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Travel Efficiency in Urban Traffic Networks Based on Routing Strategies

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Abstract. We study the average travel efficiency of drivers of all origin-destination (OD) pairs on urban traffic networks. To this end, we design a new routing strategy which takes advantage of both the shortest paths and the local dynamic traffic information. This strategy aims at choosing the best neighbor and drivers can change their routes at any road intersection. Implementing the routing strategy in Watts-Strogatz (WS) and Barabási-Albert (BA) networks, we compare the impacts of behavior weights and road flow fluctuation on the average travel efficiency of drivers, and make comparisons between WS and BA networks. Finally, we also make simulations on Jilin bus network.

Introduction

Urban traffic systems are complex networks where nodes and edges are abstracted from road intersections and roads respectively. Since every edge has a finite capacity, traffic congestion will happen if its flow exceeds the capacity at all times. Then what are the best routs for people to drive to their destinations in such a congestion condition? To answer this question, many scholars have been engaged in transport optimization on complex networks in recent years[1-18]. Generally, two techniques are often applied to the enhancement of transportation efficiency of networks. Compared to the huge cost of making appropriate changes to the underling structures of the networks[2-4], developing efficient routing strategies is undoubtedly the most economical and effective way[5-10].

The study to routing strategies in complex networks has mainly focused on improving the efficiency of delivering information packets in information systems. The shortest paths (SP) that has the least number of hops between any source-destination pair is the most common strategy, but is seldom used alone nowadays. The reason for this is that the shortest path strategy can easily lead to congestion on hub nodes for so many paths will go through them, and this kind of traffic congestion will easily propagate to other nodes in the network. Beyond that here are still some new routing strategies in recent years[11-18]. Chen et al. [11] built a routing strategy based on a generalized betweenness centrality by evaluating node processing capacity, which performed better in improving traffic efficiency and traffic capacity than the traditional betweenness routing strategy. Yan et al. [12] proposed a kind of efficient routing strategy based on efficient paths, which have the minimum total summations of weights assigned to nodes according to node degree between any source-destination. Danila et al. [13] introduced an optimal routing strategy that can ease the traffic congestion caused by the overload of hub nodes. Kawamoto et al. [14] provided improvement measures for the long convergence time of the algorithm in [13]. The routing strategies mentioned above were mostly built based on the topological network structures. As for strategies involving dynamic processes happened on networks, we can refer to the traffic-awareness protocol (TAP) proposed by Echenique et al. [15-18]. TAP, in which a node forwards an information packet to the neighbor with the shortest distance from the neighbor to the destination and the waiting time at the neighbor node, has proved to enhance packets delivery efficiency notably [15-16]. Based on TAP, some improvements were done by other scholars [17-18].

Though urban traffic networks have some dynamic characteristics in common with that of information networks, they still display some unique features. Firstly, drivers in urban traffic networks are advanced intelligent decision makers, and their personal behavior preferences will affect their route choice. This is different from what happened in information networks, because information packets are delivered according to the routing strategies designed beforehand, and they do not have the ability of decision making. Secondly, edges are carriers of vehicular flow in urban traffic networks, so all types of dynamic properties shown by vehicles are all on edges. Therefore, to design proper traffic routing strategy in urban traffic networks, it is necessary to consider local dynamic traffic information along the outgoing edges, rather than node information in information systems.

Note that the travel efficiency can be well improved if every individual use the best strategy to drive. So in this paper, we study the average travel efficiency of drivers of all origin-destination (OD) pairs on urban traffic networks. To this end, we develop a novel routing strategy considering the global static structural information and local dynamic traffic information. As the travel efficiency relates to the routes drivers choose and the traffic volume of each edge, we implement the strategy on both WS and BA networks to seek the impacts of behavior weights and edge flow fluctuation on the average travel efficiency. At last, we also make simulations on Jilin bus network.

The outline of this paper is as follows. In section 2, we introduce our model. In section 3, we show the approach to define the traffic flow of an edge which can be calculated through the average of the traffic flow. In section 4, we propose our new routing strategy. In section 5, we do numerical simulations on WS, BA networks and Jilin bus network, and study the average travel efficiency of all drivers using the new routing strategy. In section 6, we summarize our results and state some conclusions.

