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Dissemination of information in complex networks with congestion

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Abstract

We address the problem of message transfer in complex networks with congestion. We propose a new strategy aimed at improving routing efficiency. Such a strategy, contrary to the shortest available path length from a given source to its destination (perhaps the most widely analyzed routing strategy), takes into account the congestion of nodes and can be deployed, with a minimal overhead, on top of it. Our results show that, by distributing more homogeneously the congestion of nodes, it significantly reduces the average network load as well as the collapse point.

Keywords: Complex networks; Routing strategies; Congestion control

1. Introduction

In recent years, there has been a great interest in understanding the properties of complex networks [1,2]. Among the issues that have attracted the attention of the research community interested in complex networks, one of the most important practical problems is to find efficient strategies for information delivery between a given sending node and its destination host. To this end, a number of protocols for the dissemination of information (i.e., routing protocols) has been developed in the last few years (see for instance, in the context of Internet, Ref. [3]).

Ideally, routing protocols should be able to disseminate such information along the most efficient routes. However, it is unrealistic to assume that data will be delivered following optimal routes since this implies checking all possible scenarios, which is not feasible in practice. In turn, most of the studies in complex networks take the criterion of using the shortest available path length from a given source to its destination [4–6], or a strategy based on it (as done in Ref. [7], where the shortest available path criterion is improved to take into account aspects such as the amount of data awaiting in the nodes).

In this paper, we develop a routing strategy that, contrary to the shortest path, denoted *SP*, takes into account the congestion of nodes. We will show that, although it may increase the packets' path length, it also

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significantly reduces the average load of the network. Furthermore, it can be implemented on top of a system using *SP* with a minimal overhead.

1.1. The routing strategy

In the new routing strategy, each node is set up with a *threshold* value (the same for all nodes) that indicates the maximum congestion that the node "agrees" to support. When a route from node A to node B is going to be established, the *SP* is used, but taking into account that such a route cannot cross nodes whose congestion surpasses the *threshold* value. If more than one shortest route exists, we select one of them at random (as has been shown in Ref. [4], since this provides better results than making a deterministic choice). However, it may occur that, by respecting the above-mentioned threshold limiting rule, no route could be established between node A and node B. In this case, the *threshold* value is increased (at all nodes) and the new routes are established by taking into account this new value. We call this strategy the *congestion-aware shortest path*, denoted SP_{CA}.

To evaluate the performance of SP_{CA}, we consider a scenario similar to that in Refs. [5,6]. To specify the congestion of a node i, we consider that each node generates packets at a rate ρ per unit of time, independently of the rest of the nodes. Congestion is thus defined in terms of packets per unit of time. The destination of each of these packets is randomly set in the moment they are created and they move in parallel (according to the routing strategy). We assume that the nodes have queues with the capacity to store as many packets as needed. This means that no packet is ever dropped. However and without loss of generality, the processing power of a node is set to only one packet per unit of time. Hence, we say that a node *collapses* when $c_i \geqslant 1$. Taking into account the result of Guimerà et al. [5], which provides the number of packets that arrive at the node, on average, as a function of ρ, its betweenness centrality [8], denoted β_i, (the *betweenness centrality* of a node is defined as the number of routes, along shortest paths, that cross it) and the number of nodes in the system (denoted n),

$$c_i = \frac{\rho\beta_i}{n-1}. \tag{1}$$

We consider a general scenario where packets are generated at random and independently, at each node, with the same probability. Therefore, this can be modeled by assuming that the arrival of packets at a given node i is a Poisson process with mean c_i. We also consider that the service rates are the same for all processes. Under these assumptions, the delivery of packets is also a Poisson process [9]. In this picture, the queues are called M/M/1 in the computer science literature and we have that the average size of the queues is given by [9]

$$\langle v_i \rangle = \frac{c_i}{1-c_i} = \frac{(\rho\beta_i/n-1)}{1-(\rho\beta_i/n-1)}. \tag{2}$$

Therefore, we have that the average load of the network $\langle N(t) \rangle$ is given by

$$\langle N(t) \rangle = \sum_{i=1}^{n} \langle v_i \rangle = \sum_{i=1}^{n} \frac{c_i}{1-c_i} = \sum_{i=1}^{n} \frac{(\rho\beta_i/n-1)}{1-(\rho\beta_i/n-1)}. \tag{3}$$

According to Little's law [9], the average time needed by a packet to reach its destination is proportional to the total load of the network, and therefore minimizing $\langle N(t) \rangle$ is equivalent to minimizing the average cost of a search.

