Relationship between microscopic dynamics in traffic flow and complexity in networks

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Complex networks are constructed in the evolution process of traffic flow, and the states of traffic flow are represented by nodes in the network. The traffic dynamics can then be studied by investigating the statistical properties of those networks. According to Kerner's three-phase theory, there are two different phases in congested traffic, synchronized flow and wide moving jam. In the framework of this theory, we study different properties of synchronized flow and moving jam in relation to complex network. Scale-free network is constructed in stop-and-go traffic, i.e., a sequence of moving jams [Chin. Phys. Lett. **10**, 2711 (2005)]. In this work, the networks generated in synchronized flow are investigated in detail. Simulation results show that the degree distribution of the networks constructed in synchronized flow has two power law regions, so the distinction in topological structure can really reflect the different dynamics in traffic flow. Furthermore, the real traffic data are investigated by this method, and the results are consistent with the simulations.

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I. INTRODUCTION

There are several traffic flow theories and a huge number of various traffic flow models which are based on the theories reviewed in Refs. [1,2]. This paper is in the framework of Kerner's three-phase traffic theory. In this traffic flow theory [3], there are two qualitatively different traffic phases in congested traffic: (1) Synchronized flow and (2) wide moving jam. These traffic phases are defined based on empirical spatiotemporal criteria [S] and [J]. (i) Definition of wide moving jam traffic phase [J]: A wide moving jam is a moving jam that exhibits the characteristic feature to propagate through other traffic states and bottlenecks while maintaining the mean velocity of the downstream jam front. (ii) Definition of synchronized flow traffic phase [S]: Synchronized flow does not exhibit the wide moving jam characteristic feature, in particular, the downstream front of the synchronized flow is often fixed at a bottleneck.

The properties of synchronized flow and wide moving jam are investigated with experimental traffic data from several freeways in Germany [4–7]. In empirical investigations, congested traffic usually occurs at highway bottlenecks then highway capacity will break down to the value which is often lower than the capacity in free flow. In order to eliminating such break down, the mechanism of the emergence of traffic congestion should be completely studied.

A network is a set of items, which we will call nodes, with connections between them, called links [8]. Many complex systems take the form of network in the world, such as the internet, the World Wide Web, social networks, organization networks, metabolic networks, networks of citations between papers, etc. In recent years, the development of computer science makes research of networks using the analysis of single small graphs to that of large-scale statistical properties of graphs. The past few years have witnessed considerable advances in the field of complex network [9–11]. Empirical data have revealed the existence of three classes of small-world networks [12]: (a) Scale-free networks; (b) broad-scale or truncated scale-free networks, characterized by a degree distribution that has a power-law regime followed by a sharp cutoff that is not due to the finite size of the network; and (c) single-scale networks, characterized by a degree distribution with a fast decaying tail, such as exponential or Gaussian.

Gao *et al.* [13] proposed a model which can convert the dynamics in traffic flow into the topology of complex network, and scale-free behavior is observed in the stop-and-go traffic. The traffic states are represented by nodes in network, and the evolution relationships between traffic states determine the links. Based on a similar idea, Li *et al.* investigated the Hang Seng Index in the Hong Kong Stock Market [14], and Zhang *et al.* studied the pseudoperiodic time series [15]. Thus the dynamics in time domain can be transformed into topology of complex network, and statistical properties of the network, such as the degree of distribution, average path length, and clustering coefficient, are investigated using the information embedded in the original time series.

In this paper, the microscopic properties of traffic flow, both in synchronized flow and stop-and-go traffic, are transformed into the topology of complex network. Simulation results show that there are relationships between the states of traffic flow and the topology of network, which means that stop-and-go traffic corresponds to scale-free network, while synchronized flow corresponds to the network with two power law parts degree distribution. Some real traffic data are also investigated, and it is consistent with simulation results.

The paper is organized as follows. The model for transforming the dynamics in traffic flow into topology of network is proposed in the next section. The simulation results are analyzed in Sec. III. In Sec. IV, the real traffic data are investigated. Finally, in Sec. V, the conclusion is given.

