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Optimizing Performance of Communication Networks: An Application of Network Science

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Abstract—In this paper we describe a method for optimising the performance of communication networks from a network science perspective. For efficient and reliable data transmission, the traffic load should be as uniformly distributed as possible in the network and the average distance travelled by the data should be short. With a fixed network topology, the traffic load distribution and the node usage probability are determined by the specific routing algorithm. In this paper we apply a simulated annealing algorithm to find the near-optimal configuration of routing paths, which effectively balances traffic loads and improves the overall traffic performance.

1. Introduction

Digital networked technologies play an essential role in our daily life, and the rapid development of society has inevitably escalated traffic congestion in many communication networks. In the past decades, the study of traffic congestion has attracted much attention from the physics and engineering communities.

In digital transmission, the data is presented as "packets" and transmitted through a set of relay nodes in the network [1]. Much previous work has shown that the underlying network structure is highly relevant to the traffic performance of the networks [2, 3]. When the topology of network is fixed, the routing algorithm determines the path for each packet to reach its destination from its source. Thus, the routing method plays a deciding role in relating the structure of a network with its ultimate traffic performance.

Shortest path (SP) routing is a widely used algorithm in many real communication networks because of its simplicity and efficiency. Empirical studies have demonstrated that many real-life communication networks such as Internet are heterogeneous networks and exhibit small-world and scale-free topological properties [4,5]. However, in heterogeneous networks, shortest path (SP) routing strategy leads to high traffic loads at some hubs in the network, causing congestion of the whole network.

To avoid high traffic congestion in hubs and improve the the efficiency and reliability of information flow, a number of routing algorithms were proposed, such as the traffic awareness algorithm [6], the degree-based routing algorithm [7], the local routing algorithm [8], and so on [9–11].

In our previous work [12], we have shown that for efficient and reliable data transmission, the traffic load should be as uniformly distributed as possible in the network and the average distance traveled by the data should be short. We introduce the *node usage probability* as an effective metric for characterizing the traffic load distribution and how frequently a node is chosen to relay packets in a network. Based on the concept of node usage probability, we design a simulated annealing algorithm to find the near-optimal configuration of routing paths, which can effectively balance the node usage and keep the average distance relatively low.

2. Communication Network Operation

2.1. Operation Model

Empirical studies have revealed that many kinds of real-world communication networks are scale-free. In this paper, we adopt the widely used BA scale-free network model to construct the scale-free network.

In the network, all nodes can work as either hosts or routers to generate or forward packets. Packets are generated by the nodes and sent through the links one hop at a time until they reach the destinations. Also, each node in the network has an infinite buffer to store the packets waiting for processing. Then, the data traffic operates as follows:

1. Packet generation: At each time step, new packets are generated. The average number of generated packets by each node is λ, which is defined as the generation rate of each node. When a packet is generated, its destination is randomly chosen from the rest of the network. The newly generated packets are put at the end of the buffer of the source.

2. Packet transmission: The transmission rate for node i is $R(i)$ packets. Packets already arrived at their destinations are released from the buffer. At each time step, the first $R(i)$ packets of node i are forwarded to their destinations by one step according to the routing algorithms which we will describe in detail in Section 3.

2.2. Critical Point and Concept of Node Usage Probability

In irregular networks, especially some heterogeneous networks like the scale-free and Internet-like networks, nodes have various degrees and varying importance. To indicate how frequently a node is chosen as a router under a specific routing algorithm, we define *node usage probability* $U(i)$ for node i as

$$U(i) = \frac{\sum_{\substack{u,w \in V,\\ u \neq w \neq i}} \sigma_{uw}(i)}{\sum_{j \in V} \sum_{\substack{u,w \in V,\\ u \neq w \neq j}} \sigma_{uw}(j)}, \tag{1}$$

where V is the set of all nodes in the network, $\sigma_{uw}(i)$ is define as 1 if node i lies on the path between nodes u and w under a specific routing algorithm, and as 0 otherwise.

The total number of paths that pass through node i, denoted by $C(i)$, can be expressed as

$$C(i) = \sum_{\substack{u,w \in V,\\ u \neq w \neq i}} \sigma_{uw}(i) \tag{2}$$

Therefore, we have

$$U(i) = \frac{C(i)}{\sum_{j \in V} C(j)} \tag{3}$$

And the average transmission distance $\tilde{D}$ can be approximate as

$$\tilde{D} \approx \frac{\sum_{j \in V} C(j)}{N(N-1)} \tag{4}$$

where N is the total node number in the network.

Previous studies [13, 14] have shown that there exists a phase transition point from a *free* state to a *congestion* state. To ensure reliable data transmission, it is necessary to keep the network in the free state. Here we define the *critical generation rate* λ_c, where the phase transition occurs, as an indicator of the network *throughput*.

If $\lambda < \lambda_c$, the network reaches a steady state when the numbers of packets generated and successfully arrived are balanced. In this case, very few packets are dropped. If $\lambda > \lambda_c$, packets accumulate in some nodes and traffic congestion occurs.

