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Research Article

A Cellular Automaton Traffic Flow Model with Advanced Decelerations

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A one-dimensional cellular automaton traffic flow model, which considers the deceleration in advance, is addressed in this paper. The model reflects the situation in the real traffic that drivers usually adjust the current velocity by forecasting its velocities in a short time of future, in order to avoid the sharp deceleration. The fundamental diagram obtained by simulation shows the ability of this model to capture the essential features of traffic flow, for example, synchronized flow, metastable state, and phase separation at the high density. Contrasting with the simulation results of the VE model, this model shows a higher maximum flux closer to the measured data, more stability, more efficient dissolving blockage, lower vehicle deceleration, and more reasonable distribution of vehicles. The results indicate that advanced deceleration has an important impact on traffic flow, and this model has some practical significance as the result matching to the actual situation.

1. Introduction

With the drastic growth in the vehicle amount, traffic congestion has become more and more serious. The transportation problems have caused extensive attention to transportation industry, physics community, and mathematics community [1–13]. Owing to the properties of cellular automaton model (CA Model), such as the discreteness of space and time, the simplicity and flexibility of algorithm and the easiness to be simulated on computer, it could effectively simulate the vehicles movement in traffic and be widely used and developed in the study of traffic flow [1–8]. In 1992, Nagel and Schreckenberg proposed the famous NaSch model [1]. The model deals with single-lane traffic flow of cars moving in a one-dimensional cellular chain under periodic boundary conditions, which only considers vehicle acceleration, deceleration, random delays, and update of vehicle location. According to the above simple rules, this model can be used to reproduce the basic phenomena encountered in real traffic, for example, the occurrence of phantom traffic jams. However, some features have not been considered in the NaSch model, such as the metastable state. To fix the omission, a number of improvements for the evolution rules have been proposed [2–8]. Literature [2] proposed the BJH model, which considers a possible delay before a car pulls away from being stationary due to the blocking of the leading vehicle. Literature [3] considered a velocity-dependent randomization delay probability and presented the VDR Model. Literature [4] took into account the velocity effect of a car on the successive and proposed the VE (velocity effect) model. Literature [5] presented a cellular automaton model for single-lane traffic flow, and the model considers the effect of headway distance between two successive cars on the randomization of the latter car. Literature [6] took into account the diversity of traffic behaviors under real traffic situations induced by various driving characters and habits to modify the weighted probabilistic cellular automaton model. Literature [7] modified the NaSch model by enabling the randomization probability to be adjusted on the bases of drivers' memory. Literature [8] proposed an improved cellular automaton model to describe the urban traffic flow with the consideration of traffic light and driving behavior effects. All of the CA Models adjust the current velocity only based on considering the velocity of vehicle itself, correlating velocity, vehicle distance, safe distance, and so forth in the perspective of space, and the adjustment of the vehicle velocity is often achieved by different random deceleration properties P. In the process of evolution, all the vehicles view the maximum velocity as the desired velocity, in other words, all the vehicles expect to reach the maximum velocity by gradual acceleration if the travel condition ahead permits. However, because the models do not take into account the deceleration of vehicles, it can lead to a terrible situation: if the following vehicle moves close to a still vehicle at the maximum velocity, it will have a sharp deceleration from the maximum velocity to zero in the next second. If that situation does occur, it is inevitably to get a rear-end collision in the actual traffic.

In the actual traffic, in order to avoid the happening of sudden deceleration and rear-end collision and to drive the vehicle steadily, the current vehicle velocity depends not only on the velocity of itself, the relative velocity with the leading vehicle, the distance between the vehicles, the safety distance, and so forth, but also on the velocity changing trend of the current vehicle and the leading vehicles. Therefore, at any time of driving, drivers must estimate the velocity in next few seconds and decide whether to accelerate, decelerate, or keep the velocity. For example, when meeting a red traffic light or the front vehicle moving slowly and not accelerating in next few seconds, the vehicle needs decelerate in advance. On the basis of the NaSch model of traffic flow, this paper proposes a one-dimensional cellular automaton traffic flow Model with advanced decelerations. Considering time factor, the model adjusts the current velocity by the forecasting velocity of the next several time steps to avoid the sharp deceleration to some extent, enhances the stable performance of traffic flow and keeping the smooth flow of traffic better. Our model shows the metastable state, phase separation, and hysteresis phenomenon by computer simulating, which exists in actual traffic.

2. The Establishment of Model

In the NaSch Model, vehicles randomly distributed in a one-dimensional discrete cellular chain, whose length is L. Each cell may either be empty or be occupied by one vehicle. All vehicles are assumed to move from the left to the right. The nth vehicle in the time-step t is located at the position $x_n(t)$, moving with an integral velocity $v_n(t) \in \{0, \dots, v_{\max}\}$, where $n \in \{1, 2, \dots, N\}$ and $v_{\max}$ ($v_{\max} \geq 1$) are the maximum velocity which a vehicle can reach. The gap between consecutive vehicles is $d_n(t) = x_{n+1}(t) - x_n(t) - l_{n+1}$, which is the number of empty cells in front of the nth vehicle in the time-step t. At each discrete time-step $t \rightarrow t+1$, an arbitrary arrangement of N vehicles is updated in parallel according to the following rules:

(i) acceleration: $v_n(t+1) = v_n(t) + 1$;

(ii) deceleration: $v_n(t+1) = \min(v_n(t+1), d_n)$;

(iii) randomization: $v_n(t+1) = \max(v_n(t+1) - 1, 0)$ with the probability P;

(iv) update of location: $x_n(t+1) = x_n(t) + v_n(t+1)$.

