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RAILWAY NETWORK RELIABILITY ANALYSIS BASED ON KEY STATION IDENTIFICATION USING COMPLEX NETWORK THEORY: A REAL-WORLD CASE STUDY OF HIGH-SPEED RAIL NETWORK

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Abstract: The railway infrastructures have been rapidly developed around the world in the recent years. As a consequence, topology structures and operation modes of the railway network are greatly changed to very complicated network systems. Reliability analysis of a railway network combining topology structures with operation functions will help to optimize the railway network infrastructures. This paper presents a new reliability analysis method of the railway network, combining the physical topology with operation strategies. Firstly, two network models of railway physical network and train flow network are proposed. Then key stations identification indexes can be gained from such two network models, which include degree, strength, betweenness clustering coefficient and a comprehensive index. Given the key stations, railway network efficiency can be analysed under selective and random modes of the stations failure. A real-world case study of the high-speed railway network in China is presented to demonstrate the key stations playing an important role in improving the whole network reliability. In the end, some recommendations are given to improve the network reliability. The proposed method can provide useful information to railway developers, designers and engineers in the railway infrastructure projects for sustainable development.

Keywords: reliability analysis, railway network infrastructure, complex network, train flow network, key stations

1. INTRODUCTION

The railway infrastructures have been rapidly developed around the world in the recent years. The total length of the railway network in the world is more than 1,370,000km and the high-speed railway is 29,792km by 1 April 2015 (UIC, 2015). With the continuous construction and development of the railway system, the temporal and spatial dynamics of the network and the organization relationship between the rail lines are getting stronger. Due to the rapid increase, operation and maintenance of the whole railway network are becoming more difficult. The trains traveling bring more complex relationship between the stations. If there is a failure at the key station, it would decline the transportation efficiency of the whole network. Therefore, identifying the key stations and analysing the reliability of the network is one of the most important things in the railway development. Since the railway network is a complex system with lots of stations and tracks and operation correlation, it can be analysed based on complex network theory. Therefore, the reliability analysis is becoming more important to ensure the safe operation. This paper proposes a new method to analyse the reliability of railway network based on the key station identification and efficiency evaluation of the network in different failure modes of the stations, which will help to provide comprehensive suggestions for the infrastructure planning and transportation operations.

Many researchers have found that there are many complex networks in the real world, such as biology network (Zenil et al, 2014), Internet (Zquez et al, 2002), research cooperating network (Yin et al, 2006, Koseoglu, 2016), electricity system(Chassin et al, 2005) and traffic network (An et al, 2014, Meng et al, 2015). Furthermore, based on the complex network theory, a lot of empirical studies show that some transportation system infrastructure topologies have exponential degree distributions, such as Chinese bus-transport systems (Xu et al, 2007), Indian railway system (Sen et al, 2003), urban street networks (Porta et al, 2006, Wang et al, 2017), Indian airline network (Bagler, 2008) and USA airline network (Dall'Asta et al, 2006), They all have the small-world network or scale-free network characteristic. In addition, complex network theory has also been applied to the research of the safety and reliability of some complex systems (Zio and Sansavini, 2011, Dey, 2016). Furthermore, their research established various network models and studied the structural characters by the system indicators, which includes nodes degree, average path length, clustering coefficient etc. Some researchers described the complex system vulnerability by cascading failures theory under random or selective node failure modes (Buldyrev et al, 2010, Ren et al, 2016, Yan, 2014, Wilkinson, 2017). While some researchers developed reliability analysing methods for the transportation systems.

Guidotti et al (2017) proposed a probabilistic methodology to quantify the network reliability based on existing (diameter and efficiency) and new (eccentricity and heterogeneity) measures of connectivity and was applied to a highway transportation network. Qian et al (2015) proposed a cascading failure model of the complex network to simulate the road traffic states using different time delays, incident dissipation factor and load capacity. Chen et al (2014) presented a directed chaos mutation sorted discrete PSO algorithm to optimize the invulnerability of Chinese railway traffic network by adding edges to the network. Lin et al (2016) and Li et al (2015) treated high-speed train as a complex system accompanied by a lot of components and connections, and studied the safety and reliability based on complex network theory. Ouyang et al (2014) applied complex network to study the performance and vulnerability of Chinese railway under various types of attacks and hazards.