Traffic flows of edges

Generally, the traffic depends on the physical network structure, and the traffic flow of an edge can be determined by the physical features of its two nodes. As we known, degree and efficiency are two important statistical characteristics of a node. Node degree that is the number of edges connecting to this node is the simplest and straightforward measure of node importance. Bigger node degree corresponds to bigger direct influence in a local scope. So the node with bigger degree will attract more traffic locally for its bigger connectivity. Node efficiency reflects the average difficulty of a node reaching other nodes in the network. The bigger the node efficiency is, the more conveniently vehicles are away from this node to other nodes. Hence the node with bigger efficiency will naturally have a large amount of traffic attractions.

We establish the average traffic flow of edge (i, j) as follows:

$$\bar{q}_{ij} = k_i e_i k_j e_j \tag{1}$$

Where k_i and e_i denote the degree and efficiency of node i respectively. Similarly, k_j and e_j represent the degree and efficiency of node j respectively.

Here we assume that in normal travel time, the traffic flow of an edge will fluctuate around the average flow up and down in a certain range. So the traffic flow of edge (i, j) at decision time τ is

$$q_{ij}(\tau) = (1+f(\tau))\bar{q}_{ij} \quad (|f|>0) \tag{2}$$

Where $f(\tau)$ is the flow fluctuation rate at decision time τ. And we set the time when vehicles reach nodes the decision time.

Considering the fact that each edge has a fixed capacity, or to say the fixed vehicle-processing ability, we suppose that the vehicle-processing ability C_{ij} of edge (i, j) is proportional to its average traffic flow $\bar{q}_{ij}$. Hence for a give edge (i, j),

$$C_{ij} = (1+\alpha)\bar{q}_{ij} \tag{3}$$

Where α is a tolerance parameter, and we set $\alpha \geq 0$. Note that the edge is stuck in traffic congestion when $f \geq \alpha$. Otherwise, this edge sill has residual vehicle-processing ability, and vehicles still can pass it.

The routing strategy

As we know, local dynamic information can help drivers choose the least congested adjacent edge and thus reach the destination in the shortest time, but only focusing on the local information tends to cause the travel direction deviation and the consequence of not reaching the destination. However, global topological information can help to grasp the direction of vehicle's travel, and ensure that the vehicle reaches the destination with the least number of edges. So integrating global structural information and local dynamic information to design the routing strategy can improve the average travel efficiency notably.

Nowadays, drivers can dynamically update their routes to destinations at any road intersection according to the real-time information about the surrounding traffic flow and nearby road conditions (with the help of the Advanced Traveler Information Systems (ATIS)). So the kind of traffic-awareness protocols seems more appropriate to be used to describe drivers' real decision behavior when they travel. Then borrowing ideas from TAP, we combine both the network topology characteristics and local dynamic information to propose a new routing strategy. This strategy aims at choosing a best neighbor node, and allows drivers to modify their routs at every node.

Since drivers have different preferences for elements affecting route choice, we add a preference parameter to the new routing strategy to reflect the preference differences between structural information and local dynamic information. As the shortest path from the vehicle's current position to the destination may not be unique, the driver would like to choose the best neighbor with the aid of the corresponding dynamic information of the outgoing edges. At each time step, the driver will move from his current position i to its neighbor node j in the path with the minimum z. This procedure is repeated for every edge and every driver at each time step.

$$z = min\{l_{js}^{w}[(\frac{C_{ij}-q_{ij}(\tau)}{\sum_{v\in\Gamma_i, v\in path(i,s)}(C_{iv}-q_{iv}(\tau))})^{-1}(\frac{q_{ij}(\tau)}{C_{ij}})]^{1-w})\} \quad j\in path(i,s) \tag{4}$$

Where l_{js} is the shortest path from node j to the destination node s. As we mentioned above, the shortest path means the smallest hop numbers of edges from the neighbor to the destination. Γ_i is the set consisting of all neighbors of node i. $path(i,s)$ is the set of nodes in all shortest paths from node i to destination s. $q_{ij}(\tau)$ $(j\in\Gamma_i, j\in path(i,s))$ represents the traffic flow along edge (i,j) at time τ. w is the preference weight. We set $w\in[0,1]$, and especially when $w=1$, the travel mechanism relates only to the shortest path strategy.

We assume vehicles have the same travel speed in roads without traffic congestion, so shorter l_{js} means higher travel efficiency. On the other, the residual vehicle-processing ability $C_{ij}-q_{ij}(\tau)$ reflects the maximum number of vehicles edge (i,j) can accommodate at time τ.