In some expansion and amendments to the NS Model, a variety of ways to preestimate the velocity $v'_{n+1}(t+1)$ of the leading vehicle in the next time-step were used, such as the VE model [4], and deceleration rules were updated as follows:

$$v_n(t+1) = \min\left(d_n(t) + v'_{n+1}(t+1), v_{\max}\right). \tag{2.1}$$

Because the deceleration rules in NaSch and its expansive models are based on the greedy mechanism, the vehicles move forward by the currently allowed maximum velocity as much as possible. When the velocity difference is bigger, and the gap is smaller between consecutive vehicles, according to the given decelerating rules, it is inevitable that the following vehicle will abruptly decelerate. In the model of this paper, in order to avoid this condition, the velocities in the next *steps* time-steps are firstly estimated before determining the velocity in current time. If the abrupt deceleration exists in these next *steps* time-steps, the method that the vehicle gradually decelerates in advance is used to ensure the safe driving. Of course, as the result of the increasing of time-steps *steps*, there are more errors caused by estimation. So the paper sets $steps \le 3$, equal to predicting velocity in 3 seconds. The vehicle velocity estimation is based on greedy mechanism.

(i) From a given configuration at time-step t, the forward effective distance $d_n^{\mathrm{eff}}(t+1)$ at the next time-step $t+1$ can be obtained by

$$d_n^{\mathrm{eff}}(t+1) = d_n + \max\left(v_{n+1}^{\mathrm{anti}} - \mathrm{gap}_{\mathrm{safe}}, 0\right). \tag{2.2}$$

Among $v_{n+1}^{\mathrm{anti}} = \min(d_{n+1}(t), v_{n+1}(t))$ is the anticipated velocity of the leading vehicle, $\mathrm{gap}_{\mathrm{safe}}$ is the security gap. Then calculate estimated velocity $v_n^{\mathrm{est}}(t+1)$ at the time-step $t+1$ by

$$v_n^{\mathrm{est}}(t+1) = \min\left(d_n^{\mathrm{eff}}(t+1), \min(v_n(t)+1, v_{\max})\right). \tag{2.3}$$

At the same time, this step also confirms the permitted maximum velocity at the time-step $t+1$.

(ii) Using the same method, the vehicle velocity at the time-step $t+i+1$ can be calculated according to estimated velocity $v_n^{\mathrm{est}}(t+i)$ and estimated effective distance $d_n^{\mathrm{est}}(t+i)$ at the time-step $t+i$ $(i = 2 \cdots steps - 1)$, until the estimated velocity $v_n^{\mathrm{est}}(t+steps)$ at the time-step $t+steps$ is obtained.

(iii) Calculate the possible moving distance $l_{\text{steps}}^{\text{est}} = \sum_{i=1}^{\text{steps}} v_n^{\text{est}}(t+i)$ of the nth vehicle in the *steps* time-steps, if $l_{\text{steps}}^{\text{est}} \geq steps \times v_n(t)$, it means the n-th vehicle will accelerate or keep current velocity during the period from time-step $t+1$ to time-step $t+steps$. The velocity at the time-step $t+1$ determined as

$$v_n(t+1) = v_n^{\text{est}}(t+1). \tag{2.4}$$

Otherwise, it means the nth vehicle must abrupt deceleration during the period from time-step $t+1$ to time-step $t+steps$. In order to decelerate gradually, given the descent velocity difference of each time-step is Δv during the *steps* time-steps, the moving distance $l_{\text{steps}}^{\text{est}}$ can be expressed as

$$l_{\text{steps}}^{\text{est}} = \sum_{i=1}^{\text{steps}} \left(v_n(t) - i \times \Delta v\right). \tag{2.5}$$

Thus the descent velocity difference Δv is further attained as follows:

$$\Delta v = \frac{2 \times steps \times v_n(t) - 2 \times l_{\text{steps}}^{\text{est}}}{steps \times (steps + 1)}. \tag{2.6}$$

And the velocity at the time-step $t+1$ determined as

$$v_n(t+1) = \min\left(v_n(t) - \Delta v, v_n^{\text{est}}(t+1)\right). \tag{2.7}$$

In the process of the velocity estimated, the security gap gap_{safe} is important. Accidents can be avoided only if the security gap is ensured. Here we claim that the security gap is variable according to the velocity of the leading car. Because the gradually deceleration rule is used in this model, the velocity of the leading car may be less than anticipated velocity v_{n+1}^{anti} when it decelerate in advance. In order to drive safely, we always consider the velocity of the leading car as the worst condition and define the security gap as

$$\text{gap}_{\text{safe}} = \frac{v_{n+1}^{\text{anti}}}{steps + 1}. \tag{2.8}$$

In order to analyze the impact of driver's skill level and psychological conditions on the flow, the cars are divided into two types, AD and NAD. The cars in AD can judge the velocity at the next time-step depending on the rules in this model. While the cars in NAD always use the estimate velocity $v_n^{\text{est}}(t+1)$ as the velocity at the time-step $t+1$, r_{ad} is used to represent the ratio of drivers in AD and meanwhile $r_{\text{ad}} = 1$ means all of the drivers are decelerating in advance.

Based on the above, the rules of the traffic flow model based on Advanced Decelerations are set as follows.

(i) Acceleration: $v_n(t+1) = \min(v_n(t)+1, v_{\max})$.

(ii) Estimated velocity from time-step $t+1$ to $t + steps$:

$$v_n^{\text{est}}(t+1) = \min\left(d_n^{\text{eff}}(t+1), \min(v_n(t)+1, v_{\max})\right)$$
$$v_n^{\text{est}}(t+i) = \min\left(d_n^{\text{eff}}(t+i-1), \min(v_n^{\text{est}}(t+i-1)+1, v_{\max})\right) \quad (i = 2 \cdots steps). \tag{2.9}$$

(iii) Deceleration: calculate prediction driving distance $l_{\text{steps}}^{\text{est}}$ and descent velocity difference Δv in *steps* time-steps, then

$$v_n(t+1) = \begin{cases} \min\left(v_n(t) - \Delta v, v_n^{\text{est}}(t+1)\right) & \text{if } n \in \text{AD},\ l_{\text{steps}}^{\text{est}} < steps \times v_n(t), \\ v_n^{\text{est}}(t+1) & \text{otherwise.} \end{cases} \tag{2.10}$$

(iv) Randomization: with a certain probability p do

$$v_n(t+1) = \max(v_n(t+1) - 1, 0). \tag{2.11}$$

(v) Update of location

$$x_n(t+1) = x_n(t) + v_n(t+1). \tag{2.12}$$

In this model, when the current vehicle velocity is decided, the space factors, such as the security gap and the velocity of itself and the leading, are not only considered, but also the space factors, the velocities in the next *steps* time-steps are estimated. When *steps* = 1, the model degenerate to the VE model [4].