II. MODEL

In cellular automaton (CA) models for traffic flow, the road is divided into L cells. Each vehicle has a length of u

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cell(s). The vehicles move on the road according to some updating rules. If appropriate rules are adopted, empirical traffic dynamics, which are reflected by the vehicle distributions in space and time, can be reproduced. In this paper we study the traffic dynamics in respect to complex network, and the dynamics are transformed into topology of complex network by the following model. Taking the vehicle length u as a unit, the road is first divided into L/u sites. So each site contains u cell(s). The state of each site $s=1(0)$ represents the site (do not) contains the cell which is occupied by the head of a vehicle. Here $u\times M$ ($\ll L$) successive cells, which lie in the center of the road, are selected, so the configuration contains M sites. The state of the configuration can be described by M binary digits, namely, $S(t)=(s_1,s_2,\ldots,s_M)$, which can be described by the value $\pi_r=\Sigma_{i=1}^{M}2^{i-1}s_i$. The number of vehicles in the selected configuration is $n_v=\Sigma_{i=1}^{M}s_i$. The number of possible states of the configuration is 2^M. In the evolution process of traffic flow, a time series $S=\{S(1),S(2),S(3),\ldots\}$ is obtained. The states, which are obtained at different time step but have the same value of π_r, are deemed as the same state. We know that traffic as a system of interacting particles far from equilibrium is very complex [1]. So S will perform complex behaviors. The network construction model can transform the traffic dynamics in time domain into complex network topology. Next we briefly review the model.

In our model, each state of the selected configuration is regarded as a node. We start construction of the network when the traffic flow evolves into a steady state and the first 10 000 time steps are discarded. The state obtained at 10 001 time step is regarded as $S(1)$ and it corresponds to the first node of the network. Then a state $S(t)$ will be obtained at each time step. If $S(t)$ is a newborn state, another node is added to the network. This corresponds to the introduction of a new node, and a link between this node and its precursor is created. If the state $S(t)$ had appeared in previous time step, that is to say, the corresponding node has been added to the network, only a link between the corresponding node and its precursor is created. Here, multiple links are prohibited. As time passes, the number of nodes (N) and the number of links (E) of the network will increase. Two terminations are considered in our model: (1) The network is constructed in finite T time steps and (2) the procedure is iterated until the total number of links in the network is K times the total number of nodes in the network. The first termination makes the network constructed with a series of length T, and the second one means that the average degree of the evolution network is $2K$.

As mentioned above, each state is considered as a node. For any node, it is the output of its precursor. Meanwhile, it is also the input of its subsequence. Therefore, a direct graph can be obtained. Then, we have an evolution network whose dynamic is completely defined by the updating rules outlined in the simulation models.

We note that the vehicle distributions in time and space are used to construct the network. Such distributions can be easily obtained in microscopic traffic flow models, especially in CA models. So the vehicle distributions in time and space in any traffic conditions, stop-and-go traffic, or synchronized flow, can be investigated by the above model.

The Nagel-Schreckenberg (NS) model [16] was used in Ref. [13] to simulate the evolution of traffic flow. We know that stop-and-go wave, i.e., a sequence of moving jams, can be well reproduced in the NS model as observed in real highway traffic, but the synchronization state which is also a congested state can be simulated by other models under open boundary conditions or periodic boundary conditions (especially when ramps are incorporated) [17–21]. The model in Ref. [17] is the first microscopic traffic flow model that has described synchronized flow. The first CA traffic flow model that was able to describe all features of synchronized flow and wide moving jams is the Kerner-Klenov-Wolf (KKW) model [18]. The comfortable driving (CD) model [20] and the modified comfortable driving (MCD) model [21] can also describe the basic features of synchronized flow. In this paper, we further investigate topology properties of the network constructed in the evolution process of synchronized flow, and the MCD model, which can describe both light synchronized flow and heavy synchronized flow, is used to simulate the evolution process of synchronized flow. Next, we briefly review the updating rules in the NS model and the MCD model.

In the NS model, the parallel updating rules are as follows: (1) Acceleration $v_n\rightarrow\min(v_n+1,v_{\max})$, (2) deceleration $v_n\rightarrow\min(v_n,d_n)$, (3) randomization $v_n\rightarrow\max(v_n-1,0)$ with probability p, and (4) position update $x_n\rightarrow x_n+v_n$. Here v_n and x_n denote the velocity and position of the vehicle n, respectively, $v_{\max}$ is the maximum velocity and $d_n=x_{n+1}-x_n-u$ denotes the number of empty cells in front of the vehicle n, and p is the randomization probability. A vehicle has a length of $u=1$ cell, which corresponds to 7.5 m. The model parameters are $v_{\max}=5$ and $p=0.3$.

In the MCD model, the parallel rules for vehicle moving are as follows.