Simulations and results

In this section, simulations are based on artificial WS and BA networks. We focus on the impacts of preference weights and flow fluctuation on the average travel efficiency of drivers of all OD pairs, and comparisons of the average travel efficiency are made based on different network structures. Here, we let WS and BA networks have the same network size and average degree, and are set 100 and 4 respectively. The rewiring probability of each edge at random is set to 0.1 in the process of WS network generation. Throughout this paper, each result is got by averaging 5 realizations.

We introduce three indexes to reflect the average travel efficiency, and that are the average number of traversed edges $(\overline{edges})$, the average number of used time steps $(\overline{steps})$, and the average

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travel cost $(\overline{cost} = \overline{edges} \times \overline{steps})$. We standardize these indexes as follows:

$$x = \frac{\bar{x} - \bar{x}_{min}}{\bar{x}_{max} - \bar{x}_{min}} \tag{5}$$

Where $\bar{x}$ represents each index variable of $\overline{edges}$, $\overline{steps}$ and $\overline{cost}$. $\bar{x}_{max}$ and $\bar{x}_{min}$ are the maximum and the minimum of the index variables respectively. x is the index variable after standardization, and represent $edges$, $steps$ and $Cost'$ respectively.

In order to investigate the impact differences between network structures, we process the average travel cost $(Cost')$ as bellow:

$$Cost_u = Cost'_u \times \frac{\overline{Cost_u}}{\sum_v \overline{Cost_v}} \tag{6}$$

Where u and v represent the types of networks. $Cost_u$ is the new variable after process.

Impacts of preference weights on the average travel efficiency. In this section, we will analyze the impacts of preference weights in our routing strategy on the average travel efficiency. More specifically, what we are interested is how the average travel efficiency is changing when drivers' preferences for the shortest paths alter. Fig. 1 shows the impacts of preference weights on the average travel efficiency on both WS and BA networks. In the simulation, we set $\alpha = 0.2$, and $|f| = 0.3$.

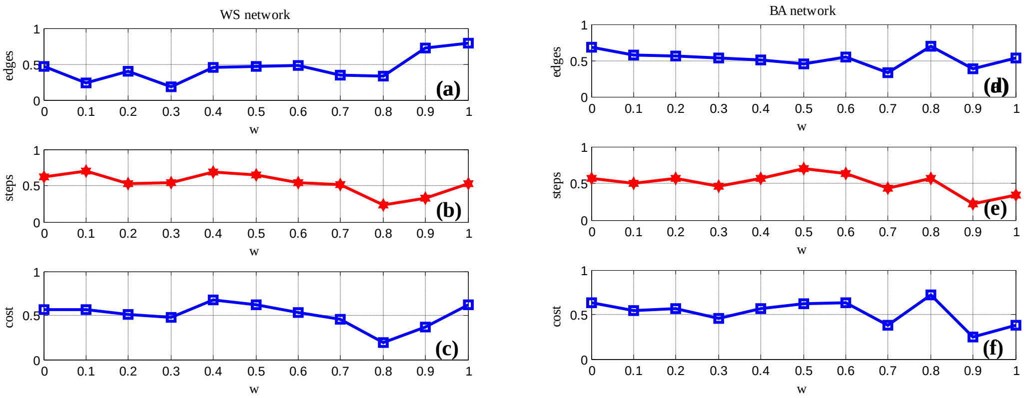

Fig. 1 The impacts of preference weights on the average travel efficiency in WS and BA networks

In Fig.1 (a), (b), (d) and (e), since the preference weights that make the $edges$ and $steps$ minimum are different no matter in WS or in BA network, we cannot judge the optimal preference weights in both networks. However, as both $edges$ and $steps$ are two important indexes of measuring the average travel efficiency, we need to analyze the average travel efficiency taking both $edges$ and $steps$ into account. So we display the $cost$ curves in Fig. 1 (c) and (f). It is easy to see that the $cost$ reaches the minimum value when w =0.8 in WS network, while the corresponding weight in BA network is 0.9. So drivers need to pay more attention to the information of the shortest paths in BA network than in WS network. For further comparisons of the impacts of preference weights on the average travel efficiency between WS and BA networks, we exhibit the average travel cost curves being processed following Eq.(6) in Fig. 2. Then we discover that the average travel cost is lower in BA network than in WS network in general, except for the value when w =0.8.

