Biham–Middleton–Levine model in consideration of cooperative willingness*

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In this paper, the Biham–Middleton–Levine (BML) model with consideration of cooperative willingness has been proposed to study the traffic flow in urban networks. An evolutionary game with a cooperative willingness profile is introduced to deal with conflicts between disturbing neighbors. Simulation results suggest that imitating cooperative willingness can ease the effect of premature seizure on traffic flow due to the introduction of evolutionary games. Phase diagrams with a strategy profile and cooperative willingness profile have been investigated in detail. Our findings also prove that by imitating the more successful, cooperative willingness instead of simply the more successful strategies, the evolution of cooperation is significantly promoted, hence improving the order of cooperation and relieving the pressure of traffic networks.

Keywords: traffic flow, phase transition, cooperative willingness, evolutionary game

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1. Introduction

City traffic is considered to be a compulsory part of city civilization. However, the study on traffic flow concerns not only the urban environmental design but also the complex physical characters of such non-equilibrium systems. Various models have been established to study the problem of traffic flow.[1–7] Among those, the Biham–Middleton–Levine (BML) model[1] is a typical cellular automata (CA) traffic model, also the most commonly used one, to simulate the traffic flow of urban networks. Afterwards, fruitful results of traffic flow have been reported.[8–18] The popularity of the original BML model is mainly due to its simplicity of evolution rules, which makes it a fully deterministic model despite the initial distribution of agents on the spatial grid. Without considering human factors, thus, the traffic flow expressed by the original BML model is no more than an ideal case.

In real life, individuals will sometimes choose to break the rules when dealing with conflicts. Based on the assumption of a perfect ration of strategies among all players,[19] the classical game theory, possessing well defined, consistent goals and preferences, is suitable to handle the problems of contradiction. According to this, Perc[20] studied the impact of evolutionary strategy games (e.g., violation of traffic rules) on traffic flow and found that the jamming phase appeared in advance by a substantially lower initial density of cars as in the absence of evolutionary games, which was then named the premature seizure of traffic flow. Later, Sun *et al.*[21] explored the random walk coupled with an evolutionary game on one-dimensional periodic lattices and Tanimoto *et al.*[22] investigated the bottleneck effect at emergency evacuation exit by using the game theory. Then Hao *et al.*[23] tackled the influence of the evolutionary game on unidirectional pedestrian flow; Xie *et al.*[24] introduced the boycott strength into the strategies update process and discussed its impact on the evacuation efficiency. Recently, several researchers reported further studies in relevant topics, e.g., Sun *et al.*[29] proposed a modified two-lane traffic model disobeying the provided information; Zhang and Zou proposed an acceleration model for single-lane highway traffic to analyze the equilibrium state solution and the corresponding stability under certain perturbations;[30] Li *et al.*[31] developed a new car-following model based on the effects of driving resistance on car movement.

Nevertheless, human beings do not always make rational choices, and more often we imitate friends or acquaintances without any strategic consideration. In fact, although it is not the optimal one, most of us make our decision according to the belief we stick to. One may think it would be fine to let a customer get in the taxi passing by coincidently under urgent need (e.g., raining). Another case encountered is that the customer ahead gives up and forwards the priority to others in favor, even those not in the queue. Things can also go on in a totally different way. What is more, we might not always behave the same way towards all we are facing. This is the so-called cooperative willingness, rather than strategy, which helps us to make decisions. One of the evolutionary games works with non-strategic concern was done by Szolnoki *et al.*[25] They

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proposed an emotional profile to each player x with a parameter pair $(\alpha_x, \beta_x) \in [0,1]$, namely how to behave towards less or more successful neighbors, which they call the emotion of goodwill and envy respectively. In addition, they found that by imitating the more successful emotional profiles instead of simply the more successful strategies, the evolution of cooperation is significantly promoted and a substantially higher social welfare is attainable. Hence, a major challenge for all players is how to play the game with others, since games are inevitable in real-life. Recently, they applied the emotional idea into network study, and indicated that the heterogeneity of the interaction network would determine our willingness to help others.[26] In this study, we build on Perc's work with consideration of cooperative willingness in addition to study the traffic flow in urban networks. One should note that, players in Szolnoki's model are immobile, which is similar to the opinion model. However, agents in the BML model are all ambitious to step forward. Hence, the subject of the study presented here is a dynamic problem rather than a static one.

