Effects of node buffer and capacity on network traffic*

Ling Xiang(凌 翔)[a], Hu Mao-Bin(胡茂彬)[b], and Ding Jian-Xun(丁建勋)[a]†

[a] School of Transportation Engineering, Hefei University of Technology, Hefei 230009, China

[b] School of Engineering Science, University of Science and Technology of China, Hefei 230026, China

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In this paper, we study the optimization of network traffic by considering the effects of the node's buffer ability and capacity. Two node buffer settings are considered. The node capacity is considered to be proportional to its buffer ability. The node effects on network traffic systems are studied with the shortest path protocol and an extension of the optimal routing [*Phys. Rev.* E 74 046106 (2006)]. In the diagrams of flux–density relation, it is shown that the node's buffer ability and capacity have profound effects on the network traffic.

Keywords: scale-free network, small-world network, routing strategy, flux–density relation

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1. Introduction

The dynamical properties of network traffic have attracted much attention in physics, sociology, biology, and engineering.[1−3] The prototypes include the information traffic in the Internet, the vehicle traffic in the urban network, flights between airports, and the carbon migration in bio-systems. Since the discovery of small-world phenomenon[4] and scale-free property,[5] it is widely shown that the topology and the degree distribution of networks have profound effects on the processes taking place in these networks, including the traffic flow.

In the past few years, the evolution of traffic network structure,[6] the process of epidemic spreading,[7,8] the phase transition phenomena,[9−11] and the scaling of traffic fluctuation[12,13] have been widely studied. And the studies focus on three ways to optimize network traffic systems, which are (i) developing new routing strategies,[14−18] (ii) modifying underlying network structure,[19] and (iii) reallocating network traffic resources.[20,21] Compared with the high cost of changing the infrastructure, developing a better routing strategy is usually preferred.

In Ref. [15], Danila *et al.* proposed an optimal routing for scale-free networks. The algorithm picks the least fit element (node with maximal betweenness) and changes the weight of its edges. The resulting routing paths can sustain significantly higher traffic without jamming than the shortest paths. However, in their work (and also in most previous works), the node's buffer and delivering abilities are considered to be infinity. This is not true. In practice, the node's buffer and capacity limits often lead to the traffic congestion. A theoretical investigation on the effects of the node's buffer ability and capacity is needed.

In this paper, we study the effects of the node's buffer ability and capacity (delivering ability) on the traffic optimization in complex networks. We propose an extension of the optimal routing[15] by considering the effects of the finite buffer ability and capacity. We find that the node's buffer ability and capacity have different effects on the traffic dynamics. The optimization of network traffic should take these factors into consideration.

2. Network traffic model and simulation results

The traffic model is described as follows. For simplicity, all nodes are considered to be hosts and routers at the same time, so they all can generate and deliver packets. Two node buffer settings are considered: (i) all nodes have the same buffer ability, $L_i = \text{const.}$; (ii) the hub nodes have higher buffer abilites, $L_i = \alpha \times k_i$,

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†Corresponding author. E-mail: dingjianxun@hfut.edu.cn

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where k_i is the degree of node i. The node's delivery capacity is considered to be proportional to the node's buffer ability, $C_i = \beta \times L_i$. Here α and β ($0 \leq \beta \leq 1.0$) are adjustable parameters for the traffic system. Different from that in Ref. [15], the network's traffic efficiency is investigated by using the diagrams of flux–density relation. Here the flux is recorded as the number of packets successfully arrived at the destinations per time step, and the packet density is defined as $\rho = N_{\rm p}/L$, where $N_{\rm p}$ is the total packet number, and L is the sum of the nodes' buffer abilities in the system. In order to investigate the flux–density relation, we need to simulate a constant packet density situation. For each simulation of given packet density ρ, $N_{\rm p} = \rho \times L$ packets are generated and forwarded in the system with randomly chosen sources and destinations. Once arriving at their destinations, the packets will remain in the system and be sent to new destinations. Thus the packet density will be a constant. Moreover, the first-in-first-out (FIFO) rule is applied to each node's queue.