At this point, we would like to remark that Eq. (1) is only valid for values of ρ such that c_i does not become collapsed. When at least one of the nodes in the network collapses (which can occur for values of ρ lower than 1), the average load of the network $\langle N(t) \rangle$ diverges [5].

2. Dynamics of the routing strategies

Our experiments are carried out using simulations. We considered three network topologies: a random topology [10], a scale-free topology [11] and a star-like topology (a star-like topology, for k links per node, is formed by k central nodes with the rest of the nodes connecting their outgoing links to these). Such networks consisted of 64 nodes, and we varied the number of links that each node established with other nodes from 2 to 4 (qualitatively similar results were obtained by using 32, 128 and 1024 nodes).

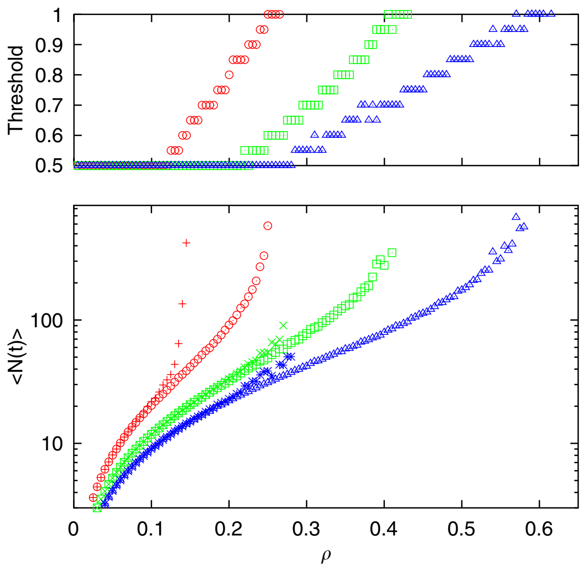

Fig. 1. Average load ($\langle N(t)\rangle$) and *threshold* value as a function of ρ. We consider a random network with 64 nodes and 2–4 links per node. Curves with symbols +, × and ∗ represent results for 2–4 links per node and *SP*. Curves with symbols ∘, □ and △ represent results for 2–4 links per node and SP_{CA}. The *threshold* can also be seen as an upper bound of the maximum congestion of the nodes.

In each simulation, we take a given network topology and increase the value of ρ (initially 0) until reaching the value such that some node becomes collapsed (i.e., until $c_i \geqslant 1$ for some i). For each value of ρ, we take a single node and randomly choose a destination node. Then, in accordance with the routing strategy, we establish a route. We note that, in order to decide if a node has collapsed or not, in the previous step we use the current node congestion. We repeat the same process for another node, until the whole set of nodes in the network (a *round*) has been covered. This process is repeated until each node has established a route with the rest of the nodes in the network. The initial value of the *threshold* is 0.5 and the increase value is 0.05 (until *threshold* reaches the value of 1).

The value of the average load of the network is evaluated, for each value of ρ, at the end of the last round. We provide average values after repeating the experiments. It must be noted that the simulations are based on calculating the betweenness centrality and then obtaining the value of the congestion of each node, rather than making nodes to inject packets into the network and measuring the congestion of each node.

Note that, in our simulations, it is always true that the value of $\langle N(t)\rangle$ is given by Eq. (3). This happens since the assumption that queues are M/M/1 always hold.

2.1. Performance evaluation

We have observed that a common feature of both *SP* and SP_{CA} (considered in isolation) is that, in the three network topologies, the value of the average network load decreases as the number of links per node increases (see Figs. 1–3). This is not surprising since increasing the number of links makes nodes in the networks more connected and hence the shortest paths are less dependent on the heavily linked nodes. Consequently, congestion on the heavily linked nodes is reduced.[1] Another common feature is that random networks are more tolerant to collapse than scale-free networks, which are also more tolerant than star-like networks [5,6].

When considering similar scenarios (i.e., the same network topologies and the same number of links per node), we found that, for small to moderate values of ρ, the two routing strategies offer almost the same performance (see Figs. 1–3). This was an expected result since both routing strategies behave in the same way when the congestion of nodes is below the threshold value (which occurs when the generation of packets is small).