Although, the complex network theory was widely developed in the reliability analysis of the complex system, however these studies limited to the physical topological properties, the railway operation functions are neglected. The aim of this paper is to present a new method to analyse the reliability of the railway network by identification of the key stations. Not only the physical network topology, such as degree and clustering coefficient, but also the dynamic operation parameters, such as train running paths, stop-schedules and service frequencies, are considered in this method. Given the key stations, railway network efficiency is analysed under random and selective modes of the station failure, and demonstrates the key stations playing an important role in improving the whole network reliability.

This paper is organised into the following sections. Section 2 proposes the reliability analysis method of railway network based on key stations identification and network efficiency using network complex theory. In section 3, a case study of the high-speed railway network in China illustrates the proposed method. Section 4 presents some recommendations in terms of infrastructure planning and transportation operation of in order to satisfy the safety and economic development in the future. Section 5 gives the conclusions.

2. RELIABILITY ANALYSIS METHOD

In this section, a new reliability analysis method of the railway network is proposed combining the infrastructure topology structure with operation function. It includes three main stages, railway network models, key station identification indexes and network efficiency analysis under random and selective modes of nodes failure as shown in Fig.1. In the railway network models, railway physical network (RPN) that has been further developed on the basis of Guidotti et al (2017) and Meng et al (2015), and a train flow network (TFN) of a service plan can be then obtained by integrating RPN in taking operation strategies into consideration, for example, train running routes, stop-schedules and service frequencies as stated in section 1. Afterwards, key station identification indices are used to evaluate the nodes of TFN, which provided the rank of the stations. Finally, network efficiency analysis is simulated by the selective and random station failure.

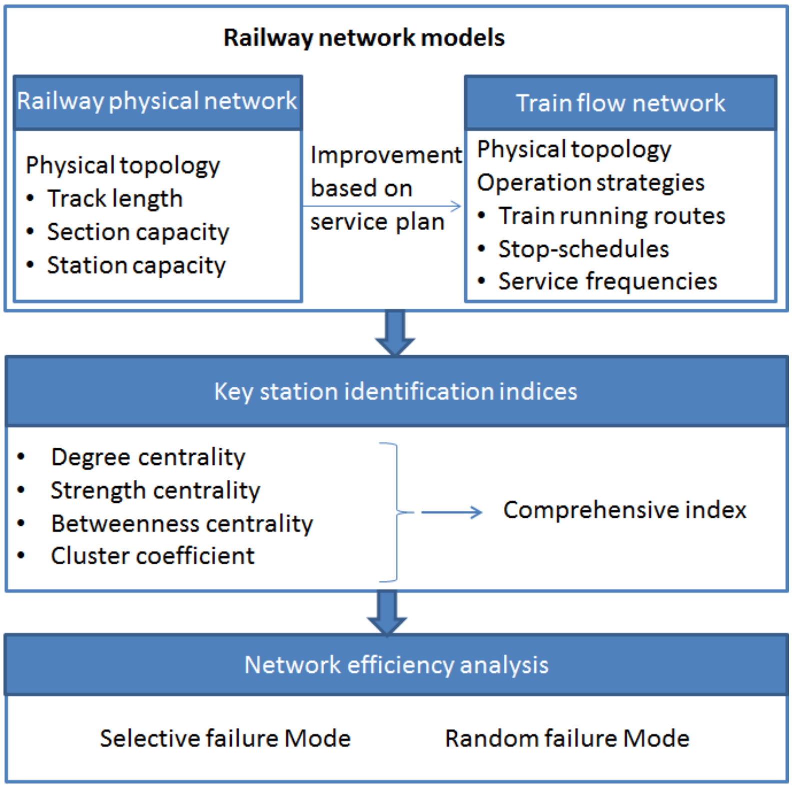

Fig.1: Reliability analysis process

2.1. Railway Network Model

Two models, railway physical network and train flow network are proposed in this section. The former shows the physical connecting properties and provides constraints to the train flow network, whereas, the latter shows train service plan and the operation properties of railway physical network, which improved railway physical networks.

