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Effective Gravitation Path Routing Strategy on Scale-Free Networks

JINLONG MA, JUNFENG ZHANG, AND YONGQIANG ZHANG
School of Information Science and Engineering, Hebei University of Science and Technology, Shijiazhuang 050018, China

Corresponding author: Yongqiang Zhang (fuctj@qq.com)

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ABSTRACT Information routing strategy is a hot issue in the study of complex network traffic dynamics. In this paper, we define a new gravitational centrality and introduce parameter α_1 to control the centrality of nodes. When α_1 is appropriate value, the gravitational centrality has the function of dividing the centrality of the same degree nodes. According to the gravitational centrality, we propose an effective gravitation path routing strategy in which the optimal paths between all pairs of nodes are chosen according to a cost function that incorporates gravitational centrality of nodes in paths. The purpose of this strategy is to improve network traffic capacity. The simulation results on the scale-free networks show that our routing strategy is more effective than the efficient routing strategy proposed by Yan *et al.* [Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top. 73, 046108 (2006)].

INDEX TERMS Complex networks, scale-free networks, congestion, traffic capacity.

I. INTRODUCTION

In many interconnected networks, such as the Internet, transportation networks, power networks, communication networks and so on, have been well studied in the past few decades [1]–[3]. In these actual networks, packets overload is the main reason for congestion. Large number of packets can be transmitted in time, which has a positive effect on user experience. An important topic related to these networks is how to improve traffic capacity and avoid traffic congestion by optimizing network structure [4]–[7], designing routing strategy [8]–[12] and allocating resource reasonably [13]–[18]. Most of the existing studies on the optimization of the structure are focused on deleting, adding, making certain links unidirectional and rewiring certain links [19]–[24]. The main method of resource allocation is how to effectively allocate node delivery capabilities [25], [26]. In addition, there are also some other types of resource allocation methods. Such as, in order to solve the problem of 5G optical network and data center network are often sudden traffic congestion and performance degradation, Yu *et al.* proposed to improve the scheduling efficiency of burst traffic method which is the burst traffic scheduling for hybrid E/O switching DCN: an error feedback spiking neural network approach [27], and Yao *et al.* proposed a core and spectrum allocation algorithm based on association rules which can effectively make improvement on the blocking and resource utilization [28]. Optimizing network structure and allocating resource require a higher economic and labor cost. The industry declares the optical network and data center network in 5G can use better routing strategy to avoid congestion. This is because that the routing strategy is a technology that modifies routing information to change the path through which network traffic passes, and only needs to modify the routing algorithm through software, which is relatively easy to implement, and economic and manpower cost are relatively low. By far, many scholars have done a lot of researches on routing strategy.

Under the shortest path (SP) routing strategy [29], [30], large number of packets usually accumulate on the core nodes of a network. In the above case, some packets cannot reach the destination in time, which leads to congestion. Yan *et al.* proposed an efficient routing (ER) strategy which made the packets bypass the larger degree nodes, so that the packets were more evenly distributed in the network [31]. Danila *et al.* presented an heuristic algorithm for the optimization of

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transport on complex networks, their algorithm balanced traffic on a network by minimizing the maximum node betweenness with as little path lengthening as possible as [32]. Wu *et al.* studied the information packet routing process in scale-free network by mimicking Internet traffic delivery and, incorporated both the global shortest paths information and local degree information of the network in the dynamic process, via two tunable parameters, α and β, to guide the packet routing [33]. Beacuse betweenness centrality can more accurately reflect the traffic load situation of the network, Jiang and Liang proposed an improved efficient routing strategy based on the betweenness centrality to enhance the network traffic capacity [34]. Jiang and Liang decomposed the routing process into N (the network size) steps and, at each step, computed all paths or calculated the spanning tree for one source node by considering dynamic betweenness centrality and degree information, while propose the incremental routing (IR) strategy [35]. Li *et al.* used punishment selection method to bypass the nodes with larger betweenness centrality, so that the betweenness centrality of the network are more evenly distributed, and the traffic load of each node in the network is balanced [36]. Liu *et al.* presented a simple dynamic routing strategy that allowed each vehicle to dynamically choose the path to its destination while imposing the minimum travel time, it balances traffic load distribution [37]. Considering the different node delivery capability, Shao and Cheng proposed two novel routing strategies which specified the shortest path according to three kinds of different node delivery capability schemes to enhance the network transfer capacity in weighted networks [38]. For scale-free network, Gao *et al.* proposed a global hybrid routing strategy integrated the dynamic queue length information and the static degree information which achieved higher traffic capacity and shorter average packets travel time compared with the state-of-the-art global dynamic routing strategy and ER strategy [39].

