Minimize Congestion for Random-Walks in Networks via Local Adaptive Congestion Control

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Abstract —The routing method of random-walks is robust to the change of network topology. However, congestion occurs easily for random-walks because packets usually take a long trip in the networks to arrive at their destinations. In this paper, we propose a method to minimize the congestion for random-walks via local adaptive congestion control. The method uses linear-prediction to estimate the queue length for nodes and local adaptive evolution equations that enable nodes to self-coordinate their accepting probabilities to the incoming packets. We apply the method to the BA scale-free networks. The results show that the congestion is delayed remarkably and the phase transition from free-flow to congestion occurs in a smooth way with the increase of prediction orders. We also investigate the distribution of accepting probability of nodes as a function of node degrees, and find a hierarchical (degree-based) organization of the accepting rates is strongly beneficial to avoiding the network congestion. Furthermore, we compare our method with several existing methods on the performance of avoiding congestion on the BA networks and a real example. The results show that our method performs best under the same packet generation probability in the networks.

Index Terms—Random-walks, self-coordinate, adaptive congestion control, networks

I. Introduction

Random walks is an efficient tool for designing searching and routing strategies and has attracted a lot of attentions in many real larger systems such as the Internet [1], the power grid [2], the transportation networks [3], and so on. Since these real systems can be efficiently described by networks and typically show a scale-free distribution [4], we can investigate the dynamical properties of them by using various methods inherited from the modern complex network theories and statistical physics.

Congestion can be considered as the case in networks that the load of packets increases and causes the failure of information flow. Recently, many literatures on networks focus on the critical properties of the transitions from free-flow to congestion [5]-[7]. These studies are mainly designing efficient routing strategies to provide short delivery times and avoid the congestion. Apart from the load of information on networks, the network topologies also have great influence on the routing strategies [8], [9]. Many routing strategies have been investigated and show that the homogeneous networks can bear high network load due to the lack of high betweenness nodes [10]. However, it is impossible and of high cost to change the network topologies. Several feasible strategies have been proposed recently, such as the implementation of cutting information flow on the edges between the nodes with large degrees [11] or the packet-dropping mechanisms [12], for avoiding congestion. It has been observed in the applications of these strategies that the efficiency of network transmission is decreased or the lose probability of packets is increased. Other reasonable methods are to develop better routing strategies for avoiding congestion. These strategies include the biased-shortest path [13], the efficient path [14], the optimal path search [15], the hybrid routing [16], and so on. Congestion-aware schemes have been employed in some of these strategies and allow the paths to be changed to bypass the congested nodes. However, the strategies proposed above are generally from the global and static perspective of node behavior that the nodes are unable to locally adjust their own state to avoid congestion. Since the optimal routing policy depends strongly on the state of congestion of the systems, in order to avoid congestion, it is reasonable to enable the nodes to have a local adaptive strategy to deliver packets.

In this paper, we propose a method to minimize the congestion for random-walks via local adaptive congestion control. The method uses linear-prediction to estimate the queue length for nodes and local adaptive evolution equations that enable nodes to self-coordinate their accepting probabilities to the incoming packets. We apply our method to the BA scale-free networks. The results show that congestion is delayed remarkably and the phase transition from free-flow to congestion occurs in a smooth way with the increase of prediction orders. We also investigate the distribution of accepting probability of nodes as a function of node degrees to reveal the intrinsic mechanism of our method for minimizing congestion, and find that a hierarchical (degree-based) organization of the accepting rates is strongly beneficial to avoiding the network congestion. In the end, we compare our method with several existing

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methods on the performance of avoiding congestion on the BA networks and a real example. The results show that our method performs best under the same packet generation probability in the networks.

The rest of this paper is organized as follows: In Section II, we present our method and describe in detail the implementation of it. In Section III, we investigate the performance of our method on minimizing congestion and show the correlation between the accepting probability and the node degrees. Furthermore, comparisons between our method and other existing methods on avoiding congestion are also presented. In Section IV we give the conclusions of this paper.