[1]Whereas this result, in the case of the *SP* routing strategy, is consistent with previous results [4] (although it was restricted to a two-dimensional lattice), now we observe the same behavior for SP_{CA}.

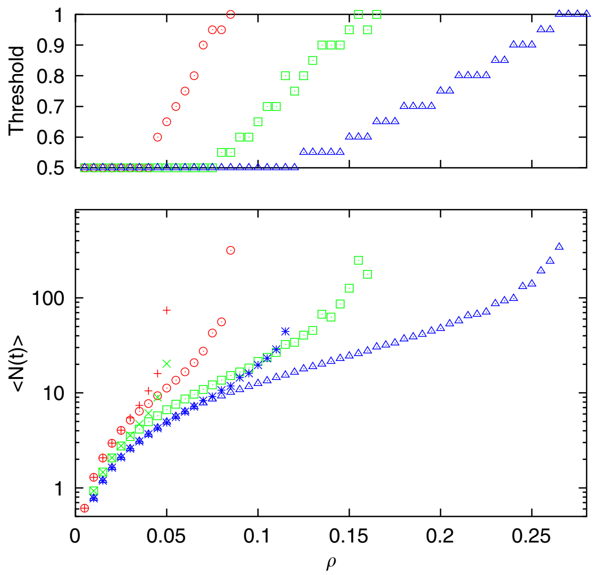

Fig. 2. Average load ($\langle N(t)\rangle$) and *threshold* value as a function of ρ. We consider a scale-free network with 64 nodes and 2–4 links per node. Curves with symbols $+$, $\times$ and $*$ represent results for 2–4 links per node and *SP*. Curves with symbols $\circ$, $\square$ and $\triangle$ represent results for 2–4 links per node and SP_{CA}.

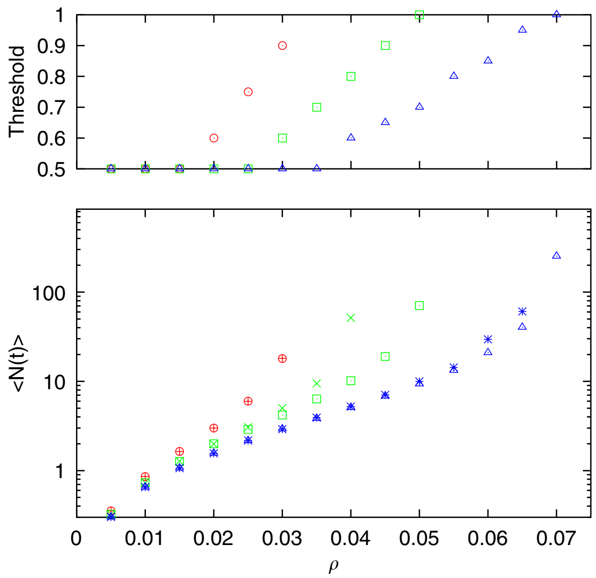

Fig. 3. Average load ($\langle N(t)\rangle$) and *threshold* value as a function of ρ. We consider a star-like network with 64 nodes and 2–4 links per node. Curves with symbols $+$, $\times$ and $*$ represent results for 2–4 links per node and *SP*. Curves with symbols $\circ$, $\square$ and $\triangle$ represent results for 2–4 links per node and SP_{CA}.

In turn, when we increased the value of ρ, we observed significant differences between *SP* and SP_{CA}.[2] Firstly, the average load is always lower when using SP_{CA} than when using *SP*. Intuitively, such differences can be explained if we take into account the fact that, in the case of SP_{CA}, routes self-adapt dynamically to

[2] Except for the case of star-like topologies where, since almost all routes had to cross, necessarily, over the central nodes, there was no possibility of significantly improving *SP* (although SP_{CA} always performed better than *SP*).