Considering that the different centralities of the same degree nodes on the overall network may be led to not completely homogeneous of the traffic load distribution on the network. In this paper, we explore the different centralities of the same degree nodes and propose a new routing strategy. We test our strategy on scale-free networks. According to the simulation results, our strategy outperforms ER strategy in terms of traffic capacity and the average packet travel time.

The remainder of this paper is organized as follows: Section II describes the related models and concepts. Models included the network model and traffic model are used for experimental simulations. Concepts included gravitational centrality and routing strategy are defined. In addition, some performance parameters used to evaluate the performance of our routing strategy also be introduced. Section III introduces and discusses the experimental results of our strategy and ER strategy on scale-free networks. Finally, we conclude our work in Section IV.

II. THE MODEL AND DEFINITIONS

A. THE NETWORK MODEL

As most of large communication networks are scale-free properties [40], we will employ the famous Barabási-Albert model [41] to generate the underlying networks. This model is defined with three steps:

1) Initial network: there are m_0 nodes in an fully connected state.

2) Growth network: at each time step, a new node with $m(m \leq m_0)$ number of edges joins the network.

3) Connection rule: the probability of each new node connecting to the existing node v_i is proportional to node v_i degree:

$$P(v_i) = \frac{k_{v_i}}{\sum_{v_j} k_{v_j}} \tag{1}$$

where k_{v_i} is the degree of node v_i, and $\sum_{v_j} k_{v_j}$ is the sum of the degree of all nodes in the network. The size of the network is N with adding $N - m_0$ nodes to the network, the degree distribution of the network follows a power law which is $p(k_{v_i}) \approx k_{v_i}^{-3}$. Average degree is $\langle k \rangle = 2m$.

B. TRAFFIC MODEL

The traffic model is used to describe the transmission behavior of packets, and can also show the relationship between traffic capacity and network state [29]. The model is introduced as follows:

1) Setting about node: each node has the function of producing and delivering packets. The queue length of each node is assumed to be unlimited. The first in first out (FIFO) discipline is employed at the queue of each node.

2) Packet generation: at each time step, R packets are generated in the network, the source and destination of each packet are random determined.

3) Packet transmission: if the current node where a packet arrives is not the destination, the packet will be delivered to a neighboring node according to some routing strategy used. All nodes in the network have the same delivering capability C.

4) Packet reception: the node delivers C packets generated form other nodes and the cache queue of the node save the undelivered packets which are handled at the next time step. If the packet reaches the destination, it is removed from the network immediately.

C. GRAVITATIONAL CENTRALITY

The law of universal gravitation discovered by Newton in 1687 is a law of interaction between objects [42]. There is mutual attraction between any objects. The magnitude of this force is proportional to the mass of each object and inversely proportional to the square of the distance between them. If m_1 and m_2 are used to represent the masses of two objects, and r is the distance between them, the mutual attraction between objects is $f = G * m_1 m_2 / r^2$, G is called the gravitational constant.