II. The Method

In this section, we first present the traffic model of our method. Then, we present the local adaptive evolution equations for calculating the accepting probability for nodes. Finally, we show the method of linear-prediction of queue length used in our method for further avoiding congestion.

A. The Traffic Model

In a network, the delivery of packets between adjacent nodes can be considered as a probabilistic event. For random-walks, the probability for a packet delivered from node i to its neighbor j is written as $p_{ij}=1/k_i$, where k_i is the degree of node i. The packet will be removed from the network when it arrives at its destination. A set of dynamic equations can be used to describe the queue length of the nodes $q_i^t (i=1,2,\dots,N)$ at time t, where N is the network size. A packet is generated on node i with probability p at each time step and with a destination chosen at random. In the time step from t to $t+1$, node i select one of its neighbors at random and send a packet to it. The neighbor will accept the packet with probability λ, called accepting probability. If the packet is accepted, it will be removed from the queue of node i. We assume that a finite number of packets can be delivered by a node at each time step. For simplicity, we set this number to be 1.

We present the traffic model as follows. At time t, the number of packets that arrives at node i is

$$q_{in}^t=\lambda_i^t\sum_{j=1}^{N}\theta(q_j^t)A_{ji}p_{ji} \tag{1}$$

and the probability that a packet is delivered from node i to a neighbor is

$$q_{out}^t=\sum_{j=1}^{N}\lambda_j^t\theta(q_i^t)A_{ij}p_{ij} \tag{2}$$

where $\theta(x)$ denotes the Heaviside step function that $\theta(x)=1$ if $x>0$ and $\theta(x)=0$ otherwise. A_{ij} is the matrix element which is defined as $A_{ij}=1$ if nodes i and j are connected and $A_{ij}=0$ otherwise. The queue of nodes obeys FIFO (first in and first out) rule, and the traffic model of node i is written as:

$$q_i^{t+1}=q_i^t+p+q_{in}^t-q_{out}^t \tag{3}$$

B. The Local Adaptive Evolution Equations

The congestion occurs if the incoming flow of new packets is not balanced with the successful delivery of old ones. Therefore, in order to avoid the congestion, we should make λ_i^t operate at the adverse case of free-flow regime of a network. We allow each node to be able to choose its own accepting probability λ_i^t and attempt to reach an optimal queue length. Based on the idea that homogeneous traffic can lead to the improvement of network capacity, we set the optimal queue length to be $\left(1+\langle k\rangle\right)p$, where $\langle k\rangle$ is the average node degrees and p is the packet generation probability. The local adaptive evolution equations λ_i^t of node i is

$$\lambda_i^{t+1}=\exp\left(-\beta\hat{q}_i^{t+1}\right) \tag{4}$$

where β is the parameter that controls the speed of the variation of the accepting probability.

C. Linear-prediction of Queue Length for Nodes

For further avoiding congestion, it is necessary to know the traffic state of nodes in advance. Here we use linear-prediction to predict the traffic state of nodes, and $\hat{q}_i^{t+1}$ is the L-order linear-prediction value of the real q_i^{t+1}.

According to (4), for node i, $\hat{q}_i^{t+1}\to 0$ will tend to total accepting $\lambda_i^{t+1}\to 1$, whereas the $\hat{q}_i^{t+1}\to +\infty$ will tend to total rejection $\lambda_i^{t+1}\to 0$. Here λ_i^{t+1} is set to be 0.5 whenever $\hat{q}_i^{t+1}=\left(1+\langle k\rangle\right)p$ for achieving homogeneous network flow. Then, we obtain $\beta=\ln 2/\left(\left(1+\langle k\rangle\right)p\right)$. Based on linear-prediction, $\hat{q}_i^{t+1}$ is written as:

$$\hat{q}_i^{t+1}=-\sum_{k=1}^{L}a_k q_i^{t+1-k} \tag{5}$$

where a_k are the predicting coefficients and q_i^{t+1-k} are the previous queue length of node i. The error of the prediction is

$$e(t)=q_i^{t+1}-\hat{q}_i^{t+1}=q_i^{t+1}+\sum_{k=1}^{L}a_k q_i^{t+1-k}=\sum_{k=0}^{L}a_k q_i^{t+1-k} \tag{6}$$