Firstly, we investigate the effects of the node's buffer ability and delivering capacity on traffic dynamics in Barabàsi–Albert (BA) scale-free networks.[5] Many communication systems are not homogeneous, but heterogeneous with a degree distribution following the power law $P(k) = k^{-\gamma}$. The BA model[5] is a well-known model that can generate networks with power-law degree distributions. This model starts from m_0 fully connected nodes. In each step, a new node with m edges ($m \leq m_0$) is added to the existing graph according to the preferential attachment, i.e., the probability of being connected to the existing node i is proportional to the degree k_i of the node.

We show the results of the network traffic with the shortest path protocol. Figure 1 shows the flux–density relations of the BA networks with the two node buffer settings considered. We can see that the systems with the different buffer settings behave differently. For $L_i = 100$, the flux increases linearly with the increasing packet density to a platform and then suddenly drops to a very small value at the density threshold $\rho_{\rm c}$, where the system changes from the free-flow state to the congested state. For $L_i = 10k_i$, the traffic flux increases without reaching a platform (except $\beta = 0.1$) before dropping to around zero. The platforms appear because the hub nodes' capacities become the bottleneck of the system. The system's traffic performance can be measured by the maximal flux and the density threshold $\rho_{\rm c}$ of transition. From the results, we can see that the system performs much better with $L_i = 10k_i$. For example, when $\beta = 1.0$, for the two buffer settings, the system's maximal fluxes are 3640 and 409, and the critical densities are 0.28 and 0.065, respectively. Note that the system's total buffer abilities are $L = 50000$ ($L_i = 100$) and $L = 40000$ ($L_i = 10k_i$), respectively. Thus, the buffer setting according to degree greatly outperforms the even distribution with less buffer resources. This is because the hub nodes bear more traffic load in the shortest path protocol. So the buffer setting favoring hub nodes will benefit the system's performance. In Fig. 1, we can also see that the system's capacity increases with β. When $\beta = 1.0$, for both buffer settings, the values of maximal flux and critical density $\rho_{\rm c}$ ($\rho_{\rm c} = 0.065$ for $L_i = 100$, $\rho_{\rm c} = 0.28$ for $L_i = 10k_i$) are the largest.

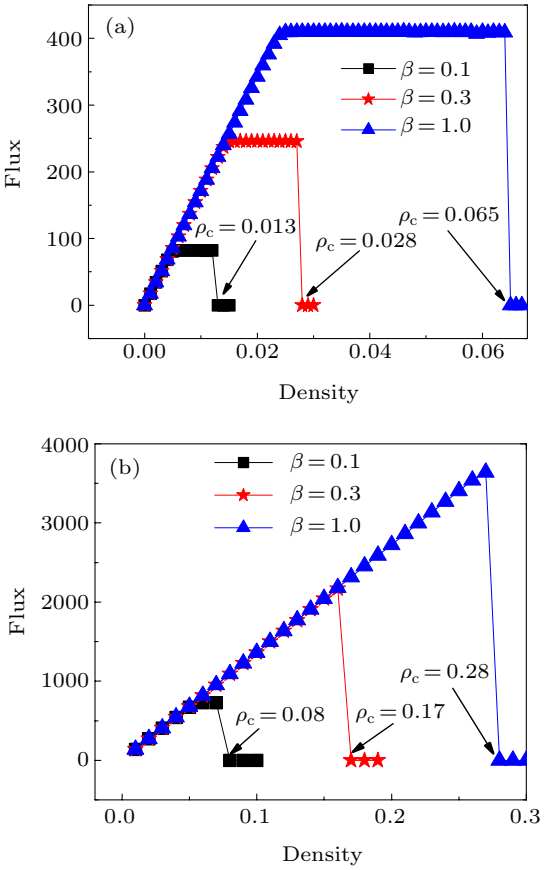


Fig. 1. (colour online) Flux–density relations of the Barabási–Albert scale-free networks with the shortest path protocol and (a) $L_i = 100$ and (b) $L_i = 10k_i$. The other parameters are network size $N = 500$ and average degree $\langle k \rangle = 8$.

