# Integrating local static and dynamic information for routing traffic

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The efficiency of traffic routing on complex networks can be reflected by two key measurements, i.e., the network capacity and the average travel time of data packets. In this paper we propose a mixing routing strategy by integrating local static and dynamic information for enhancing the efficiency of traffic on scale-free networks. The strategy is governed by a single parameter. Simulation results show that maximizing the network capacity and reducing the packet travel time can generate an optimal parameter value. Compared with the strategy of adopting exclusive local static information, the new strategy shows its advantages in improving the efficiency of the system. The detailed analysis of the mixing strategy is provided for explaining its effects on traffic routing. The work indicates that effectively utilizing the larger degree nodes plays a key role in scale-free traffic systems.

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## I. INTRODUCTION

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 [1–10]. 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 [11–13] or developing better routing strategies [14–19]. In view 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 the network on the traffic dynamics is a central issue.

Since the surprising discovery of scale-free property of real-world networks by Barabási and Albert [20,21], 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 [14,15], hierarchical trees [4], and Barabási-Albert network [6], has been extensively investigated. A variety of empirically observed dynamical behaviors 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 [3,14,15,22–26]. Moreover, some previous work pointed out that traffic processes taking place on the networks do also remarkably affect the evolution of the underlying network [27,28]. To model traffic dynamics on the networks, the rate of generating data packets together with their randomly selected sources and destinations are introduced by previous work [29]. Some models assume that packets are routed along the shortest paths from origins to destinations [4,6]. However, due to the difficulty in searching and storing the 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 [14,15,17].

The efficiency of a traffic network is determined by the topology and the routing strategy. In Ref. [11], Guimerà *et al.* investigated optimal network topologies for local search while considering congestion. They optimized the network structure with respect to better efficiency of the network, where the efficiency can be quantified by a phase transition point from a free flow state to congestion. They also found analytically that the maximum effective betweenness is a deterministic factor for the network efficiency given a certain routing strategy. Enlightened by Guimerà *et al.*, we aim to enhance the efficiency of traffic networks by considering improved routing strategy. The efficiency of a network can be measured by both the network capacity and the communication velocity. The former is reflected by the onset of congestion states, and the latter is reflected by the average packet travel time. Note that these two quantities are not equivalent for estimating the efficiency, but even contradictory to each other. Take scale-free networks for example. Scale-free networks possess shorter average path length in contrast to random and regular networks, attributed to the existence of hub nodes. Thus, data packets can transmit much faster in the scale-free networks. However, suppose that too much data flow passes through those hub nodes, it will lead to the congestion at those nodes and decrease the network capacity. To solve the conflict between the network capacity and the communication velocity, we propose a new routing strategy adopted in scale-free networks based on local static and dynamic information, i.e., the local structure and the traffic

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flux, respectively. Compared with the strategy based on the exclusive local static information [17], both the network capacity and the communication velocity are considerably enhanced by adopting the new mixing strategy. The effects of the new strategy on the efficiency of the scale-free traffic system are discussed in detail. It may has potential applications in peer-to-peer networks.

The paper is organized as follows. In the following section, we describe the model rules and the relevant definitions in detail. In Sec. III, we demonstrate the simulation results and the discussion. In the last section, the present work is concluded.

## II. THE MODEL AND DEFINITIONS

The Barabási-Albert model is the simplest and well-known model which can generate networks with power-law degree distribution $P(k) \sim k^{-\gamma}$, with $\gamma=3$. Without losing generality, we construct the network structure by following the same method used in Ref. [20]: Starting from $m_0$ fully connected nodes, a new node with $m_0$ edges is added to the existing graph at each time step according to preferential attachment, i.e., the probability $\Pi_i$ of being connected to the existing node $i$ is proportional to its degree $k_i$. Then we model the traffic of packets on the given graph. At each time step, there are $R$ packets generated in the system, with randomly selected sources and destinations. We treat all the nodes as both hosts and routers [6,14,15] and assume that each node can deliver at most $C$ packets per time step towards their destinations. All the nodes perform a parallel local search among their immediate neighbors. If a packet's destination is found within the searched area of node $l$, i.e., the immediate neighbors of $l$, the packet will be delivered from $l$ directly to its target and then removed from the system. Otherwise, the probability of a neighbor node $i$, to which the packet will be delivered is

$$P_{l\to i} = \frac{k_i(n_i+1)^{\beta}}{\sum_j k_j(n_j+1)^{\beta}}, \tag{1}$$

where, the sum runs over the immediate neighbors of the node $l$. $k_i$ is the degree of node $i$ and $n_i$ is the number of packets in the queue of $i$. $\beta$ is an introduced tunable parameter. $k_i$ and $n_i$ are the so-called static and dynamic information, respectively. Adding one to $n_i$ is to guarantee the nodes without packets have a probability to receive packets. During the evolution of the system, the FIFO (first-in first-out) rule is applied and each packet has no memory of previous steps. Under the control of the routing strategy, all packets perform a biased random-walk-like move. All the simulations are performed by choosing $C=5$.