The remainder of the paper is organized as follows. First, we re-assess the BML model with cooperative willingness and its evolutionary rules. Next, we present the results and compare it with the pure strategy model. The conclusion is given at the end of this paper.

2. Traffic flow model with cooperative willingness profile

The original BML model contains two kinds of agents, which can only advance towards north or east respectively. Two types of agents are randomly distributed with equal probability $\rho/2$ in a two-dimensional periodic square lattice with size of $L \times L$. Since a traffic light operates on every intersection, eastbound and northbound vehicles take turns to move one step forward. Normally, eastbound agents are arranged to move on even steps. Then the BML traffic model proposed by Perc, based on the evolutionary prisoner's dilemma game, is as follows. Initially, all agents have to choose the moving directions (either eastbound or northbound) and the initial assignment strategies (either cooperate or defect) they hold. A parameter κ is proposed to decide the initial density of cooperators among all agents. Without changing the basic rules of the original BML model, Perc let agents play the game with the nearest neighbors who are prohibiting them in making one step forward on every even iteration step. Initiators of the game are made in an alternative fashion for eastbound and northbound agents, which means that by the first even iteration, only eastbound vehicles could be in charge of playing the game with their disturbing neighbors; while only the northbound agents have the right to do the same by the next even iteration. When two cooperators come across, the classical BML model is regained. If both agents defect, on the other hand, it will result in staying put, which implies that no one can advance at the following even or odd iterations. The encounter of a cooperator and a defector leading to the former having to go one step backward, while the latter can go two steps forward at maximum. The correlated evolutionary rules can be clearly understood by the payoff matrix listed in Table 1, where i and j represent those two agents in the game, and C and D represent cooperation and defection respectively. Lastly, they both use the best-takes-over strategy adoption rule[27] for agents to change their strategies accordingly.

Table 1. The payoff matrix of the BML model with strategy profile.

i/j	C	D
C	1 / 1	2/−1
D	−1/2	0 / 0

In this study, we employ the cooperative willingness, which is similar to the emotional profile introduced in Ref. [25], to investigate the urban traffic flow. Different from the BML model of the evolutionary prisoner's dilemma game, after chosing the direction of movement, all agents will receive their own cooperative willingness profiles instead of a profile of strategy, i.e., a parameter pair $(\alpha_i, \beta_i) \in [0,1]$ is assigned, which characterizes the willingness to cooperate with less or more successful opponents respectively. To date, if the payoff of the game is only decided by decimals of the cooperative willingness profile, the agents in the spatial grid would all become too sensitive, which is inconsistent with the fact. Jones and George[28] reported that trust leads to a set of behavioral expectations among people, allowing them to manage the uncertainty or risk associated with their interactions so that they can jointly optimize the gains resulted from cooperative behavior. In Ref. [28], the trust evolution refers to parties, with their own interpretive schemes or perspectives respectively, are involved in creating a joint definition to the social situation. In addition, during this process, parties will develop or make adjustments to their interpretive schemes to define the social situation they suffered in, which depend on the degree of congruence or similarity within their values, attitudes, and emotions. Thus, the trust lies in whether we would like to cooperate with someone met or not. Moreover, the urban traffic system is a complex system with various nonlinear interactions between vehicles. The physical meaning of the trust evolution in urban traffic lies in whether the interactive vehicles can reach a trust consensus for the sake of moving without congestion. Concerning the difficulty to quantify the trust evolution directly and the degree of impact on cooperative behavior, it is assumed that the willingness of cooperation is reached by trusting each other in order to chase the largest payoff. In this paper, we focus on discussing how the willingness of cooperation influences the traffic system. Moreover, a parameter c is proposed to represent in what level people consider someone else's cooperative willingness state is the same

as theirs, which is called the coefficient of cooperative willingness consensus.

Hence, the dynamical process of the BML model in combining with the evolutionary cooperative willingness game is proposed and described herein. Apart from the most evolutionary rules described in Ref. [20], we use the cooperative willingness profile instead of strategies to decide the payoff of the encounters. For agent i, if agent j is on the way of prohibiting him from making one step forward, then a cooperative willingness game starts. Firstly, we should choose the right cooperative willingness parameter to describe the situation agent i is suffering. More precisely, if $p_i \geq p_j$ (p represents the accumulation payoff, and is only related to the accumulation performance of the player in this game), we use α to decide whether agent i should cooperate with agent j or not, while β is considered when $p_i \leq p_j$. Hence, how a player in the game behaves is determined by this pair of parameters. Then, during the interaction of two encounter agents i and j, we define c as the scope of the cooperative willingness to reach consensus.

