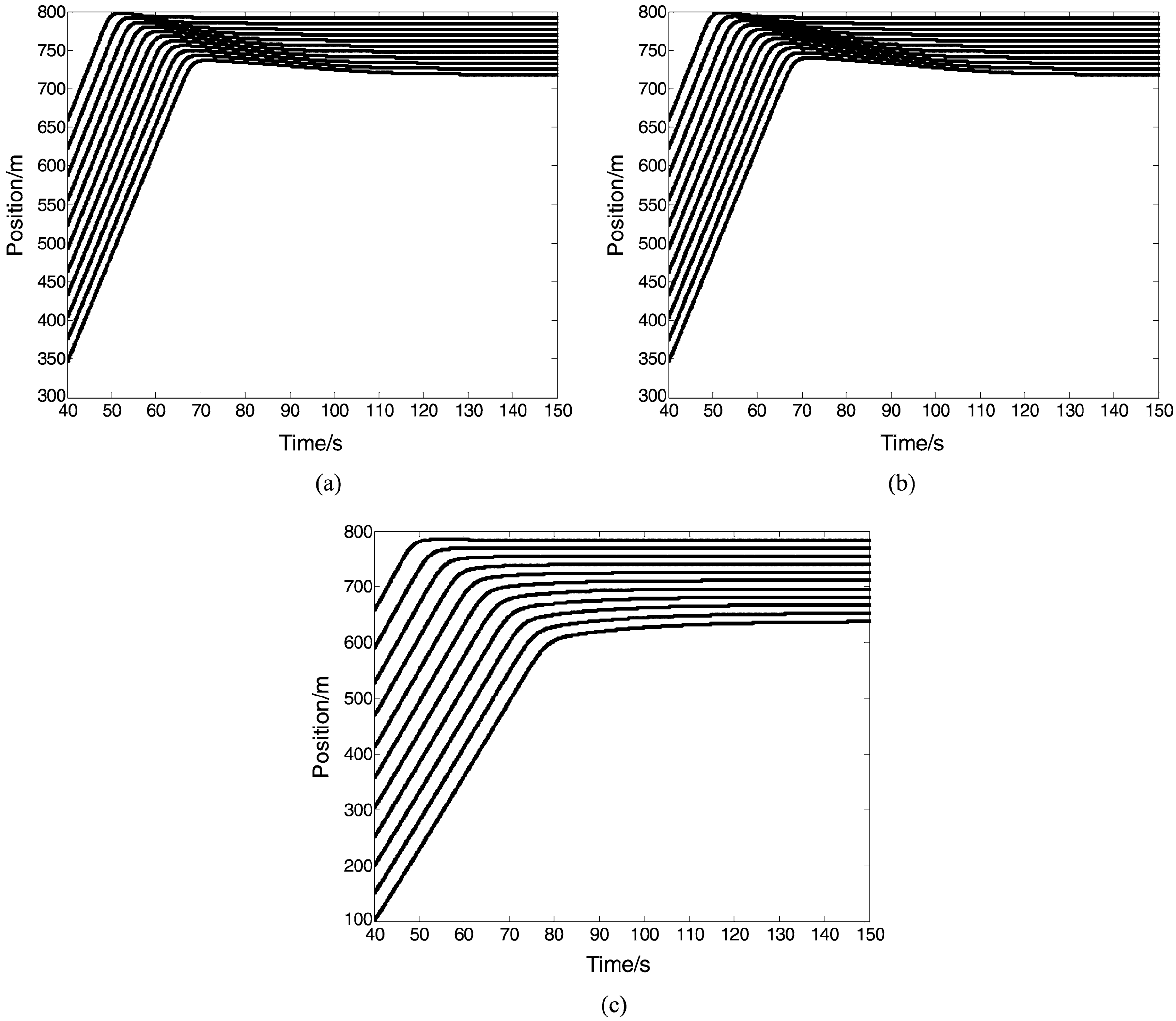

Fig. 8 The position distribution of vehicles stopping at a red traffic signal (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

ity v_0. The oscillation amplitude converges along the increasing of the car indices. That indicates that traffic jams appears in the noisy FVD model and the FVAD model. While from Fig. 9c, we can see that the vehicles in the MHVAD model move freely with the constant velocity v_0.

In addition, Figs. 10a, 10b, and 10c show the space headway behaviors of all vehicles at $t = 100$ s. From Fig. 10, it has been found obviously that the space headway oscillates around the constant space headway x_c upstream, and gradually becomes constant downstream. The oscillation amplitude converges along the increasing of the car indices.