(1) Determination of the randomization parameter p:

$$p=p(v_n(t),b_{n+1}(t),t_h,t_s).$$

(2) Acceleration:

$$\text{if } [b_{n+1}(t)=0 \text{ or } t_h\geqslant t_s] \text{ and } [v_n(t)>0] \text{ then } v_n(t+1)=\min[v_n(t)+2,v_{\max}]$$

$$\text{else if } v_n(t)=0 \text{ then } v_n(t+1)=\min[v_n(t)+1,v_{\max}]$$

$$\text{else } v_n(t+1)=v_n(t).$$

(3) Braking rule:

$$v_n(t+1)=\min[d_n^{\text{eff}},v_n(t+1)].$$

(4) Randomization and braking:

$$\text{if } r(\cdots)<p \text{ then } v_n(t+1)=\max[v_n(t+1)-1,0].$$

(5) The determination of $b_n(t+1)$:

$$\text{if } v_n(t+1)<v_n(t) \text{ then } b_n(t+1)=1,$$

$$\text{if } v_n(t+1)>v_n(t) \text{ then } b_n(t+1)=0,$$

$$\text{if } v_n(t+1) = v_n(t) \text{ then } b_n(t+1) = b_n(t).$$

(6) The determination of $t_{st,n}$:

$$\text{if } v_n(t+1) = 0 \text{ then } t_{st,n} = t_{st,n} + 1,$$

$$\text{if } v_n(t+1) > 0 \text{ then } t_{st,n} = 0.$$

(7) Vehicle motion:

$$x_n(t+1) = x_n(t) + v_n(t+1).$$

Here b_n is the status of the brake light [on(off) $\rightarrow b_n = 1(0)$]. The two times, $t_h = d_n / v_n(t)$ and $t_s = \min[v_n(t), h]$, where h determines the range of interaction with the brake light, are introduced to compare the time t_h needed to reach the position of the leading vehicle with a velocity-dependent interaction horizon t_s. $d_n^{\text{eff}} = d_n + \max(v_{\text{anti}} - g_{\text{safety}}, 0)$ is the effective distance, where $v_{\text{anti}} = \min(d_{n+1}, v_{n+1})$ is the expected velocity of the preceding vehicle in the next time step and g_{safety} controls the effectiveness of the anticipation. $r(\cdots)$ is a random number between 0 and 1. The randomization probability p is defined as

$$p(v_n(t), b_{n+1}(t), t_h, t_s) = \begin{cases} p_b: & \text{if } b_{n+1} = 1 \text{ and } t_h < t_s, \\ p_0: & \text{if } v_n = 0 \text{ and } t_{st,n} \geqslant t_c, \\ p_d: & \text{in all other cases.} \end{cases} \quad (1)$$

Here, $t_{st,n}$ denotes the time that vehicle n stops, and t_c is a constant. In step 2, the acceleration capacity of a stopped vehicle is assumed to be 1 and that of a moving vehicle is 2. The model parameters $v_{\max} = 20$, $p_d = 0.1$, $p_b = 0.94$, $p_0 = 0.5$, $h = 6$, $g_{\text{safety}} = 7$, and $t_c = 10$ are used. Each cell corresponds to 1.5 m and a vehicle has a length of $u = 5$ cells.

III. SIMULATION RESULTS

The network is a directed graph, so each node has both in-degree and out-degree, which represent the number of incoming links of a node and the number of outgoing links of a node, respectively. In this paper, the distributions of both in-degree $P_{\text{in}}(k)$, which gives the probability that a randomly selected node has in-degree k, and out-degree $P_{\text{out}}(k)$, which gives the probability that a randomly chosen node has out-degree k, are studied. The in-degree (out-degree) distribution $P_{\text{in}}(k)$ $[P_{\text{out}}(k)]$ is defined as the ratio of the number of nodes with in-degree (out-degree) k to the total number of nodes N. Furthermore, the average path length l—the average of the minimum number of links necessary to connect all pairs of nodes, and the clustering coefficient c, are also discussed. We choose the density $\rho = 0.2$ in the NS model and $\rho = 0.3$ in the MCD model, for the stop-and-go traffic [Fig. 1(a)] and synchronized flow [Fig. 1(b)] can be reproduced well by the two model at such densities, respectively.

As the networks are constructed in the evolution process of traffic flow, the structure of the network depending on t is studied first. Here the network constructed in stop-and-go traffic is denoted as N_m and in synchronized flow is represented as N_s. In Fig. 2, we show the number of nodes N and