3. Results and Analysis of Numerical Simulation

In the simulations, the length of each cell is given by 1.5 m, and $L = 5 \times 10^3$ cells are assumed. The length of each vehicle is 7.5 meters, which occupies $l = 5$ cells. The periodic boundary condition is assumed. One time-step is taken as 1 s. The maximum velocity is taken as $v_{\max} = 20$, which corresponds to the speed 108 km/h in real traffic. N is the total number of the vehicles distributed on the selected road and v_n is the velocity of the nth vehicle. The mean flow is calculated via the relation $q = \rho \times \overline{v}$, meanwhile the car density is $\rho = N \times l/L$ and the mean velocity is $\overline{v} = (1/N)\sum_{i=1}^{N} v_i$.

When we started to perform numerical simulation, all vehicles with a given density were initially arranged randomly on the whole lane. Each run was conducted 1×10^4 time-steps, in order to remove the transient effects, we discarded the data of the first 4×10^4 time-steps. The mean velocities were obtained by averaging over 30 runs. Because the flux from the

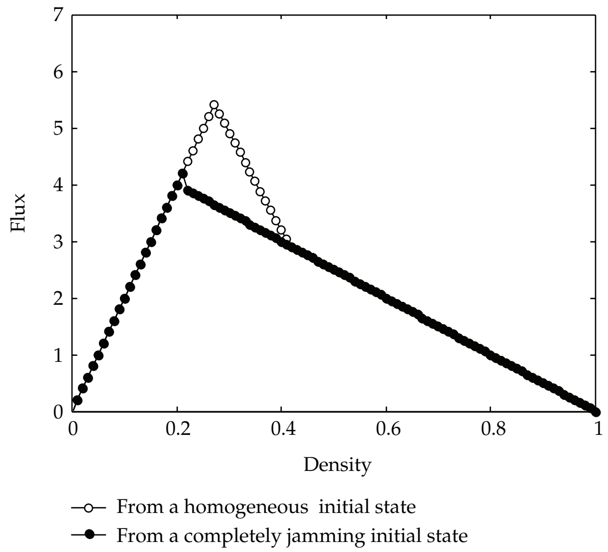

Figure 1: The fundamental diagram under $P = 0$, $r_{\mathrm{ad}} = 1$, and *steps* = 1, 2, 3.

VE model are higher than those from the NS model and are much closer to the measurements results [4], the VE model is used as comparison.

Figure 1 depicts the fundamental diagram under the deceleration probability $P = 0$ and AD ratio $r_{\mathrm{ad}} = 1$ together with the different estimated time-steps *steps*. In the diagram, the model curves under different estimated steps *steps* coincide with each other, at the same time, the hysteresis phenomenon which is similar to VE Model [4] can be observed. The fundamental diagrams are obtained from two different types of initial states: the homogeneous state and the completely jamming state.

Figure 2 depicts the fundamental diagram under the deceleration probability $P = 0.3$ and AD ratio $r_{\mathrm{ad}} = 1$ together with the different estimated time-steps *steps* which are also obtained from two different types of initial states. In Figure 2, ρ_1 and ρ_2 show the positions of the two phase transition points, which divide the whole density scale into three phases having different macroscopic characters of traffic flow. A tiny difference in densities near the two phase-transition points can produce totally different steady states in the end. For example, Figures 3(b) and 3(c) show the phase-transition near ρ_1; Figures 3(d) and 3(e) show the phase transition near ρ_2. In the region $\rho < \rho_1$, homogeneous states are steady as shown in Figures 3(a) and 4(b). Jamming states will dissolve soon, and the traffic will turn into a homogeneous free flow after evolvement. In the region $\rho > \rho_2$, jamming states are steady as shown in Figures 3(e) and 3(f). Little Jamming states will assemble to large ones, and the traffic will be steady on a phase-separated state in the end. There are one or more large jams and several free flow regimes in the final system. In the $\rho_1 < \rho < \rho_2$ region, the global prospect of the steady states is reflected in Figures 3(c), 3(d), 3(e), and 3(f). The hysteresis curves, which are characteristics similar to that of VE models [4], can be observed. The metastable states can stay long and finally evolve to different steady states determined by the initial conditions. For example, Figure 3(c) shows the diagram from a homogeneous initial state while the diagram in Figure 3(d) is from a jamming initial state. The former is

