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Enhancing network transmission capacity by efficiently allocating node capability

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ABSTRACT

A network's transmission capacity is the maximal rate of traffic inflow that the network can handle without causing congestion. Here we study how to enhance this quantity by allocating resource to individual nodes while preserving the total amount of the resource available. We propose a practical and effective scheme which redistributes node capability based on the local knowledge of node connectivity. We show that our scheme enhances the transmission capacity of networks with heterogeneous structures by up to two orders of magnitude.

1. Introduction

A network's transmission capacity is the maximal amount of traffic flow that the network can handle without causing congestion [1]. Increasing network transmission capacity is one of the major goals for network design and engineering.

There are different ways to enhance a network's transmission capacity. A number of routing strategies [2–4] have been introduced to enhance this quantity by routing traffic based on the topological properties of a network or the real-time distribution of traffic load on links. Recently we reported [5] that a network's transmission capacity can be increased by removing a small number of links with certain topological properties. However in practice it is often difficult to change a network's routing protocol or topology. The above works have assumed that all nodes or links are assigned with uniform resources. This simplified scenario allows researchers to study the pure contribution of the routing algorithms and the topology. However it is unrealistic as in real networks resources are rarely distributed uniformly.

A practical and effective approach is to allocate the resources in a network such that network elements that handle higher volumes of traffic load have more resources whereas those that handle less load have fewer resources. Node capability and link bandwidth are two major resources to be allocated. Whether to redistribute the node capability or the link bandwidth depends on what is the major cause for congestion in a network. For example when a new generation of routers are deployed on the Internet, the processing power of routers are greatly improved. Then the congestion is mainly caused by the lack of link bandwidth. Whereas when optical fibres replace cables, the bandwidth of links are increased by a number of magnitudes, then the congestion is mainly caused by the lack of node processing power. Over the time these two situations may happen

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Table 1
Topological properties of the Erdös–Rényi (ER) model [7], the Barabási–Albert (BA) model [8] and the Positive-Feedback Preference (PFP) model [9,10]. For each model we grow ten networks using random seeds, and properties shown are averaged over the ten networks.

	ER	BA	PFP
Number of nodes	4000	4000	4000
Number of links	12,000	12,000	12,000
Degree distribution	Poisson	Power law	Power law
Power-law exponent		−3	−2.2
Maximum degree	18	156	979
Average shortest path distance	4.82	4.17	3.12
Average clustering coefficient	0.001	0.007	0.253

alternately in communication networks. In this paper we study the allocation of node capability and assume that links have sufficient bandwidth. We will study the allocation of link capacity in our future work.

This paper is organised as follows. In Section 2 we introduce three typical communication network topology models. We also present the widely used traffic-flow model based on the shortest path routing. In Section 3 we examine a number of degree-based node-capability allocation schemes using simulations based on the traffic-flow and topology models. We introduce a scheme which enhances a network's transmission capacity by up to two orders of magnitude by allocating a node's capability as a power function of the node's connectivity. In Section 4 we discuss an alternative way to estimate the optimal power exponent used in our scheme, and compares our scheme with a previous scheme which is based on the topological property of betweenness [6]. Finally we conclude this paper in Section 5.

2. Background

We consider three network models as examples of typical topologies of computer and communication networks, which are the Erdös–Rényi (ER) model [7], the Barabási–Albert (BA) model [8] and the Positive-Feedback Preference (PFP) model [9,10]. In graph theory, degree k is defined as the number of links a node has. The ER model generates random networks with a Poisson degree distribution, where most nodes have a degree close to the average degree. The ER model has been used to describe the structure of LAN and wireless ad hoc networks. The BA model generates the so-called 'scale-free' networks with a power-law degree distribution, where a few nodes have very large degrees and the majority nodes have only a few links. Many communication networks are found to be scale-free [11] and the BA model has been used to study the error and attack tolerance of such networks [12]. The PFP model generates a network structure which is very similar to the Internet at the autonomous system level [13–17]. For each model we grow ten networks using random seeds to the same numbers of nodes and links. Table 1 shows properties of the three models.