a_0 is usually set to be 1 for avoiding trivial solution[14] to minimize $e(t)$. The Yule-Walker equations can be written as $\mathbf{Ra}=[1,0,\dots,0]^{\mathrm{T}}$. The elements of $\mathbf{R}$ are $r_{ij}=R(i-j)$, where $R(m)=E\left\{q_i^t\cdot q_i^{t-m}\right\}$ denotes the self-correlation of queue length of node i. $\mathbf{R}$ Is a symmetrical matrix and we can use fast Levinson recursion method [17] to calculate $\mathbf{a}$.

III. THE EXPERIMENTS

In this section, we first study the phase transition from free-flow to congestion of our method, and investigate the influence of prediction orders on the performance of our method. Then, we present the distribution of accepting probability as a function of node degrees. Finally, we compare our method with two existing methods on avoiding congestion on the BA networks and a real example.

A. *The BA Testing Network Model*

The structure of many real networks is far from being purely random. Quite on the contrary, they typically show a Scale-Free (SF) distribution [18]. We start the simulations by adopting the well-known BA (Barabási-Albert) scale-free network model [19].

This model is defined with two steps as follows:

1) *Growth*: at the beginning, there are m_0 initial nodes. At each time step, a new node is added into the network, and this new node will connect to $m(m \le m_0)$ different nodes which are already present in the network.

2) *Preferential attachment*: node i will link to the new node with probability $P(k_i) = k_i / \sum_{j=1} k_j$, where k_i is the degree of node i . This model will generate a scale-free network with $t + m_0$ nodes and mt edges in t steps, and the average degree of the BA network is approximately $2m$.

B. *The Phase Transition*

A new packet is generated on a node with probability p and with a randomly chosen destination in each time step, and the packet will be removed from the network when it arrives at its destination. With the increase of p, the congestion will occur inevitability. We are interested in where a phase transition takes places from free flow to congestion. For $p < p_c$, the system is in free-flow state and the sum of all the queue length $Q(t) = \sum_{i=1}^{N} q_i^t$ fluctuates around a finite value. In other words, the system can balance the generated and delivered packets. For $p > p_c$, the congestion appears because $Q(t)$ increases with time. It is obviously that the maximal capacity of a system can be effectively evaluated by the critical value p_c. We use the following order parameter H to monitor the phase transition and investigate p_c .

$$H(t) = \lim_{\Delta t \to \infty} \frac{1}{Np} \frac{Q(t+\Delta t) - Q(t)}{\Delta t} \tag{7}$$

We can see H is in the range from 0 to 1 . When $H = 0$, the system is in the free-flow phase, and is in the congested phase when $H > 0$.

Here we use BA scale-free model [19] to investigate our method because many real networks typically show a Scale-Free (SF) distribution [4]. We generate the BA networks with size $N = 2000$ and average degree $\langle k \rangle = 6$. Fig. 1 shows the experiment results. The conventional random-walks without our local adaptive scheme, which means $\lambda = 1$, is investigated for making comparison. L are investigated. For clarity, we here plot the value for $L = 1, 2, 4, 8, 16$. All data points are obtained by averaging over 400 networks and 10^5 independent runs.

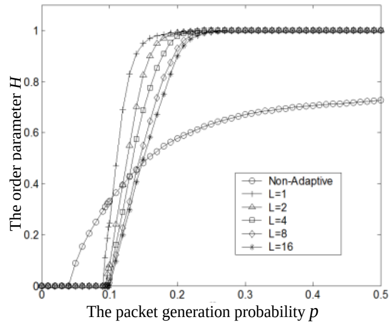

Fig. 1. The order parameter H versus p for our method.

In our method, the accepting probability λ_i^t can be adjusted dynamically according to the traffic state of nodes. This leads to the re-distribution of the flux of packets and enhance the capacity of the whole network remarkably. From Fig. 1 we can see that the critical point p_c of our method is improved greatly compared with the conventional random-walks. We increase L from 1 to 25 . The range is large enough to investigate in detail the influence of L on the phase transition. With the increase of L, we observe that the critical point p_c increases and the transition curve becomes smooth. Moreover, the limits of p_c and the transition are occurs quickly.