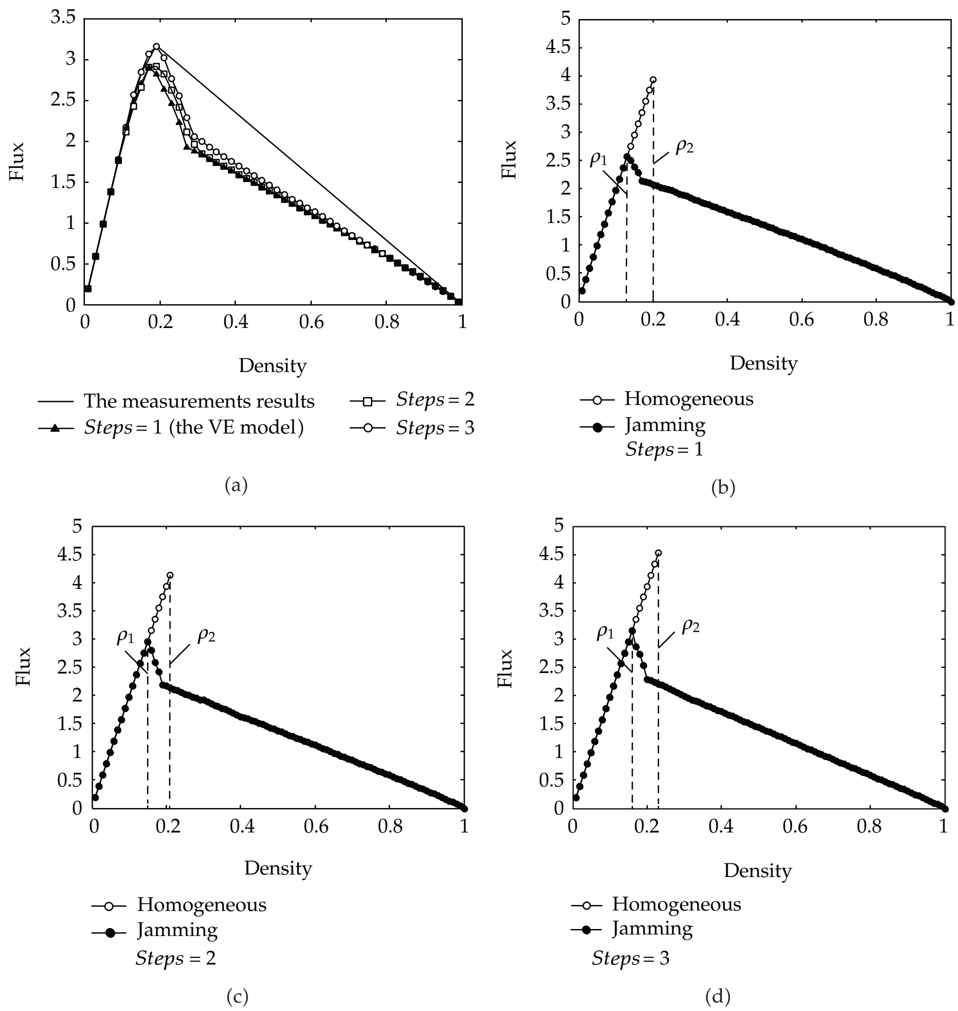

Figure 2: The fundamental diagram under $P = 0.3$ and $r_{\text{ad}} = 1$ (a) *steps* = 1, 2, 3; (b) *steps* = 1; (c) *steps* = 2; (d) *steps* = 3. “homogeneous” is obtained from a homogeneous initial state while the lower, “jamming” is from a completely jamming initial state.

symmetrical everywhere, while the following shows a road which consists of a jamming part and a homogeneous part. Both of the global densities are $\rho = 0.154$. Only from different initial states, different outcomes are totally obtained.

Although similarity can be found in the different estimated time-steps *steps*, there is essential distinction between them. In Figure 2(b), the critical points are $\rho_1 = 0.137$, $\rho_2 = 0.20$, and the maximum flux is 3.939 under *steps* = 1 (the VE model). In Figure 2(c), the critical points are $\rho_1 = 0.145$, $\rho_2 = 0.21$, and the maximum flux is 4.134 under *steps* = 2. In Figure 2(d), the critical points are $\rho_1 = 0.154$, $\rho_2 = 0.23$, and the maximum flux is 4.523 under *steps* = 3. One can see that with the increase of estimated time-steps, the critical points and the maximum flux become increasingly big; meanwhile, they are closer and closer to the real data.

Figure 4 depicts the maximum change of the velocity at each step versus the density under the different p. Figure 4(a) shows that the maximum changing quantity of the velocity

