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Routing strategies in traffic network and phase transition in network traffic flow

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Abstract. The dynamics of information traffic over scale-free networks has been investigated systematically. A series of routing strategies of data packets have been proposed, including the local routing strategy, the next-nearest-neighbour routing strategy, and the mixed routing strategy based on local static and dynamic information. The capacity of the network can be quantified by the phase transition from free flow state to congestion state. The optimal parameter values of each model leading to the highest efficiency of scale-free networked traffic systems have been found. Moreover, we have found hysteretic loop in networked traffic systems with finite packets delivering ability. Such hysteretic loop indicates the existence of the bi-stable state in the traffic dynamics over scale-free networks.

Keywords. Routing strategy; network traffic flow; hysteretic loop; phase transition from free flow state to congestion state; scale-free network; bi-stable state; traffic dynamics.

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1. Traffic dynamics based on local routing strategy on scale-free networks

Communication networks such as the Internet, World-Wide-Web and peer-to-peer networks play a significant role in modern society. Dynamical properties of these systems have attracted tremendous interests and devotion among engineering as well as physics communities. The ultimate goal of studying these large communication networks is to control the increasing traffic congestion and improve the efficiency of information transportation. Many recent studies have focused on the efficiency improvement of communication networks which is usually considered from two aspects: modifying the underlying network structure or developing better routing strategies [1,2]. Because of the high cost of changing the underlying structure, the latter is comparatively preferable. In traffic systems, the underlying network structure plays a significant role in the traffic dynamics. In order to develop practical routing strategies, understanding the effect of network on the traffic dynamics is the central issue.

Since the surprising discovery of scale-free property of real world networks by Barabási and Albert, it is worthwhile to investigate traffic dynamics on scale-free networks instead of random and regular networks. How the traffic dynamics are influenced by many kinds of structures, such as Web graph, hierarchical trees and Barabási–Albert network, has been extensively investigated. A variety of empirically observed dynamical behaviours have been reproduced by such traffic models, including $1/f$-like noise of load series, phase transition from free flow state to congestion, power-law scaling correlation between flux and the relevant variance and cascading. Moreover, some previous work pointed out that traffic processes taking place on the networks do also remarkably affect the evolution of the underlying network. The modelling of traffic dynamics on networks, generating rate of data packets together with their randomly selected sources and destinations are introduced in a previous work. Some models assume that packets are routed along the shortest paths from origins to destinations. However, due to the difficulty in searching and storing shortest paths between any pair of nodes of large networks, the routing strategies based on local topological information have been proposed for better mimicking real traffic systems and for more widely potential applications, such as peer-to-peer networks.

We present a traffic model in which packets are routed based only on local topological information with a single tunable parameter α [3,4]. As free traffic flow on the communication networks is the key to their normal and efficient functioning, we focus on the network capacity that can be measured by the critical point of phase transition from free flow to congestion. Simulations show that the maximal capacity corresponds to $\alpha = -1$ in the case of identical nodes' delivering ability. To explain this, we investigate the number of packets of each node depending on its degree in the free flow state and observe the power-law behaviour. Other dynamic properties including average packets' travelling time and traffic load are also studied. The dynamics right after the critical generating rate R_c exhibits some interesting properties independent of α, indicate that although the system enters the jammed state, it possesses partial capacity for forwarding packets. Our model can be considered as a preferential walk among neighbour nodes. Inspiringly, our results indicate that some fundamental relationships exist between the dynamics of synchronization and traffic on the scale-free networks.

Furthermore, on the basis of next-nearest-neighbour (NNN) routing searching strategy, we propose a new routing strategy, namely, preferential next-nearest-neighbour (PNNN) searching strategy which can further alleviate the traffic congestion and greatly improve the packets handling capacity of the network compared to NNN strategy [1–4]. In PNNN strategy, a parameter α is introduced. The probability that the ith node with degree k_i receives packets from its neighbours is proportional to k_i^α in each time step. We treat all the nodes as both hosts and routers. The phase transition from free flow to the jammed state with different α is studied. We find that the network capacity is considerably improved by decreasing α and tends to be stable when α is lower than a specific value. Moreover, by considering the travel time of average packets with the maximal network capacity, the optimal parameter value $\alpha = -2$ is obtained. Near the phase transition point, a big fluctuation of traffic load is observed and the extent of the fluctuation with PNNN strategy is larger than that with the normal NNN strategy in the cases of large α. Another meaningful phenomenon is the exhibition of $1/f$-like noise of power spectrum of traffic load series, which indicates the long-range correlation. If the system shows the behaviour of $1/f^2$-like noise, it reflects the zero correlation of the series. The $1/f$ noise is supported by real traffic systems such as vehicular flow in the highway networks and data packets flow in the computer networks. Simulation results show that when R is far away from the critical packets generating rate $R_{\rm c}$, $1/f$ noise emerges. The exponent ϕ of power spectrum $S(f) \sim f^{-\phi}$ not only depends on R but also correlates with parameter α. The connectivity (link) density of Barabási–Albert model (BA) can be adjusted by a parameter m, thus we also investigate $R_{\rm c}$ as a function of m. The position of phase transition point influenced by node delivering ability C and network size N is also studied in detail. Our strategy may be useful for designing communication protocols for large scale-free networks due to the low cost of local information requirement and the strongly improved network capacity.

