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Optimal Routing Strategy on Weighted Networks

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ABSTRACT
How to improve the transfer capability of the weighted networks is one of the most important problems in complex networks. In this paper, a novel and effective routing strategy is proposed by deleting edges in proper order according to their different definitions of edge weight. Kicking out few specified edges can enhance the transfer capability of weighted networks greatly. Simulations on both compute generated and real world networks show that the routing strategy kicking out edges according to the product of the strengths of two nodes of the edge is more effective. Moreover, we analyse the curve of critical packet generation rate of kicking out all deletable edges and find that there is a sharp transition after kicking out some edges. Due to the strongly improved network capacity, easy realization on networks, and low cost, the strategy may be useful for real communication networks.

General Terms
Complex networks, System science, Social networks.

Keywords
Weighted network, Barrat-Barthelemy-Vespignani (BBV) network, Routing strategy, Transfer capability.

1. INTRODUCTION
In the present big-data era, complex networks have attracted considerable attention of the researchers from different fields, and are greatly promoting the development of complex networks and complexity science. The scholars in complex networks are facing ten opportunities and challenges, including basic theory, modelling, algorithms, engineering of complex networks, and universality, controllability, stabilization, self-organized evolutionary of complex network dynamics, and so on[1]. Due to the constantly growing significance of large communication networks such as the Internet, the study of network transfer capability is becoming increasingly important in the past few years consequently. These real world networks can be properly described as complex networks while nodes representing individuals and edges representing the interactions among them. Many people take tremendous interests in the topology of complex networks, such as the small-world phenomenon[1-2] and the scale free property[3], to make the network transfer capability maximal so as to control the increasing traffic congestion in these real world networks. And also some networks are found to be specified not only by the topology but also by the weight of edges, such as the scientific collaboration networks[4], the world-wide airport network[5] and the Internet [6]. For understanding the structure and functions of networks, an algorithm which considered the historic community structure of networks was proposed [7] to automatically discover evolutionary community structure in dynamic weighted networks. A social network is modeled [8] by a weighted graph generated by an inhomogeneous Reed-Frost epidemic network for a tunable degree-degree correlation. Recently, lots of optimal routing strategies are proposed to control traffic congestion and improve network transfer capability. Some of them are based on the global information: the shortest path routing strategy [9] where the packets are forwarded through the minimum number of nodes and the effective routing strategy[10] which can enhance the network capability in processing traffic more than 10 times by redistributing traffic load in central nodes to other non-central nodes. Some others focus on local information since global information is usually unavailable in large-scale networks: neighbour information [11], next nearest neighbour information[12]. The traffic dynamics on weighted scale-free networks is investigated with a local routing strategy based on link weight information. The overall capacity can be enhanced by taking advantage of links with large bandwidth[13]. Making appropriate adjustments to the network topology structure is also proved to be effective in some networks[14-15]. Kicking out some black sheep edges, the edges linking to nodes with large betweenness, is effective to enhance network transfer capability of scale-free networks[16,17].

Based on the idea, we have put forward novel routing strategies for Barrat- Barthelemy- Vespignani (BBV) weighted network. By defining the weight of edges as the product of node degree, the product of node strength and also the original weight of edges, we delete some edges according to the different definitions of edge weight and compare the critical packet generation rate with the routing strategy of deleting edges randomly.

This paper is organized as follows. Next section gives some brief descriptions of the BBV weighted network model and the traffic model. Then our routing strategy is proposed in section 3, followed by the simulations on computer generated networks and real world network in section 4. Finally, the conclusions are given in section 5.

2. MODELS
2.1 Network Model
Networked structures arise in a wide array of different contexts such as technological and transportation infrastructures, social phenomena, and biological systems. These highly interconnected systems have recently been the focus of a great deal of attention that has uncovered and characterized their topological complexity. In those models presented to describe the weighted real world networks [18-

20], the BBV weighted network model is most widely used. It can also be described by an adjacency matrix ***W***, whose elements w_{ij} denote the weight of the edge between node *i* and *j* which we call it the original weight in our paper. The BBV weighted network[9,15] is generated as two followed steps:

1) Growth. Starting from a small number of N_0 nodes connected by edges with assigned weight w_0, one node is added at every time step. The new added node is connected to *m* different previously existing nodes with equal weight w_0 for every edge and chooses preferentially nodes with large strength according to the probability $\prod_{n\to i} = s_i \Big/ \sum_l s_l$, where s_i is the node strength described as $s_i = \sum_j w_{ij}$.