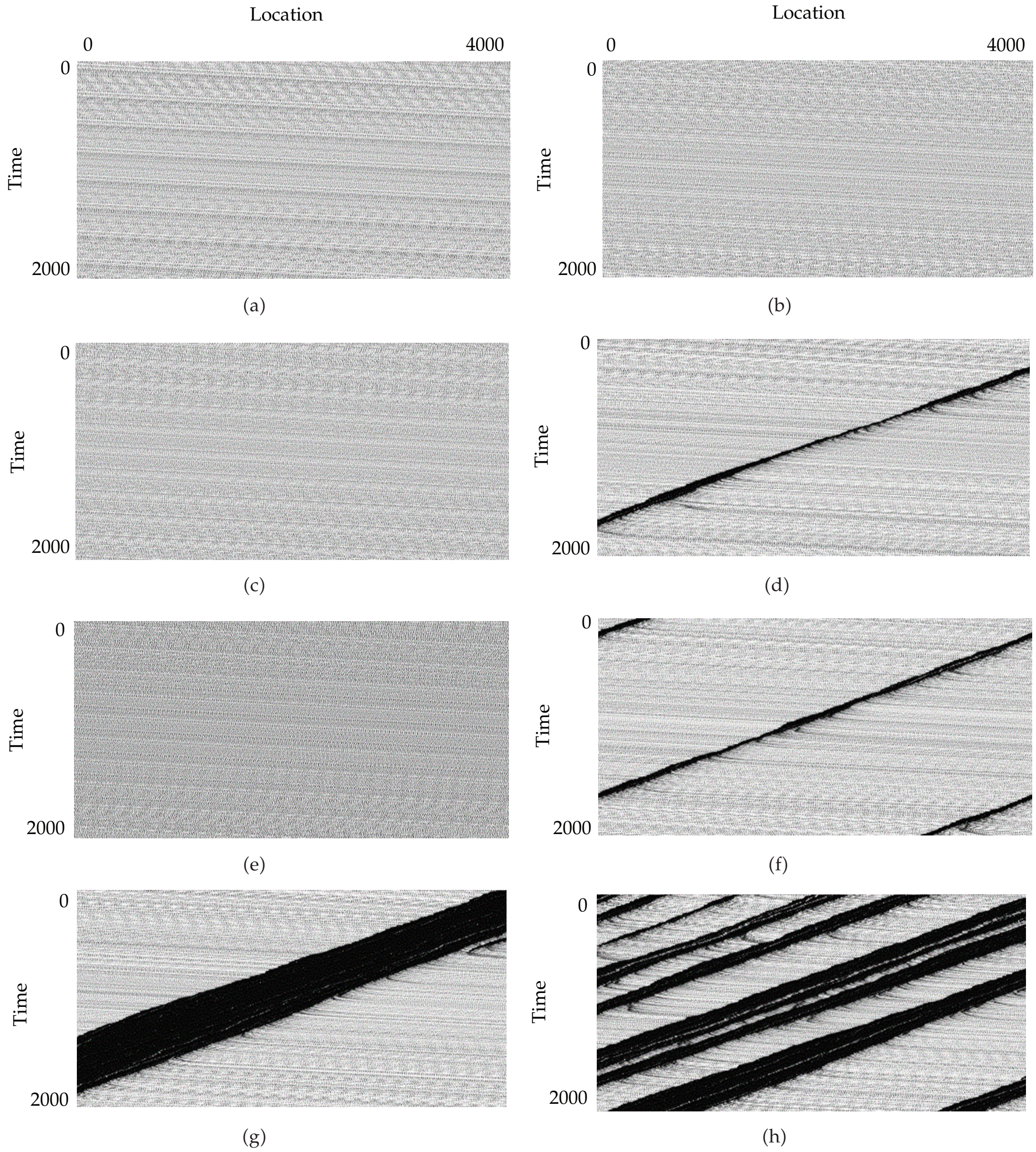

Figure 3: The spatial-temporal diagrams about phase transitions under *steps* = 3 (a), (b) $\rho = 0.153$; (c), (d) $\rho = 0.154$; (e), (f) $\rho = 0.23$; (g) $\rho = 0.24$; (h) $\rho = 0.4$. (a), (c), (e), and (g) are from homogeneous initial states, while (b), (d), (f), and (h) are from a jamming initial state.

under $p = 0$ will reach 19 cells when *steps* = 1, while it is 6 and 4, respectively, when *steps* = 2 and 3. Figure 4(b) shows that the maximum changing quantity of the velocity under $P = 0.3$ reach 20 cells where *steps* = 1, while it is 11 and 9, respectively, under *steps* = 2 and 3. These show that with the increase of estimated time-steps, the maximum changing quantity of each time-step velocity decreases obviously which is in accordance with the real conditions.

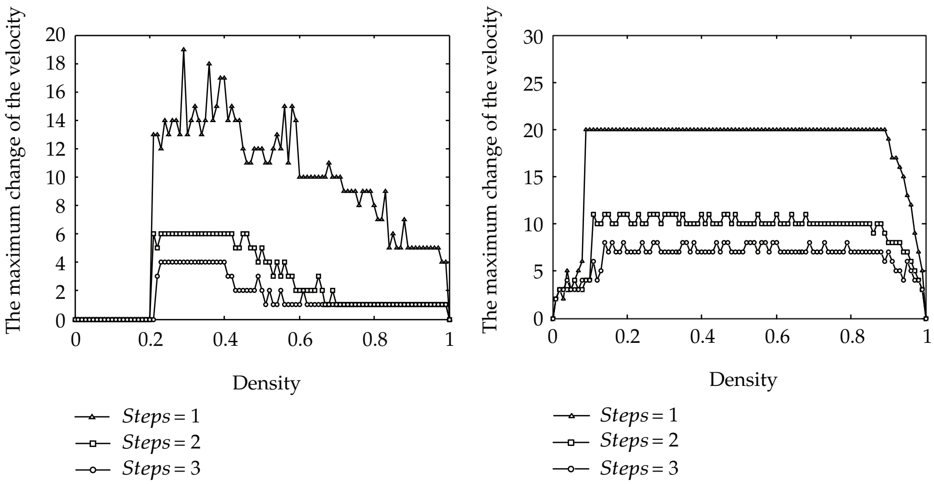

Figure 4: The maximum change of the velocity at each step versus the density under the different P (a) $P = 0$; (b) $P = 0.3$.

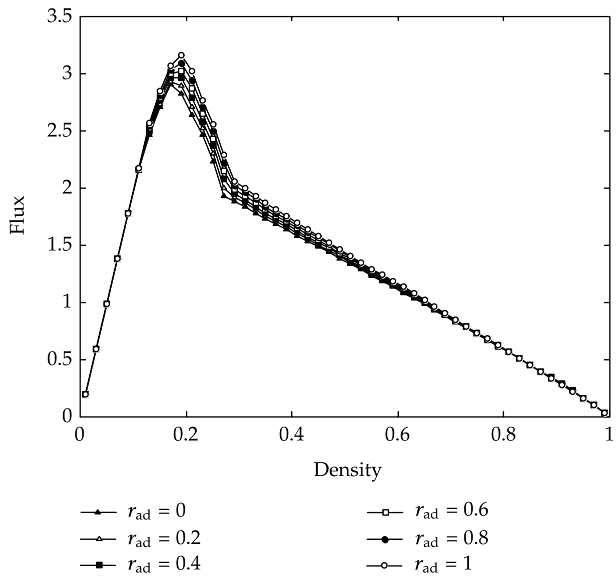

Figure 5: The fundamental diagram under $P = 0.3$ and $steps = 3$.

It means that according to estimated results to adjust vehicle velocity in advance can reduce the sudden deceleration and improve the driving safety.

Figure 5 shows the fundamental diagram under the deceleration probability $P = 0.3$ together with the different AD ratio r_{ad}. In Figure 5, the flux is almost the same as above when traffic is a homogeneous free flow. However, the flux gradually improves under the same estimated time-steps with the increase of the AD ratio r_{ad} while it also gradually