We have also proposed a new routing strategy by integrating local static and dynamic information [5,6]. The advantages of this strategy for delivering data packets on scale-free networks have been demonstrated from two aspects of network capacity and mean packet travel time. The short mean packet travel time is mainly due to the sufficient use of hub nodes. The large network capacity is caused by the utilization of dynamic information which reflects the traffic burden on nodes. Our study indicates that large degree nodes play an important role in the delivery of packets. Packets can find their targets with higher probability if they pass by the large degree nodes, which results in shorter average travel time. However, the large degree nodes are also easily congested if large amount of packets are prone to pass through them. The introduced strategy can make the large degree nodes fully used when packet generating rate is low, and also allow packets to bypass those nodes when they afford heavy traffic burden. Thus the system's efficiency is greatly improved. In addition, we note that the new strategy should not be hard for implementation. The local static, i.e. topology information can be easily acquired and stored in each router. The local dynamic information could be obtained by using the keep-alive messages that routers continuously exchange with their peers. Thus, the strategy may have potential applications in peer-to-peer networks.

2. Phase transition and hysteretic loop of traffic flow in scale-free networks

We model information traffic on scale-free networks by introducing the node queue length L proportional to the node degree and its delivering ability C proportional to L [7]. we report for the first time the fundamental diagram of flow against density, in which hysteresis is found, and thus we can classify the traffic flow into four states: free flow, saturated flow, bi-stable and jammed.

Previous studies usually assumed that the capacity of each node, i.e., the maximum queue length of each node for holding packets, is unlimited and the node handling capability, that is the number of data packets a node can forward to other nodes each time step, is either a constant or proportional to the degree of each node.

But, obviously, the capacity and delivering ability of a node are limited and can be changed from node to node in real systems, and in most cases, these restrictions could be very important in triggering congestion in traffic systems.

Since the analysis on the effects of the node capacity and delivering ability restrictions on traffic efficiency is still missing, we propose a new model for the traffic dynamics of such networks by taking into account the maximum queue length L and handling capacity C of each node. The phase transition from free flow to congestion is well captured and, for the first time, we introduce the fundamental diagram (flux against density) to characterize the overall capacity and efficiency of the networked system. Hysteresis in such network traffic is also produced.

To generate the traffic network, our simulation starts with the most general Barabási–Albert scale-free network model. The capacity of each node is restricted by two parameters: (1) its maximum packet queue length L, which is proportional to its degree k (a hub node ordinarily has more memory): $L = \alpha \times k$; (2) the maximum number of packets it can handle per time step: $C = \beta \times L$.

Motivated by the previous models, the system evolves in parallel according to the following rules:

(1) *Add packets* – Packets are added with a given rate R (packets per time step) at randomly selected nodes. Each packet is given a random destination.

(2) *Navigate packets* – Each node performs a local search among its neighbours. If a packet's destination is found in its nearest-neighbourhood, its direction will be directly set to the target. Otherwise, its direction will be set to a neighbouring node h with preferential probability: $P_h = k_h^{\phi}/(\sum_i k_i^{\phi})$. Here the sum runs over the neighbouring nodes, and ϕ is an adjustable parameter. It is assumed that the nodes are unaware of the entire network topology and only know the neighbouring nodes' degree k_i.

(3) *Deliver packets* – At each step, all nodes can deliver at most C packets towards its destinations and FIFO (first-in-first-out) queuing discipline is applied at each node. When the queue at a selected node is full, the node will not accept any more packets and the packet will wait for the next opportunity. Once a packet arrives at its destination, it will be removed from the system. As in other models, we treat all nodes as both hosts and routers for generating and delivering packets.

We study the fundamental diagram of network traffic with our model. Fundamental diagram (flux–density relation) is one of the most important criterion that evaluates the transit capacity for a traffic system. Obviously, if the nodes are not controlled with the queue length L, the network system will not have a maximum number of packets it can hold and the packet density cannot be calculated, so that the fundamental diagram cannot be reproduced.

To simulate a conservative system, we count the number of removed packets at each time step and add the same number of packets to the system at the next step. The flux is calculated as the number of successful packets delivered from node to node through links per step. In figure 1, the fundamental diagrams for $\phi = 0.0, 0.3, -0.5$ and -0.7 are shown.

