

Suppressing traffic-driven epidemic spreading by adaptive routing strategy

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The design of routing strategies for traffic-driven epidemic spreading has received increasing attention in recent years. In this paper, we propose an adaptive routing strategy that incorporates topological distance with local epidemic information through a tunable parameter h . In the case where the traffic is free of congestion, there exists an optimal value of routing parameter h , leading to the maximal epidemic threshold. This means that epidemic spreading can be more effectively controlled by adaptive routing, compared to that of the static shortest path routing scheme. Besides, we find that the optimal value of h can greatly relieve the traffic congestion in the case of finite node-delivering capacity. We expect our work to provide new insights into the effects of dynamic routings on traffic-driven epidemic spreading.

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I. INTRODUCTION

Epidemic spreading [1–14] and traffic dynamics [15–21] on complex networks [22–24] have attracted much attention in the past decade. For a long time, the two types of dynamical processes have been studied independently. However, epidemic spreading often depends on traffic transportation. For example, a computer virus can spread over Internet via data transmission. Another example is that air transport tremendously accelerates the propagation of infectious diseases among different countries.

The first attempt to incorporate traffic into epidemic spreading is based on metapopulation model [25]. This framework describes a set of spatially structured interacting subpopulations as a network, whose links denote the traveling path of individuals across different subpopulations. Each subpopulation consists of a large number of individuals. An infected individual can infect other individuals in the same subpopulation. The metapopulation model is often used to simulate the spread of human and animal diseases (such as SARS and H1N1) among different cities. In a recent work, Meloni *et al.* proposed another traffic-driven epidemic spreading model which can be applied to study the propagation of computer virus on the Internet [26]. In Meloni model, each node of a network represents a router on the Internet and the epidemic can spread between nodes by the transmission of packets. A susceptible node will be infected with some probability every time it receives a packet from an infected neighboring node.

Meloni model has received increasing attention in recent years [27–32]. It has been found that the routing strategy can greatly effects epidemic spreading [33, 34].

Three routing algorithms have been used in Meloni model. The first is the shortest-path routing algorithm. The second is the local routing protocol [35], in which each node does not know the whole network’s topological information and the packet is forwarded to a neighboring node i with a probability that is proportional to the power of i ’s degree. The third is the efficient routing protocol [36], in which each node in a network is assigned a weight that is proportional to the power of its degree and The efficient path between any two nodes corresponds to the route that makes the sum of the nodes’ weight (along the path) minimal.

All the above routing strategies are based on the network structure and packets follow the fixed routes for a given network. In this paper, we propose an adaptive routing strategy that integrates topological distance with local epidemic information through a tunable parameter h . In the adaptive routing strategy, a packet can timely adjust its route according to the epidemic information of its neighbors. Interestingly, we find that there exists an optimal value of h , leading to the maximal epidemic threshold.

The paper is organized as follows. In Sec. II, we formalize the problem by introducing the adaptive routing strategy into traffic-driven epidemic spreading. In Sec. III and Sec. IV, we present the results for infinite and finite node-delivering capacity respectively. Finally, we give a conclusion in Sec. V.

II. MODEL

Following the work of Meloni *et al.* [26], we incorporate the traffic dynamics into the classical susceptible-infected-susceptible model [37] of epidemic spreading as follows.

(i) *Adaptive routing protocol.* In a network of size N , at each time step, λN new packets are generated with randomly chosen sources and destinations (we call λ as

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the packet-generation rate), and each node can deliver at most C packets towards their destinations. To deliver a packet to its destination, a node performs a local search within its neighbors. If the packet's destination is found inside the searched area, it will be delivered directly to the destination. Otherwise, the packet is forwarded to a neighboring node i toward its destination j with the smallest value of effective distance, denoted by

$$d_{eff}^{ij} = h \cdot D_{ij} + (1 - h)\delta_i, \quad (1)$$

where h is the routing parameter ($0 \leq h \leq 1$), D_{ij} is the topological distance between nodes i and j , and $\delta_i = 1$ ($\delta_i = 0$) if node i is infected (uninfected) in the previous time step.

It is worth noting that when $h = 1$, the adaptive routing recovers to the traditional shortest path routing. Once a packet reaches its destination, it is removed from the system. The queue length of each node is assumed to be unlimited and the first-in-first-out principle holds for the queue.

(ii) *Epidemic dynamics.* After a transient time, the total number of delivered packets at each time will reach a steady value, then an initial fraction of nodes ρ_0 is set to be infected (e.g., we set $\rho_0 = 0.1$ in numerical experiments). The infection spreads in the network *through packet exchanges*. Each susceptible node has the probability β of being infected every time it receives a packet from an infected neighbor. The infected nodes recover at rate μ (we set $\mu = 1$ in this paper).