To implement our strategy, each node should know the traffic loads of its neighbors, which can be realized by using the *keep-alive* messages that routers (nodes) continuously exchange in real-time information with their peers [16]. However, taking into account the information transmission cost, the exchanged information may be updated every few seconds between neighbors. Therefore, we study the effect of transmission delay on the traffic dynamics. The delay in our model is defined as the number of time steps (period) in receiving updated information from the neighbors.

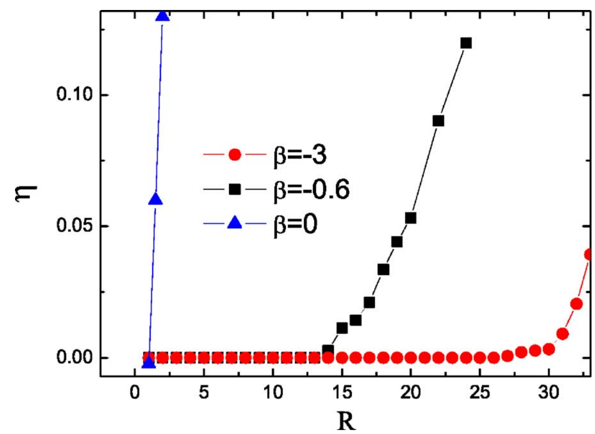


FIG. 1. (Color online) The order parameter $\eta$ as a function of generating rate $R$ for different value of parameter $\beta$. Other parameters are $d=0$, $C=5$, and $N=1000$.

In order to characterize the network capacity, we use the order parameter presented in Ref. [4]:

$$\eta(R) = \lim_{t\to\infty} \frac{\langle \Delta L\rangle}{R\Delta t}, \tag{2}$$

where $L(t)$ is defined as the number of packets within the network at time $t$. $\Delta L = L(t+\Delta t) - L(t)$ with $\langle \cdots \rangle$ indicating the average over time windows of width $\Delta t$. The order parameter represents the ratio between the outflow and the inflow of packets calculated over long enough periods. In the free flow state, due to the balance of created and removed packets, the load does not depend on time, which brings a steady state. Thus, when time tends to be unlimited, $\eta$ is around zero. Otherwise, when $R$ exceeds a critical value $R_c$, the packets will continuously pile up within the network, which destroys the steady state. Hence, the quantities of packets within the system will be a function of time, which makes $\eta$ constant more than zero. A sudden increment of $\eta$ from zero to nonzero characterizes the onset of the phase transition from the free flow state to congestion, and the network capacity can be measured by the maximal generating rate $R_c$ at the phase transition point.

## III. SIMULATION RESULTS

As mentioned earlier, the efficiency of the system is reflected by both the network capacity and the communication velocity. We first investigate the order parameter $\eta$ as a function of the generating rate $R$ for different model parameter $\beta$. As shown in Fig. 1, one can find that for each $\beta$, when $R$ is less than a specific value $R_c$, $\eta$ is zero; it suddenly increases when $R$ is slightly larger than $R_c$. Moreover, in this figure, different $\beta$ corresponds to different $R_c$, thus we investigate the network capacity $R_c$ depending on $\beta$ for finding the optimal value of parameter $\beta$. Figure 2 shows that in the case of no time delay, the network capacity is considerably enhanced by reducing $\beta$, and when $\beta$ is less than a specific value,

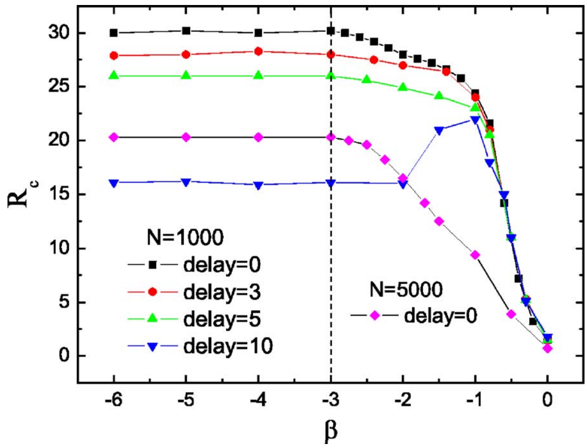


FIG. 2. (Color online) The network capacity $R_c$ vs parameter $\beta$ for different time delay and for different network size $N$. The other parameter is $C=5$.