Considering that the node degree characterized the network local structure cannot completely describe the overall structure of the network, so the same degree nodes may have different centralities, it is flawed to simply use the node degree as an evaluation index of node centrality. We define gravitation between nodes based on the law of universal gravitation. Mean value of gravitation of the node to each node (including node itself) is defined as the node centrality which named as gravitational centrality (GC). GC is comprehensively integrated the local (degree) and overall (path) structure of the network. Some nodes which are the same degree centrality may have different centralities under the GC. The relevant definition is as follows:

$$f_{v_iv_j} = G\frac{k_{v_i}k_{v_j}}{(r_{v_iv_j})^{\alpha_1}}, G\epsilon R \tag{2}$$

$$r_{v_iv_j} = \frac{p^l_{v_iv_j}}{l!} + \sum_{k>l}\frac{w^k_{v_iv_j}}{k!} \tag{3}$$

$$GC_{v_i} = \frac{1}{N}\sum_{j=1}^{N} f_{v_iv_j} \tag{4}$$

where $f_{v_iv_j}$ represents the gravitation between node v_i and node v_j when $v_i \neq v_j$. $f_{v_iv_j}$ represents the self-gravitation of node v_i when $v_i = v_j$. G is the gravitation constant, but it can be any constant in GC. k_{v_i} represents the degree of node v_i. α_1 represents the control parameter of gravitational centrality. $p^l_{v_iv_j}$ is the number of shortest paths between nodes v_i and v_j of length l, and $w^k_{v_iv_j}$ is the number of steps connecting v_i and v_j of length k. The path $r_{v_iv_j}$ not only represents a single path connecting two nodes, but also needs to consider all paths through the node v_j to the target node v_i. Since some of these detours can be very long, the totals are weighted in descending order of path length. GC_{v_i} represents the centrality of nodes v_i.

In order to easily calculate $r_{v_iv_j}$, we make $l = 0$ and $k = \infty$, so, equation (3) becomes as equation (5). Equation (5) is as follows:

$$r_{v_iv_j} = (\sum_{l=0}^{\infty}\frac{1}{l!}A^l)_{v_iv_j} \tag{5}$$

Figure 2 shows the comparison the node GC of different parameters α_1 with node degree centrality under the example network shown in Figure 1. When $\alpha_1 = 0$, we can find that the node GC distribution trend is completely equivalent to the node degree centrality distribution trend. When α_1 is a small value, the node GC distribution trend is similar to the node degree centrality distribution trend, but the nodes with same degree centrality may have different GCs. From the GC perspective, GC can distinguish different centralities in these nodes. As the α_1 value becomes more larger, the difference between the GC distribution trend and the node degree centrality distribution trend is getting bigger and bigger. At the same time, the overall trend of GC distribution is severely disrupted. When the overall trend of GC distribution is extremely different from the overall trend of node degree centrality distribution, it is no longer just distinguish GC of nodes with the same degree centrality.

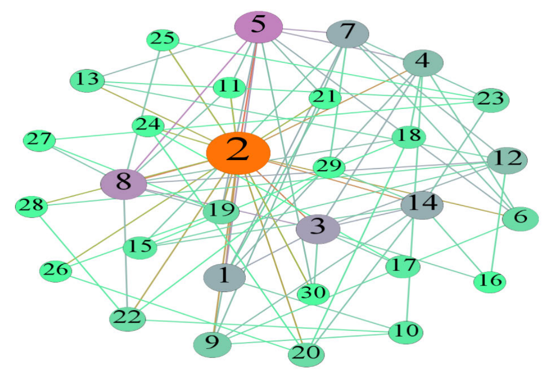

FIGURE 1. Example network.

Table 1 shows the difference between GC and degree centrality in the example network when $\alpha_1 = 0.1$ (α_1 can be adjusted according to the strategy) and the constant $G = 10$. From the perspective of degree centrality, nodes v_{24}, v_{25}, v_{26}, v_{27}, v_{28}, v_{29}, v_{30} have the same degree centrality, which means that they have the same importance. From the perspective of GC, the nodes v_{24}, v_{25}, v_{26}, v_{27}, v_{28}, v_{29}, v_{30} have different GCs, which means that they have different importance.

