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Enhancing transport efficiency by hybrid routing strategy

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Abstract – Traffic is essential for many dynamical processes on real-world networks, such as internet or urban traffic systems. The transport efficiency of the traffic system can be improved by taking full advantage of the resources in the system. In this paper, we propose a hybrid routing strategy model for network traffic system, to realize the plenary utility of the whole network. The packets are delivered according to different "efficient routing strategies" (Yan G. *et al.*, *Phys. Rev. E*, **73** (2006) 046108). We introduce the accumulating rate of packets, η, to measure the performance of traffic system in the congested phase, and propose the so-called equivalent generation rate of packet to analyze the jamming processes. From analytical and numerical results, we find that, for proper selection of strategies, the hybrid routing strategy system performs better than the single-strategy system in a broad region of strategy mixing ratio. The analytical solution to the jamming processes is verified by estimating the number of jammed nodes, which agrees well with the result from simulation.

Introduction. – Recently, the real transportation or communication systems such as computer networks [1,2], power grid [3,4], airport line [5], and so on, have attracted much attention due to the discovery of the topological features of their self-organized structures. The complex network theory [6–8], as well as the tools inherited from nonequilibrium statistical physics [9] have been successfully applied to studying the dynamical properties of these real systems. A common character for these transportation or communication systems is to perform certain functions by transporting objects among connected elements, which often take the form of large sparse networks. Free traffic flow on these networks is key to their normal and efficient functioning. However, they may actually suffer from the overload or traffic jam, which always disables the system partially for a period of time, or even be fatal to the whole system due to the consequential cascades of overload failures [10–15]. Therefore, many recent studies on traffic networks have focused on the critical properties of the jamming and congestion transitions [16–26]. Moreover, the schemes to improve the performance of traffic systems are dominantly from *two aspects*, namely, designing efficient routing strategies [27–36], or optimizing the topology of the underlying network [19,37–40]. The objectives of these schemes are, on the one hand, to avoid the onset of congestion and, on the other hand, to have short delivery times so as to enhance the throughput of the system.

The routing algorithm proposed in recent works are relied on the structural properties, as well as the global or local information about the dynamical state of the communication networks [27–36]. For example, the works of biased random walk scheme introduce that the probability to visit a node should depend on its degree [28,29], or the queue length of packets [30]. The works of the shortest-path scheme assume that the delivering paths should have minimized distance from any pair of source and destination [31]. For this scheme, the central nodes (with highest connectivity) are highly over-congested, inducing the bottleneck effect of the communication capacity for the whole system. The expended version of the shortest-path scheme with "effective distance" involving the congestion state (queue length of routers) may bypass the congested nodes locally and thus improve the performance [32]. Meanwhile, the works of efficient-path schemes [33] propose that the routing table of paths should have the minimum summary of k^{β}, with a tunable β. For the value of $\beta = 1.0$ this scheme can effectively redistribute

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the heavy load on the central nodes to some of the lower-degree nodes, and the system can reach a capacity which is more than ten times higher than that with shortest-path scheme. We can see that, for a certain amount of traffic request, the way to improve the performance of the system is to take full advantage of all kinds of nodes.

These aforementioned researches have discussed the system with a single routing strategy. However, in realistic traffic systems, the routing strategy can be diverse. Therefore, how the diversity of routing strategy performs is of high importance, yet such a diversity scheme is barely investigated in the current literature. In this way, the enhancement of transport capacity by better exertion of all nodes in the system might be expected. In this paper, we put forward a mechanism, that the communication system possesses, of two different routing strategies. Here we make use of the efficient-path schemes proposed in ref. [33], and consider the routing strategies to be denoted by different β. Then, the transport system with this multi-strategy protocol will send packets according to different fixed routing tables of efficient-path schemes. Though the fixed routing algorithm becomes less advantageous in huge communication systems, it is still widely used in medium-sized or small systems [41,42], for its obvious advantages in economical and technical costs, compared with the dynamical routing algorithm and information feedback mechanism. In this case, the diversity of the fixed routing strategy is, of course, practical if it performs better than the single-strategy scheme. Actually, through our study, this improvement by the diversified strategy is widely observed.