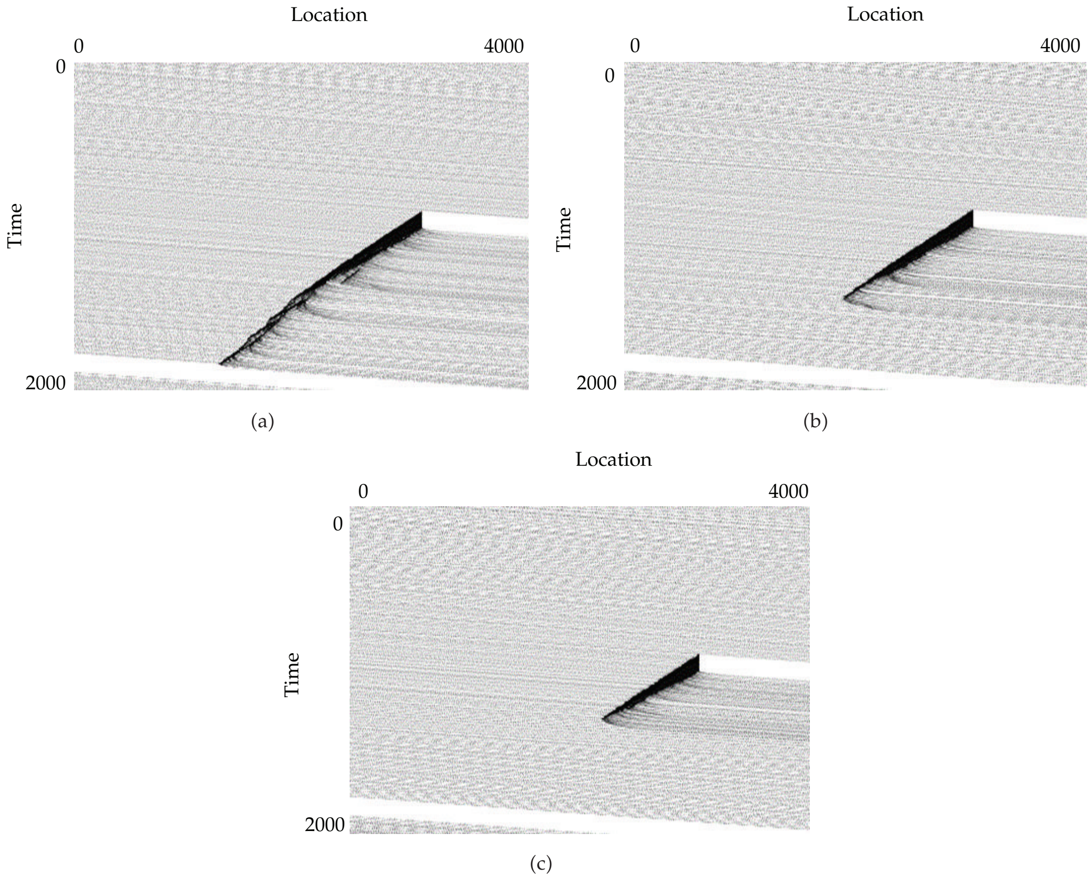

Figure 6: Blockage ablation simulation figure under $\rho = 0.1$, $P = 0.1$, $r_{\text{ad}} = 1$ (a) *steps* = 1; (b) *steps* = 2; (3) *steps* = 3.

improves under the same AD ratio r_{ad} with the increase of the estimated time-steps when the traffic density is higher. These illustrate that when the driver chooses the currently permitted maximum velocity as much as possible, traffic flow may not achieve maximum actually. However, it is beneficial to improve traffic flow by adjusting their driving behaviors in advance, which is in accordance with the real conditions.

A signal light is placed in the middle of the lane. When it evolves to 10000 time step, the green light turns to red light lasting for 100 steps, and then the green light on. The simulation results of Figure 6 show that the traffic jam caused by red light can be eliminated in a shorter time and be restored to the free flow state when *steps* > 1 (Figures 6(b), 6(c)). Although he traffic jam can be eliminated when *steps* = 1 (Figure 6(a)), it must go through a long time. Comparing with the simulation results, these illustrate that the driver can be better to respond to emergencies that may occur at anytime in traffic when he selects the appropriate speed forward. As a result, this will enhance the stability of the traffic flow and be better to maintain the traffic flow smooth. But the blindly following will worsen traffic congestion (see Figure 7).

Figure 7 shows the velocity fluctuations in evolution process of 1000 steps. In Figures 7(a), 7(b), and 7(c), when the density is lower ($\rho = 0.1$) under the state of *steps* = 1, 2, and 3, vehicle can be maintained at a relatively smooth moving, and the velocity fluctuations stay