In the following, we carry out simulations systematically by employing traffic-driven epidemic spreading on the Barabási-Albert (BA) scale-free networks [38]. The size of the BA network is set to be $N = 2000$ and the average degree of the network is $\langle k \rangle = 4$. Each data point results from an average over 30 different realizations.

III. RESULTS FOR INFINITE NODE-DELIVERING CAPACITY

In the case where the node-delivering capacity is infinite ($C \rightarrow \infty$), traffic congestion will not occur in the network.

Previous studies have shown that there exists an epidemic threshold β_c , below which the epidemic goes extinct [26]. Figure 1 shows the dependence of β_c on h for different values of the packet-generation rate λ . We find that for each value of λ , there exists an optimal region of h (around 0.4), leading to the maximum β_c . This phenomenon indicates that the integration of topological structure and epidemic information can effectively suppress the outbreak of epidemic.

To understand the emergence of the optimal h , we study the density of infected nodes ρ_k as a function of the degree k for different values of the routing parameter h when the packet-generation rate $\lambda = 0.5$ and the spreading rate $\beta = 0.13$. From Fig. 2, one can see that ρ_k increases as k increases for each value of h , indicating

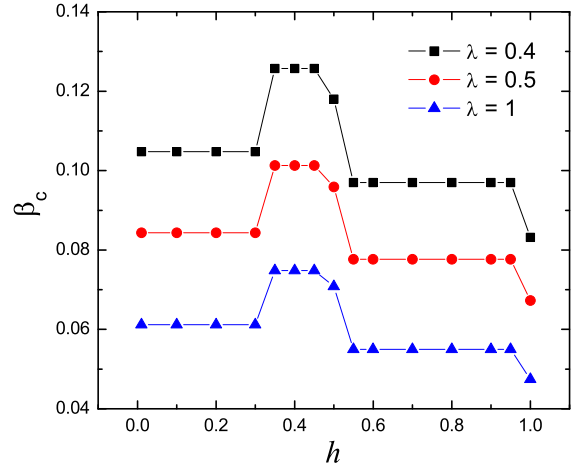


FIG. 1: (Color online) The epidemic threshold β_c as a function of the routing parameter h for different values of the packet-generation rate λ . The node-delivering capacity is infinite.

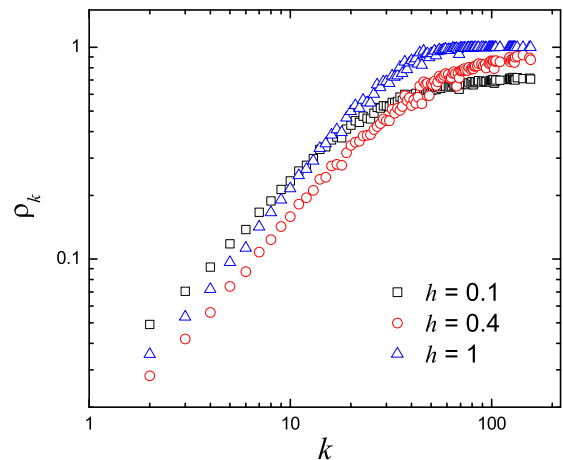


FIG. 2: (Color online) The density of infected nodes ρ_k as a function of the degree k for different values of the routing parameter h . The packet-generation rate $\lambda = 0.5$ and the spreading rate $\beta = 0.13$. The node-delivering capacity is infinite.

that larger-degree nodes are more likely to be infected. As h decreases from 1 to 0.1, the infection probability for large-degree nodes (e.g., $k > 50$) decreases while small-degree nodes (e.g., $k < 10$) are more likely to be infected.

For $h = 1$, many shortest paths go through large-degree nodes, leading to a heavy traffic load and a high infection probability for large-degree nodes. For $h < 1$,

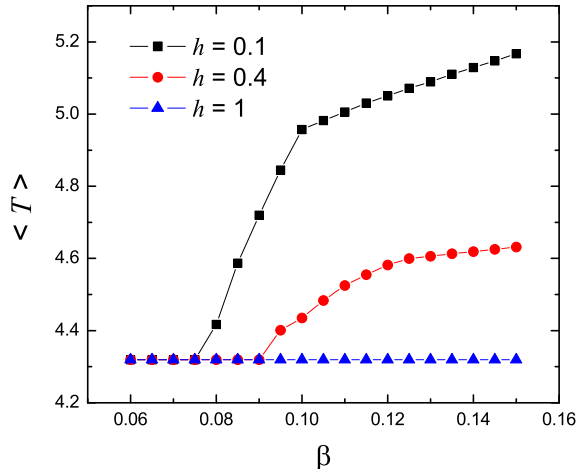


FIG. 3: (Color online) The average traveling time of a packet $\langle T \rangle$ as a function of the spreading rate β for different values of the routing parameter h . The packet-generation rate $\lambda = 0.5$. The node-delivering capacity is infinite.