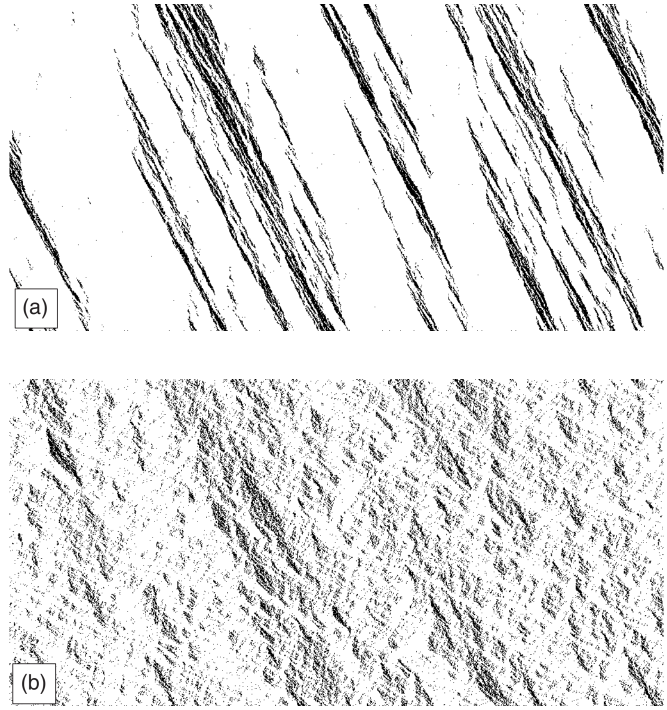

FIG. 1. Typical spatiotemporal diagrams of (a) the NS model and (b) the MCD model. The parameters are $\rho = 0.2$ and $p = 0.3$ in the NS model and $\rho = 0.3$ in the MCD model. Vehicles are driving from left to right and the vertical direction (up) is (increasing) time.

the number of links E in the network as a function of t. We note that within the finite time steps ($t \leqslant 10^5$), there are power laws, which can be defined as $N \sim t^{\alpha}$ and $E \sim t^{\beta}$. The exponents are α_m and β_m in N_m and that in N_s are α_s and β_s. Figure 2 shows that α_m is larger than α_s, while β_m and β_s have almost the same value. The link distributions of N_m and N_s at different t are shown in Fig. 3. We can see that the distributions of in-degree and out-degree exhibit the same behavior, so in-degree and out-degree are not specifically distinguished in the following analysis and k is either in-degree or out-degree. N_m is scale-free network because the distribution of links obey power law $P(k) \sim k^{-\gamma_m}$. γ_m will become large as t increases. At $t = 10^4$, the exponent of N_m is $\gamma_m = 2.18$ and at $t = 10^5$, $\gamma_m = 2.39$. Moreover, the link distribution of N_s has a complex form that consists of two power law parts with different exponents. The two parts are separated by k_c. At $t = 10^5$ the exponent of part $k < k_c$ in N_s is $\gamma_s^l = 1.33$ and that of the part $k > k_c$ is $\gamma_s^r = 3.18$. This quality is also observed in Word web [23]. As t increases, k_c will move to higher values. When $t < 5 \times 10^5$, the exponents of the two parts change to a small degree. With increasing t, the exponents of the two parts will decrease and the difference between them become small (Fig. 4).

In stop-and-go traffic, N will not increase after 10^6 time steps, while E continues to grow after 10^8 time steps. In synchronized flow, N and E are saturated after 2×10^7 time steps. We choose N_m at $t = 10^6$ and N_s at $t = 2 \times 10^7$ as typical networks which represent the properties of stop-and-go traffic and synchronized flow, respectively. The link distributions of the two networks are shown in Fig. 4. In N_m, the distribution in the region with small k deviates from the straight line

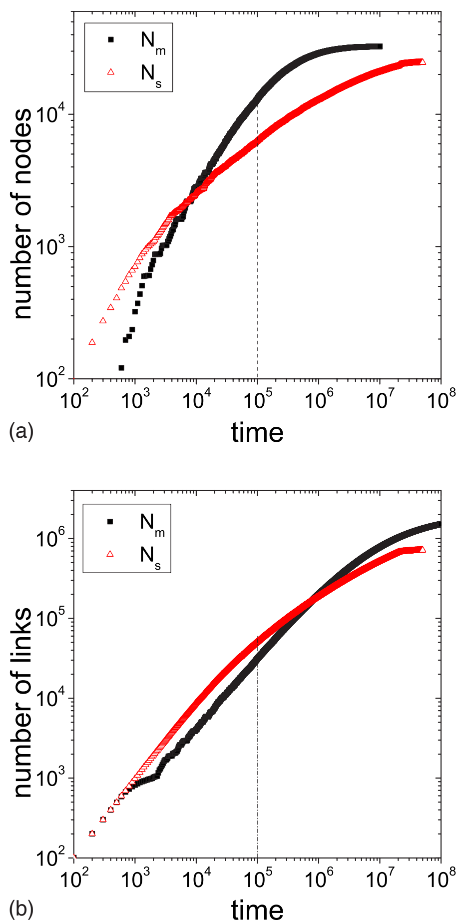

FIG. 2. (Color online) Time evolution of the number of nodes (a) and the number of links (b) in the network.