TABLE 1. The GC of part nodes with same degree in example network.

node number	degree centrality	GC
24	3	122.12
25	3	119.93
26	3	120.98
27	3	125.21
28	3	120.95
29	3	125.46
30	3	117.23

D. ROUTING STRATEGY

A large number of packets accumulate in the central nodes, which will lead to a longer waiting time for packets in the network, so congestion will easily occur. The ER strategy constructs a cost function according to the node degree to make packets avoid the core nodes of the network reasonably during the transmission process, the traffic load of core nodes with larger degree is distributed to other non-core nodes, which is good for improving network traffic capability. If there are some nodes with the same degree have different influences (centralities) in the entire network, network traffic capacity will be affected. Therefore, we are inspired by ER strategy to study a new effective path based on GC and propose a new strategy called effective gravitation path routing (EGPR) strategy which can make the packets more reasonably through transmission path. Under EGPR strategy, $P(v_i \rightarrow v_j) := v_i \equiv x_0, x_1, x_2, \cdots, x_{n-1}, x_n \equiv v_j$, that is the sequence of nodes from the source to the destination, represents the effective path between any two nodes. The cost

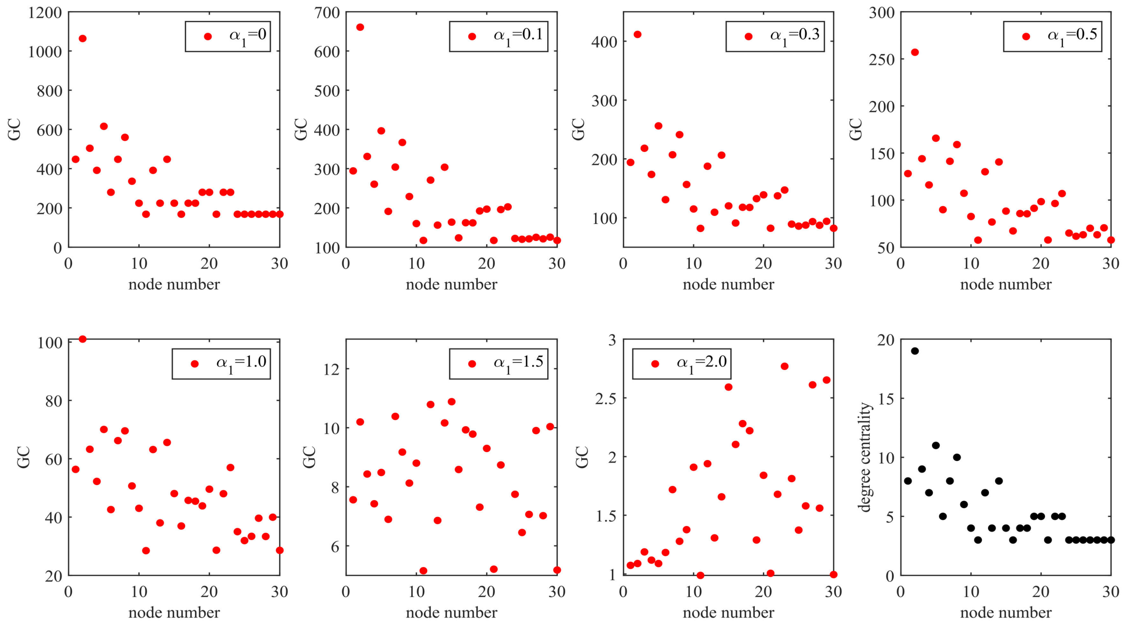

FIGURE 2. In example network, comparison of node GC distribution under different control parameters α_1 and distribution of node degree centrality.