approximately $-3$, the capacity reaches an upper limit. The dynamic information $n_i$ represents the amount of traffic flux of node $i$. The target of decreasing $\beta$ is to allow packets to circumvent the nodes with heavier traffic burden and alleviate the congestion on those nodes. While for the case of only adopting local topological information (static strategy) [17,30], the maximal network capacity is 23 when choosing $C=5$. The higher maximal capacity by adopting the new strategy indicates that the dynamic information is a better reflection of congestion than the static one. Moreover, the capacity with time delay is also studied, as shown in Fig. 2. When the delay is not long, $R_c$ is slightly reduced as the delay increases, and the onset of the upper limit is still at $\beta=-3$. However, for the long delay, such as $d=10$, it has a remarkable influence on the network capacity. There exists a maximal value of $R_c$ at the point of $\beta=-1$ instead of reaching the upper limit and the network capacity is reduced. The long period feedback information cannot well reflect the real circumstance of neighbor nodes, which leads to the instabilities in the system, and, consequently, the capacity decreases. Furthermore, we perform simulations with larger network size, $N=5000$, as exhibited in Fig. 2. The curve of $R_c$ vs $\beta$ displays the same trend as that of $N=1000$. It is the longer average shortest path length that results in the decrease of network capacity compared with the cases of $N=1000$.

The communication velocity of the system can be estimated by the mean travel time of the packets from their origins to destinations over a long period. The mean travel time $\langle T\rangle$ vs generating rate $R$ for different parameter $\beta$ are demonstrated in Fig. 3. We also compare the behavior of $\langle T\rangle$ by adopting static strategy [30] with that adopting the new one upon the identical network structure, where $\alpha=-1$ corresponds to the optimal parameter value of the static strategy as shown in Fig. 3. All the simulations are performed within the steady state, in which $\langle T\rangle$ is independent of time step. While if the system enters the jammed state, $\langle T\rangle$ increases as time grows, ultimately, it will be prone to be unlimited due to the packets' continuous accumulation in the system. By adopting the static strategy, $\langle T\rangle$ is approximately independent of $R$, which is because the static routing algorithm is based

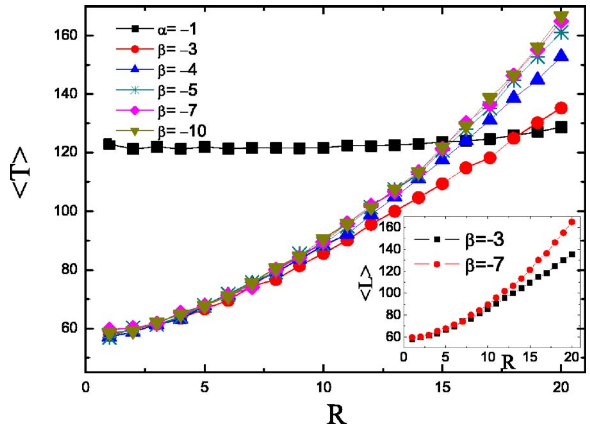


FIG. 3. (Color online) Mean packets travel time $\langle T\rangle$ vs $R$ for static and the new strategy, respectively. $\alpha=-1$ corresponds to the optimal value of static strategy. $\beta$ is the parameter of the mixing strategy. The inset is the average distances traveled by packets $\langle L\rangle$ as a function of $R$ for different $\beta$. The network size $N=1000$, node delivering ability $C=5$.

on exclusive topological information. Although the static strategy strongly improves the network capacity, it ignores the importance of hub nodes, i.e., greatly reducing the diameter of the network. In contrast to the static strategy, the new strategy, by integrating the local static and dynamic information, cannot only considerably enhance the network capacity but also make the hub nodes efficiently utilized. One can see in Fig. 3 when $R$ is not too large, $\langle T\rangle$, adopting the new strategy for all $\beta$, is much shorter than $R$ by adopting the static strategy. The advantages of using the new strategy can be explained from Eq. (1). For very small $R$, few packets accumulate in the queue, thus $P_i\sim k_i$, which is consistent with the search algorithm proposed in Ref. [31]. The high efficiency of this algorithm for searching target nodes has been demonstrated by numerical simulations [31]. Hence, it is the shorter average distances traveled by packets $\langle L\rangle$ that induces the shorter $\langle T\rangle$ in the free flow state, which can be seen in the inset of Fig. 3, where $\langle L\rangle$ is nearly the same as $\langle T\rangle$ for the identical value of $\beta$. When increasing $R$, packets start to accumulate on the large degree nodes, the new strategy can automatically decrease the probability of delivering packets to those hub nodes according to the dynamic information. Then, when $R$ approaches $R_c$, packets are routed by the mixing strategy to circumvent those hub nodes, which become the bottlenecks of the system. Therefore, near the phase transition point, $\langle T\rangle$ shows the same value by adopting two different strategies. Combing the results that $\beta=-3$ is not only the onset of the upper limit of the network capacity but also corresponds to the shortest $\langle T\rangle$ in the case of maximal network capacity, we can conclude that $\beta=-3$ is the optimal choice.