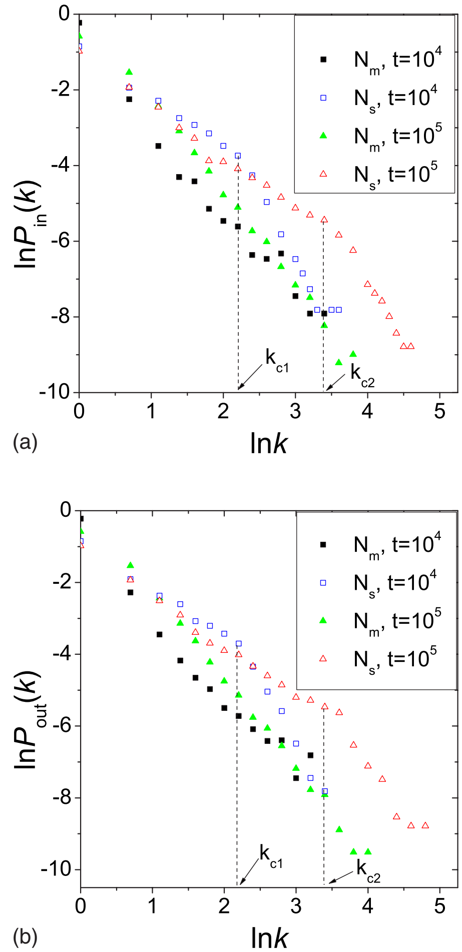

FIG. 3. (Color online) Plots of the distributions of links with different traffic states: (a) ln $P_{\text{in}}(k)$ versus ln(k); (b) ln $P_{\text{out}}(k)$ versus ln(k). The parameter $M=15$ is used.

and drops to small values. This means that the proportion of the nodes with small degree becomes less. This indicates that most of the new added links are attached to the nodes with small degree. As t further increases, the number of links E in N_m increases and the distribution of the region with smaller k drops to much small values (not shown). But the distribution of the region with large k does not change and has the exponent $\gamma_m=2.92$. While in N_s there are still two power law regions. We note that the exponent of part $k<k_c$ is $\gamma_s^l=0.92$ and that of part $k>k_c$ is $\gamma_s^r=1.92$. Both γ_s^l and γ_s^r decrease and the difference between the two exponents becomes small. This indicates that most of the new links are attached among the nodes with small degree or high degree. The different structure properties in N_m and N_s indicate that the relationships among traffic states in stop-and-go traffic and synchronized flow are not the same.

We argue that the degree of node has a linear relationship with the emerging times of the corresponding traffic state. If a traffic state can emerge many times in the evolution process of traffic flow, that is to say, the state can be reproduced from lots of other traffic states; at the same time, it also has high probability to evolve into many other traffic states. Thus the corresponding node in the network may have large in-degree and out-degree. Such results are clearly shown in Fig. 5(b). In synchronized flow, the linear relationship is obvious. But in stop-and-go traffic, there are some different properties. Three regions are formed in the diagram: In region (I), the points correspond to the traffic states which contains only one vehicle, i.e., $n_v=1$; in region (II), $n_v=2$; in region (III), most of the traffic states with $n_v\geqslant 3$, only a few of them with $n_v=2$. In each region, the linear relationship commonly exists. Figure 5(a) shows the distributions of emerging times of traffic states $P(n)$ and the power law behavior is obvious, $P(n)\sim n^{-\eta}$. The exponents η_m and η_s correspond to the cases in stop-and-go traffic and synchronized flow respectively, and η_m is larger than η_s. The scale-free behavior is caused by the power law distribution of emerging times of traffic states.

In stop-and-go traffic, both free and congested states will propagate through the selected configuration. The free flow states correspond to the traffic states which contain small number of vehicles ($n_v\leqslant 2$), and they are ordered. Not many new nodes are generated when the selected configuration is in free flow region, instead, most of the same traffic states will reproduce repeatedly. When the jam pass through the selected configuration, the traffic states with $n_v>2$ can emerge. At $\rho=0.2$, the jam happens only in a small region of the road. Most of the time the selected configuration is in