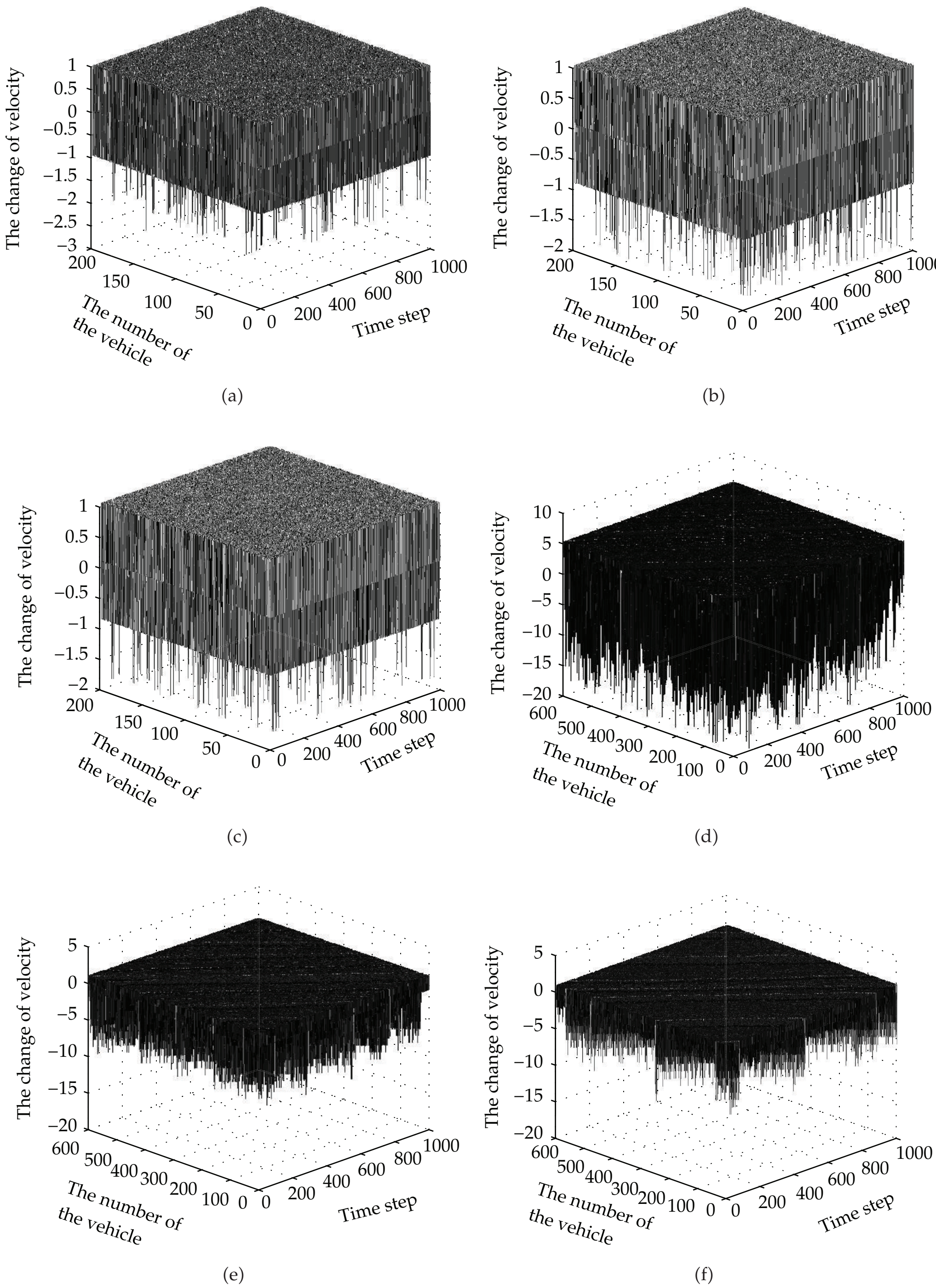

Figure 7: The velocity fluctuations map in 1000 time steps under $P = 0.1$, $r_{\mathrm{ad}} = 1$ (a) $\rho = 0.1$, *steps* = 1; (b) $\rho = 0.1$, *steps* = 2; (c) $\rho = 0.1$, *steps* = 3; (d) $\rho = 0.3$, *steps* = 1; (e) $\rho = 0.3$, *steps* = 2; (f) $\rho = 0.3$, *steps* = 3.

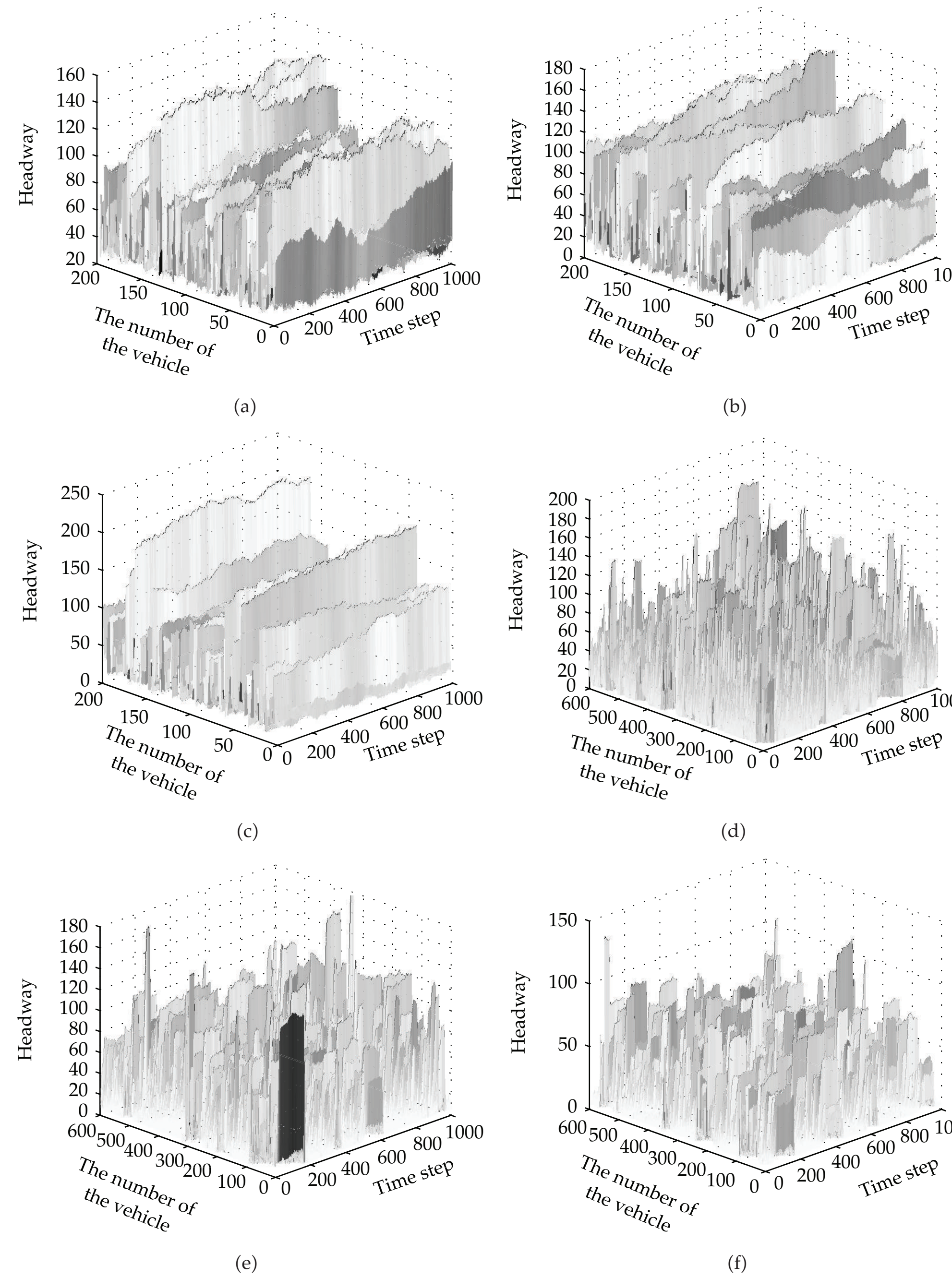

Figure 8: The headway fluctuations map in 1000 time steps under $P = 0.1$, $r_{\mathrm{ad}} = 1$ (a) $\rho = 0.1$, *steps* = 1; (b) $\rho = 0.1$, *steps* = 2; (c) $\rho = 0.1$, *steps* = 3; (d) $\rho = 0.3$, *steps* = 1; (e) $\rho = 0.3$, *steps* = 2; (f) $\rho = 0.3$, *steps* = 3.

between −2 to 1. In Figures 7(d), 7(e), and 7(f), under the density is higher ($\rho = 0.3$), when the state of *steps* = 1, the vehicle velocity fluctuations are serious and sometimes the fluctuation is up to −20, that is to say, the velocity reduces from maximum 20 to 0 directly; at the same time, when the state of *steps* > 1, the vehicle can be maintained at a relatively smooth moving, and along with the increasing of *steps*, the vehicle velocity fluctuation amplitude decreases.