2) Weight dynamics. The weight of each new added edge is initially set to a given value w_0 which is often set to 1 for simplicity. But the adding of edge connecting to node *i* will result in increasing the weight of the other edges linked to node *i* which is proportional to the edge weights. If the total increase is δ (we will focus on the simplest form: $\delta_i=\delta$), we can get

$$w_{ij} = w_{ij} + \Delta w_{ij} = w_{ij} + \delta * \frac{w_{ij}}{s_i} \quad (1)$$

This will yield the strength increase of node *i* as:

$$s_i = s_i + \delta + w_0 \quad (2)$$

The degree distribution of BBV network $P(k) \propto k^{-\gamma_k}$ and the strength distribution $P(s) \propto s^{-\gamma_s}$ yield scale-free properties with the same exponent [15]:

$$\gamma_k = \gamma_s = \frac{4\delta+3}{2\delta+1} \quad (3)$$

2.2 Traffic model

Recently, some models have been proposed to mimic the traffic routing on complex networks by introducing packets generating rate and homogeneously selected sources and destinations of data packets, in which the capacity of networks is measured by a critical generating rate[21,22]. The traffic model can be described as follows:

1) All the nodes as treated as both hosts and routers. A host can create packets with addresses of destination and receive packets from other hosts while a router routes the data packets to their destinations.

2) At each time step *t*, *R* packets are generated in the network with randomly chosen sources and destinations. Once a packet is created, it is placed at the end of the queue if this node already has several packets waiting to be delivered to their destinations. At the same time, a destination node, different from the original one, is chosen at random in the network.

3) At each time step, the first C_i packets at the top of the queue of each node *i*, if it has more than C_i packets in its queue, are forwarded one step toward their destinations and placed at the end of the queues of the selected nodes. Otherwise, all packets in the queue are forwarded one step. In our model, each node has the same packet delivery capability C_i and we set C_i=1 for simplicity.

4) A packet, upon reaching its destination, is removed from the system.

As *R* is increased from zero, two phases will be observed: free flow for small *R* and congested phase for large *R*, with a phase transition from the former to the latter at the critical value $\boldsymbol{R_c}$. This critical value R_c can best reflect the maximum network transfer capability. In particular, for $R<R_c$, the numbers of created and delivered packets are balanced, resulting in a steady free flow of traffic. For $R>R_c$, traffic congestion occurs as the number of accumulated packets increases with time, due to the fact that the capacities of nodes for delivering packets are limited. We are interested in determining critical value R_c in order to address which kind of routing strategy is more effective.

The betweenness b_i is often introduced to estimate the possible packet passing through a node *i* under the given routing strategy which is defined as

$$b_i = \sum_{s,t} \frac{\sigma(s,i,t)}{\sigma(s,t)} \quad (4)$$

where $\sigma(s,i,t)$ is the number of paths under the given routing strategy between nodes *s* and *t* that pass through node *i* and $\sigma(s,t)$ is the total number of paths under the given routing strategy between nodes *s* and *t* and the sum is over all pairs *s*, *t* of all distinct nodes.

A created packet will pass through the node *i* with the probability $b_i / \sum_{j=1}^{n} b_j$. Thus, the average number of packets that the node *i* receives at each time step is $R*b_i/(n*(n-1)))$. Congestion occurs when the number of incoming packets is larger than the outgoing packets, that is $R*b_i/(n*(n-1)) \geq C_i = 1$. So the critical packet generation rate R_c is

$$R_c = \min(n*(n-1)/b_i) \quad (5)$$

3. PROPOSED ROUTING STRATEGIES

We give our routing strategies as follows:

1) We defined the weight of the edge linking two nodes *i* and *j*, W_{ij}, in different way according to different routing strategies, namely WD, DPD, and SPD, respectively. The definitions are described in Table 1, where k_i is the degree of node *i* which is same as the number of neighbours of node *i*.

2) We sort the edges by their definition weights in decreasing order and delete the edge ranked first. However, we should maintain the integrity of the network which means that, if deleting an edge will cause some nodes to be disconnected, we will not delete it, and go to deal with the edge ranked next.

3) Recalculate the definition weight W_{ij} and repeat step 2 until a fraction f_e of edges are deleted.

4) The shortest path routing strategy[6] is applied in the 'new' network where a fraction f_e of edges are deleted.