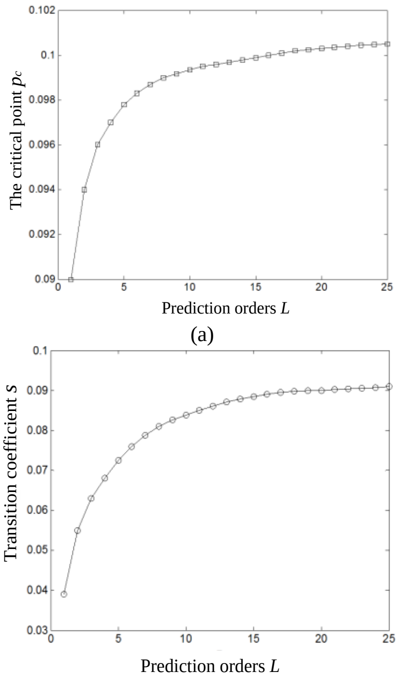

Fig. 2. The influence of prediction orders. (a) and (b) are the critical point p_c and s as a function of L respectively.

C. The Influence of Prediction Orders on Congestion

We define a transition coefficient s that measures the range of p from p_c to the point where H firstly arrives at 0.8 . In this range, we can see the transition curves show a linear-like increase and clear discrimination. s can be used to describe the transition of the curve of H . The BA network is presented in section 3.1. Fig. 2(a) and 2(b) show the critical point p_c and s as a function of L, respectively. We can see from Fig. 2 that p_c and s increase quickly with L when L is small. However, for large L, the two parameters almost stop increasing. The results show that using small value of L has already allowed us to obtain obvious improvement of p_c and smooth phase transition.

D. The Distribution of Accepting Probability

To have a deeper insight into the microscopic configurations that allow delaying the onset of congestion, we show in Fig. 3 the distribution of average accepting rates $\langle\lambda\rangle_k$ of nodes with degree k, as a function of node degrees. We adopt $L = 8$ here since obvious improvement of p_c and smooth phase transitions have been obtained as shown in Fig. 1. From Fig. 3 we can see the correlation between $\langle\lambda\rangle_k$ and the node degrees k is clear since all the nodes within the same degree-class display similar accepting rates. For different values of packet generating probability p, we observe that the nodes with small degrees are self-organized homogeneously. For the same p, with the increase of node degrees, the accepting rates decrease rapidly after the region of the self-organization. With the increase of p, the accepting rates of the nodes with small degrees increase while the nodes with large degrees start to close their doors progressively. We can see from Fig. 3 that a hierarchical (degree-based) organization of the accepting rates by the system is strongly beneficial to avoiding the network congestion.

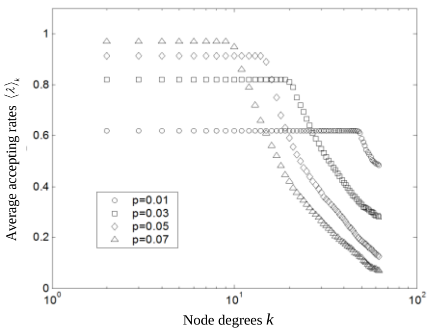

Fig. 3. The distribution of $\langle\lambda\rangle_k$ as a function of node degrees.

E. Compared with Other Existing Methods on Avoiding Congestion

In this section, we compare our method with three existing routing strategies, the efficient path strategy (EPS) [14], the Optimal Path Strategy (OPS) [15], and the hybrid routing [16], on avoiding congestion. Before comparisons, it is necessary to show the main idea of the three methods briefly.