In this study we adopt a simple and widely used traffic-flow model [18–21,4,5]. For a network with N nodes, at each time step, λ packets are generated at randomly selected nodes. The destination is chosen randomly. A packet is routed following the shortest path between source and destination. If there are multiple shortest paths, one is selected at random. In this work we only consider the shortest path routing strategy which is widely used in communication networks, such as the Open Shortest Path First (OSPF) routing protocol. A node i is assigned a capability, C_i, which is the maximal number of packets the node can route at a time step. When the total number of arrived and newly created packets is larger than C_i, the packets are stored in the node's queue and will be processed in the following time steps on a first-in first-out basis. If there are several shortest paths for one packet, one is chosen randomly. Packets reaching their destination are deleted from the system. As in Refs. [4,5,20,21], node buffer size in this traffic-flow model is set as infinite as it is not relevant to the *occurrence* of congestion.

For small values of the packet-generating rate λ, the number of packets on the network is small so that every packet can be processed and delivered in time. Typically, after a short transient time, a steady state for the traffic flow is reached where, on average, the total numbers of packets created and delivered are equal, resulting in a free-flow state. For larger values of λ, the number of packets generated is more likely to exceed what the network can process in time. In this case traffic congestion occurs. As λ increases from zero, we expect to observe two phases: free flow for small λ and congestion for large λ. The phase transition occurs at the *critical packet-generating rate* λ_c, which is a measure of the network transmission capacity.

3. Enhancing network transmission capacity

In the following we study the impact of the node-capability allocation schemes on the network transmission capacity by running the traffic-flow simulation on the three network models introduced above.

In our simulation, the critical packet-generating rate λ_c is determined by observing the order parameter η [22]. It is defined as

$$\eta = \lim_{t\to\infty} \frac{\langle \Delta\Theta \rangle}{\lambda \Delta t}, \tag{1}$$

where $\Theta(t)$ is the total number of packets in the network at time t, $\Delta\Theta = \Theta(t+\Delta t) - \Theta(t)$, and $\langle \cdots \rangle$ indicates the average over time window Δt. For $\lambda < \lambda_c$ the network is in the free-flow state, i.e. $\Delta\Theta \approx 0$ and $\eta \approx 0$; whereas for $\lambda > \lambda_c$, $\Delta\Theta$ increases with Δt and therefore $\eta > 0$. Thus λ_c is the transition point where η deviates from zero.

Table 2
Critical package-generating rate λ_c of the three network models for different node-capability allocation schemes. Also shown are the optimal exponent and the fitting exponent in Figs. 1 and 2 respectively.

	ER	BA	PFP
Uniform, $C \propto 1$	$885_{\pm 21}$	$57_{\pm 17}$	$48_{\pm 9}$
Degree proportional, $C \propto k$	$2616_{\pm 82}$	$1289_{\pm 65}$	$4419_{\pm 108}$
Degree exponential, $C \propto k^{1.5}$	$4319_{\pm 117}$	$2954_{\pm 302}$	$1636_{\pm 83}$
Degree exponential $C \propto k^{\alpha^*}$	$4319_{\pm 117}$	$3284_{\pm 241}$	$5126_{\pm 177}$
Betweenness proportional, $C \propto B$	$6576_{\pm 215}$	$7604_{\pm 184}$	$11,592_{\pm 204}$
Optimal exponent α^* (see Fig. 1)	$1.50_{\pm 0.05}$	$1.40_{\pm 0.03}$	$1.10_{\pm 0.03}$
Fitting exponent α' (see Fig. 2)	$1.49_{\pm 0.03}$	$1.37_{\pm 0.03}$	$1.11_{\pm 0.02}$