Table 1. the definitions weight W_{ij} in different strategies

	WD	DPD	SPD
W_{ij}	w_{ij}	k_i*k_j	s_i*s_j

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In BBV network there are about n*m edges. And there should be at least n-1 edges to maintain the integrity of the network with n nodes. So we can kick out about n*m-n+1 edges at most. After kicking out some edges, there are fewer connections between the hub nodes which will reduce the load of these nodes and enhance the transfer capability. But after kicking out all the deletable edges, which are about n*m-n+1edges, the network become a treelike topology and a smaller value of packet generation rate can cause traffic congestion. So there must be a critical point where a phase transition occurs, if more edges are deleted, the effect of the routing strategy is less obvious or even worse than in the original network.

We utilize another routing strategy, namely RAN, which randomly delete edges, to check the validity of our routing strategies.

4. SIMULATIONS AND ANALYSIS

To evaluate effectiveness of the proposed strategies, simulations on both randomly generated and real world networks are conducted under different settings. For every network, 50 instances are generated and for each instance, we run 50 simulations. The results are the average over all the simulations. We obtain the critical packet generation rate R_c using different routing strategies in BBV network with n=100, δ=4, m=4 and ω_0=1. The results are shown in figure 1.

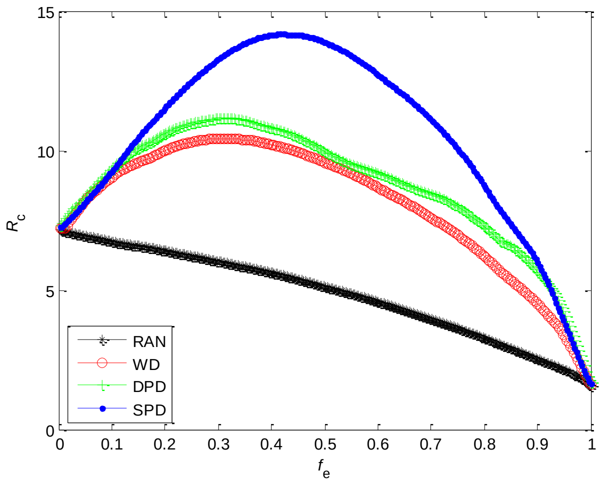

Fig1: R_c VS f_e. BBV network with n=100, δ=4, m=4, ω_0=1, C_i=1.

Figure 1 exhibits the relationship of the critical packet generation rate and the fraction of delete edges. In all routing strategies, the critical packet generation rate R_c varies with the fraction of delete edges f_e. The SPD routing strategy which kick out edges with higher product of the strengths of two nodes of the edge obtain the maximum transfer capability when about half of deletable edges are deleted. The maximum transfer capability of the SPD routing strategy (f_e is about 0.5) is 95.8% greater than in the original network (f_e = 0) while the DPD routing strategy and the WD routing strategy is 52.8% and 44.4% correspondingly. And the maximum transfer capability of the SPD routing strategy is better than the other two strategies (28.14 % higher than DPD and 35.60% higher than WD). The RAN routing strategy cannot enhance the transfer capability.

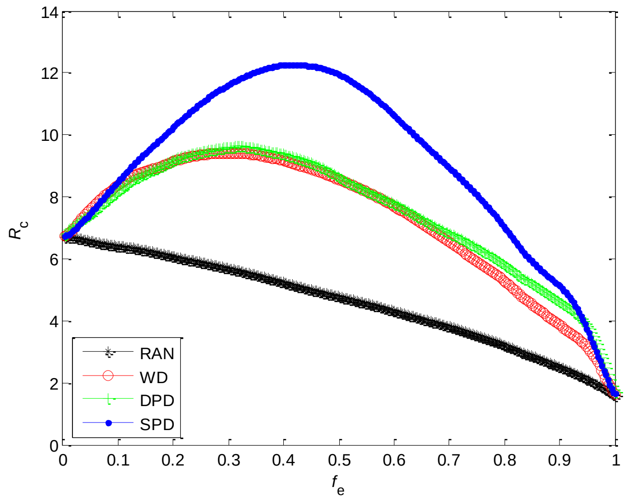

Fig 2: R_c VS f_e. BBV network with n=100, δ=8, m=4, ω_0=1, C_i=1.