In the EPS [14], for any path from node i to node j, as $P(i \to j): i \equiv x_0, x_1, \ldots, x_{n-1}, x_n \equiv j$, the L is denoted as [14],

$$L((P \to j):\beta) = \sum_{i=0}^{n-1} k(x_i)^{\beta} \tag{8}$$

where β denotes a tunable parameter, and $k(x_i)$ denotes the degree of node x_i . The efficient routing path between nodes i and j corresponds to the route that the sum of L is minimized. The EPS [14] depends on even-distributed load and finding a short path between a pair of nodes. To achieve this, packets should be delivered on the paths that avoid the large-degree nodes because the large-degree nodes are easy in congested states. The results in references [14] show that the performance of minimizing congestion depends strongly on β . Thus, before using the EPS, one must determine the optimal β at first. However, it is a heuristic process and is more difficult than finding the shortest path. In fact, when load on networks is zero or very small, finding the efficient path is equivalent to finding the shortest path which is $O(N^2)$ [14]. With the increase of load, more computation cost based on the global traffic information on routes are required for obtaining the efficient path, and it is mainly decided by the network traffic and topologies.

The OPS [15] is a heuristic method which depends on finding the maximum betweenness $B^*_{\max}$ for the efficient paths. In a network, the betweenness $b_i^{(o,d)}$ of node i is defined as the sum of the probabilities of all paths between source o and destination d that pass through i . The total betweenness B_i is found by summing up the contributions from all pair of sources and destinations. $B_{\max}$ is the highest betweenness of any node on the network. To achieve optimal routing, the highest betweenness $B_{\max}$ should be minimized. The problem of finding the exact optimal routing is mathematically tied to the problem of finding the minimal sparsity vertex separator [20], which has been shown to be an NP hard problem [21]. This means that the computation of an exact solution increases with the network size faster than any polynomial. The OPS [15] use a heuristic algorithm to find near-optimal solutions for the routing problem in polynomial time. For networks with N nodes, the running time is $O(N^3 \log N)$, where $O(N^2 \log N)$ for one iteration and requiring $O(N)$ iterations [15].

The hybrid routing mechanism [16] is composed of the shortest path routing and a global routing strategy to improve the network traffic capacity. In the method, the packets are sent along the shortest paths or by using source routing information. Then, a global source routing strategy is employed as a supplementary routing mechanism. In the routing strategy, the optimal path between any source node and destination is defined as the path with minimum sum of queue length of nodes. The cost of finding the optimal path is similar to the shortest path which is $O(N^2)$ [16] for a network with N nodes.

We first make comparison on the BA networks. The BA networks have the average degrees $\langle k \rangle = 6$ and the network size $N = 2000$. We show in Fig. 4 the curves of the parameter H for our method (squares), for the EPS[14] (circularities) the OPS[15] (triangles), and hybrid routing[16], as a function of the packet generation rate p. All data points are averaged over 400 networks and 10^5 independent runs.

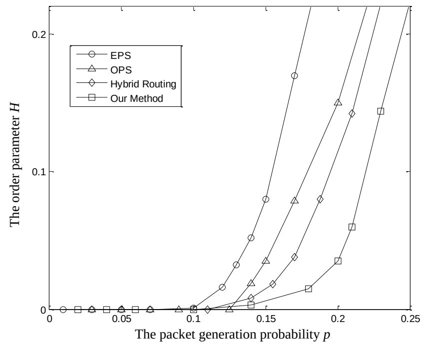

Fig. 4. Plots of order parameter H versus p for the EPS, the OPS, the hybrid routing, and our method.

From Fig. 4, we observe that our method has the smallest value of H among the four methods under the same packet generation probability p, which indicates that our method performs best on avoiding congestion. The reason is that our method is dynamic and the optimal paths are self-organized by nodes with local traffic information. Furthermore, the local adaptive scheme used in our method allows the nodes to be able to redistribute the traffic for avoiding congestion efficiently. This is different from the EPS[14], the OPS[15], and the hybrid routing[16], that their optimal paths are obtained from the perspective of static view and based on the global traffic information.

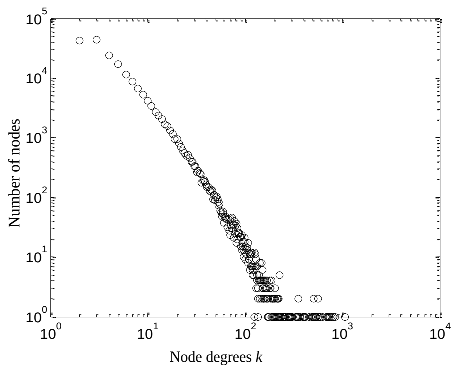

Fig. 5. The degree distribution of the CAIDA network.