When two agents interact with each other, we assume that those two with the familiar cooperative willingness status will be more likely to cooperate with each other as collaboration seems to happen more easily between those who hold the same intrinsic value. Therefore, parameter c means in which level people consider someone else's cooperative willingness state is familiar to them and provides a cooperation criterion concurrently. Once the cooperative willingness consensus cannot be reached, we suppose the probability of staying put is 1/3. Otherwise, the more kind (high α) or less envious (high β) agent will make a sacrifice in this game to do others a favor. Then the corresponding payoff is given by

$$\text{payoff}(i,j) = \begin{cases} (1,1), & \text{if } |\alpha_i - \alpha_j| \leq c, \\ (0,0), & \text{if } |\alpha_i - \alpha_j| \succ c,\ r \leq 1/3, \\ (2,-1), & \text{if } |\alpha_i - \alpha_j| \succ c,\ r \succ 1/3,\ \alpha_i \leq \alpha_j, \\ (-1,2), & \text{if } |\alpha_i - \alpha_j| \succ c,\ r \succ 1/3,\ \alpha_i \succ \alpha_j, \end{cases} \tag{1}$$

$$\text{payoff}(i,j) = \begin{cases} (1,1), & \text{if } |\beta_i - \beta_j| \leq c, \\ (0,0), & \text{if } |\beta_i - \beta_j| \succ c,\ r \leq 1/3, \\ (2,-1), & \text{if } |\beta_i - \beta_j| \succ c,\ r \succ 1/3,\ \beta_i \leq \beta_j, \\ (-1,2), & \text{if } |\beta_i - \beta_j| \succ c,\ r \succ 1/3,\ \beta_i \succ \beta_j, \end{cases} \tag{2}$$

where r is the probability that two agents will stay put when the consensus of cooperative willingness cannot be reached. Finally, in order to make a comparison with the result of the BML model with the strategic one, we allow all agents, eastbound and northbound, to change their cooperative willingness profiles every even iteration step after finishing their moves, with the best-takes-over strategy adoption rule. Note that by $c = 1$, which means that all agents have full consensus of the cooperative willingness, the original BML model is regained. It should be pointed out that there is always a fixation of the emotional profile in Refs. [25] and [26], while a similar situation will occasionally happen on a specific condition in our model, which will be illustrated in the next section. In general, the average velocity is obtained by averaging over 100 independent initial realizations up to 10^6 iteration steps for each run and discarding the first 9×10^5 iteration steps as transient time.

3. Simulation and results

We start by presenting the results of average velocity $\langle V \rangle$ against density ρ for the original BML model, evolutionary BML model with strategy profile and cooperative willingness profile of system size $L = 128$. The original BML model and the BML model with strategy profile on the case of $\kappa = 0.50$ exhibit the phase transition at $\rho = 0.370$ and $\rho = 0.185$ on average, corresponding to the black line and red line in Fig. 1, respectively. However, the critical point of the BML model with cooperative willingness profile is $\rho = 0.275$ on average for $c = 0.50$, as indicated by the blue line in Fig. 1. The result presented in Fig. 1 is a specific case which explicitly shows that instead of imitating the more successful strategies, imitating the more successful cooperative willingness is a better choice. Figure 2 presents the static configurations of the traffic flow for the evolutionary BML model with strategy profile and cooperative willingness profile at different initial densities ρ. It is clear that the emergence of gridlock for the strategy type is much earlier than in the cooperative willingness one.

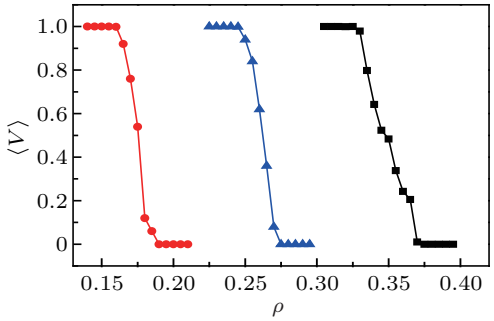


Fig. 1. (color online) Average velocity $\langle V \rangle$ against density ρ in the cases of original BML model (black squares), evolutionary BML model with strategy profile (red circles) and cooperative willingness profile (blue triangles). The initial fraction of cooperators and the coefficient of cooperative willingness consensus among all agents on the 128×128 square lattice in the evolutionary cases are $\kappa = 0.50$ and $c = 0.50$ respectively.