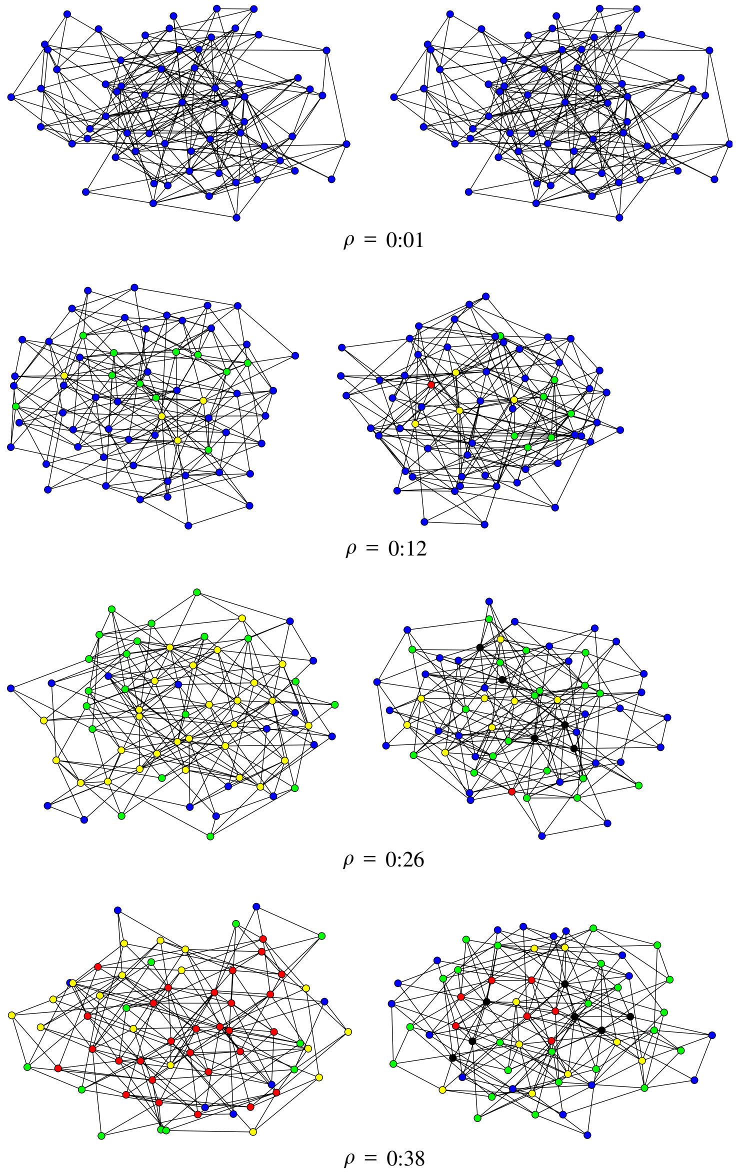

Fig. 4. Illustration of the congestion of each node for different values of ρ in a scenario formed by a random network with 64 nodes and three links per node. For each value of ρ, we show the same scenario using SP_{CA} (left) and SP (right). Blue, green, yellow, red and black represent node congestions in the intervals [0..0.25], (0.25..0.5], (0.50..0.75], (0.75..1] and above 1.

avoid congestion (by choosing less overloaded nodes), which results in a decrease in the average load of the network. Secondly, we observed drastic differences in the values of ρ at which the networks collapse. Such "collapse values" can be identified as the values of ρ at which the curves "stop" (since the average network load goes to infinity). Our experiments reveal improvements (favorable to SP_{CA}) ranging from 70% to more than 150% in the case of random and scale-free topologies.

2.2. Network dynamics

To illustrate the evolution of the network dynamics, we focus on a random topology formed by 64 nodes with three links per node.

In Fig. 4, we represent the congestion of each node for four different values of ρ, using both SP and SP_{CA}. When we consider a small value of ρ (0.01), we see that all nodes are underloaded, regardless of the routing strategy. However, when we increase the value of ρ to 0.12, whereas in the scenario using SP_{CA} all nodes have a congestion below 0.75, in the scenario using SP there is already one node with a congestion above 0.75. This becomes more apparent when we increase the value of ρ to 0.26. Indeed, whereas the scenario using SP_{CA} tolerates such an increase quite well, in the scenario using SP several nodes have already collapsed. If we increase the value of ρ further, the differences are even more notable. Using SP, about 10% of the nodes are collapsed, while 38% have a congestion below 0.25, and 65% have a congestion below 0.50. In turn, using SP_{CA}, about 50% of the nodes have a congestion above 0.75, but none has collapsed. Therefore, we conclude that the congestion distribution is, in general, more homogeneous using SP_{CA} than using SP.