packets can bypass these infected large-degree nodes, which reduces the infection probability for large-degree nodes. However, for too small value of h , small-degree become more likely to be infected since packets reroute via small-degree nodes more frequently. For the moderate value of h , epidemic can simultaneously die out in both large and small degree classes, leading to the maximal epidemic threshold.

Figure 3 shows the average traveling time of a packet $\langle T \rangle$ as a function of the spreading rate β for different values of the routing parameter h . One can see that for the shortest path routing ($h = 1$), $\langle T \rangle$ is independence of β . For $h < 1$, $\langle T \rangle$ keeps unchanged when $\beta < \beta_c$ while $\langle T \rangle$ increases with β when $\beta > \beta_c$. This is because when $\beta < \beta_c$, epidemic dies out in the network and all packets are delivered along the shortest path. When $h < 1$ and $\beta > \beta_c$, packets bypass infected large-degree nodes and reroute via small-degree nodes, leading to a longer traveling time. From Fig. 3, we can also observe that for a fixed value of β (e.g., $\beta = 0.12$), $\langle T \rangle$ increases as h decreases from 1 to 0.1.

Figure 4 shows the epidemic threshold β_c as a function of the packet-generation rate λ for different values of the routing parameter h . One can see that for each value of h , β_c scales inversely with λ , indicating that the increase of traffic flow facilitates the outbreak of epidemic. The similar result has also been found in Ref. [26].

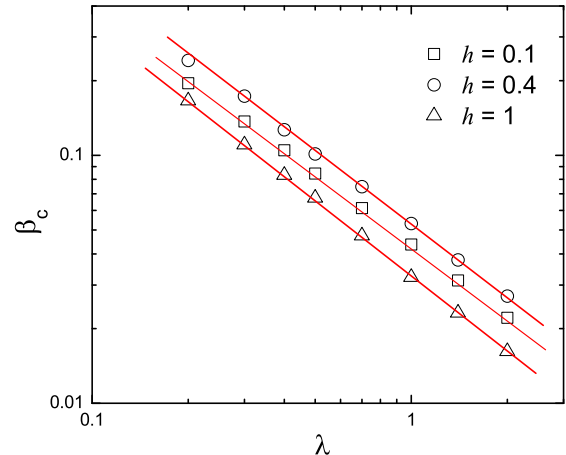


FIG. 4: (Color online) The epidemic threshold β_c as a function of the packet-generation rate λ for different values of the routing parameter h . The slopes of the fitted lines are about -1. The node-delivering capacity is infinite.

IV. RESULTS FOR FINITE NODE-DELIVERING CAPACITY

When the node-delivering capacity is finite, traffic congestion can occur if the packet-generating rate exceeds a critical value λ_c [39, 40]. The traffic throughput of a network can be characterized by the critical value λ_c .

Figure 5 shows the critical packet-generating rate λ_c as a function of the spreading rate β for different values of the routing parameter h . One can see that for $h = 1$, λ_c keeps unchanged for different values of β . For $h = 0.1$ or $h = 0.4$, there exists an optimal value of β , leading to the maximum λ_c . This non-monotonic relationship can be explained as follows. For $\beta < \beta_c$, epidemic dies out and all packets are delivered along the shortest path, leading to a heavy load on large-degree nodes. When β is a little larger than β_c , packets bypass infected large-degree nodes, which reduces the traffic load of large-degree nodes and enhances the traffic throughput of the network. However, for too large value of β , epidemic spreads so widely in the network that packets reroute many times, which increases the average traveling time of a packet and reduces the traffic throughput of the network.

Figure 6 shows the dependence of λ_c on h for different values of β . One can see that for the small value of β (e.g., $\beta = 0.1$), λ_c is independence of h since epidemic dies out and all packets are delivered along the shortest path. For $\beta = 0.2$ or $\beta = 0.4$, λ_c maximized at $h = 0.4$. Note that the optimal value of h resulting in the maximum λ_c for finite node-delivering capacity and the maximum β_c for infinite node-delivering capacity is almost the same.