Traffic model. – In our traffic model of hybrid routing strategy protocol, the packets with given sources and destinations will be sent according to several different fixed routing tables of efficient-path schemes (EPS). For the EPS proposed in ref. [33], node i in the graph is weighted by $w_i = k_i^{\beta}$. k_i is the degree of node i, and β can be considered as the label of "routing strategy". A packet with source j_1 and destination j_2 will choose a route with a minimum sum of weights: $\sum_{i\in\sigma_{j_1 j_2}} k_i^{\beta}$. $\sigma_{j_1 j_2}$ is the path from j_1 to j_2. Adjusted by the parameter β, the single-strategy system will favor a certain kind of nodes in routing, and may also leave some space to improve the performance further. In our hybrid routing strategy model, taking a two-strategies system with β_1, and β_2 as an example, packets are assigned to the two corresponding routing tables, with probability $1-p$ and p, respectively. Here we name p as the *mixing rate*. For $p=0$ (or 1), the system returns to the single-strategy system with $\beta=\beta_1$ (or β_2).

Similar to the former work, at each time step, R packets enter the system with randomly chosen sources and destinations. All the nodes (routers) are assumed to have the same capabilities in delivering packets, that is, at each time step all the nodes can deliver at most C packets one step toward their destinations according to the routing tables. Here, we set delivery capacity $C=1$ for simplicity. The maximal queue length of each node is assumed to be unlimited, and the first-in-first-out (FIFO) discipline is applied at each queue. Once a packet reaches its destination, it is removed from the system.

In the previous study, the phase transition of traffic flow is described by the the order parameter [16]

$$H(R) = \lim_{t\to\infty} \frac{C}{R}\frac{\langle \Delta W\rangle}{\Delta t}, \tag{1}$$

where $\Delta W = W(t+\Delta t) - W(t)$, with $\langle \Delta W\rangle$ calculated on average over different time windows of width Δt, and $W(t)$ is the total number of packets in the network at time t. The critical value R_c (the packet generation rate) where a phase transition takes place from free flow to congested traffic, can reflect the maximum capability of a system.

The behavior of the critical point R_c on different networks can be simply explained by their different betweenness centralities (BC) distributions [31,43,44]. The BC of a node i for the single-strategy EPS system [33] is defined as

$$g_i(\beta) = \sum_{j_1\neq j_2} \frac{\sigma_{j_1 j_2}(\beta, i)}{\sigma_{j_1 j_2}(\beta)}, \tag{2}$$

where $\sigma_{j_1 j_2}(\beta)$ is the number of routes going from j_1 to j_2, according to the EPS routing table with β, while $\sigma_{j_1 j_2}(\beta, i)$ is the number of those also passing through i. The critical value R_c can be estimated by the maximal BC as in ref. [33],

$$R_c = \frac{C\cdot N\cdot (N-1)}{\mathrm{Max}[g_i(\beta)]}, \tag{3}$$

where $\mathrm{Max}[g_i(\beta)]$ is the maximal BC of the system with strategy β.

For the hybrid routing strategy system with strategies β_1, β_2, and probability p, the effective BC of one given node i is

$$G_i(\beta_1, \beta_2, p) = (1-p)\cdot g_i(\beta_1) + p\cdot g_i(\beta_2). \tag{4}$$

Then, we have the expected load of node i, assigned from the whole transport requirement of the system as

$$L_i = \frac{G_i(\beta_1, \beta_2, p)\cdot R}{N\cdot (N-1)}. \tag{5}$$

The load of a node increases as R is increased. Therefore, the critical value R_c can be estimated as

$$R_c = \frac{C\cdot N\cdot (N-1)}{\mathrm{Max}[G_i(\beta_1, \beta_2, p)]}; \tag{6}$$

here, $\mathrm{Max}[G_i(\beta_1, \beta_2, p)]$ is the maximal effective BC of the hybrid routing strategy system.

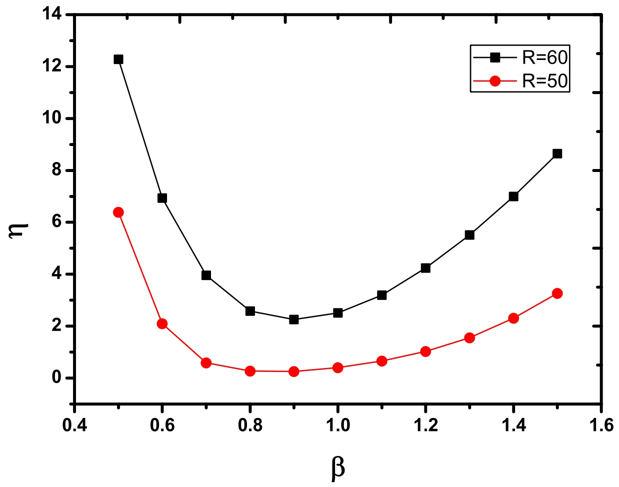

Fig. 1: (Color online) The accumulating rate η as a function of β in the single-strategy system, for the systems of $R=50$ and 60. The results are averaged over 10 realizations for each network, 20 network ensembles, with size $N=1225$.