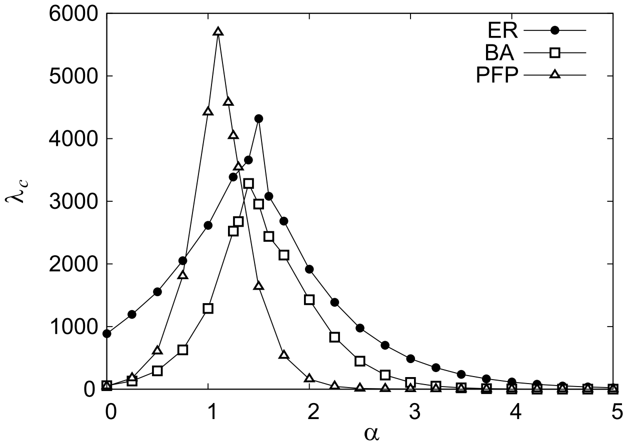

Fig. 1. Critical packet-generating rate λ_c as a function of the exponent α of the node-capability allocation schemes ($C \propto k^\alpha$) for the ER, BA and PFP network models. For each model, λ_c peaks at an optimal exponent value α^* shown in Table 2.

Table 2 shows the average and the bounds of λ_c of the network models for different node-capability allocation schemes. For comparison purpose, in our simulation we keep the sum of node capability the same for all schemes, i.e. $\sum_i C_i = \sum_i k_i = 2L$, where L is the number of links. For a node with capacity $C < 1$, at each time step it processes a packet with probability C. For a node with, for example, capacity $C = 4.3$, it processes 5 packets with probability 0.3 and otherwise 4 packets.

The first node-capability allocation scheme is a simplistic baseline case where we assign all nodes with a uniform capability. The second scheme is to allocate a node's capability proportional to its degree k, i.e. $C \propto k$. The underlying heuristic is that the larger degree of a node, the more incoming traffic from its neighbours the node needs to handle. Table 2 shows that there is a substantial increase of λ_c for all the three network models when the allocation of node capability changes from the uniform scheme to the degree-proportional scheme. For the ER network, λ_c increases three times; for the BA network, it increases 22 times; and for the PFP model, it increases two orders of magnitude. This result highlights the relevance of respecting the connectivity difference among individual nodes for capability allocation. This is particularly true for networks featuring a heterogeneous structure where node degrees vary hugely following a power law, such as the BA and PFP models.

In the third scheme we assign the capability of a node proportional to the node's degree raised to the power of 1.5, i.e. $C \propto k^{1.5}$. This scheme further differentiates the degree difference among nodes. As shown in Table 2, it produces better results for the ER and BA networks, but it overdoes for the PFP network. This is because the PFP network model characterises a few nodes with disproportionally large degrees (see the maximum degree in Table 1). These nodes, although a small number, take too large a share of the total node capability. This leaves the majority of nodes, which are poorly connected, with very little capability and therefore restrains the network's overall transmission capacity. This suggests that there is an optimisation problem as how to achieve the balance between individual and collective interest.

In order to examine this issue systematically, we define a generic degree-based scheme as $C \propto k^\alpha$. When $\alpha = 0$ it is the uniform scheme and when $\alpha = 1$ it is the degree-proportional scheme. Fig. 1 shows the critical package-generating rate λ_c as a function of the exponent α. For each network model the λ_c peaks at a characteristic value of α^*, which is the optimal exponent for the degree-based scheme. Table 2 gives the value of α^* and the corresponding peak value of λ_c.

4. Discussion

For any network topology we can obtain the optimal exponent α^* by running the traffic-flow simulation as described above. This, however, is time-consuming. Here we introduce an alternative way to estimate α^* without having to run the simulation.