***Railway physical network (RPN)*:** The stations are regarded as nodes and the connecting tracks between any two stations are regarded as edges based on the network theory (Xu et al. 2007; Wang et al. 2017; Bagler 2008; Dey 2016).Thus, the RPN can be represented as undirected graph G_g=(V_g, E_g), where V_g is the railway station set, and E_g is the rail track set.

The RPN shows the physical connectivity between the stations. Furthermore, the track length, section capacity and station capacity can be added to the network, hence, the RPN can carry the transportation capacity constraints for train service plan.

***Train flow network (TFN)*:** As the stations are regarded as nodes, therefore, if a train stops at two stations, there will be one edge between them. The number of trains' stop at two stations is defined as the weight of the edge (Meng et al 2015). Based on this definition, there will be 6 edges if one train stops at 4 stations. Thus, the TFN can be represented as undirected graph G_t=(V_t, E_t), where V_t is the station set where any train can stop at, and E_t is the edge set that created by any two stops at any station of all trains. According to the definition, the TFN can be established according to train service plan, in which the stop-schedules can create the nodes and edges, and trains' frequencies decide the weights of edges.

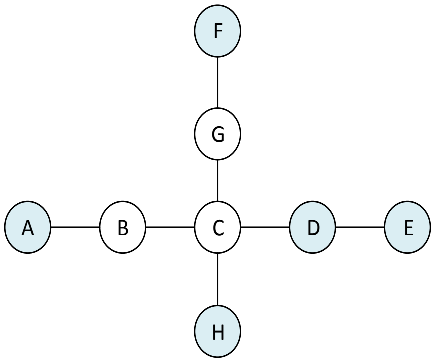

Fig.2(a): Railway physical network

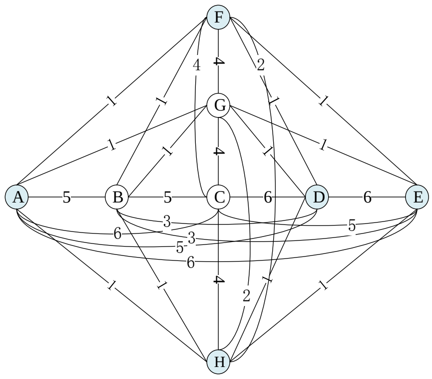

Fig.2(b): Train flow network

Fig.2: Railway networks

According to the proposed models, the RPN can be improved to a TFN by including the train service plan. A simple case of two rail lines for the two network models is given in Fig.2. Fig.2 (a) represents two rail lines in the RPN. One includes 5 stations marked as A, B, C, D and E, and the other includes 4 stations marked as F, G, C and H. The station C is a junction, and the blue nodes mean terminal stations that can be starts and ends of the trains. While, Fig.2 (b) shows the TFN that is developed by adding train service plan to the RPN, whereas the service plan is shown in Fig. 3.