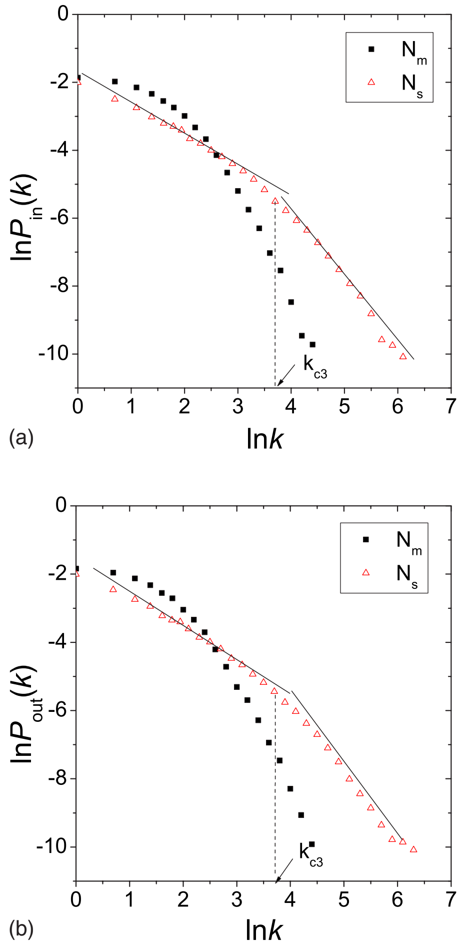

FIG. 4. (Color online) Plots of the distributions of links with different traffic states: (a) ln $P_{\text{in}}(k)$ versus ln(k); (b) ln $P_{\text{out}}(k)$ versus ln(k). The parameter $M=15$ is used. N_m at $t=10^6$ and N_s at $t=2\times10^7$.

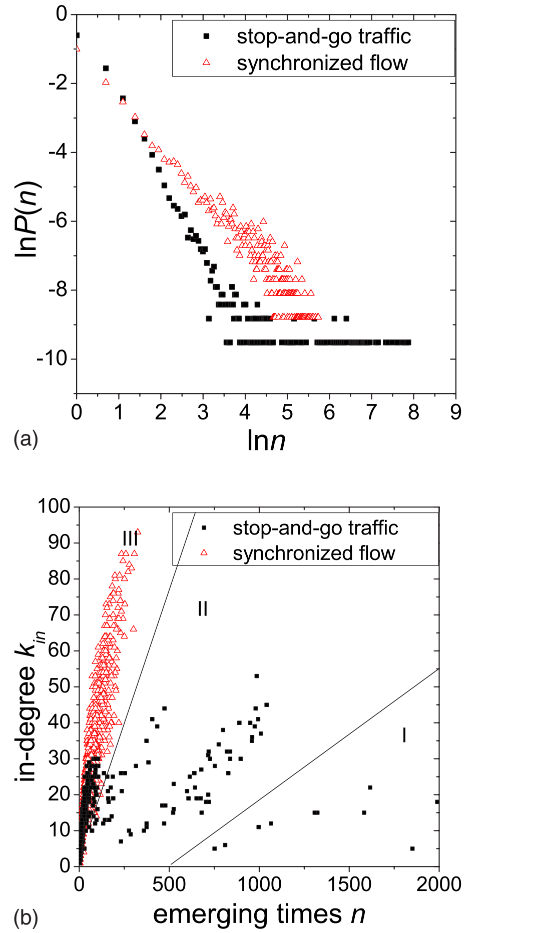

FIG. 5. (Color online) (a) The distributions of emerging times of traffic state n. (b) The relationship between in-degree k_{in} of nodes and emerging times n of the corresponding traffic states. The out-degree has the same behavior but is not shown.

free flow, so the traffic states with $n_v=1,2$ emerge many times. However, the jam states cannot be captured very often and the traffic states with $n_v \geqslant 3$ emerge infrequently, while synchronized flow is homogenous and such difference does not exist. We note that the nodes with large degree in N_m correspond to the traffic states with $n_v=2$ [Fig. 5(b)]. In N_s, the nodes, which correspond to the traffic states emerging only several hundred times, have larger degree than that in N_m with $n_v=2$. Those nodes correspond to the traffic states with $n_v=4,5$. As pointed out in Ref. [22], synchronized flow has some complex features. Here we focus on the two features: (1) The complex transitions effect and (2) the speed correlation effect. The vehicles are usually homogeneously distributed on the road for the speed are highly correlated, and the transition behaviors among traffic states are complex. The two features make the nodes in N_s have larger degree.