We further investigate the behavior of traffic loads influenced by the mixing routing strategy. Figure 4 displays the average load $\langle L\rangle$ as a function of $R$ for two strategies with different parameters. For the static strategy with the optimal parameter, $\langle L\rangle$ is a linear function of $R$. The load under the new strategy is lower than that under the static one for a wide

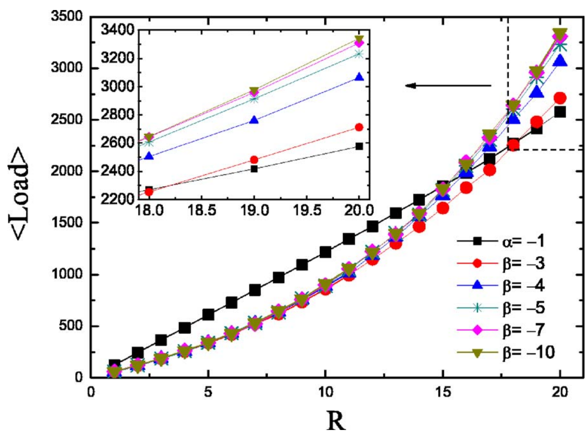


FIG. 4. (Color online). Traffic load vs $R$ for static and the new strategy, respectively. $\alpha=-1$ corresponds to the optimal value of static strategy. $\beta$ is the tunable parameter of the new strategy. The network size $N=1000$, $C=5$.

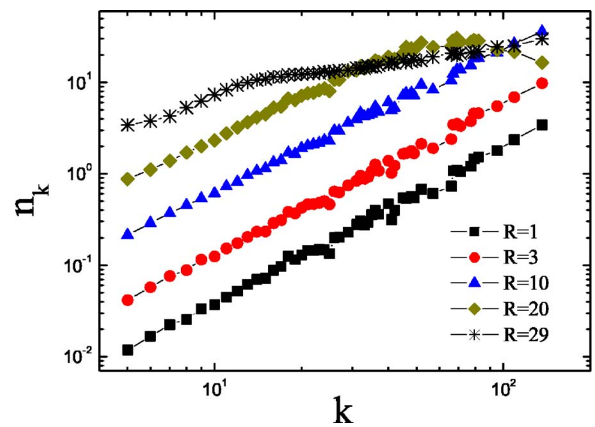


FIG. 5. (Color online) The queue length of the nodes as a function of their degree with $\beta=-3$ for different $R$. The network size $N=1000$, $C=5$.

range of $R$. When $R$ approaches the critical value $R_c$, the load under the new strategy turns out to be larger. We also observe that by choosing $\beta=-3$, the system affords the lowest traffic load among the whole range of $R$, which also indicates that $\beta=-3$ is the optimal choice. Actually, there exists a certain relationship between the mean packet travel time and the average load. According to Little's law [32] in the queueing theory, one can easily obtain $\langle L\rangle=R\langle T\rangle$. Note that this result is only satisfied in the steady state due to the balance between created and removed nodes.

To give a detailed insight into the effect of the new strategy, we investigate the queue length of a node $n_k$ as a function of its degree $k$ by selecting the optimal parameter for different $R$. The queue length of a node is defined as the number of packets in the queue of that node. The results are shown in Fig. 5. One can see that when $R$ is not large, $n_k$ vs $k$ shows power-law properties and the slope for different $R$ is the same. These behaviors are attributed to the domination of static information. In Eq. (1), small $R$ leads to the small $n_i$, and the forwarding probability is mainly determined by the node degree, i.e., static information. Therefore, $n_k$ vs $k$ demonstrates universal scaling property [17]. For the medium value of $R$, such as $R=20$, the new strategy mainly affects traffic loads on large degree nodes. The strategy, according to Eq. (1), allows packets to circumvent the large degree nodes which bear heavier traffic burden. When $R$ approaches to the phase transition point $R_c$, we can see in Fig. 5 that the traffic burden on all different degree nodes is almost the same. This average effect results in the maximal network capacity in the case of identical node delivering ability.

## IV. CONCLUSION

We have proposed a routing strategy by integrating local static and dynamic information. 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 packets 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. The present study indicates that large degree nodes play an important role in the packets delivery. 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 a 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 our 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 router continuously exchange with their peers [16]. Thus, the strategy may have potential applications in peer-to-peer networks.

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