Simulation result and analysis. – The communication networks typically show a scale-free (SF) distribution for the number of links departing from and arriving to a system element. In this paper, we choose the Barabási-Albert (BA) network as the model of the communicating network [45]. For this network model, starting from $m_0=3$ fully connected nodes, a new node with $m=2$ is added to the existing network on by one, until the network size reaches $N=1225$. The average degree of the network is $\langle k\rangle=4$.

For the single-strategy system, the phase transition from free flow to congested traffic has been discussed by Yan *et al.* [33]. When the value of R crosses R_c, the number of accumulated packets will increase with time (*i.e.*, a phase transition takes place from free flow to congested traffic). Similarly, for the multi-strategy system, the phase transition can also take place. The effect of the different strategies, in free flow phase, leads to a difference of the packet delivery time, while in the congested phase, many more abundant phenomena occur. In the following, we shall mainly focus on the congested phase as follows.

Firstly, let us revisit the behavior of the single-strategy system in the congested phase. According to the work of Yan *et al.* [33], the largest R_c (around 43), *i.e.*, the best performance of the system is achieved with strategy $\beta=1.0$ on BA network of $N=1225$ and $\langle k\rangle=4$. From systematic simulation of various β systems in the congested phase, we notice that the number of accumulated packets increases linearly with t (with small fluctuation). Namely, the accumulating rate η, defined as

$$\eta=\lim_{t\to\infty}\frac{\langle\Delta W\rangle}{\Delta t}, \tag{7}$$

is a constant on average. In fig. 1, we plot η as a function of strategy β, with R in the region of the congested phase ($R=50$ and 60, larger than R_c). It is necessary to emphasize that, although the so-called congestion occurs, there still are, on average, $R-\eta$ packets successfully delivered to their destinations per unit time. This number is actually much larger than $R-R_c$. That is to say, while some nodes are jammed when $R>R_c$, a noticeable part of the transport still functions in the system. This can be understood from two aspects: 1) the "free flow" still takes place on a large part of the system formed by the unjammed nodes; and 2) the packets through the jammed nodes are not stopped but just delayed.

We may say that the parameter R_c merely distinguishes the so-called free and congested phases, which actually indicates the free or jammed state of the most "fragile" node (see eq. (3)). R_c cannot reflect the extent of congestion, and the impact of the jammed nodes to the performance of the system. Alternatively, the accumulating rate η is a good parameter to measure the performance of the system in the congested phase. Obviously, η is the sum of individual accumulating rate η_i over the whole system as $\eta=\sum_i\eta_i$, with $\eta_i=\lim_{t\to\infty}\frac{\langle\Delta w_i\rangle}{\Delta t}$, where $\Delta w_i=w_i(t+\Delta t)-w_i(t)$, and w_i is the queue length of node i. η indicates the extent of the jamming. Small η implies that the system accumulates packets slowly, and also the number of jammed nodes is small, and the majority part of the system still have free flows. Large η indicates that the system accumulates packets fast, usually accompanied with a large number of jammed nodes which affects the delivering efficiency significantly. Therefore, η describes the performance of the jammed system, and a smaller η is desired when a congested phase is inevitable.

For the sake of the detailed description to the jamming processes, here, we introduce the *individual jammed factor* of node i denoted by η_i',

$$\eta_i'\equiv L_i-C=\frac{G_i(\beta_1\beta_2,p)\cdot R}{N\cdot(N-1)}-C \tag{8}$$

with L_i (from eq. (5)) being the expected load of node i assigned from the whole transport requirement. We may notice that as R is increased, L_i may increase over the capability C and thus η_i' increases from negative to positive. For positive η_i', it exactly equals the individual accumulating rate, *i.e.*, $\eta_i'=\eta_i$. The negative η_i' (with $L_i<C$) is also meaningful, which corresponds to the redundance of node i. Then, we have $\eta_i=\eta_i'\cdot\Theta(\eta_i')$, where $\Theta(\cdot)$ is the Heaviside function.