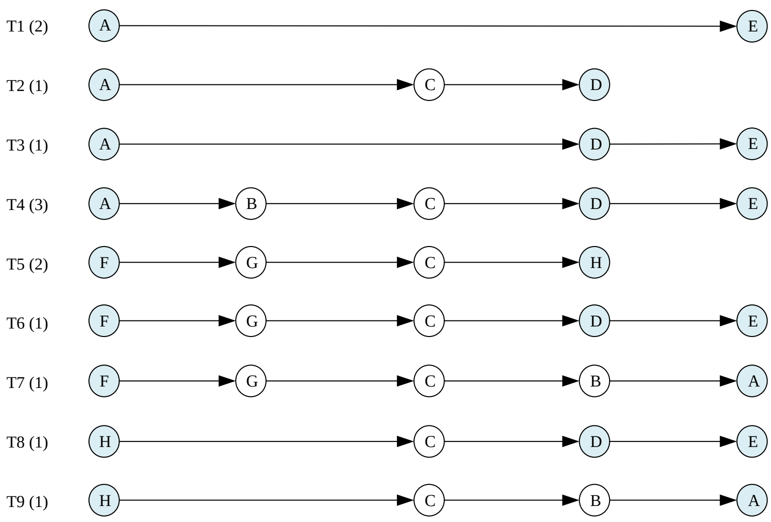

Fig.3: Train service plan

As shown in Fig.3, the train service plan includes 9 stop-schedules marked from T1 to T9, and their frequencies are 2, 1, 1, 3, 2, 1, 1, 1 and1 respectively (shown in the bracket). The nodes shown in one line mean the train with this stop-schedule will stop at these stations. For example, T4 (3) means there are 3 trains take the same stop-schedule but with different departure times. And all of them will stop at stations A, B, C, D and E. According to the definition of TFN, the edge between node A and B is created by stop-schedule T4, T7 and T9, and the edge weight is the sum of frequencies of the three stop-schedules. Similarly, other edges and the weights in TFN are generated by the same way. With the constraints to RPN, the railway network physical topology and the operation strategies such as train running routes, origins and destinations, stop-schedules, and service frequencies can be transferred to the topological relations and weights of edges in TFN.

2.2. Key Station Identification Index

Given the train flow network model, we can present the key station identification indices combining physical topological structure and train operation strategies. A set of function index in the view of TFN based on complex network theory will be proposed in this section, which shows the importance of different stations in the railway network.

a. Degree centrality (DC)

Degree centrality of a node v_i is the number of the connection between v_i and other nodes. It describes the physical connective influence of a node by the number of its neighbours. For the TFN, the degree centrality k_i of a node v_i is defined as Eq. 1.

$$k_i = \sum_{j=1}^{N} n_{i,j} \tag{1}$$

Where N is the number of the nodes in the network; $n_{i,j}$ is a variable of 0 and 1. If there is a connection between nodes v_i and v_j, $n_{i,j}$=1; otherwise, $n_{i,j}$=0. A node with a larger degree is likely to connect to more edges than a node with a smaller degree, which means a higher influence of connectivity in the whole network. In the TFN, the degree k_i of a node v_i is the number of stations that can be reached without a transfer from the station represented by v_i. The degree of a node in the TFN describes the topological reachability of the station.

b. Strength centrality (SC)

A very important feature of TFN is that each edge is not equally important. Some edges are more important than others, therefore, carry a higher weight, which depends on the service frequencies of different trains and therefore plays a greater role in contributing to the functioning of the whole network. Strength centrality can describe the weight of an edge. Strength centrality of a node v_i is the sum of the weights of the edges between v_i and other nodes. For the TFN, the strength centrality s_i of a node v_i is defined as Eq. 2.

$$s_i = \sum_{j=1}^{N} w_{i,j} \tag{2}$$

Where $w_{i,j}$ is the weight of the edge between node v_i and v_j. In the TFN, the weight $w_{i,j}$ of an edge between node v_i and v_j is the number of trains that stop at stations i and j. The strength of a node describes the service capability of the specific station, which represents the convenience of the passenger from this station to other stations that can be reached without a transfer.

c. Betweenness centrality (BC)

Betweenness centrality describes the influence of a node over the information spread through the network, which is based on shortest paths. For every pair of nodes in a network, there is at least one shortest path either the minimum number of edges that the path passes through or the minimum sum of the weights of the edges. In the TFN, the betweenness centrality (b_i) of a node v_i without the weights of edges is defined as topological betweenness centrality (TBC) and b_i can be represented by Eq. 3. Similarly, the betweenness centrality (b_i^w) of a node v_i with the weights is defined as capacity betweenness centrality (CBC) and b_i^w is represented by Eq. 4.