To compare the difference between the BML model with a strategy profile and the one with a cooperative willingness profile more precisely, we calculate $\langle V \rangle$ for various κ and c under different densities ρ in Fig. 3. Noticeably, the area of the moving phase is greatly enlarged when the cooperative willingness profile is considered. Note that by $\kappa = 1$ and $c = 1$, corresponding to the fully cooperative state and the totally cooperative willingness consensus has been reached among

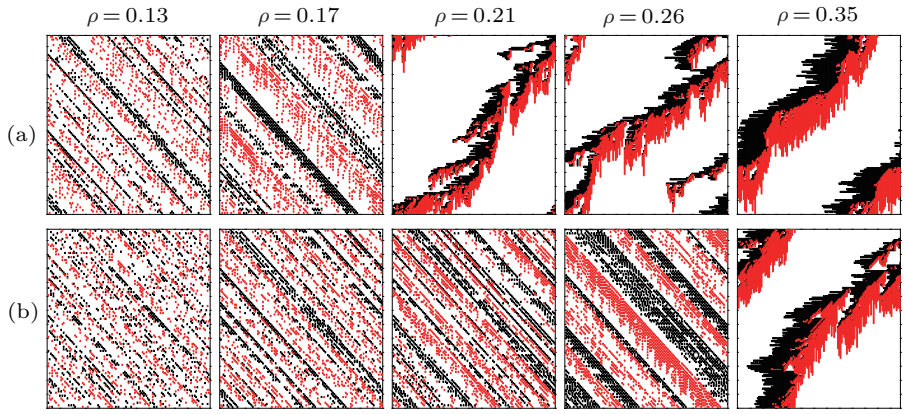


Fig. 2. (color online) Static configurations of traffic flow for the evolutionary BML model with strategy profile (a) and cooperative willingness profile (b) at different initial densities ρ on the 128×128 spatial grid. The corresponding initial fraction of cooperators and the coefficient of cooperative willingness consensus are $\kappa = 0.50$ and $c = 0.50$ respectively. The red points and black points represent the cars facing towards the north and east respectively.

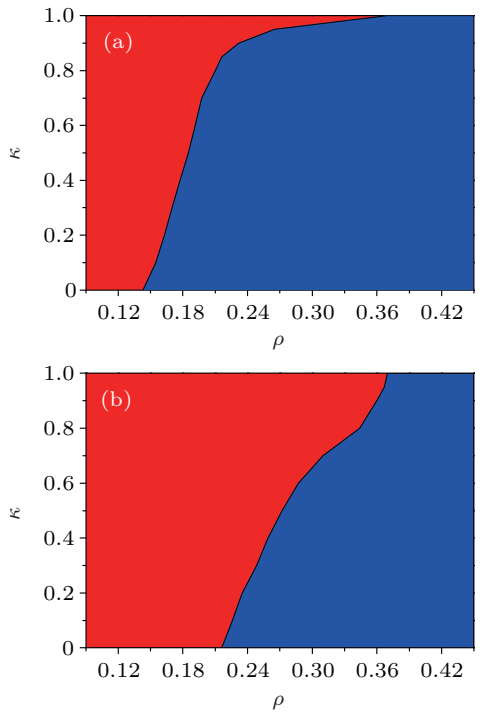


Fig. 3. (color online) Phase diagrams of the two evolutionary BML models with different profiles. Both panels feature results for the system size of 128×128. The red and blue regions correspond to $\langle V \rangle > 0$ and $\langle V \rangle = 0$, respectively, which represent the moving phase and jamming phase respectively. The above panel (a) gives the results obtained with the strategy profile by increasing the initial fraction of cooperators κ, while the one below (b) features with the cooperative willingness profile by increasing the coefficient of cooperative willingness consensus c.

all agents respectively, the original BML model is regained. Although the introduction of the cooperative willingness profile cannot completely stop the trend of a premature jamming phase, it indeed postpones the gridlock effect and increases the value of critical point.