If the network is deemed as undirected, the degree of node is the sum of its in-degree and out-degree. The average degree of the network is $\bar{k}=2\frac{E}{N}$. In the first 10^6 time steps, the number of nodes increase with the scale $N\sim t^{\alpha}$ and the number of links grow with the scale $E\sim t^{\beta}$. So $\bar{k}$ has the scale $\bar{k}\sim t^{\beta-\alpha}$. In this period, the network becomes more connective. If different values of M are used, the number of possible node in the network is not the same and the period in which N and E of the network have power law behavior is not of the same length. However, the same structure of the networks will be obtained at different M if they have the same average degree $\bar{k}$. Next the average path length l and the clustering coefficient c of the networks with the same $\bar{k}$ and different N are studied. Here the termination (2) is used. According to the large difference of average degree between the networks constructed in stop-and-go traffic ($\bar{k}=4.67$) and in synchronized flow ($\bar{k}=19.48$), $K=2$ and $K=5$ are selected, respectively. The number of nodes N in the network that depend on M is shown in Fig. 6(a) and it increases exponentially as M increases. Figure 6(b) shows that l increases logarithmically with N. The relationship between clustering coefficient c and network size N is shown in Fig. 6(c) and c decreases as $N^{-\alpha}$. Such results indicate that the small-world properties of the constructed networks both in stop-and-go traffic and synchronized flow diminish rapidly.

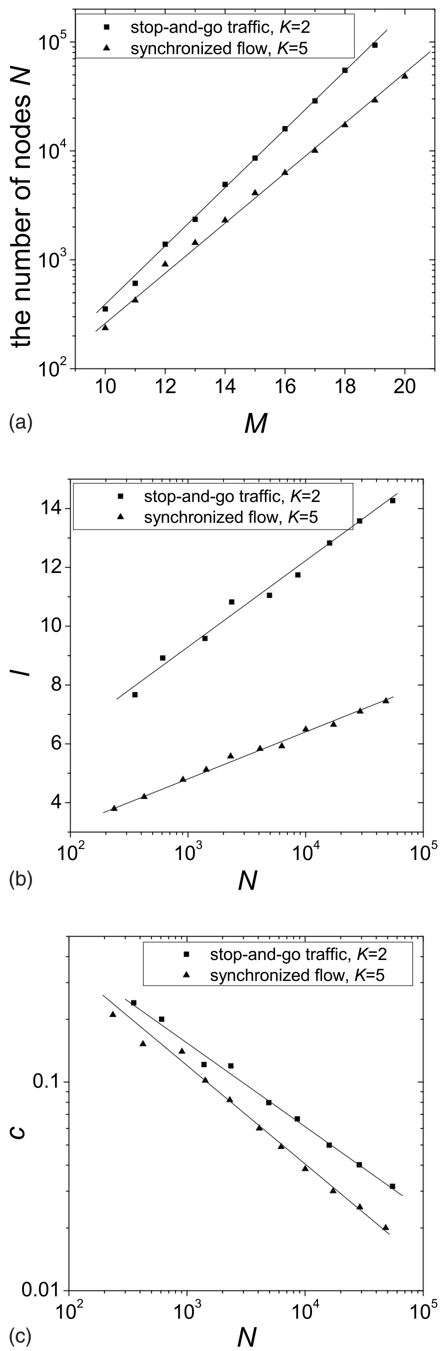

FIG. 6. (a) Number of nodes of the constructed network N at different M. Statistical properties of the constructed networks: (b) Average path length l versus network size N; (c) clustering coefficient c versus network size N. $K=2$ is selected when the network is constructed in stop-and-go traffic and $K=5$ is chosen in synchronized flow.

IV. VERIFICATION WITH REAL TRAFFIC DATA

In the above analysis, the networks are constructed by using CA models for traffic flow. We know that CA model is an excellent tool to simulate real traffic. Most of the real features can be captured by CA models. We argue that the scaling behaviors also exist in real traffic. The following verification proves this.

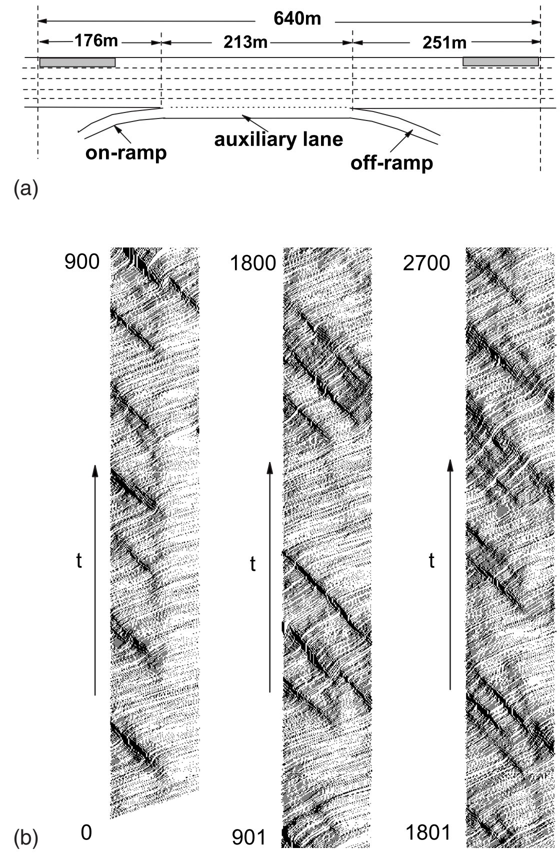

FIG. 7. Properties of the real traffic data. (a) The schematic of the study area. The top lane is the first lane and the bottom lane is the last one. The two shadow parts are the selected regions from which the traffic states are obtained. (b) Space-time plots of the real traffic data of the 640 m length top lane. There is a clear difference that stop-and-go traffic emerges more often in the left part than in the right part.

