Pheromone routing protocol on a scale-free network

Xiang Ling,1 Mao-Bin Hu,1,* Rui Jiang,1,3 Ruili Wang,2 Xian-Bin Cao,3 and Qing-Song Wu1
1School of Engineering Science, University of Science and Technology of China, Hefei 230026, People’s Republic of China
2School of Engineering and Advanced Technology, Massey University, Turitea, Palmerston North 4442, New Zealand
3Department of Computer Science and Technology, University of Science and Technology of China, Hefei 230026, People’s Republic of China

(Received 26 April 2009; revised manuscript received 7 October 2009; published 11 December 2009)

This paper proposes a routing strategy for network systems based on the local information of “pheromone.” The overall traffic capacity of a network system can be evaluated by the critical packet generating rate $R_c$. Under this critical generating rate, the total packet number in the system first increases and then decreases to reach a balance state. The system behaves differently from that with a local routing strategy based on the node degree or shortest path routing strategy. Moreover, the pheromone routing strategy performs much better than the local routing strategy, which is demonstrated by a larger value of the critical generating rate. This protocol can be an alternation for superlarge networks, in which the global topology may not be available.

DOI: 10.1103/PhysRevE.80.066110 PACS number: 89.75.Hc, 45.70.Vn, 05.70.Fh

I. INTRODUCTION

Complex networks can describe many natural and social systems in which entities or people are connected by physical links or some abstract relationship. Since the discovery of the small-world phenomenon [1], and scale-free property [2], complex networks have attracted growing interest among the community of physicists [3–6].

The traffic is one of the hot topics of recent research of dynamical processes taking place in complex network systems. In the past few years, the phase transition in network traffic [7–10], the scaling of traffic fluctuations [11–14], and the routing strategies (including global and local information routing [15–32]) have been widely studied. Our focus here is the routing strategy for networked systems, such as the Internet, urban traffic, airway system, and power grids. For modern networked systems, one important problem is to find an efficient routing strategy in a growing superlarge system without knowing the whole topological information. The shortest path strategy, however, often leads to the failure of hub routers with high degree and high betweenness. In this light, some new routing strategies have been suggested based on the local topological information. For example, Wang et al. [30] and Yin et al. [31] proposed a local routing strategy based on the local information of neighbors’ degree. Hu et al. proposed a local routing strategy based on the local information of link bandwidth [32].

Recently, the study of ant colonies, swarm intelligence, and trails have become a hot topic [33–37]. The ant colony algorithm is a good method for achieving a best solution for the traffic problem [38]. In this paper, we propose a routing strategy based on the local information of pheromone. In biology, pheromone is a chemical signal for the guidance of following ants to find the correct path from the nest to the food [36]. In their paper [36], Coloni et al. studied the behavior of ant colonies, in which all ants only communicated with their neighbors. In the process of moving, the ants will release a special kind of secretion pheromone which helps other ants to look for a path. The ants choose a path $i$ with the probability of $P_i = \rho_i / \sum_j \rho_j$, where $\rho_j$ is the concentration of pheromone in path $i$ and the sum runs over the paths. For a path, the more ants select it, the more pheromone will be left in this path. The larger concentration of pheromone will attract more ants, thus producing a positive feedback mechanism. So the concentration of pheromone on the optimal path will increase, while other path’s pheromone will decrease until disappear.

In this paper, we extend the ant colony algorithm to scale-free networks and study the behavior of the traffic dynamics. We focus on the network capacity that can be measured by the critical point of phase transition from free flow to congestion. In our model, there is only one adjustable parameter $\alpha$. Numerical simulations have demonstrated that the system behaves differently from the other strategies. We also find that the maximal capacity corresponds to $\alpha = 1.0$ in the case of identical nodes’ delivering ability. Most importantly, the system’s overall capacity is much higher than that with a routing strategy based on local degree or bandwidth information.

The paper is organized as follows. In the next section, the underlying network model and the traffic model are introduced. Section III gives the simulation results of our pheromone routing strategy. The paper is concluded in Sec. IV.

II. NETWORK AND TRAFFIC MODEL

Recent studies indicate that many communication systems such as the Internet and the World Wide Web are not homogeneous as random or regular networks, but heterogeneous with degree distribution following the power-law distribution $P(k) = k^{-\gamma}$. The Barabási-Albert (BA) model [2] is a well-known model which can generate networks with power-law degree distribution. Without lose of generality, we construct the underlying network structure with the BA network

*huobaoin@ustc.edu.cn
†rjiang@ustc.edu.cn

©2009 The American Physical Society
model: starting from $m_0$ fully connected nodes, a new node with $m$ ($m \leq m_0$) 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 the degree $k_i$ of the existing node. In this paper, we set $m_0=m=5$ and the network size $N=1000$.