The curves of each diagram show four flow states: free flow, saturated flow, bi-stable and jammed. For simplicity, we focus on the $\phi = 0.3$ chart with the maximum flux = 1319 in the following description. As we can see, when the density

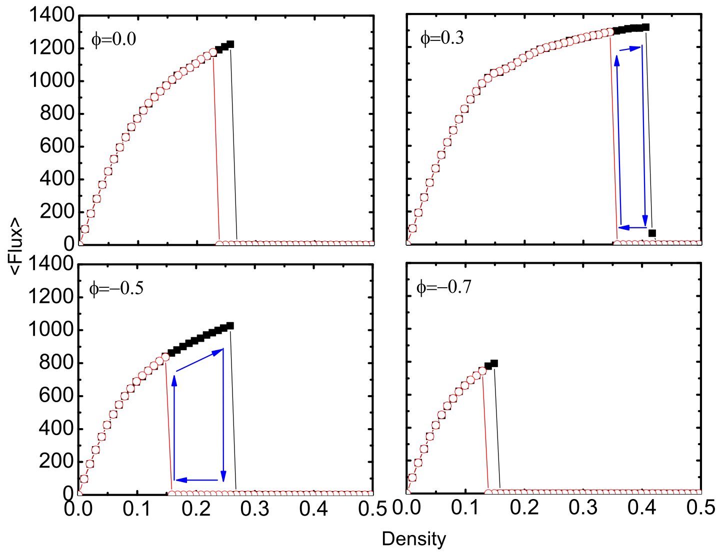

Figure 1. Fundamental diagram for a $N = 1000$ network with $m_0 = m = 5$, $\alpha = 1$, $\beta = 0.2$ and different ϕ. The data are averaged over 10 typical simulations on one realization of network. In each chart, the solid square line shows the flux variation when adding packets to the system (increase density), while the empty circle line shows the flux variation when drawing out packet from the system (decrease density). The sudden transition density values are: 0.26 and 0.23 ($\phi = 0.0$), 0.40 and 0.34 ($\phi = 0.3$), 0.26 and 0.15 ($\phi = -0.5$), 0.15 and 0.13 ($\phi = -0.7$). For different realizations of network, the fundamental charts are similar, but with small difference in the transition values. The arrows in charts of $\phi = 0.3$ and -0.5 showing the hysteresis are guide for the eyes.

is low (less than ≈0.10), all packets move freely and the flux increases linearly with packet density, which is attributed to the fact that in the free flow state, all nodes are operated below its maximum delivering ability C. Then the flux's increment slows down and the flux gradually comes to saturation (0.10–0.34), where the flux is restricted mainly by the delivering ability C of the nodes.

At the region of medium density, the model reproduces an important character of traffic flow – 'hysteretic' character, which means that two branches of the fundamental diagram coexist between 0.34 and 0.40. The upper branch is calculated by adding packets to the system, while the lower branch is calculated by removing packets from a jammed state and allowing the system to relax after the intervention. In this way a hysteretic loop can be traced (arrows in figure 1), indicating that the system is bi-stable in a certain range of packet density. As we know so far, it is the first time that the hysteretic phenomenon is reported in the scale-free traffic system.

In order to test the finite-size effect of our model, we simulate some systems with bigger size. The simulation shows similar phase transition and hysteretic character in fundamental diagram as shown in figure 2a.

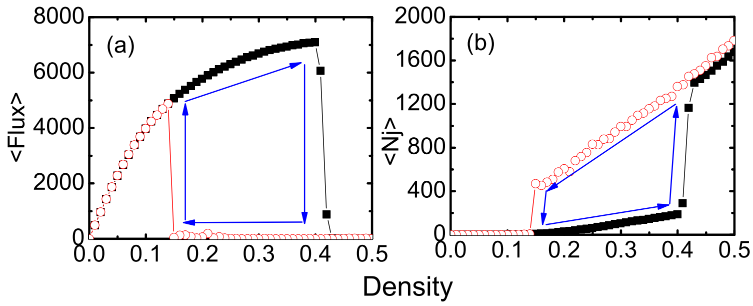

Figure 2. (**a**) Fundamental diagram for a $N = 5000$ network with $m_0 = m = 5$, $\alpha = 1$, $\beta = 0.2$ and $\phi = 0.1$. (**b**) The averaged number of jammed nodes $\langle N_j \rangle$. The symbols for increasing/decreasing density are the same as in figure 1. One can see that the two sudden change points 0.40 and 0.14 in both charts are equal. The arrows showing the hysteresis are guides for the eyes.

The flux's sudden drop to a jammed state from a saturated flow indicates a first-order phase transition, which can be explained by the sudden increment of full (jammed) nodes in the system (see figure 2b). According to the evolutionary rules, when a given node is full, packets in neighbouring nodes cannot get in the node. Thus, the packets may also accumulate on the neighbouring nodes and get jammed. This mechanism can trigger an avalanche across the system when the packet density is high. As shown in figure 2b, the number of full nodes increases suddenly at the same density where the flux drop to zero and almost no packet can reach its destination. As for the lower branch in the bi-stable state, starting from an initial jammed configuration, the data packages accumulated in the very jammed nodes will be difficult to be sent out and hard to disappear. Hence these nodes will debase the system's transmission efficiency by affecting the surrounding nodes until all nodes are not jammed, thus we get the lower branch of the loop.

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