$$b_i = \frac{\sum_{j \neq k} g_{j,k}(i)}{\sum_{j \neq k} g_{j,k}} \tag{3}$$

$$b_i^w = \frac{\sum_{j \neq k} g_{j,k}^w(i)}{\sum_{j \neq k} g_{j,k}^w} \tag{4}$$

Where $g_{j,k}$ is the number of shortest paths with the minimal number of the edges from a node v_j to a node v_k; $g_{j,k}(i)$ is the number of shortest paths with the minimal number of the edges, which pass through the node v_i from a node v_j to a node v_k. Likewise, $g_{j,k}^w$ is the number of shortest paths with the minimal sum of the weights of the edges from a node v_j to a node v_k; $g^w_{j,k}(i)$ is the number of shortest paths with the minimal sum of the weights of the edges, which pass through the node v_i from a node v_j to a node v_k. The betweenness centrality reflects the influence of the nodes throughout the network. Influential nodes are those that are visited by the largest number of shortest paths from all nodes to the rest. Therefore, we can get the influential nodes in different perspectives of topological connectivity and transportation capacity.

d. Clustering coefficient (CC)

The clustering coefficient is a key quantity that characterizes the extent to which the nodes in the neighbourhood of a certain node are connected. The higher the value of a clustering coefficient of a node, the more densely connected the nodes in its neighbourhood will be. The clustering coefficient c_i of a node v_i is defined as Eq. 5.

$$c_i = \frac{2m_i}{k_i(k_i+1)} \tag{5}$$

Where the k_i nodes are the neighbours of the node v_i, and k_i is also the degree centrality of v_i. Thus, there are at most k_i (k_i -1)/2 arcs between the k_i nodes. The m_i is the real number of the arcs between the k_i nodes. A node with a higher clustering coefficient means the node and its neighbours tend to be a close organization. In the TFN, the higher clustering coefficient means an intensive requirement between the stations for the transportation of passengers and goods. It shows the influence of the station in the local area of the network.

e. Comprehensive index (CI)

The key station set and the rank of the stations identified by the five indices may be different, due to the influence of the stations evaluated by these indexes is in different points of view. To balance these different, a comprehensive index C_i should be given based on the five basic indexes. First, the basic indexes can be normalized by Eq. 6. Then, the comprehensive index C_i of a node v_i can be the sum of these normalized indices, formulated as Eq. 7.

$$\overline{z}_i^{\alpha} = \frac{z_i^{\alpha} - z_{\alpha}^{\min}}{z_{\alpha}^{\max} - z_{\alpha}^{\min}}, \quad \alpha = 1, 2, \text{L} \ ,5 \tag{6}$$

$$C_i = \sum \lambda_{\alpha} \overline{z}_i^{\alpha}, \quad \alpha = 1, 2, \text{L} \ ,5 \tag{7}$$

Where z_i^{α} represents the value of any of the basic indexes of a node v_i; $z_{\alpha}^{\min}$ is the minimum value of the basic index α of the stations in TFN; $z_{\alpha}^{\max}$ is the maximum value of the basic index α of the stations in TFN; $\overline{z}_i^{\alpha}$ is normalized value of the basic index α of the station v_i; λ_{α} is the weight of the basic index α, which shows the impact of different basic indexes in the comprehensive index. The principle for selection of λ_{α} is reflecting the evaluation purpose such as the topological connectivity, transportation capacity and local influence. Some methods, such as the trial and error method and the Delphi method can be used in the selection of λ_{α}.

2.3. Network Efficiency Analysis

Network reliability can be obtained by the analysis of the characteristics of the network under random and selective modes of stations failure (Lin et al. 2016). The difference between the two modes is to decide the failure order of the stations. In the first mode, the failure stations are randomly selected, however, the node and its edges are removed to form a new network. In the second mode, the failure order should be consistent with the ranks of the stations which can be obtained by CI. The two indexes of network efficiency (E) and relative network efficiency (R) are given to evaluate the reliability of the TFN, which are derived from Eq. 8 and Eq. 9.

$$E = \frac{2}{n(n-1)} \sum_{i \geq j}^{n} d_{i,j} \tag{8}$$

$$R = \frac{E}{E_0} \tag{9}$$

Where n is the number of nodes in the network after the failure of the stations and edges, $d_{i,j}$ represents the shortest network distance between node v_i and v_j but when they are not connected $d_{ij} = +\infty$, E is the network efficiency after the failure and E_0 is the initial network efficiency.