Based on the above analysis, it has been shown that the evolution dynamic performance of the MHVAD model is better than FVD model and FVAD model, in terms of the velocity and space headway distribution of the vehicles.

5 Conclusion

Based on the application of the intelligent transportation system (ITS) which can provide the information of other vehicles for the driver on the same lane, the present paper puts forward a multiple headway,

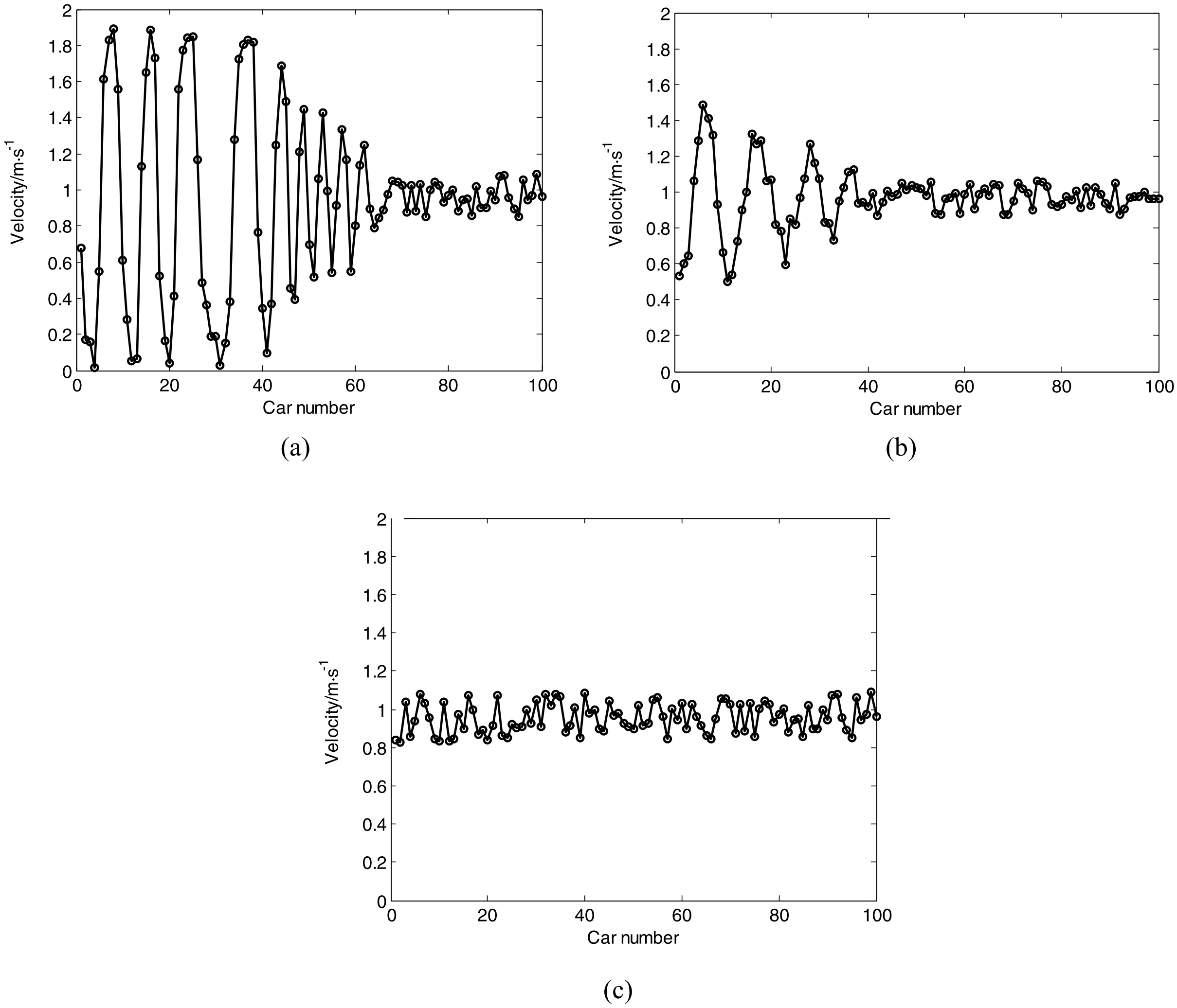

Fig. 9 The velocity distribution of moving vehicles (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

velocity, and acceleration difference (MHVAD) microscopic car-following model to describe the traffic phenomenon. Compared with the other existing models, the presented novel model does not only take the headway, velocity, and acceleration difference information into account, but also considers more than one vehicle in front of the following vehicle. Therefore, the description of the traffic is more actual and reasonable. The theoretical analysis and simulation results have shown that the model can further improve the stability of the traffic flow and effectively restrain the traffic jams. Moreover, the start process performance, stop process performance, and the evolution process dynamic performance are better than those of the FVD model and FVAD model, in terms of the acceleration, velocity, and headway distribution of the vehicles. However, as the complexity of the traffic system, the future research needs to consider some uncertainties during the car-following process.