The traffic model is described as follows. At each time step, there are $R$ packets generated in the system, with randomly chosen sources and destinations. One node can deliver to $N_p$ neighboring nodes. If a packet’s destination is found within the searched area, it is delivered directly to its target. Otherwise, the packet is delivered to a neighboring node $j$ with probability

$$P_{i-j} = \frac{p_{ij}^\alpha}{\sum_j p_{ij}^\alpha},$$  

(1)

where $p_{ij}$ is the pheromone of the link pointing from node $i$ to node $j$, the sum runs over all neighbors of node $i$, and $\alpha$ is a tunable parameter characterizing the routing preference. Note that $P_{ij}$ can be different from $P_{ji}$, as shown in Fig. 1(a). Once arriving at its destination, the packet will be removed from the system. The queue length of each node is assumed to be unlimited and the first in first out rule is applied to all queues.

Next we introduce the updating rule for the pheromone of a link. Initially, the value of the pheromone concentration on each link is set to a small unit value of $\delta p$. The pheromone of each link cannot be smaller than this value $\delta p$. Whenever a packet is delivered successfully from node $i$ to node $j$, the pheromone of link $ij$ will be updated according to the following rule: if the queue length of node $j$ is larger than a critical value, i.e., $L_j > L_c$, the pheromone of link $ij$ will decrease by a unit,

$$p_{ij} = \max(p_{ij} - \delta p, 0).$$  

(2)

Otherwise, if the queue length $L_j \leq L_c$, the pheromone will increase by a unit value,

$$p_{ij} = p_{ij} + \alpha \delta p.$$

In this paper, we set the unit value as $\delta p=0.001$. The critical queue length is set to be proportional to the delivery ability of the node: $L_c=\beta C$. Then we investigate the effects of $\alpha$ and $\beta$ on the traffic dynamics of the system.

### III. Simulation Results

In this section, we show the simulation results of the pheromone routing strategy on a BA scale-free network. Figure 2 shows the typical evolution of total packets number $N_p$ over time with the pheromone routing strategy. When $R$ is smaller than a critical value $R_c$ ($R_c$ characterizes the overall capacity of the system, which will be introduced later), one can see that the variation of $N_p$ can be divided into two stages: the relaxation and balanced stages. In the relaxation stage, $N_p$ first increases to a maximum and then decreases to a balanced state. In the balanced stage, $N_p$ is almost constant, indicating that the numbers of generated and removed packets are balanced. When $R$ is larger than the critical value of $R_c$, $N_p$ increases to infinity, indicating that the system enters a jam state.

In the relaxation stage, the concentration of pheromone is automatically adjusted to achieve an optimal state. One can investigate the normalized average node pheromone $\langle p_k \rangle$ as a function of node degree $k$. A node’s pheromone is defined as the sum of the link pheromone going toward the node, as shown in Fig. 1(b). The normalized average node pheromone is calculated by

$$\text{Normalized } \langle p_k \rangle = \frac{\langle p_k \rangle}{\langle p_k \rangle_{\text{max}}},$$  

(4)

with

$$\langle p_k \rangle = \frac{\sum p(\text{degree}=k)}{\text{Number of nodes (degree }= k)}.$$

Figure 3 shows the normalized pheromone $\langle p_k \rangle$ for different evolution times for the system. In both the increasing and
decreasing periods of the relaxation stage ($T=30,000$ and 60,000), the normalized pheromone ($p_k$) follows a power law. The average pheromone of low-degree nodes is higher than that of high-degree nodes. Because the hub nodes bear more traffic load, the node pheromone decreases according to Eq. (2). On the other hand, in the balanced stage ($T = 300,000$), the normalized pheromone ($p_k$) is almost independent of $k$. At this point, the hub nodes have roughly the same pheromone as the low-degree nodes. Thus, the pheromone of the links going to hub nodes are much lower than that of the links going to low-degree nodes. According to the delivering rule, the packets are encouraged to go to low-degree nodes. However, because the hub nodes have more links, the total delivering probabilities of going to hub nodes and low-degree nodes are similar. The ability of both hub nodes and low-degree nodes can be fully utilized. Thus, the system achieves its optimum.

Figure 4 shows the relaxation stage of $N_p$ with different values of $\beta$. One can see that the behavior of $N_p$ is similar for different $\beta$. One important issue here is to figure out the optimal value of $\beta$, at which the relaxation stage will be shortest for the system. We can investigate the critical time $T_c$, at which $N_p$ reaches the balanced stage. Figure 6 inset shows $T_c$ with different values of $\beta$. When $\beta = 2$, $T_c$ reaches its minimum. Thus, we can see that $\beta = 2$ is the optimum for the system to quickly reach the balanced state.