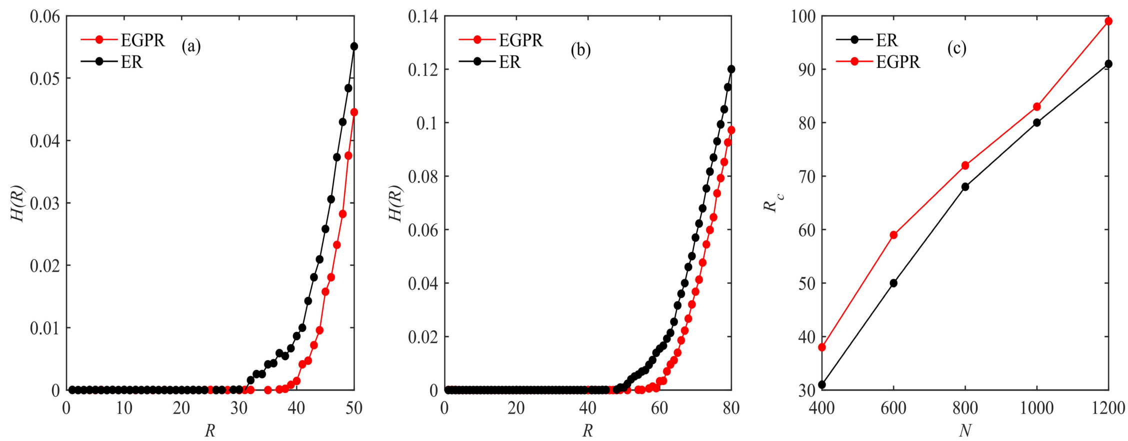

FIGURE 3. (a) The relationship between the order parameter $H(R)$ and the packet generation rate R in network size $N = 400$ under EGPR and ER strategies. (b) The relationship between the order parameter $H(R)$ and the packet generation rate R in network size $N = 600$ under EGPR and ER strategies. (c) The relationship between traffic capacity R_c and network size N under EGPR and ER strategies. Network average degree $\langle k \rangle = 6$ and node delivering capacity $C = 1$ with EGPR and ER strategies.

function of effective path is as follows:

$$L\left(P(v_i \to v_j) : \alpha_2\right) = \sum_{i=0}^{n-1} \left(GC_{x_i}\right)^{\alpha_2} \tag{6}$$

where a_2 is the control parameter, n represents the effective path length. we select the optimal effective path that has the smallest cost as the transmission path of packets. If the cost function values of the two paths are equal, one is selected randomly. When α_2=0, EGPR strategy equivalent to SP routing strategy. In EGPR strategy, α_2 takes the optimal control parameter value.

E. PERFORMANCE PARAMETER

1) THRESHOLD OF PACKET GENERATION RATE

To explore the traffic behavior on the networks, the order parameter $H(R)$ is employed to describe the transition of traffic flow [29]:

$$H(R) = \lim_{t\to\infty} \frac{C}{R} \frac{\langle \Delta W \rangle}{\Delta t} \tag{7}$$

where C is the delivering capability of each node, R is the packet generating rate, $\langle \Delta W \rangle = W(t + \Delta t) - W(t)$, $\langle \cdots \rangle$ denotes the average over the time windows of width Δt, $W(t)$ is denoted as the number of packets in the network at