In fig. 1, the non-monotonic behavior of η implies that the medium β system performs better, similar to the results in ref. [33] from the relationship between R_c and β.

For the hybrid routing strategy system with β_1 and β_2 in the congested phase, the packets are assigned to the two strategies with probability $1-p$ and p, respectively. Figure 2 plots η of the system as a function of p. Here, for $p=0$ (or 1), η returns to that of the single-strategy system with $\beta=\beta_1$ (or β_2). We can see that the mix of different strategies is nontrivial and of interest. By taking

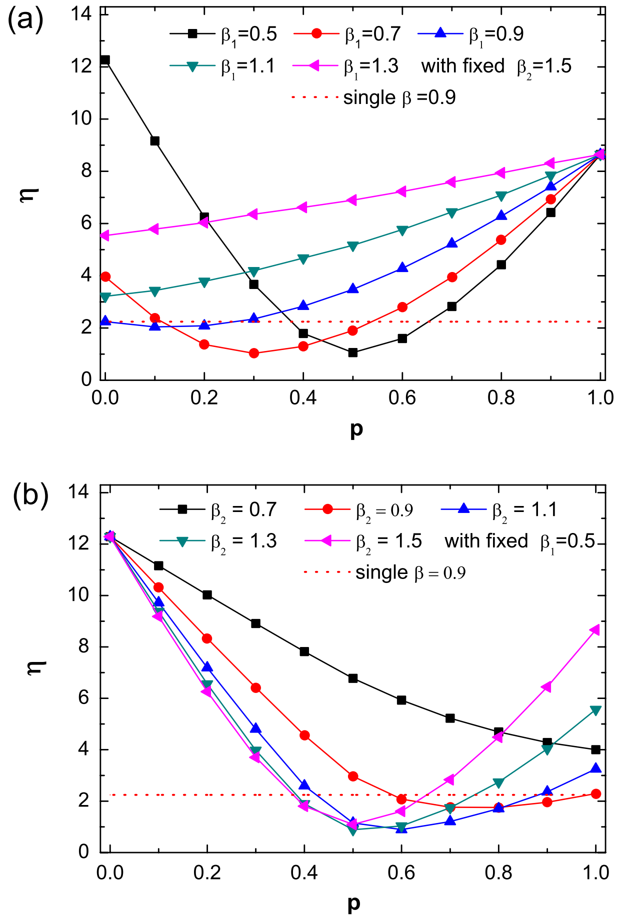

Fig. 2: (Color online) The accumulating rate η for the hybrid routing strategy system as a function of mixing ratio p of the two strategies β_1 and β_2. Here, in (a), β_2 is fixed to be 1.5, and in (b), β_1 is fixed to be 0.5. The η of the single-strategy system with optimal $\beta = 0.9$ (the red dotted line) is also plotted for comparison. The results shown are averaged over 10 realizations for 20 networks, with size $N = 1225$, and $R = 60$.

the system with $\beta_1 = 0.5$ and $\beta_2 = 1.5$ in fig. 2(a) as an example, for a certain medium value of p, it performs even better than the optimal state that the single-strategy system can achieve with $\beta = 0.9$ (which is also plotted by the red dotted line in fig. 2). Furthermore, as has been shown in fig. 2, it is also noteworthy that, when β_1 and β_2 are chosen from each side of 0.9, there always exists an optimal configuration p, which performs better than both the single-strategy systems of β_1 and β_2.

This can be understood as follows. To design routing strategy for the network transportation, there are two factors that should be considered. 1) To bypass the hub nodes which are obviously of heavy burden and prone to jamming. 2) To choose shorter path to reduce the delivery time, which helps to cat down the occupation (life time) of packets travelling in the system and thus avoiding jam. The system's delivery efficiency can be improved from the tradeoff of these two factors. However, they are inconsistent in the communicating network with heterogeneous topology. By taking the single-strategy system in the congested phase as an example (see fig. 1, the curve with $R = 60$), as β is increased from 0, the traffic through the hub nodes is bypassed to the smaller-degree nodes. The length of the paths adopted by the packets are then elongated, which increases the probability of jamming for the small-degree nodes. The system with β_0 around 0.9, to a certain extent, balances these two factors, achieving the optimal performance.