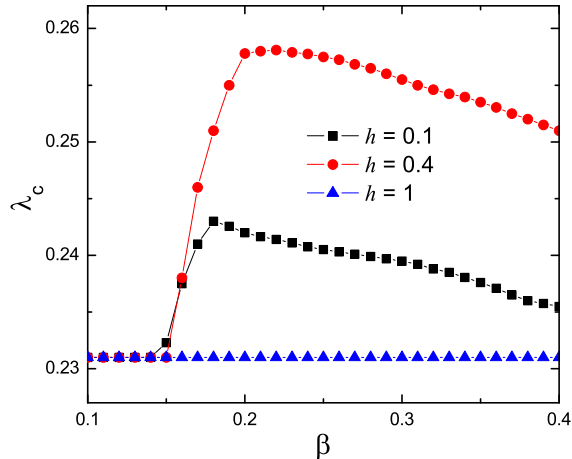


FIG. 5: (Color online) The critical packet-generating rate λ_c as a function of the spreading rate β for different values of the routing parameter h . The node-delivering capacity is $C = 100$.

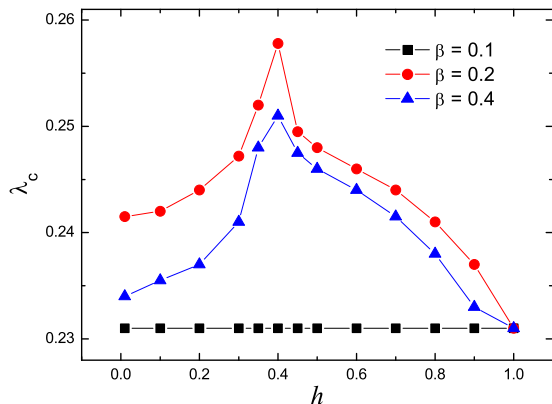


FIG. 6: (Color online) The critical packet-generating rate λ_c as a function of the routing parameter h for different values of the spreading rate β . The node-delivering capacity is $C = 100$.

Figure 7 shows the epidemic threshold β_c as a function of the routing parameter h for different values of the packet-generation rate λ when the node-delivering capacity $C = 100$. One can observe that for small values of λ (e.g., $\lambda = 0.2$), there also exists an optimal region of h (around 0.4), leading to the maximal β_c . However, when λ is large (e.g., $\lambda = 0.5$), β_c decreases with the increase of h .

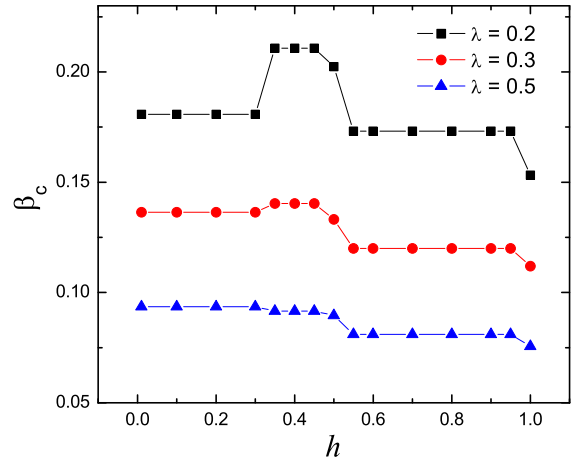


FIG. 7: (Color online) The epidemic threshold β_c as a function of the routing parameter h for different values of the packet-generation rate λ . The node-delivering capacity $C = 100$.

V. CONCLUSIONS

In conclusion, we have proposed an adaptive routing strategy which incorporates topological distance with local epidemic information through a tunable parameter h . For $h = 1$, the adaptive routing is reduced to the shortest path routing. Compared to static routings, in adaptive routing packets can change their routing paths when epidemic outbreaks.

Our main findings are as follows. (i) In the case of infinite node-delivering capacity, the epidemic threshold is maximized at about $h = 0.4$. (ii) In the case of finite node-delivering capacity, the epidemic threshold is maximized at about $h = 0.4$ when the packet-generation rate is small but the epidemic threshold decreases as h increases when the packet-generation rate is large. (iii) In the case of finite node-delivering capacity, the traffic throughput of the network is maximized at about $h = 0.4$.

It is interesting to note that in static routings such as the shortest path routing, epidemic spreading has no effect on the traffic throughput of the network. However, in adaptive routing, epidemic spreading and traffic transportation interact with each other. Through the rerouting of packets, both the infection probability and the traffic load of large-degree nodes can be reduced. Our results can provide insights into devising effective routing strategies to suppress the spreading of computer virus on the Internet.

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