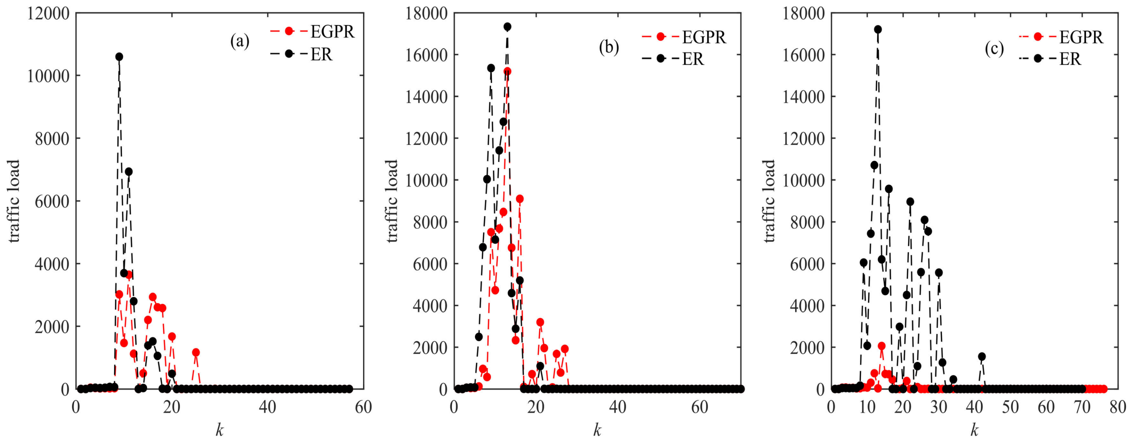

FIGURE 4. **(a) Network size $N = 400$. (b) Network size $N = 600$. (c) Network size $N = 800$. Under ER and EGPR strategies, the distribution of the traffic load versus the node degree k in the different congested networks.**

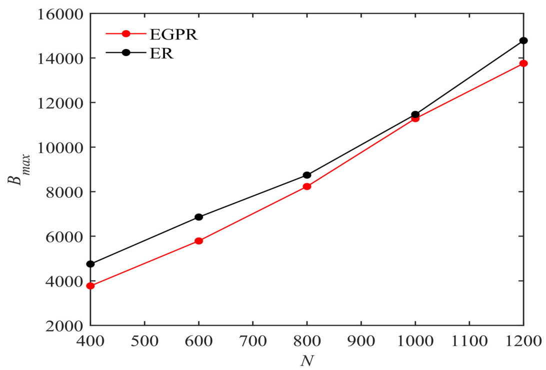

FIGURE 5. **Under EGPR and ER strategies, the relationship between the maximum node betweenness B_{max} and network size N.**

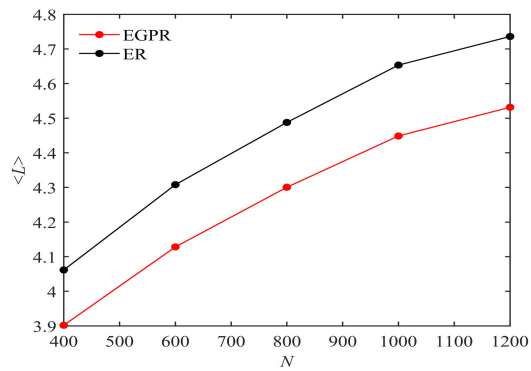

FIGURE 6. **Under EGPR and ER strategies, the relationship between the average path length $\langle L \rangle$ and network size N.**

time t. There exists a critical packet generation rate R_c at which the network undergoes a phase transition from free flow ($H = 0$) to congested phase ($H > 0$). When $R < R_c$, the number of created packets and the removed packets are in balanced state, which means that no congestion occurs. When $R > R_c$, the packets in the network accumulate continuously, which leads to network congestion because of the limited delivering capacity of each node.

2) THE NODE BETWEENNESS

The node betweenness can be used to theoretically evaluate the traffic capacity of a network [43]. If the network generates R packets at each time step, the number of packets arriving at node v_i is:

$$n_{v_i} = \frac{RB_{v_i}}{N(N-1)} \tag{8}$$

where N is the size of the network, and B_{v_i} is the betweenness of node v_i. In order to avoid network congestion, it is necessary to ensure that all nodes in the network cannot accumulate packets. Each node needs to meet the following conditions:

$$n_{v_i} \leq C_{v_i} \tag{9}$$

where C_{v_i} represents the delivering capacity of node v_i. If the delivering capacity of each node is C, then the formula are organized as follows:

$$R \leq \frac{CN(N-1))}{B_{v_i}} \tag{10}$$

from above formula, it can be known that R and B_{v_i} are inversely proportional, and the maximum node betweenness in the network becomes the restriction point of R, so the critical R_c for the packet generation rate can be expressed as follows:

$$R_c = \frac{CN(N-1))}{B_{max}} \tag{11}$$

Therefore, the traffic capacity can be calculated by observing the maximum node betweenness in the network, and the change of the network traffic capacity can be calculated by observing the fluctuation of the maximum node betweenness in the network.