3. CASE STUDY

In this section, a case study of reliability analysis of railway network in China is presented. Firstly, the TFN is established based on the model given in section 2 from the train timetable of June 2015 as described in below sections. Secondly, the key station identification indices are calculated based on TFN, and the comprehensive index can be generated from basic indices as discussed is section 2.2. Finally, the network efficiency analysis under different failure modes is discussed in detail.

3.1 High-speed Railway Network in China

China has world's longest high-speed railway network, which has rapidly been developed in the recent years. By the end of 2015, the operation mileage was over 19,000km (National railway administration of China, 2016), which is more than 50% of the world's total mileage. There are 3 kinds of High-speed trains in China, high-speed trains (with the subtitle of G), intercity trains (with the subtitle of C) and trains running on the existing line after upgraded (with the subtitle of D). The average operation speeds of these trains are 300km/h， 250km/h and 200km/h respectively. According to the train timetable on June 10, 2015, there are 2487 trains running on the high-speed railway network including 1062 G, 466 C and 959 D trains. In order to ensure the connectivity of the railway network, 2 isolated lines Haikou to Sanya and Urumqi north to Lanzhou West high-speed rail line are removed from the network for the case study. As a result, the RPN has 485 nodes and 570 edges as shown in Fig.4. Whereas, the TFN has the same number of nodes, however, due to the addition of service plan, the number of edges has reached to 68198 making it more complex than RPN.