The real traffic data, which are provided by NGSIM [24], are used to construct the network. The data recorded the trajectory information of all vehicles that drove through section of U.S. 101 on July 15th, 2005, between 7:50 and 8:35 a.m. The schematic of the study area is shown in Fig. 7(a) and it has a length of about 640 m.

Here we focus on the top lane, because the on-ramp and the off-ramp have the least impact on the top lane, and the lane changing behaviors are the least among the five lanes. First, the lane is divided into cells. As in the NS model, each cell has a length of 7.5 m, that is to say, the cell occupies an area of 7.5 m. If the position of the vehicle is (not) within this area, the state of the corresponding cell is 1 (0). Then the real traffic state is represented by binary digits. In the period of 2700 s, we map the binary digits into an image in sequence and then the space-time plots are obtained [Fig. 7(b)]. We can see that the traffic state is mainly characterized by synchronized flow. While some stop-and-go traffic emerge in synchronized flow, that happens more frequently in the left part than that in the right part. The reason is that there is an on-ramp in the left part and an off-ramp in the right part. Two regions of the first lane [shadow parts in Fig. 7(a)] are selected as the configuration from which the traffic states are obtained. Each configuration contains 15 cells, i.e., 112.5 m. The traffic state on the configuration at each time step is transformed into node in the network.

In the 2700 time steps, 1499 nodes and 2549 links are produced from the left configuration, and 1498 nodes and 2498 links are obtained from the right configuration. The distributions of links of the two networks are shown in Fig. 8. As stop-and-go traffic often happens, in the left configuration the distributions of both in-degree $P_{in}(k)$ and the out-degree $P_{out}(k)$ exhibit scale-free behavior (Fig. 8). While the distribution of links of the network corresponding to right configuration has two power law regions (Fig. 8). Such results confirm that scaling behavior really exists in traffic flow.

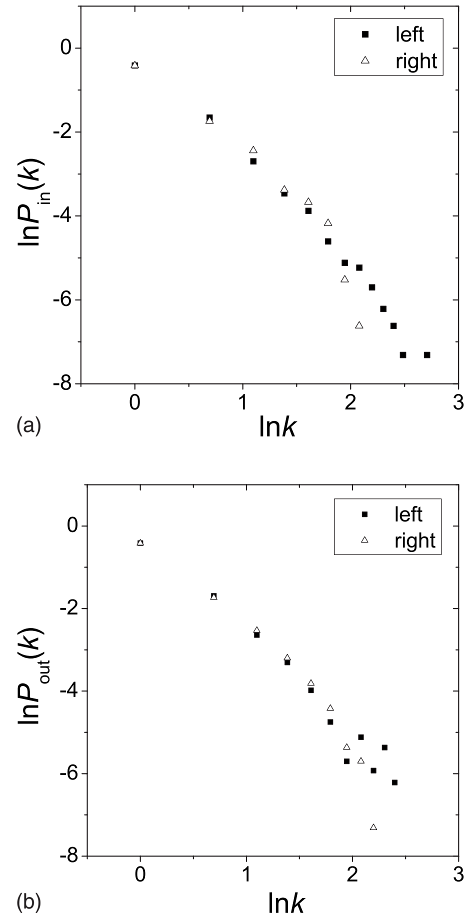

FIG. 8. Plots of the distributions of links of the networks constructed from the left and the right configuration. (a) $\ln P_{in}(k)$ versus $\ln(k)$; (b) $\ln P_{out}(k)$ versus $\ln(k)$.

V. CONCLUSION

In this work, scaling behaviors in synchronized traffic flow are investigated by using the model proposed in Ref. [13], which is a different method to study the complex properties in the evolution process of traffic flow. The simulation results indicate that there are two power law regions in the distribution of the networks constructed in synchronized flow, while scale-free behavior lies in stop-and-go traffic [13]. The real traffic data confirm such results. Thus the proposed model can be used to investigate the complex dynamics in traffic flow.

The networks constructed in traffic flow have both scale-free and random graph properties. Further research on these networks will help us understand mechanisms in traffic and their complex systems.

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