As β is increased further, the utility of the hubs is not fully employed, while the remaining parts of the system are overloaded. Actually, taking a full advantage of each node in the system will lead to better performance. Therefore, for the hybrid routing strategy system, the strategy favoring to the hubs ($\beta < \beta_0$) and that favoring to the small nodes ($\beta > \beta_0$) may complement each other and perform better than the single-strategy one. Thus, non-monotonous η can be observed when the β's from both sides of β_0 are mixed.

The effect of multiple strategies in the congested phase can also be understood analytically from the so-called *equivalent generation rate*. In this routing strategy, packets at the head of the queue on node i will be delivered to the next node j according to the routing table, no matter if node j is idle or jammed. Current servers also have this properties. In this case, congestion in the system will not spread out. Furthermore, counterintuitively, congestion will make the system more "empty". In each time step, η more packets will queue at the jammed nodes, and as a consequence, the load of the other nodes will be mitigated slightly, as if the generation rate for the *subsystem* of these remaining nodes is reduced to a smaller one R^*, which we name as the *equivalent generation rate*. Here, we have

$$R^* = R - \eta. \tag{9}$$

Different from the case that the servers discard packets when the queue length is over a threshold, in our model, the queuing packets are not abandoned, and will finally be delivered to their destination.

We sort nodes by the values of their individual jammed factor in descending order, as $\eta'_1 > \eta'_2 > \ldots > \eta'_N$. From eq. (8), we know that, when R is increased from 0, all these η'_i increases from $-C$. As soon as the maximum one, η'_1, increases from negative to positive, the system transforms from free phase to congested phase. Suppose that $\eta'_2 < 0$, there are η'_1 packets detained at the 1st node for each time step. Then, the equivalent generation rate for the subsystem (excluding the 1st node) is $R^* = R - \eta'_1$. As R is increased further, the remaining nodes will be jammed one after another (*i.e.*, have positive η'_i). Accordingly, we may propose the *theory* to predict the number of jammed nodes, and the accumulating rate of the system η from two perspectives.

On the one hand, from eqs. (8) and (9), we get

$$R^* = R - \sum_{i=1}^{I} \left[\frac{G_i(\beta_1, \beta_2, p) \cdot R^*}{N \cdot (N-1)} - C \right] \tag{10}$$

with the following constraint applying:

$$L_I = \frac{G_I(\beta_1, \beta_2, p) \cdot R^*}{N \cdot (N-1)} > C, \tag{11}$$

$$L_{I+1} = \frac{G_{I+1}(\beta_1, \beta_2, p) \cdot R^*}{N \cdot (N-1)} < C. \tag{12}$$

By solving these equations, we can get the number of jammed nodes I and η, for given parameter values of R, β_1, β_2 and p.

On the other hand, we can focus on the detailed process of successional jamming which gradually modifies the equivalent generation rate R^*, as well as the load L_i of the remaining nodes. The iterative procedure of R^* can be written as

$$\begin{aligned} R_1^* &= R - \frac{G_1(\beta_1, \beta_2, p) \cdot R}{N \cdot (N-1)} + C, \\ R_2^* &= R_1^* - \frac{G_2(\beta_1, \beta_2, p) \cdot R_1^*}{N \cdot (N-1)} + C, \\ &\dots . \end{aligned} \tag{13}$$

The iterative formula is

$$R_i^* = R_{i-1}^* - \frac{G_i(\beta_1, \beta_2, p) \cdot R_{i-1}^*}{N \cdot (N-1)} + C \qquad (i = 1, 2, 3, \dots). \tag{14}$$

R_i^* and L_i' decrease as the nodes of large load are jammed one after another, until

$$L_I' = \frac{G_I(\beta_1, \beta_2, p) \cdot R_{I-1}^*}{N \cdot (N-1)} > C, \tag{15}$$

$$L_{I+1}' = \frac{G_{I+1}(\beta_1, \beta_2, p) \cdot R_I^*}{N \cdot (N-1)} < C, \tag{16}$$

Different from eqs. (10) to (12), eqs. (14) to (16) depicts that the jamming of the first I nodes steps down R^* gradually until the value R_I^*, where the $(I+1)$-th node, as well as all its following nodes, is capable of dealing with its load. Here, from the perspective of the successional jamming process described by eq. (14), one can also get the number of jammed nodes I, and η, analytically.