In our previous work [12], we have derived analytically the λ_c in terms of the node usage probability, average distance of the communication paths and allocated resources as follows,

$$\lambda_c = \min_{i \in N} \frac{R(i)}{\tilde{D}U(i)N}, \tag{5}$$

where $R(i)$ is the transmission rate of node i.

If each node in the network has the same transmission rate, the nodes with highest node usage probability will be the first to get congested, and the critical generation rate λ_c can be simplified as

$$\lambda_c = \frac{R}{\tilde{D}U_{max}N}, \tag{6}$$

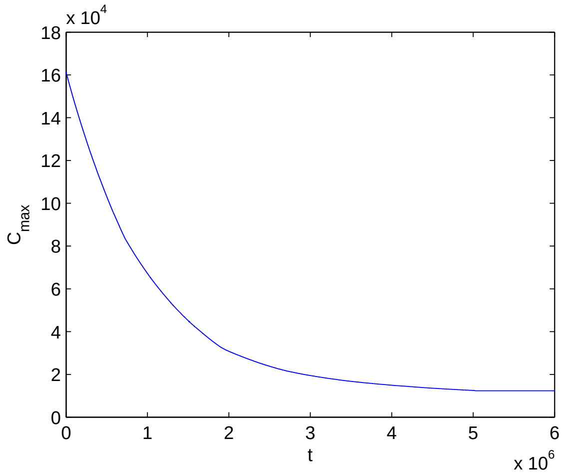

Figure 1: C_{max} vs time step t in the optimizing process of the SA algorithm.

where R is the transmission rate of each node and U_{max} is the maximum value of $U(i)$.

As shown in (6), with uniformly allocated network resource,

$$\lambda_c \propto \frac{1}{\tilde{D}U_{max}}, \tag{7}$$

With (3) and (4), we have

$$\tilde{D}U(i) \approx \frac{C(i)}{N(N-1)} \tag{8}$$

Therefore, a larger C_{max}, which is defined as the maximum value of $C(i)$, implies a larger $U_{max}\tilde{D}$ and a smaller λ_c.

3. Routing Strategy

From (1), we can see that, with the fixed network topology, the traffic load distribution and the node usage probability are determined by the selected routing algorithm. Therefore, we aim to find the optimal configuration of routing paths to make C_{max} as small as possible. However, in a large and irregular network like the scale-free network we consider here, finding the optimal configuration of routing paths by evaluating all possible paths between each pair of nodes in the network is infeasible. The problem of finding all possible paths between two nodes in the network was proven to be non-deterministic polynomial-time (NP) hard [15].

Therefore, in this paper, we propose to use a nature inspired algorithm, namely, simulated annealing (SA), to find a near-optimal solution of this problem. The procedure of the algorithm is as follows,

1. Start from an initial solution, S_0. Calculate the C^0_{max} and set the best solution as $S_{best} = S_0$ and $C^{best}_{max} = C^0_{max}$. Here for fast convergence, we start from the shortest path routing. Set the system time $t = 1$ and epoch count $k = 1$;

2. Randomly pick a pair of source and destination and change the routing path between them randomly. Denote this new configuration as S_t, and calculate the C^t_{max}.
3. If $C^t_{max} < C^{best}_{max}$, then we accept the new routing path and set $S_{best} = S_t$ and $C^{best}_{max} = C^t_{max}$. If $C^t_{max} \geq C^{best}_{max}$, we accept the new configuration with the probability $e^{-\Delta/T}$, where T is a control parameter called *temperature* and $\Delta = C^t_{max} - C^{best}_{max}$. If the new configuration is accepted, set $k = k+1$. Otherwise, the algorithm goes back to step 2 and keeps k unchanged.
4. For high-quality solution, the iteration time should be long enough. If the C^{best}_{max} is unchanged in the latest 10000 steps, we stop. If not, set $t = t + 1$ and go to step 2.

The parameter T must be carefully selected since the values of parameters may have a significant influence on the performance of the algorithm [16]. At the start of the algorithm, the value of T should be set large enough to make the initial probability of accepting new solution be close to 1 [17]. Then T is gradually decreased by a *cooling function* during the optimizing process. Here we adopt a simple cooling function which changes T to αT after every L epoch count, where α and L are control parameters called cooling ratio and epoch length, respectively. In our simulations, the values of α and L are given by the method proposed in [16].

For performance comparison, we implement two other algorithms, namely, shortest path routing and minimum degree routing algorithms.

Shortest path (SP) routing is a widely used algorithm in many real communication networks because of its simplicity and efficiency. A shortest path refers to the path with minimum hops from the source to the destination. However, in heterogeneous networks, packets are more likely to pass through the high degree nodes under SP routing, thus causing congestion of the whole network. Minimum degree (MD) routing strategy proposed by Yan *et al.* [7] aims to minimize the sum of the degrees of all nodes in the path. This algorithm can systematically avoid the high degree nodes in the network and effectively improve the overall network performance. If more than one paths are calculated by SP or MD routing, we randomly choose one.