By comparing the two evolutionary BML models with different profiles with the original one, we notice that there are differences of cooperation rates, which make them dissimilar. To provide a better illustration to this point, our statistic average should focus on the cooperation (or defection) level after a game, which means that we are only interested in what has happened to the fraction of cooperation in the game. Since without gaming, the original BML model will be regained. Firstly, we define the payoff pair of (0, 0) as defection, (1, 1) as cooperation, and $(-1, 2)$ as sub-cooperation. Then the statistic average is taken every 10^3 iteration step for over 100 different realizations. Figure 4 shows how the fractions of defection, cooperation and sub-cooperation with different profiles change with time extending. The results of the BML model with strategy profile present high defection (about $p = 0.58$), low cooperation (about $p = 0.27$), and sub-cooperation (about $p = 0.15$) with little change through all time slots shown in Fig. 4(a). Nevertheless, the BML model with the cooperative willingness profile is rather different. The life span can be divided into two stages. In the first stage (about $t = 10^4$), the agents in the game are willing to cooperate with others (more than $p = 0.8$ for cooperation and around $p = 0.1$ for sub-cooperation), and little desire for defection, as pointed by Figs. 4(b)–4(d) respectively. While in the second stage (more than 10^4 iteration steps), those three fractions change from slight fluctuations to sharp oscillations and such trends have been kept until the end of full iteration steps. This can be explained by the levels in the first stage, the stochastic distribution of cooperative willingness profiles allowing each agent to move freely within a wide range, which means that the emergence of the first stage largely depends on the randomness of the system. After that, when the system gets into certain kind of ordered status and the stochastic effect has vanished, all agents are struggling to prevent the outbreak of a jamming phase and adjust their cooperative willingness profiles to the maximum self-interests. It then becomes the system entering the second stage, with seeds of a jamming phase being spawned and this kind of struggle lasts to the end. Although the corresponding fractions are not stable in the second stage, it is still obvious that cooperation plays the main role as a whole. A premature seizure is formed during this period because the phenomena of traffic rule violations are still existing,

even if the trust evolution begins to work. Besides, the vibrations of the above fractions have no influence on the results to reach stable levels, neither does the original BML. Notably, the emergence of premature seizure is due to the introduction of the game evolution, which means that, once the game starts, the premature traffic jam is inevitable. In short, the introduction of trust evolution, one type of game evolution, has only an analgesic effect on the premature seizure caused by the pure strategy one as clarified in Ref. [20]. Results in Fig. 4 provide an insight that the low level of cooperation after the game tends to cause the premature of jamming phase. Remarkably, it also proves that the introduction of a cooperative willingness profile does improve the level of cooperation in evolutionary games, and sequentially elevates the social welfare, as indicated by Szolnoki *et al.*[25] Moreover, as shown in Fig. 3, when κ is low (less than 0.85), the increment of its value does little to the remission of the jamming phase and has a tremendous effect on promoting the cooperation when κ is larger than 0.85, but things go the opposite way for the BML model with a cooperative willingness profile. Thus, rather than the fraction of cooperators, improving the level of cooperative willingness consensus among agents is a more preferable choice from the beginning.

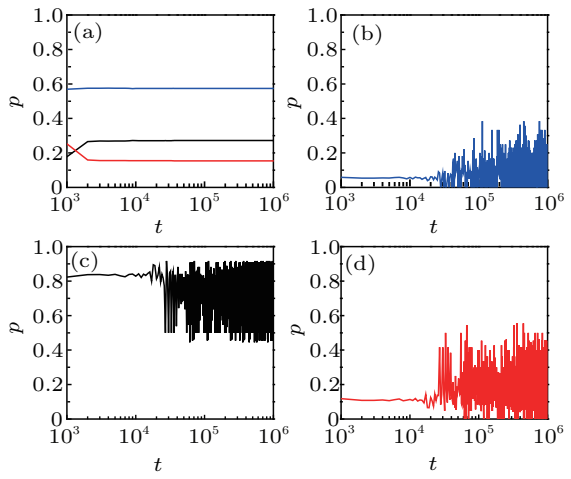


Fig. 4. (color online) Fraction of defection (blue), cooperation (black) and sub-cooperation (red) of the two evolutionary BML models with strategy profile (a) and cooperative willingness profile (b)–(d) on the 128×128 spatial grid. The initial density $\rho = 0.21$, together with the corresponding initial fraction of cooperators and the coefficient of cooperative willingness consensus are $\kappa = 0.50$ and $c = 0.50$ respectively.