Next, we study the effects of the node's buffer ability and delivering capacity on the optimization of network traffic. We introduce an extension of the optimal routing[15] by considering the node buffer limitation. To find the bottleneck of a network traffic

system, we introduce an indicator of effective betweenness for nodes

$$B_i^{\text{eff}} = \frac{B_i}{L_i}, \tag{1}$$

where B_i is the algorithmic betweenness of node i, and L_i is the node buffer ability. The congestion will first appear at the node with the largest effective betweenness. Therefore, the goal of the optimization process is to minimize the largest effective betweenness in the system. The optimization algorithm can be described as follows.

(i) Assign each link's weight to be 1 and find the shortest paths between all pairs of nodes.

(ii) Compute each node's effective betweenness.

(iii) Find the node with the largest effective betweenness $B_{\max}^{\text{eff}}$, and add 1 to the weight of every link that connects it to the other nodes.

(iv) Recompute the shortest paths. Go back to step (ii).

Figure 2 shows the evolution of the maximum effective betweenness as a function of the number of iterations in the BA network. As is shown, the maximum effective betweenness decreases with the increasing iteration to an almost constant value. In this way, the routing paths are optimized. We can see that the effective betweenness takes a smaller value for the whole process with $L_i = 10k_i$ than that with $L_i = 100$. This is in agreement with the previous results that the buffer setting of $L_i = 10k_i$ leads to a better performance.

Figure 3 depicts the flux–density relation with the optimized routing paths in the BA network. Compared with Fig. 1, the new routing paths can achieve a much larger flux and a higher density threshold ρ_c. And for both buffer settings, the flux platforms disappear except for $\beta = 0.1$, where the node capacity acts as a bottleneck. After applying the optimized routing paths, the system can remain in the free flow state in a larger range of packet densities. In Fig. 3, we can also see that for low β values ($\beta = 0.1, 0.3$), the system's critical densities for the two buffer settings take almost the same value, but the maximal flux is slightly higher with $L_i = 10k_i$. For $\beta = 1.0$, the system with $L_i = 10k_i$ further outperforms that with $L_i = 100$ in the critical density and the maximal flux. This behavior shows that the resource allocation strategy is an important factor for the system's optimization.

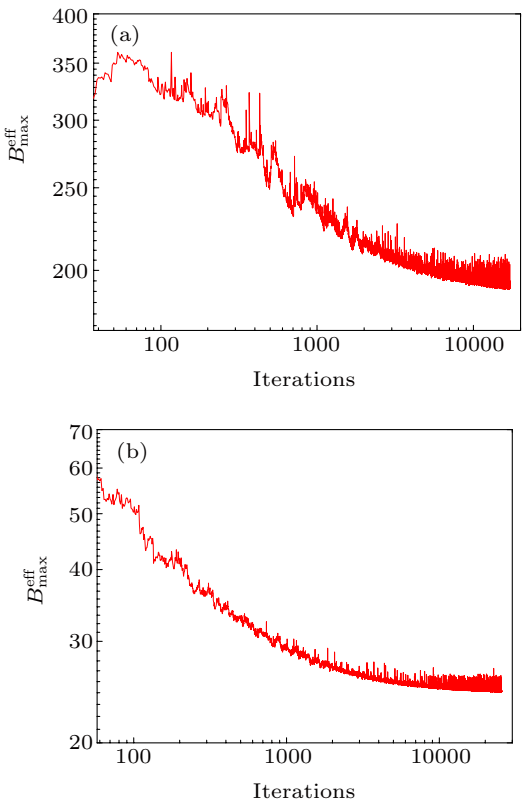


Fig. 2. (colour online) Evolutions of maximal effective betweenness each as a function of the number of iterations with (a) $L_i = 100$ and (b) $L_i = 10k_i$. The other parameters are network size $N = 500$ and average degree $\langle k \rangle = 8$.