3) AVERAGE PACKET TRAVEL TIME

In order to better describe network traffic performance, the average packet travel time $\langle T \rangle$ usually be used to measure

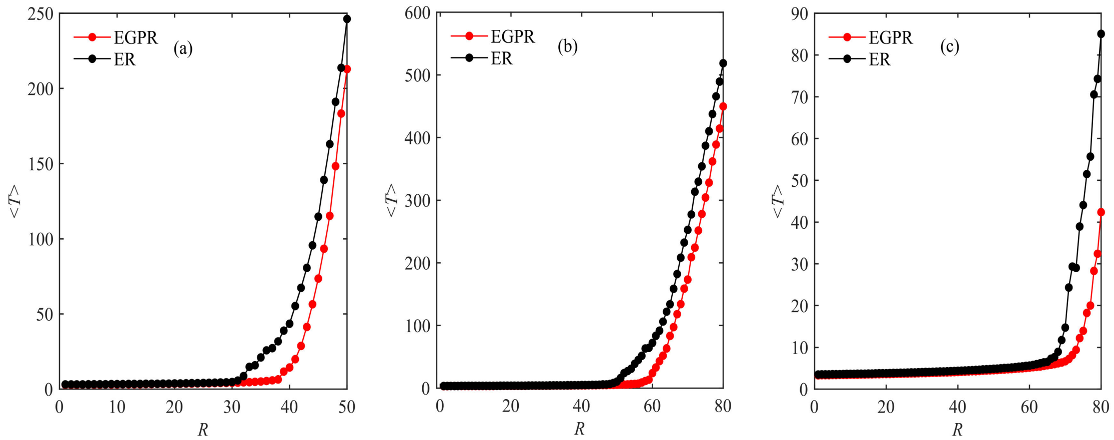

FIGURE 7. (a) Network size $N = 400$ (b) Network size $N = 600$. (c) Network size $N = 800$. Under ER and EGPR Strategies, the relationship between the average packet travel time $\langle T \rangle$ and the packet generation rate R in congested network.

the traffic performance of the network. The average packet travel time $\langle T \rangle$ is defined as follows:

$$\langle T \rangle = \lim_{t \to \infty} \frac{1}{n} \sum_{x_i=1}^{n} T_{x_i} \tag{12}$$

where n represents the number of packets arriving at the destinations within a fixed time, and T_{x_i} is the travel time of packet x_i, which includes the travel time in the network and the waiting time at the nodes.

4) AVERAGE PATH LENGTH

The average path length can be used to evaluate the traffic performance of the network. The average path length represents the average number of hops experienced from a certain source to destination. It is defined as:

$$\langle L \rangle = \frac{\sum_{v_i=1, v_j=1, v_i \neq v_j}^{N} L_{v_i v_j}}{N(N-1)} \tag{13}$$

where $L_{v_i v_j}$ represents the number of hops from node v_i to node v_j. $\langle L \rangle$ can reflect the efficiency of packet traffic in the network. When the congestion does not occur, the smaller average path length indicates that the relative distance between any two nodes in the network is closer and the packet reaches the destination faster.

III. SIMULATION RESULTS

In this section, the performance of the EGPR strategy and ER strategy are compared. Taking into account the characteristics of most actual networks, here we set $m_0 = 4$ and $m = 3$ in the Barabási-Albert model [41] to generate the scale-free networks of different network size N (N ranges from 400 to 1200 and the average degree $\langle k \rangle = 6$) for simulations. Each simulation result is the average value of more than 20 independent networks. In order to improve the accuracy, the running time steps for each packet generation rate is $10,000$ in our simulations.