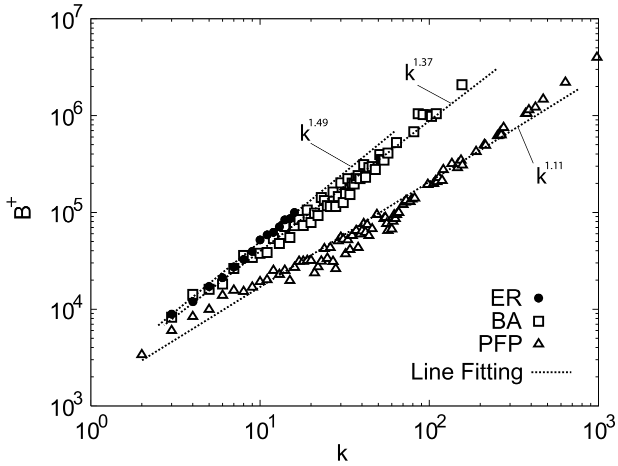

Fig. 2. The largest betweenness B^+ of nodes with degree k for the three network models shown in a log–log scale. The two quantities follow a power law $B^+ \propto k^{\alpha'}$. The fitting lines are obtained by the least squares technique.

Recently we analytically proved [23,24] that a network's critical packet-generating rate can be estimated as

$$\lambda_c = \min_{i \in V} \left\{ \frac{C_i N(N-1)}{B_i} \right\}, \tag{2}$$

where V is the set of node indices, N is the number of nodes and B_i is node i's betweenness [6]. Betweenness is defined as the number of packets passing through a node when each node sends a packet to all other nodes via the shortest path. If there are multiple shortest paths, one is selected at random.

When allocating node capability as $C \propto k^{\alpha^*}$ we have

$$\lambda_c \propto \min_{k \in K} \left\{ \frac{k^{\alpha^*} N(N-1)}{B^+(k)} \right\}, \tag{3}$$

where K is the set of possible degree values and $B^+(k)$ is the largest betweenness value of nodes with degree k. The largest betweenness (instead of the average) is used because λ_c is constrained by the largest traffic load a k-degree node has. Eq. (3) suggests that for the optimal scheme $C \propto k^{\alpha^*}$ to produce a sound result, the value of k^{α^*} should be proportional to $B^+(k)$. We plot $B^+(k)$ as a function of node degree k in Fig. 2. It is indeed the case that $B^+(k) \propto k^{\alpha'}$ and $\alpha' \simeq \alpha^*$ (see Table 2). This provides a convenient way to estimate α^* by fitting the function of $B^+(k)$. If a network has a well-defined model, the betweenness calculation can be simplified by computing on a smaller graph generated by the model.

A number of previous works [20,21,25,26] have suggested that the critical packet-generating rate λ_c of a network is maximised by allocating a node's capability according to the node's betweenness. As shown in Table 2 a betweenness-based scheme indeed produces better results. This is because in the traffic-flow model, betweenness precisely estimates the traffic load at each node. This scheme, however, faces several practical issues. Firstly, the betweenness of individual nodes is sensitive to local changes in a network topology. A minor modification to a network, e.g. adding a node or a link, could significantly alter the betweenness value of many nodes and potentially invalidate the gain of the scheme. Secondly, the calculation of betweenness requires global knowledge of a network's topology, which is not often possible in practice. Finally, the calculation of betweenness is not a trivial task for large networks. The betweenness scheme is useful for estimating the theoretical upper bound of λ_c. In practice, it can only be used for networks with static topologies, or networks with so high a requirement on transmission capacity that the benefit of applying this scheme overruns the cost.

By comparison our proposed scheme $C \propto k^{\alpha^*}$ is more practical, robust and easy to implement. We allocate a node's capability based on the local knowledge of node degree. We obtain the optimal exponent α^* by simulation or fitting the betweenness-degree function. The value of α^* of a real network is relatively stable as it is not sensitive to minor topology changes but determined by the network's macroscopic structure, i.e. the correlation between betweenness and node degree. For a network with a well-defined model, α^* can be obtained on a small network generated by the model.

5. Conclusion

A key goal for network design and engineering is to deploy limited resources to achieve the optimal network performance. We propose the degree-based node-capability allocation scheme of $C \propto k^{\alpha^*}$ which remarkably enhances a network's transmission capacity. Usually, the value of the optimal exponent α^* is determined by a network's macroscopic structure and can be estimated by fitting the function of $B^+(k)$. Our scheme can be viewed as a revision of the betweenness scheme with improved practicality and robustness.

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