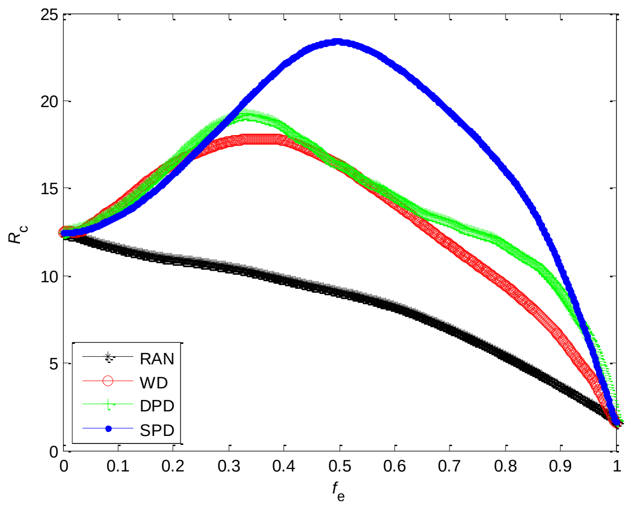

Fig 3: R_c VS f_e. BBV network with n=100, δ=4, m=8, ω_0=1, C_i=1.

To discuss the implication of the weight on critical packet generation rate, we set δ = 8 to get the corresponding simulation results in figure 2.

Figure 2 shows almost the same result as figure 1. The enhancement of three routing strategies is 82.2%, 42.3% and 39.5% correspondingly which means the total increase weight δ nearly does not affect our routing strategies.

Then we check the impact of the new added edge number m on our routing strategies to obtain results shown in figure 3.

Figure 3 also shows almost the same result as figure 1 and figure 2. The enhancement of three routing strategies is 88.2%, 54.3% and 43.0% correspondingly which means the new added edge number m also does not affect our routing strategies. And in figure 2 and figure 3, we can also discover that deleting edges randomly will not enhance the transfer capability.

Then we double the node number n to gain the results in figure 4. Compare figure 4 with figure 1, we can obtain that the critical packet generation rate R_c of our SPD routing strategy also reaches the peak when f_e is about 0.5.

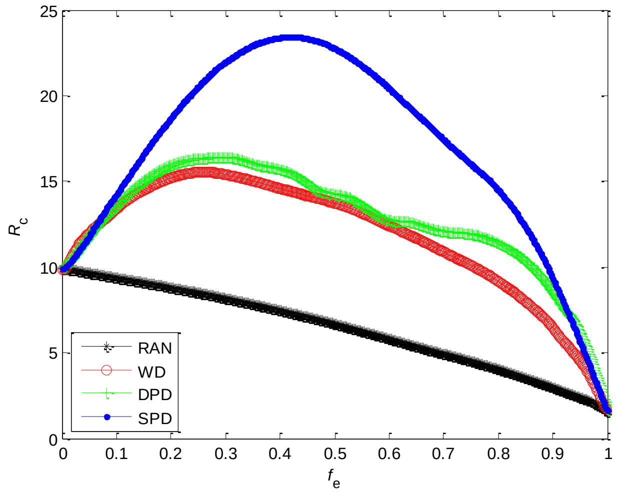

Fig 4: R_c VS f_e. BBV network with n=200, δ=4, m=4, ω_0=1, C_i=1.

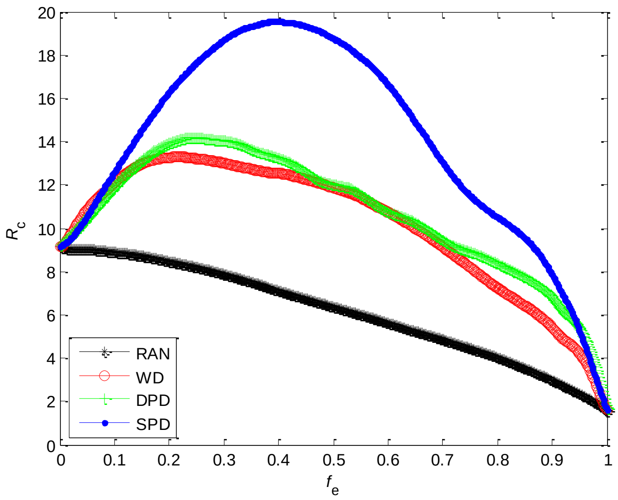

Fig 5: R_c VS f_e. BBV network with n=200, δ=8, m=4, ω_0=1, C_i=1.