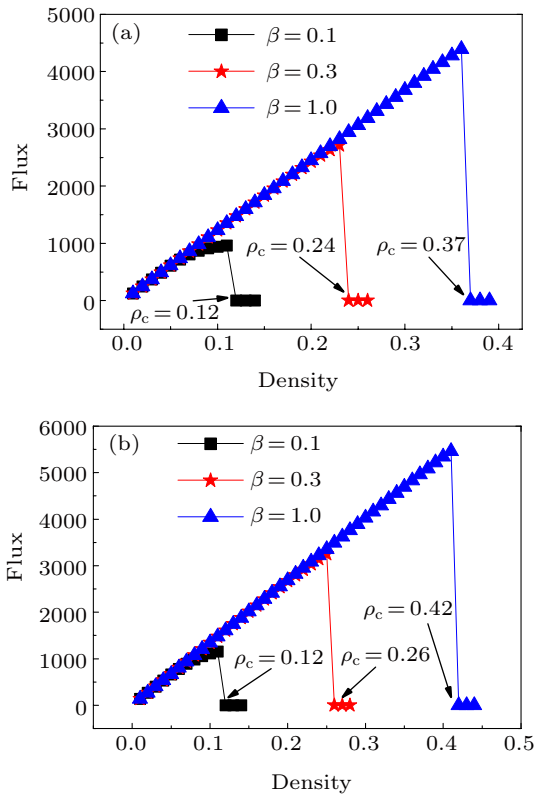


Fig. 3. (colour online) Flux-density relations of the Barabási-Albert scale-free networks with the optimized routing paths and (a) $L_i = 100$ and (b) $L_i = 10k_i$. The other parameters are network size $N = 500$ and average degree $\langle k \rangle = 8$.

In Fig. 4, we investigate the average number of full (or congested) nodes N_f as a function of density. If $N_f = 0$, the system is in the free flow state. If $N_f > 0$ and increases, the system will enter the congested state. In Figs. 4(a) and 4(b), we can see that N_f becomes positive at a larger density with the optimized routing paths than that with the shortest path protocol.

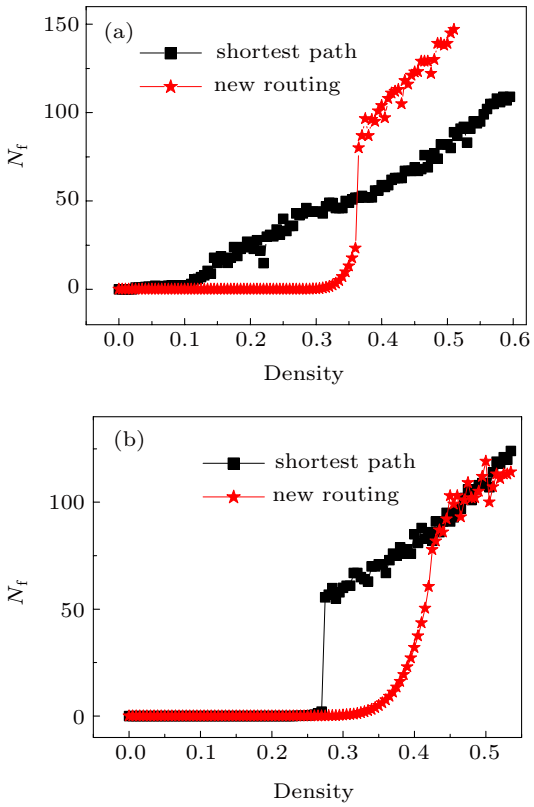


Fig. 4. (colour online) Average numbers of full nodes N_f versus packet density with (a) $L_i = 100$ and (b) $L_i = 10k_i$. The other parameters are network size $N = 500$, average degree $\langle k \rangle = 8$, and $\beta = 1.0$.