Impacts of flow fluctuation on the average efficiency. In the normal operation time of traffic networks, the traffic flow of each edge fluctuates around the average value up and down, and this fluctuation will affect drivers' travel efficiency necessarily. For example, when the traffic flow of an edge after fluctuation at time τ exceeds the edge's vehicle-processing ability, the driver will abandon this edge and choose the one with bigger residual ability and smaller load rate for high travel efficiency. In this way, what's the fluctuation range drivers can accept in real network operations? In other words, what proper range flow fluctuating in makes no difference to drivers' average travel efficiency. The exploration on this problem contributes to develop schemes of traffic mitigation and regulations.

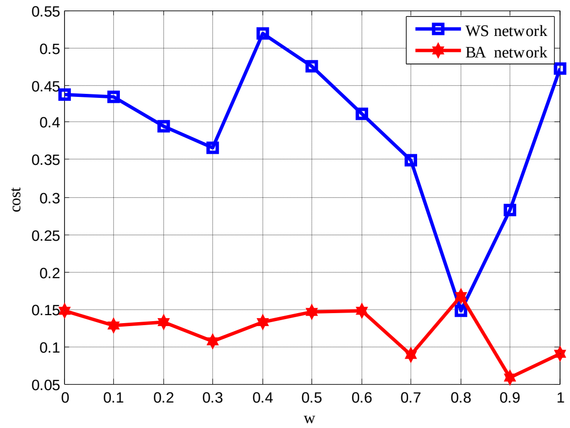

Fig. 2 The comparison of the impacts of preference weights on the average travel cost between WS and BA networks

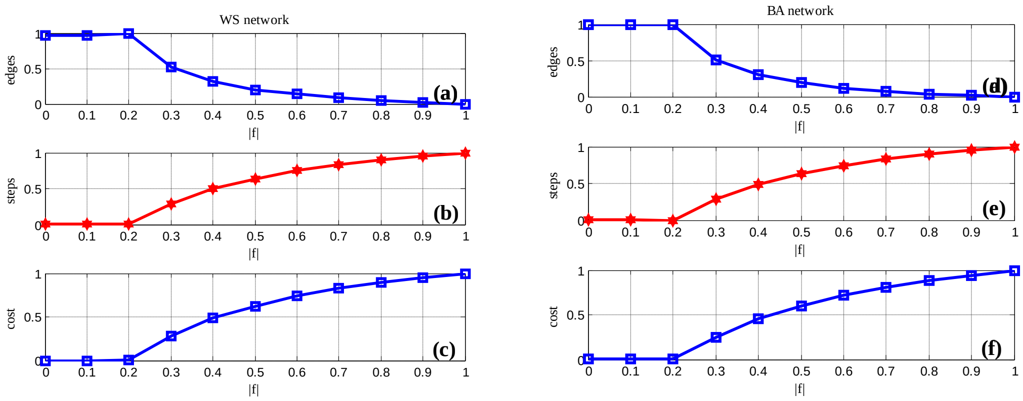

Fig. 3 The impacts of flow fluctuation rate on the average travel efficiency in WS and BA networks

We report the impacts of flow fluctuation rate on the average travel efficiency in Fig. 3, and we set $\alpha = 0.2$ and $w = 0.5$. Interestingly, we observe from the curves that the critical values of the flow fluctuation rate are the same in both WS and BA networks, regardless of *edges*, *steps* or *cost*. Note that, for $|f| \le 0.2$, flow fluctuation rate almost has no effect on these three indexes. For $|f| > 0.2$, with the growth of the flow fluctuation rate, *edges*, *steps* and *cost* show the same change trend in both WS and BA networks. Fig. 4 gives the comparison of the average travel efficiency affected by the flow fluctuation rate between WS and BA networks. The inspiration we drawn from the curve comparison is that WS network needs more control than BA network does over flow fluctuation. In other word, the control of flow fluctuation in WS network helps to enhance drivers' average travel efficiency.

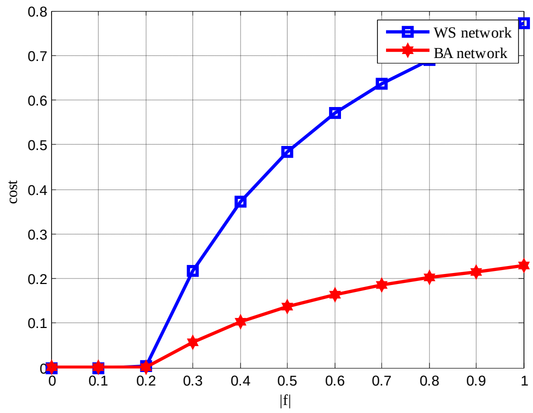

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Fig. 4 The comparison of the impacts of flow fluctuation rate on the average travel cost between WS and BA