In order to describe the phase transition of traffic flow in the network, we adopt the order parameter [7]

$$\eta(R) = \lim_{t \to \infty} \frac{C \langle \Delta N_p \rangle}{\Delta t},$$

where $\Delta N_p = N_p(t + \Delta t) - N_p(t)$ and $\langle \cdots \rangle$ indicates the average over time windows of width $\Delta t$. In Fig. 5(a), the typical variation of $\eta$ against $R$ is shown for the pheromone routing strategy and the local routing strategy. The pheromone routing strategy is with parameter $\alpha = 1.0$, at which we will demonstrate that the maximum overall capacity is achieved. The local routing strategy [30] is with the parameter of $\alpha = -1.0$, at which the maximum capacity is reached. For $R < R_c$, $\eta$ remains at zero, indicating that the system is in the free-flow state. With the increase in packet generation rate $R$, there will be a critical value of $R_c$ at which $\eta$ increases from zero, indicating that the packets accumulate in the system, and the system becomes seriously congested [7]. Therefore, $R_c$ is the maximal generating rate under which the system can maintain its normal and efficient functioning. One can see that the pheromone routing strategy can reach a larger network capacity. As shown in Fig. 5(a), the maximal overall capacity is $R_c = 3.7$ with local degree routing strategy, while it is $R_c = 5.3$ for the local pheromone routing strategy. In Fig. 5(b), the overall capacity $R_c$ is sought out for different values of routing parameter $\alpha$ with constant node capacity $C = 1$. One can see that, when $\alpha = 1.0$, the system’s capacity can be enhanced maximally.
When all nodes have the same delivering ability, this phenomenon investigates the average packet number over the nodes with the same degree. The average is over the nodes with the same degree. In Fig. 6, the average stays around 1.0, the distribution of \( n(k) \) remains the same. The fluctuations in the value of \( n(k) \), especially for large-degree nodes. We also investigate the situations of bigger \( \alpha \) value. The fluctuations of \( n(k) \) are more evident. Therefore, it is easier for the hub nodes to get congested when \( \alpha > 1.0 \). So the system capacity decreases.

Then we investigate the probability distribution of traveling time for different \( \alpha \) in a free-flow state. Packet traveling time is also an important factor for characterizing the network’s behavior. The traveling time is the time that a packet spends on traveling from a source to a destination. In Fig. 8, one can see that the distribution of traveling time follows a subpower law. Most packets can arrive at their destinations in a short time while some packets need to spend very long time to find their target nodes. We also note that, when \( \alpha = 1.0 \), the packets spend the shortest time for traveling. This is consistent with the result of Fig. 6 that the network’s capacity reached a maximum when \( \alpha = 1.0 \).

Finally, we briefly introduce the effect of node delivering ability \( C \) on the traffic dynamics. The qualitative behavior is not affected by varying \( C \). In general, the system’s overall capacity will increase with the increase in \( C \), and the optimal value of \( \alpha \) remains the same.

We also apply the pheromone routing strategy in Erdos-Renyi and Watts-Strogatz networks [1]. The former provides a uniformly random reference, while the latter accounts for several types of real-world networks. However, the improvement in network capacity is not so obvious in these two networks. The pheromone routing strategy can perform better in a heterogeneous network than in a homogeneous network.

**IV. CONCLUSION AND DISCUSSION**

In summary, we have proposed a routing protocol for a modern traffic system based on the local information of pheromone and then investigated the behavior of the traffic system. The system performs better under the pheromone routing strategy than under the local routing strategy by node degree or link bandwidth. Due to the difficulty of obtaining the information of the whole network’s topology in modern...
communication and traffic systems, the routing protocols based on the local information are attracting much interest [30–32]. The pheromone routing strategy performs best among the routing protocols of local information. This is a nontrivial improvement in the network traffic area.

In the model, the traffic system automatically adjust the distribution of pheromone to achieve a balanced state. In the balanced state, the traffic load will be homogeneously distributed among the nodes. The relaxation process depends on the traffic parameter. The optimal value of pheromone updating parameter \( \beta \) should be set to \( \beta = 2.0 \), at which the relaxation process will be minimal. Simulations have shown that the optimal routing strategy should be set to \( \alpha = 1.0 \), which is different from the local routing strategy [30]. The distribution of traveling time is also investigated. These phenomena are unique and can trigger more interest in this field. The model can be useful for the design and optimization of routing strategies in some real traffic systems such as the urban transportation systems, peer-to-peer networks, wireless sensor networks, and so on.

ACKNOWLEDGMENTS

This work was funded by the National Basic Research Program of China (Contract No. 2006CB705500), the NNSFC Key Project No. 10532060, Projects No. 70601026, No. 10672160, and No. 10872194, and the Innovation Foundation for Graduate Students of the University of Science and Technology of China under Grant No. W21103010012. R.W. and M.-B.H. acknowledge the support of Massey University International Visitor Research Fund.