The density threshold ρ_c shows the range of density in which the system can be in the free-flow state. In Fig. 5, we study the variation of ρ_c versus β for the system. We can see that ρ_c increases with the increasing β and then comes to a saturation. This might indicate that there is a theoretical limitation for the method of extending the router's delivering capability to improve the system's efficiency, because the node's buffer remains the same. We can also see that for both cases of $L_i = 100$ and $L_i = 10k_i$, ρ_c is larger with the optimized routing paths. With the shortest path protocol, ρ_c of $L_i = 10k_i$ is always higher than that of $L_i = 100$ for all β values. However, with the optimized routing paths, ρ_c of $L_i = 10k_i$ is slightly higher than that of $L_i = 100$ only when $\beta \geq 0.5$.

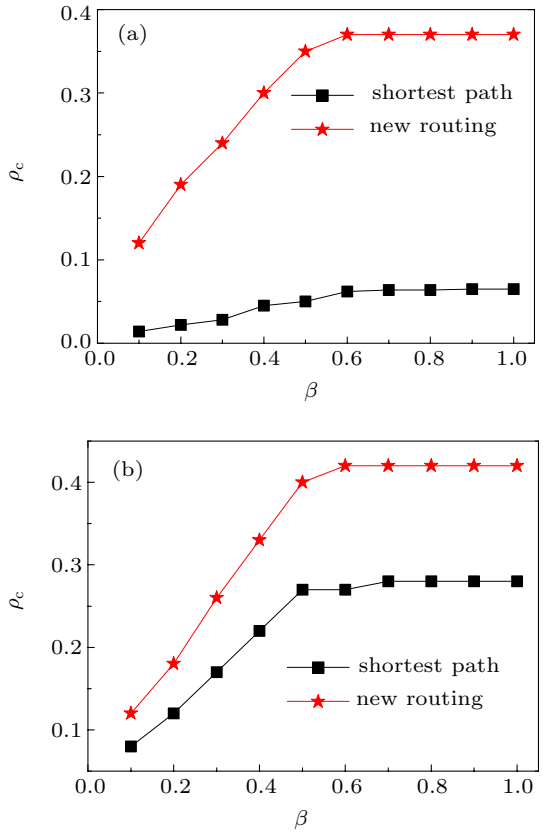


Fig. 5. (colour online) Critical density ρ_c versus β with (a) $L_i = 100$ and (b) $L_i = 10k_i$. The other parameters are network size $N = 500$ and average degree $\langle k \rangle = 8$.

Finally, we investigate the effects of the node's buffer ability and delivering ability on the optimization of network traffic in Newman–Watts (NW) small-world networks[22] and Erdös–Rényi (ER) random graphs.[23] The NW small-world networks are generated by randomly adding long-range links to a one-dimensional lattice with nearest and next-nearest interactions and periodic boundary conditions. The ER random graphs are generated by connecting couples of randomly selected nodes and prohibiting multiple connections. Figures 6 and 7 show the flux–density relations for the two network structures with the shortest path protocol and the optimized routing paths, respectively. For both NW and ER networks, the flux with the optimal routing paths can reach a larger value than that with the shortest path protocol, and the critical density threshold ρ_c increases to a bigger value. All these results prove that the system's performance can be greatly improved with the optimization algorithm proposed.

In Figs. 6 and 7, another interesting phenomenon appears in the NW and the ER networks when considering the traffic resource allocation strategy. For the shortest path protocol, we can see that the case of

$L_i = 10k_i$ performs better than that of $L_i = 100$ for both networks. However, with the optimized routing paths, the system will perform better with the buffer setting of $L_i = 100$ rather than that with $L_i = 10k_i$. This is different from the behavior of the BA networks.