The relationship between the order parameter $H(R)$ and the packet generation rate R is shown in Figure 3. When $N = 400$, $R_c = 31$ under the ER strategy, while $R_c = 38$ under the EGPR strategy. When $N = 600$, $R_c = 50$ under the ER strategy, while $R_c = 59$ under the EGPR strategy. When $N = 800$, $R_c = 68$ under the ER strategy, while $R_c = 72$ under the EGPR strategy. When $N = 1000$, $R_c = 80$ under the ER strategy, while $R_c = 83$ under the EGPR strategy. When $N = 1200$, $R_c = 91$ under the ER strategy, while $R_c = 99$ under the EGPR strategy. As the network size changes, it can be clearly found that the EGPR strategy has obvious advantages.

In order to illustrate the degree of the complexity of the routing strategy in the network, the traffic load distribution in the network is studied when the network is congested. By observing Figure 4, we find that the traffic load of the network is the largest under the ER strategy. Under the EGPR strategy, the traffic load is the smallest. It fully shows that the EGPR strategy is more adequate than the ER strategy in that the packets flow is evened and the traffic capacity of the network is improved.

The node betweenness can also be used as an index to measure network traffic capacity. Therefore, we compared the maximum node betweenness under the ER and EGPR strategies. Figure 5 shows that it can be intuitively observed that the maximum node betweenness under the EGPR strategy is less than the maximum node betweenness under the ER strategy. According to the inverse proportional relationship between the traffic capacity R_c and the maximum node betweenness B_{max}, the EGPR strategy is better than the ER strategy.

$\langle L \rangle$ represents the average path length between any two nodes based on some routing strategy. By observing Figure 6, as the network size changes, it can be found that the average path length under the ER strategy is always more than the EGPR strategy. By observing Figure 7, in a congested network, as the network size changes, the average packet travel time of the EGPR strategy is always less than the ER strategy.

From the perspective of the average packet travel time, EGPR strategy comparing with the ER strategy optimizes the traffic capacity of the network and improves the transmission efficiency of packets. Considering the average path length and the average packet travel time, the EGPR strategy is overall better than the ER strategy.

IV. CONCLUSION

In summary, considering that nodes with the same degree value have different influences in the network, we proposed a node centrality algorithm based on the universal gravitation between nodes and proposed the EGPR strategy accordingly, and then we analyzed the traffic dynamics on scale-free networks, in which the processing capacity of all nodes is the same. Under this strategy, we investigated the variation of traffic capacity R_c, the maximum node betweenness B_{max}, and the average path length $\langle L \rangle$, and the average packet travel time $\langle T \rangle$. Compared with the ER strategy, our strategy can spend a small path cost to achieve a much higher traffic capacity. The comparisons of critical values of R_c, the maximum node betweenness B_{max}, the average path length $\langle L \rangle$, and the average packet travel time $\langle T \rangle$ among the two strategies indicate that EGPR strategy is efficient to improve the whole network performance. The work of this paper also provides new ideas for the measurement of node centrality. In future work, we will apply our strategy to networks of other structures.

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JINLONG MA received the Ph.D. degree in information and communication engineering from the Harbin Institute of Technology, Harbin, China, in 2016. He is currently an Associate Professor with the School of Information Science and Engineering, Hebei University of Science and Technology, Shijiazhuang, China. His research interests include information spreading dynamics in complex networks and data analysis of online social networks.

JUNFENG ZHANG is currently pursuing the master's degree with the Hebei University of Science and Technology, Shijiazhuang, China. His research interests include traffic, information spreading dynamics, and structure of networks.

YONGQIANG ZHANG received the M.A.Eng. degree from the School of Computer Science, Anhui University of Technology, Ma'anshan, China, in 2007. He is currently an Associate Professor with the School of Information Science and Engineering, Hebei University of Science and Technology, Shijiazhuang, China. His research interests include information spreading dynamics in complex networks and data analysis of online social networks.