In our simulations, the number of nodes $N = 1000$, the mean value of node degree $k = 5.98$, the transmission rate per time step $R = 5$ packets/step.

Figs. 2, 3 and 4 show that the node usage probability $U(i)$ is related to the node degree and selected routing algorithms. When SP routing is adopted, high degree nodes tend to have a high node usage probability as they are chosen as routers more frequently. Moreover, SP routing has the shortest average distance as indicated in Table 1.

Under MD routing, the packets will systematically avoid the high degree nodes in the network and the maximum value of node usage probability under MD is much lower than that under SP routing (see Table 1). However, under MD routing, the high degree nodes are rarely used (see Fig. 3), thus increasing the average transmission distance (see Table 1) in a large scale.

As shown in Fig. 4, under SA algorithm, the upper edge of the node usage probability is quite well-defined and the nodes with a relatively high node usage probability are spread over a very wide degree range, compared with SP and MD routings. From Table 1, we observe that SA method can effectively reduce maximum node usage probability and keep the average distance relatively low. Although the U_{max} of SA algorithm is slightly larger than that of MD algorithm, the λ_c of SA routing is still the best thanks to its much shorter $\tilde{D}$ than MD routing.

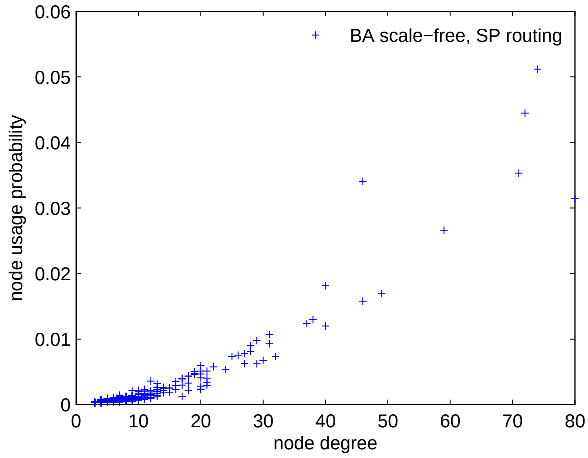

Figure 2: Node usage probability versus node degree under SP routing algorithm.

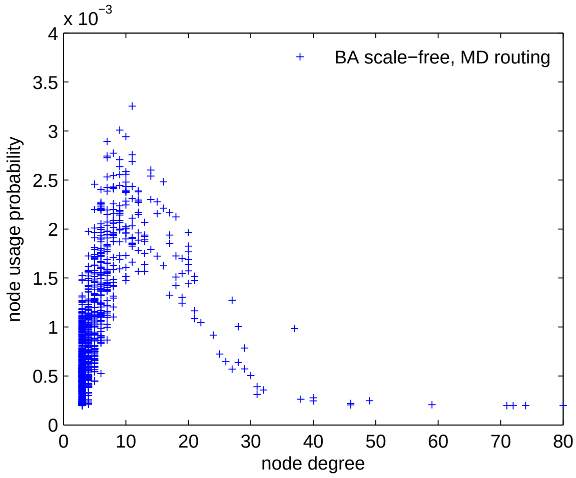

Figure 3: Node usage probability versus node degree under MD routing algorithm.

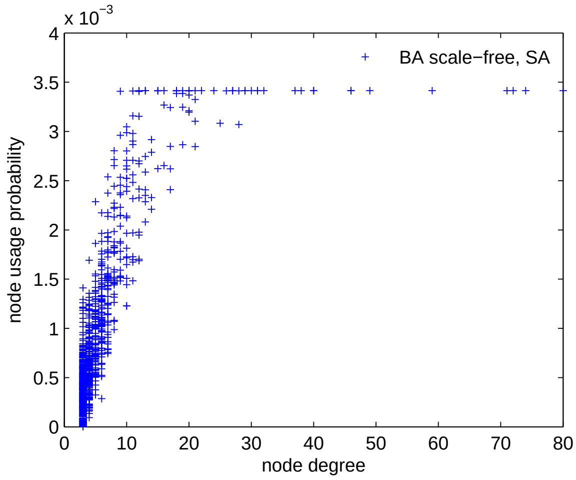

Figure 4: Node usage probability versus node degree under SA routing algorithm.

Table 1: Maximum node usage probability U_{max}, average transmission distance $\tilde{D}$, and critical generation rate λ_c under SP, MD and SA routing algorithms

Parameter	SP	MD	SA
U_{max}	0.0511	0.0033	0.0034
$\tilde{D}$	3.477	5.090	3.610
λ_c	0.028	0.298	0.407

4. Conclusion

For efficient data transmission, the traffic load should be as uniformly distributed as possible in the network and the average distance traveled by the data should be short. We therefore design a simulated annealing algorithm to find the near-optimal configuration of routing paths, which can effectively balance node usage in the network and keep the average distance relatively low. We evaluate the performance of the proposed simulated annealing algorithm with that based on shortest path (SP) and minimum degree (MD) routing. Simulation results show that the proposed algorithm can effectively balance traffic load and improve the network throughput.

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