Next, we make comparisons between our method and the three existing methods on a large real example with large network size and high clustering coefficient. Center for Applied Internet Data Analysis (CAIDA) [22] provides the macroscopic Internet topology data kit (ITDK). The corresponding date files that describe the Internet router-level graph by the adjacency matrix are available on the web of CAIDA. Here, we use the undirected version of the CAIDA network due to the bidirectional flow of packets in our method. The CAIDA network has a total of 192244 nodes and 609066 links. For illustration purpose, we first show the degree distribution of the network in Fig. 5 where k denotes the node degrees. We can see from Fig. 5 that the CAIDA network has clear scale-free properties. Most nodes have low degrees and few nodes have very large degrees.

We apply our method to the CAIDA network and compare it with the EPS [14], the OPS [15], and the hybrid routing [16], on avoiding congestion. In Fig. 6, we show the transition from free-flow to congestion of the EPS, the OPS, the hybrid routing, and our method. All data points are averaged over 400 networks and 10^5 independent runs.

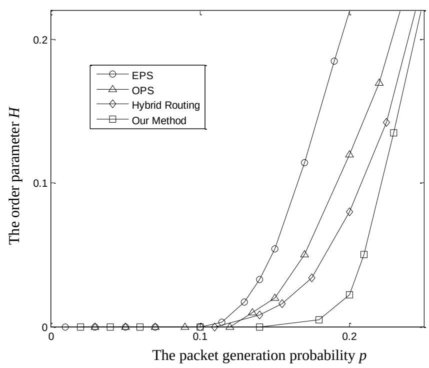

Fig. 6. Plots of order parameter H versus p for the EPS, the OPS, the hybrid routing, and our method.

We can see from Fig. 6 that the critical point p_c of our method is large that that of the EPS, the OPS, and the hybrid routing. Furthermore, with the increase of packet generation probability p, we can see that the phase transition of our method is smoother than that the other three existing methods, which means that our method is more robust for recovering from congested state.

IV. Conclusions

The routing method of Random-walks has many advantages. For example, it works without the knowledge of network topologies in advance and is robust to the change of network. Therefore, the routing method of Random-walks has been widely used as an efficient tool for designing searching and routing strategies. However, congestion always appears easily for random-walks because packets may take a long trip in the networks to arrive at the destinations. In this paper, we propose a method to minimize the congestion for random-walks via local adaptive congestion control in networks. In the method, we use linear-prediction of queue length to predict the traffic state of nodes, and propose a local adaptive evolution equations of accepting probability for nodes to decide whether accept or reject the incoming packets. In the experiments, we first analyze the critical value p_c where a phase transition from free-flow to congestion takes places. The results show that the p_c is increased remarkably by our method. Then, we investigate the influence of prediction orders on network congestion. We observe that, with the increase of prediction orders L , the value of critical point p_c increases and the phase transition curve becomes smooth. To show a deeper insight into the microscopic configurations that allow delaying the onset of congestion, we study the distribution of the average accepting probability as a function of node degrees. The results show that a hierarchical (degree-based) organization of the accepting rates is strongly beneficial to avoiding the network congestion. Finally, we compare our method with the EPS [14], the OPS [15], and the hybrid routing [16], on avoiding congestion on the BA networks and a real example. The results show that the critical point where congestion occurs for our method is large that that of the three existing methods. Furthermore, the phase transition of our method is smoother than that of the three existing methods, which means that our method is more robust for recovering from congested state.

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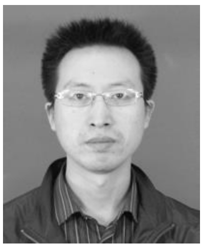

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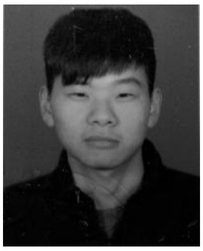

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