2.3. Deployment of the model

As has been argued in the introduction, it should not be hard to implement our proposed routing strategy on top of SP.

The first aspect that differences SP_{CA} from SP is that, in the former, each node needs to know what the congestion of its neighbors is. However, despite using the betweenness centrality (which can only be obtained by having overall network information) to obtain a node's congestion, in a realistic case, congestion can be measured directly from the node's local state. Those local values only have to be communicated to the node's neighbors.

The second aspect is related with the increase in the *threshold* value at all nodes, and the consequent propagation to the rest of the network. Similarly, this should not be a problem either, since it can be used, for instance, as rumor-based protocol [12]. At this point, it must be noted that a similar mechanism can be used to decrease the *threshold* value. This could be interesting when the *threshold* value has remained unchanged for some time, possibly revealing a decrease in the average load of the network.

We note that some work has already been done regarding issues related to the need of having the current state of the whole network as well as to the dissemination of this information over routers in networks like the Internet. For instance, the *OSPF* protocol [13], which is perhaps the most widely used *routing information protocol* in the Internet, provides suitable solutions to the above-mentioned issues. Because *OSPF* is an open and extensible protocol, our routing strategy could be implemented on top of it.

3. Conclusions

In summary, we have provided an alternative strategy for data delivery in complex networks whose main feature is that it takes into account the congestion of nodes. Through experimental evaluation, we have shown that such a feature, although it may increase the packets' path length, it significantly reduces the average network load, as well as the collapse value. Furthermore, we have also outlined its practical implementation on top of a system using SP.

Finally, some issues are still open for future work. In this paper, we have used a fixed initial *threshold* value of 0.5 and when the network congestion (at some node) surpassed such a value, we increased it by 0.05 units. We also point out that a similar strategy could be used to decrease the *threshold* value when the network congestion decreases. However, different increasing/decreasing strategies could provide better performance. One could, for instance, use a scheme similar to the *additive increase, multiplicative decrease* (AIMD) congestion control used by the TCP/IP protocol [14], which is currently the dominant transport protocol in the Internet. Applied to our case, the increase in the *threshold* will be of α units and the decrease will be to β of the current *threshold* value, where α and β are parameters.

Acknowledgements

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References

[1] R. Albert, A.-L. Barabási, Statistical mechanics of complex networks, Rev. Mod. Phys. 74 (2002) 47–97.
[2] M.E.J. Newman, The structure and function of complex networks, SIAM Rev. 45 (2003) 167–256.
[3] R. Pastor-Satorras, A. Vespignani, Evolution and Structure of the Internet, Cambridge University Press, Cambridge, 2004.
[4] T. Ohira, R. Sawatari, Phase transition in computer network traffic model, Phys. Rev. E 58 (1) (1998) 193–195.
[5] R. Guimerà, A. Díaz-Guilera, F. Vega-Redondo, A. Cabrales, A. Arenas, Optimal network topologies for local search with congestion, Phys. Rev. Lett. 89 (2002) 248701.
[6] V. Cholvi, V. Laderas, L. López, A. Fernández, Self-adapting network topologies in congested scenarios, Phys. Rev. E 71 (3) (2005) 035103.
[7] P. Echenique, J.G. Gardenes, Y. Moreno, Improved routing strategies for internet traffic delivery, Phys. Rev. E 70 (2004) 056105.
[8] L. Freeman, Centrality in social networks: conceptual clarification, Soc. Networks 1 (1979) 215–239.
[9] O. Allen, Probability, Statistics and Queueing Theory with Computer Science Applications, Academic Press, New York, 1994.
[10] B. Bollobas, Random Graphs, Academic Press, New York, 1985.
[11] A.-L. Barabasi, R. Albert, Emergence of scaling in random networks, Science 286 (1999) 509–512.
[12] Y. Moreno, M. Nekovee, A. Pacheco, Dynamics of rumor spreading in complex network, Phys. Rev. E 69 (2004) 066130.
[13] J. Moy, RFC 2178. OSPF Version 2., 1997, <http://www.faqs.org/rfcs/rfc2178.html>.
[14] S. Floyd, K. Fall, Promoting the use of end-to-end congestion control in the Internet, IEEE/ACM Trans. Networking 7 (4) (1999) 458–472.