In fig. 3, we plot the analytical and simulation results of the number of jammed nodes I in the hybrid routing strategy system with $\beta_1 = 1.5$ and $\beta_2 = 0.5$. It can be seen that the average number of jammed nodes from analysis (red solid circle) coincides well with that from simulation (black solid square). Interestingly, the value of I also behaves non-monotonically and achieves the minimum around $p = 0.5$, which is similar to the accumulating rate η of the same system shown in fig. 2. Additionally, the analytical results from eq. (10) and eq. (14) are very close to each other, thus in fig. 3 we just plot the results from eq. (14).

Here, we can also understand the non-monotonic behavior of I from the following perspectives. The packet generation rate R can be divided into two parts, the packets using routing table of β_1 is $R^{\beta_1} = (1-p)R$, and that of β_2 is $R^{\beta_2} = pR$. From eq. (5), we can get the corresponding loads of node i from these two parts of packets, denoted by $L_i^{\beta_1}$ and $L_i^{\beta_2}$ (with $L_i = L_i^{\beta_1} + L_i^{\beta_2}$). For the case that the mixing rate $p = 0$, we have $R^{\beta_1} = R$, and the jamming of nodes are all ascribed to the queue of β_1 packets. As p is increased from 0, the R^{β_1}, as well as the $L_i^{\beta_1}$ decreases, while that of β_2 increases. If the β_2 packets prefer to use those *complementary nodes* instead of the nodes already jammed by β_2 packets, the number of jammed nodes I will decrease with p. However, as p is large enough, the increase of load $L_i^{\beta_2}$ from β_2 packets induces new jamming of other nodes. Therefore, we can see the non-monotonic behavior of the number of jammed node, when the hybrid routing strategy system is composed of the two strategies from either side of β_0.

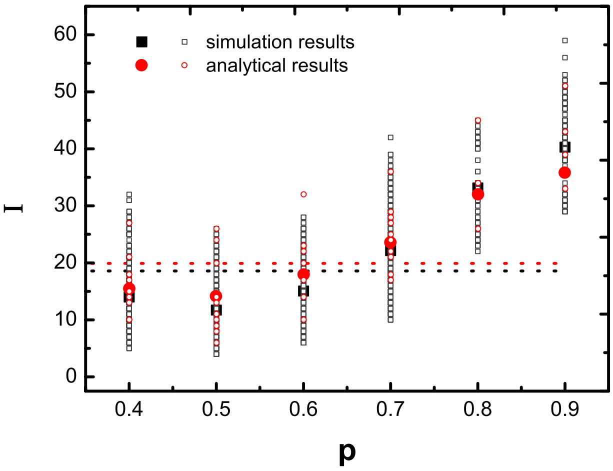

Fig. 3: (Color online) The number of jammed nodes from analytical and simulation results, for the hybrid routing strategy system with $\beta_1 = 1.5, \beta_2 = 0.5$. The sample data of analytical results (red open circle) are from 10 different networks, and that of simulation results (black open square) are from 50 realizations of traffic on these 10 networks. The average number of analytical and simulation results (red solid circle and black solid square) are averaged over the corresponding sample data. The system parameters are $N = 1225$, and $R = 60$. The analytical and simulation results (the red and black dotted lines) from single-strategy system with $\beta = 0.9$ are also plotted for comparison.

Conclusion. – In summary, we propose a hybrid routing strategy for the networked traffic system, which is proved to be a doable and effective way to enhance transport efficiency. Compared with the efficient routing strategy [33], the hybrid routing strategy can make better use of the resources in the traffic system, while there appears no increase in its algorithmic complexity. The performance of the hybrid routing strategy system can be optimized by modulating the mixing rate of the packets, in case that the two strategies share fewer key nodes. Here, we introduce the accumulating rate η to denote the performance of the communication system in the congestion phase, which shows richer phenomena than the critical generation rate R_c. Furthermore, we get analytical descriptions to the jamming processes by the accumulating rate η and the equivalent generation rate R^*. The number of jammed nodes estimated from analytical formula coincides well with that from simulations.

While our model is based on computer networks, we expect it to be relevant to many other practical transport processes in general. Actually, in realistic systems, the hybrid routing is worthy of considering, for the reason that the sources and characters of massages delivering or spreading in complex systems are diversified, which induces the hybridization of various transportation modes. In view of the common features for the networked traffic and spreading, our work may shed light on the research of packet delivery in technical networks, as well as the rumor and opinion dynamics in social networks.

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