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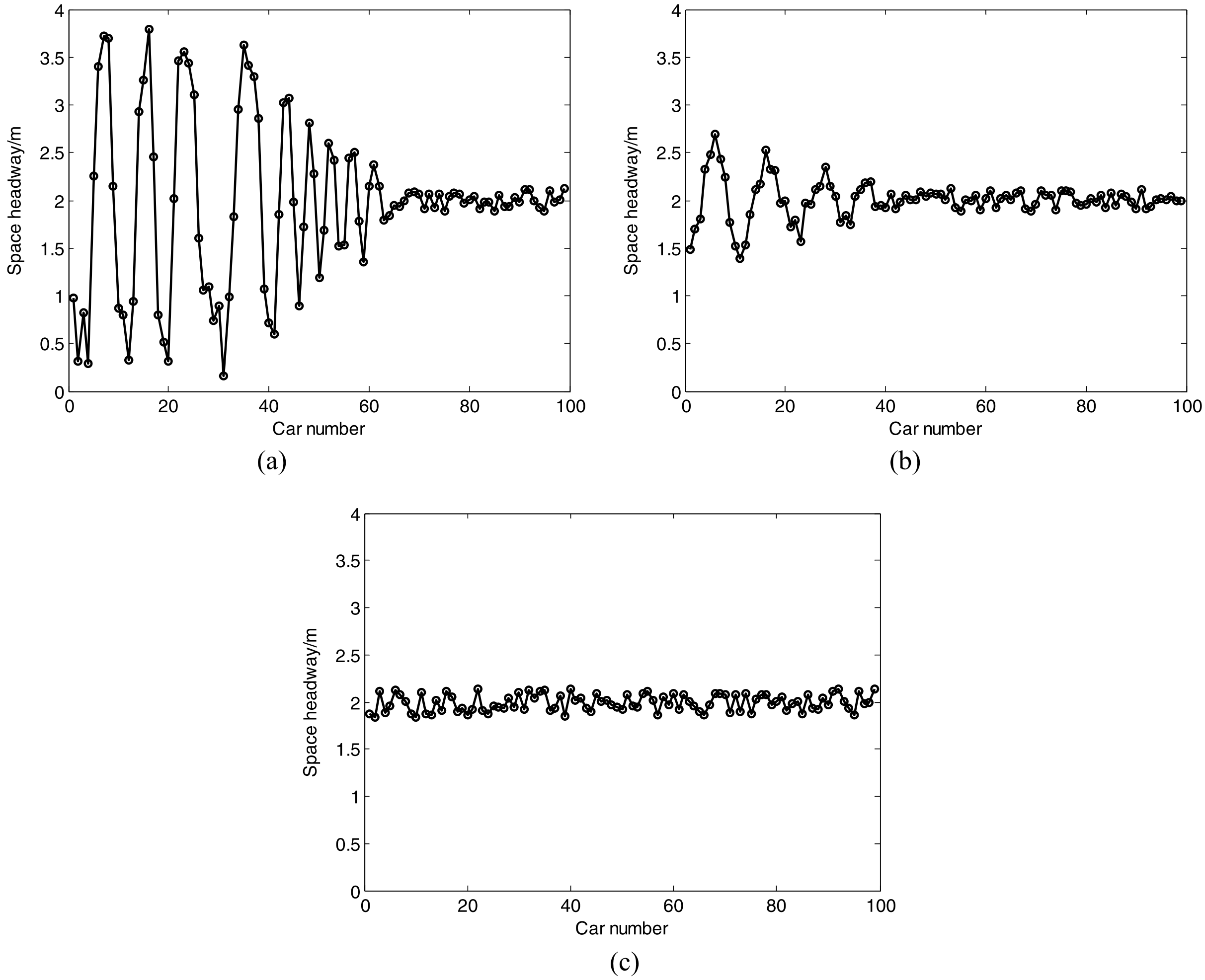

Fig. 10 The space headway distribution of moving vehicles (**a**) FVD model; (**b**) FVAD model; (**c**) MHVAD ($q = 2$) model

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