The above illustrate that the vehicle cannot decelerate abruptly if the drivers adjust their speeds in advance according to the size of the forecasted velocity, so that the traffic flow remains more stable, and the probability of traffic accident is smaller, which matches the actual traffic state.

Figure 8 shows the headway fluctuations in evolution process of 1000 steps. In Figures 8(a), 8(b), and 8(c), after a finite evolution, the results show that the headway is at a certain amplitude of the fluctuation and the fluctuation range is small when the traffic density is $\rho = 0.1$ and under the state of $steps = 1$, 2, and 3. In Figures 8(d), 8(e), and 8(f), after a finite evolution, the simulation results show that the headway is in the small range of relatively stable fluctuations when the traffic density is $\rho = 0.3$ and $steps > 1$, while the headway is in disorder substantial random fluctuations when the traffic density is $\rho = 0.3$ and $steps = 1$. All these illustrate that the vehicles can be more evenly distributed on the road if the drivers adjust their driving behavior in advance depending on the size of the predicted velocity, so that the traffic flow remains more stable and the probability of traffic accident is lower, which matches the actual traffic state.

4. Conclusion

From the views of time and space, this paper proposes the cellular automaton model based on the deceleration in advance. The model reflects the phenomenon in the actual traffic that drivers usually adjust the current velocity by forecasting its velocities in a short time of future. Computer simulations reproduce the metastable state, hysteresis, and phase separation phenomenon. After the observations of the density-flow relationship, the stability of traffic flow, the efficiency of blockage ablation, the velocity fluctuation, and the headway fluctuations, it is found that the vehicles will not suddenly decelerate and can be relatively even-distributed on the roads, the blockage caused by emergencies can be eliminated in a shorter time, the utilization rate of the road resources is higher, the traffic flow is greater; which better match the actual traffic state. All these support the view that the drivers who make the velocities prejudgment and fully respond to the actual traffic conditions in advance have an influence on traffic flow.

Acknowledgments

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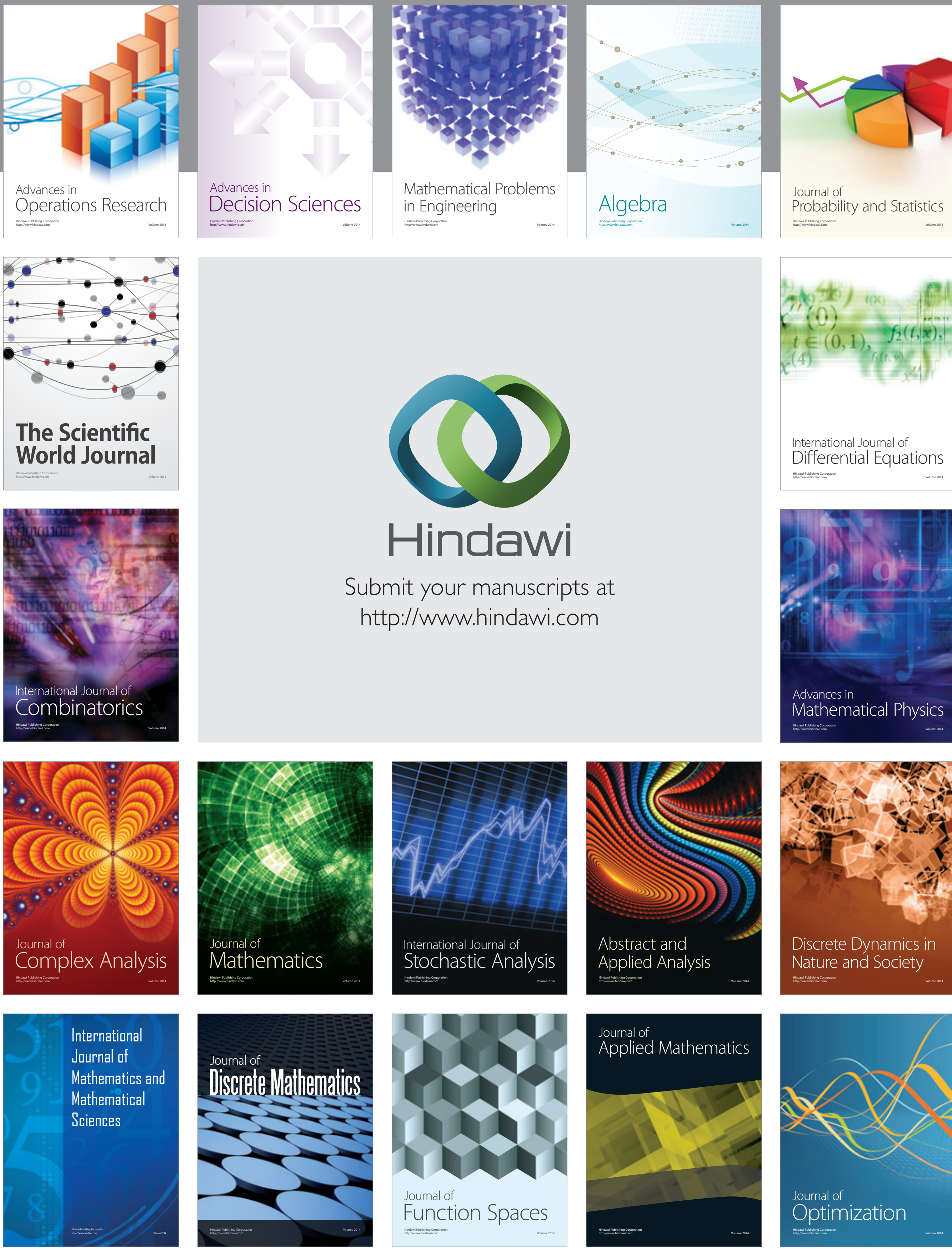
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