Finally, it is interesting to further explore the distributions of two cooperative willingnesses, namely α and β. In Refs. [25] and [26], there always appear a fixation of (α_i, β_i) pairs, which corresponds to the end of the evolutionary process. However, this is not the same in our model, i.e., our simulations suggest that the fixation pair possibly occur only with the high density of agents and the high consensus of cooperative willingness. Two individual simulations with the same initial conditions of $\rho = 0.35$ and $c = 0.90$ on the 128×128 spatial grid at different iteration steps are presented in Fig. 5. In the first simulation, shown in Fig. 5(b), there is a fixation (0.19, 0.86) at $t = 10^6$, while it is not the same as those in Fig. 5(d). The difference emerges from two phases (i.e., moving phase and jamming phase) in the BML model and all agents can change their cooperative willingness profiles by imitating the on-going changes from their neighbors. When ρ is small, despite the transient time, all agents can move and there is no need to imitate others because nobody is of priority over others. Hence, when agents are sparse on the spatial grid, we could hardly find a fixation. For situations of high density and a low level of cooperative willingness consensus, global gridlock forms early, which means no agent can take advantage of the more successful cooperative willingness. Therefore, a fixation will probably turn up on the conditions of spatial populated and the broad consensus being reached (e.g., 61 out of 100 realizations at density $\rho = 0.35$ in this study). Noteworthy but not major, an intermediate state, which is similar to D'Souza's results,[13] is obtained in Fig. 5(a) at $t = 10^4$. Moreover, there are no specific trends of those two cooperative willingness parameters, and Fig. 6 indicates that the scatter of 100 individual runs with a fixation at the end of the simulation time.

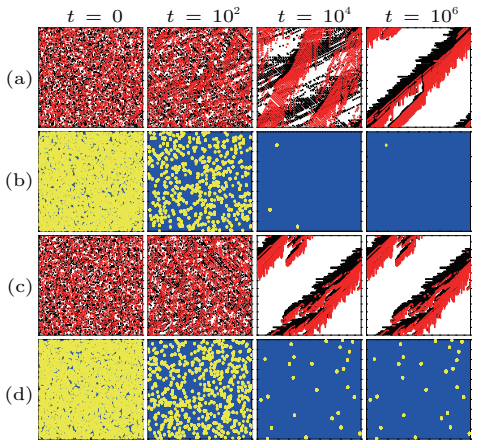


Fig. 5. (color online) Snapshots of traffic flow (a) [or (c)] with its corresponding distributions of cooperative willingness profile (b) [or (d)] at different iteration steps for $\rho = 0.35$ and $c = 0.90$ on the 128×128 spatial grid. For distributions of cooperative willingness profile, namely (b) and (d), the horizontal axis represents the value of α, and the vertical axis for β.

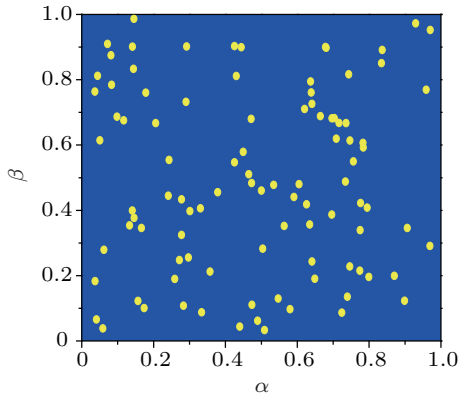


Fig. 6. (color online) Fixation distribution of 100 individual runs for $\rho = 0.35$ and $c = 0.90$ on the 128×128 spatial grid.

4. Conclusion

Based on the integrated study of combining the BML model with strategy game theory, we proposed and carried out a preliminary investigation on the traffic jamming phase with a cooperative willingness profile. A parameter c has been defined to describe the scope of reaching cooperative willingness consensus with others. In addition to the observation of similar first-order phase transition behavior, the value of critical point has been improved once considering the cooperative willingness. Upon exploring the phase diagrams carefully, we have proved that the proposed model can ease the effect of premature seizure of traffic flow due to the introduction of evolutionary games. Moreover, it is found that the cooperation fraction has been largely enhanced, which are consistent with the simulation outputs above.

As indicated in Ref. [20], the cooperative behavior can be realized by obeying the traffic rules without doubt. While according to the results presented in this paper, we would emphasize that people should be willing to cooperate and trust that others would do the same, long before observing traffic regulations entirely. In brief, the cooperative behavior implementation is likely by and only by complying with traffic regulations consciously and believing others would follow the same rule as well.

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