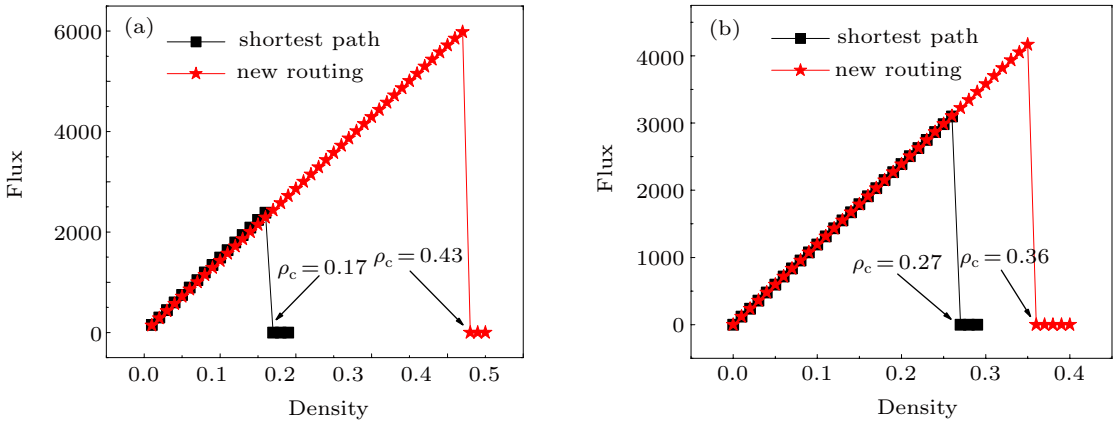


Fig. 6. (colour online) Flux-density relations of the Newman–Watts small-world networks with the shortest path protocol and the optimized paths. The buffer settings are (a) $L_i = 100$ and (b) $L_i = 10k_i$. The other parameters are network size $N = 500$, average degree $\langle k \rangle = 8$, and $\beta = 1.0$.

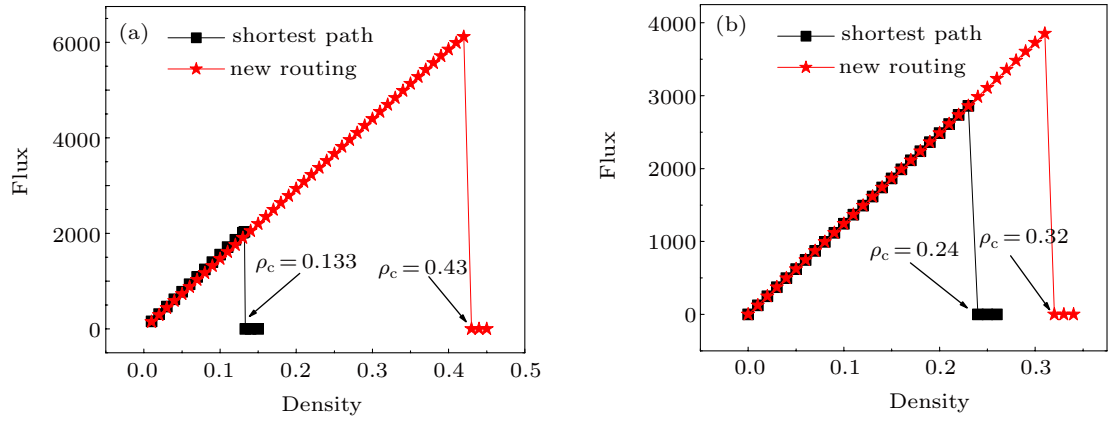


Fig. 7. (colour online) Flux-density relations of the Erdös–Rényi random graphs with the shortest path protocol and the optimized paths. The buffer settings are (a) $L_i = 100$ and (b) $L_i = 10k_i$. The other parameters are network size $N = 500$, average degree $\langle k \rangle = 8$, $\beta = 1.0$.

3. Conclusion

In summary, we have investigated the effects of the node's buffer ability and capacity on the traffic dynamics in complex networks. For three typical network structures, the routing paths can be optimized so that the systems can reach significantly higher traffic fluxes and remain in the free flow states for much wider density ranges. But the node's buffer ability and capacity can have different effects on the optimization of network traffic.

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