Simulations in Jilin bus network. In order to further investigate the impacts of preference weights and flow fluctuation on the average travel efficiency in real networks, we make simulations on Jilin bus network. We consider this network as an unweighted network with 361 nodes and 499 edges, and the average degree is about 2.76. Upon analysis, we find Jilin bus network has the characteristic of small world. The reason is as follows: firstly, the characteristic path length of this network is 7.53, larger than that of random networks, the value of which is 5.79. Secondly, the clustering coefficient of this network is 0.0548, far larger than the corresponding value of random networks, the value of which is 0.00766. Moreover, as shown in Fig. 5, we find the degree distribution of this network exhibits heterogeneity.

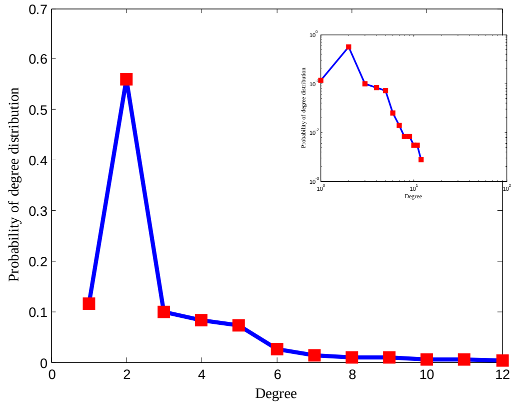

Fig. 5 The degree distribution in Jilin bus network

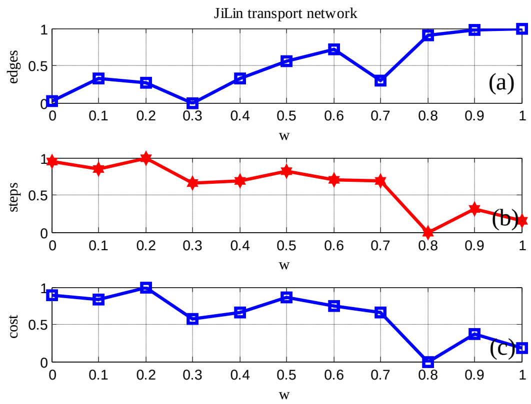

Fig. 6 The impacts of preference weights on the average travel efficiency in Jilin bus network

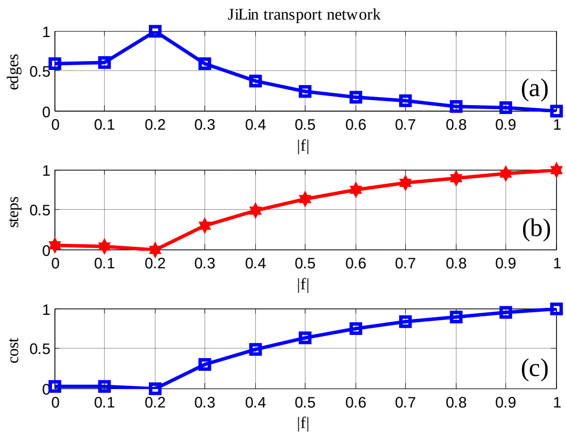

Fig. 7 The impacts of flow fluctuation in Jilin bus network on the average travel efficiency.

We show the impacts of preference weights and flow fluctuation on the average travel efficiency on Jilin bus network in Fig. 6 and Fig. 7 respectively. In Fig. 6, we see that $edges$ is optimal when w=0.3, which illustrates that drivers will pass through the least number of edges to destinations in our dynamic traffic environment when they pay 30% of the attention to the shortest paths. In Fig. 6 (a), we find the curve shows an overall upward trend. So if drivers lay emphasis on the fuel efficiency of the travel and do not care how long it takes to destinations, they may pay less attention to the shortest path and change their focus on the local dynamic traffic information. But if drivers emphasize the travel time between OD pairs, they need to pay close attention to the shortest paths to destinations, which can be concluded from Fig. 6 (b). Furthermore, if drivers want to give consideration to both fuel efficiency and travel time, they should still keep tracking of the shortest paths, which we discover from Fig. 6 (c). Fig. 7 shows the effects of the fluctuation rate on those three indexes. When drivers' preferences for the shortest paths and the local dynamic traffic information are equal, drivers will have the most numbers of edges and the least travel time to their personal destinations if the fluctuation rate is 0.2. Also 0.2, the travel cost reaches the minimum. So traffic planners and management departments can improve the average travel efficiency of drivers through control over flow fluctuation according to the curves in Fig. 7.