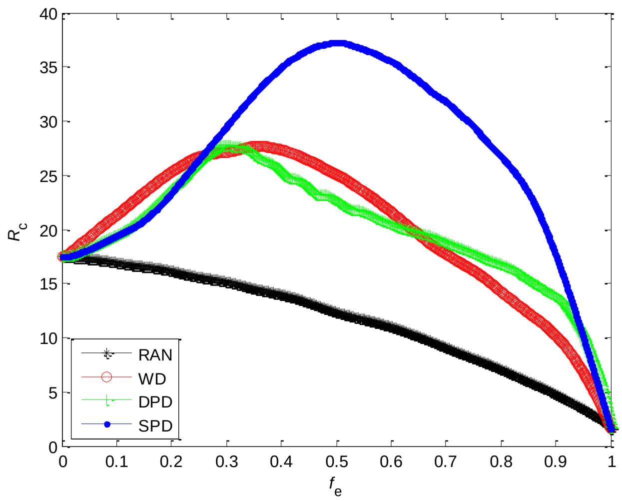

Fig 6: R_c VS f_e. BBV network with n=200, δ=4, m=8, ω_0=1, C_i=1.

The enhancement of three routing strategies is 137.51%, 64.9% and 57.5% when the node number n is increased which means our routing strategies work better in large scale networks.

Figure 5 and figure 6 prove the situations with the total increase weight δ is 8 and the new added edge number m is 8 with the node number n=200. The results shown in figure 5 and figure 6 also present the same feature that the SPD routing strategy which kick out edges with higher product of the strengths obtain the maximum transfer capability and the more nodes there are, the more efficient our routing strategies are.

Finally, we test our routing strategies on real world network. We choose a dataset of the USAir 97 network with 332 nodes and 2126 edges, which is a prototypical example network of direct flight connections between US airports for the year 1997, which can be taken from the website http://vlado.fmf.unilj.si/pub/networks/data/. Simulation results are shown in table 2. From table 2, we can see our routing strategies also work well in real world network. The average weighted average length[12-13] L_{AVE} versus the node number n is reported in Figure 7.

Table 2. the critical packet generation rate R_c of the USAir 97 network

	RAN	WD	DPD	SPD
f_e=0.1	3.42	3.66	3.74	4.12
f_e=0.2	3.34	3.84	4.02	4.68

Although the weighted average length of SPD routing strategy are higher than that of the traditional shortest path routing strategy (SHT) [10], the small-world phenomenon, i.e. $L_{AVE} \propto \ln n$, is still maintained. The transfer capability of weighted network is enhanced at the cost of increasing the average weighted average length slightly. Such a sacrifice may be worthwhile when the network requires large transfer capability.

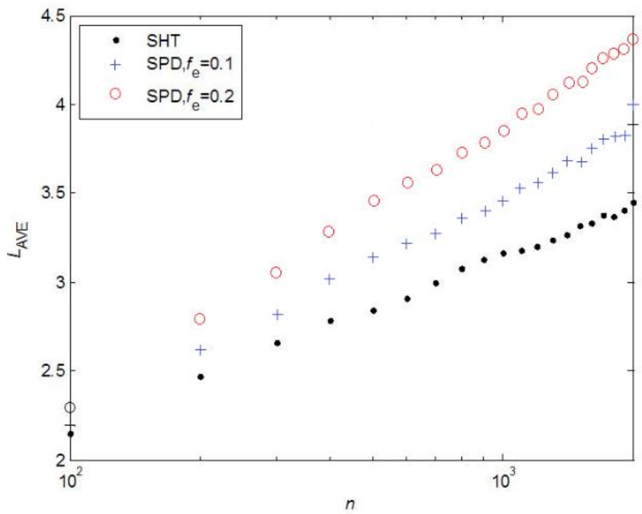

Fig 7: L_{AVE} VS n. BBV network with δ=4, m=4 and ω_0=1.

5. CONCLUSION

This paper has proposed routing strategies to enhance the transfer capability of the BBV weighted networks. By deleting some edges with larger definition weight, simulations have indicated that the critical packet generation rate R_c is enhanced greatly which means the proposed routing strategies can effectively enhance the network transfer capability when a fraction f_e of edges is about 0.5. The routing strategy which deletes the edges according to the product of the strengths of the nodes at the end of the edge is proved to be the most feasible. Meanwhile, the small-world phenomenon of the average weighted average length is still maintained. And there is a transition at the critical point after kicking out about half of deletable edges. The test for SPD on the USAir 97 network proves that the routing strategy work well in real world network. Moreover, the simulational results have shown that the suggested methods can provide novel insights relevant for routing strategies in weighted networks. Due to the strongly improved network capacity, easy realization on networks, and low cost, the strategy may be useful for modern communication networks.

Although various methods have been presented for exploring in static networks and based on the case that the node delivery capacity is constant, but the node delivery capacity in dynamic networks is sometimes proportional to the node degree or the node strength, which is needed to further study in the future.

6. ACKNOWLEDGMENTS

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