Summary

In summary, we have investigated the average travel efficiency problem of drivers of all OD pairs in networks, which is a more general and significant problem in urban traffic systems. During the research, we have developed a routing strategy considering global network structure and local dynamic edge information simultaneously. All simulations and analysis on WS and BA networks have suggested that firstly, in order to achieve the high average travel efficiency, the preference to the global structure needs to be more in BA than in WS network. Secondly, the flow fluctuation affects the average travel efficiency more in WS than in BA network with the increase of flow fluctuation rate, and hence WS needs more control of flow fluctuation than BA network does. At last, the results in Jilin bus network demonstrate that there also exist the impacts of preference weights and flow fluctuation on the average travel efficiency in actual networks.

References

[1] R. Guimera, A. Diaz-Guilera, F. Vega-Redondo, A. Cabrales, and A. Arenas: Optimal Network Topologies for Local Search with Congestion. Physical Review Letters 89 (24) 2002 248701.

[2] V. Cholvi, V. Laderas, L. Lopez, and A. Fernandez: 2005, Self-adapting Network Topologies in Congested Scenarios, Physical Review E 71(3) 2005 035103.

[3] L. Zhao, T.H. Cupertino, K. Park, Y.C. Lai, and X.G. Jin: Optimal Structure of Complex Networks for Minimizing Traffic Congestion, Chaos 17(4) 2007 043103.

[4] B. Tadic, S. Thurner, and G.-J. Rodgers: Traffic on Complex Networks: Towards Understanding Global Statistical Properties from Microscopic Density Fluctuations, Physical Review E 69(3) 2004 036102.

[5] W.X. Wang, B.H. Wang, C.Y. Yin, Y.B. Xie, and T. Zhou: Traffic Dynamics Based on Local Routing Protocol on a Scale-free Network, Physical Review E 73(2) 2006 026111.

[6] Z.H. Guan, L. Chen, and T.H. Qian: Routing in Scale-free Networks Based on Expanding Betweenness Centrality. Physica A 390(6) 2011 1131–1138.

[7] Z. Y. Chen, X. F. Wang: Effects of Network Structure and Routing Strategy on Network Capacity. Physical Review E 73(3) 2006 1-5.

[8] X. Ling, M.B. Hu, R. Jiang, R.L. Wang, X.B. Cao, and Q.-S: Wu: Pheromone Routing Protocol on a Scale-free Network. Physical Review E 80(6) 2009 1-5.

[9] M. Suvakov, and B. Tadic. Transport processes on homogeneous planar graphs with scale-free loops. Physica A 372(2) 2006 354-361.

[10] X. Ling, R. Jiang, X. Wang, M.B. Hu, and Q.S. Wu: Traffic of Packets with Non-homogeneously Selected Destinations in Scale-free Network, Physica A 387(18) 2008 4709-4715.

[11] L. Chen, J.C. Chen, Z.H. Guana, X.H. Zhang, and D. X. Zhang: Optimization of Transport Protocols in Complex Networks, Physica A 391(11) 2012 3336-3341.

[12] G. Yan, T. Zhou, B. Hu, Z.Q. Fu, and B.H. Wang: Efficient Routing on Complex Networks. Physical Review E 73(4): 046108 2006 1-5.

[13] B. Danila, Y. Yu, J.A. Marsh, and K.E. Bassler: Optimal Transport on Complex Networks, Physical Review E 74(4) 2006 046106.

[14] H. Kawamoto, and A. Igarashi: Efficient Packet Routing Strategy in Complex Networks. Physica A 391(3) 2012 895-904.

[15] P. Echenique, J. Gomez-Gardenes, and Y. Moreno: Improved Routing Strategies for Internet Traffic Delivery, Physical Review E 70(5) 2004 056105.

[16] P. Echenique, J. Gomez-Gardenes, and Y. Moreno: Dynamics of Jamming Transitions in Complex Networks. Europhysics Letters 71(2) 2005 325-331.

[17] H. Zhang, Z.H. Liu, M. Tang, and P. M. Hui: An Adaptive Routing Strategy for Packet Delivery in Complex Networks. Physics Letters A 364(3-4) 2007 177-182.

[18] M.Tang, Z.H. Liu, X.M. Liang, and P.M. Hui: Self-adjusting Routing Schemes for Time-varying Traffic in Scale-free Networks, Physical Review E 80 (2) 2009 026114.