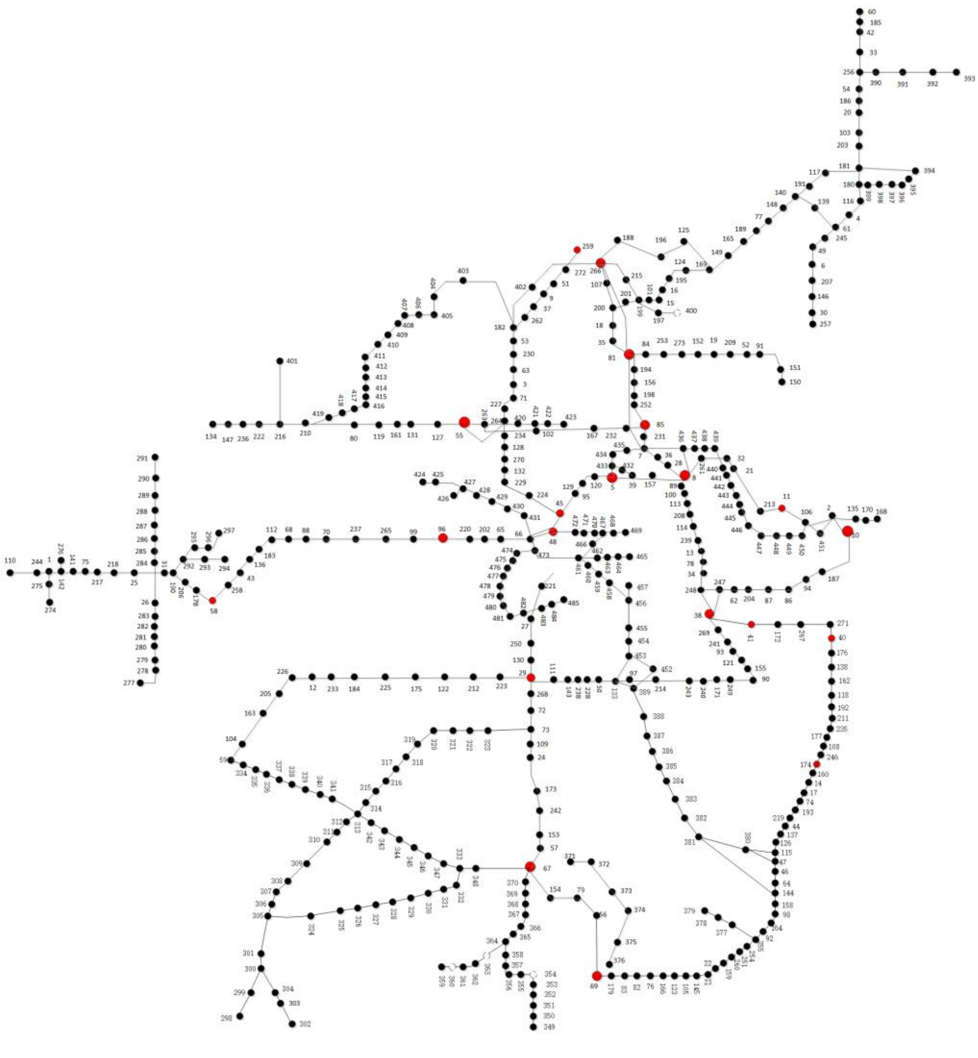

Fig.4 High-speed railway physical network in China

3.2 Key Station Identification

a. Degree centrality

The distribution and cumulative distribution of DC can be calculated by Eq. 1, which is shown in Fig. 5 and Fig. 6. In the TFN, the number of the stations with DC of more than 150 is only 2% of the whole network. And most of them are the hub stations converged by several rail lines, such as *Shanghai Hongqiao* station, *Nanjing South* station, *Wuhan* station, *Hangzhou East* station etc. It can be observed that the cumulative distribution of DC is exponential, which can be formulated as follows:

$$p(>k) = 1.09e^{-0.02} \tag{10}$$

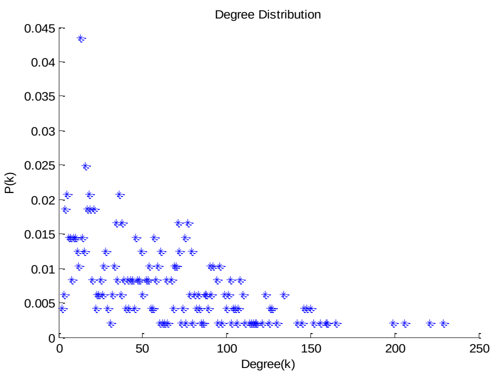

Fig.5 Distribution of DC

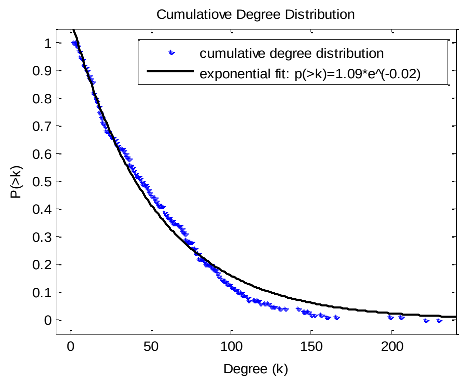

Fig.6 Cumulative distribution of DC

b. Strength centrality

The cumulative distribution of SC is shown in Fig.7. The statistics show that the SC of 4.59% stations is greater than 1000, and for 60.04% it is less than 200, indicating that the distribution of SC of the stations in the TFN is extremely deviated. There are a few stations having very high service capacity. It is more convenient for the passengers to travel from these stations than others. It can be observed that the distribution of DC versus SC follows a power law (shown as Fig. 8), which can be formulated as follows:

$$s \propto k^{1.242} \tag{11}$$

It means the growth rate of SC is faster than the DC, which shows that in the current transportation operation strategy if the topological connectivity of a station is k the ability to serve the passengers is $k^{1.242}$, therefore, the transportation capacity of a station is growing faster than the growth of topological connectivity.

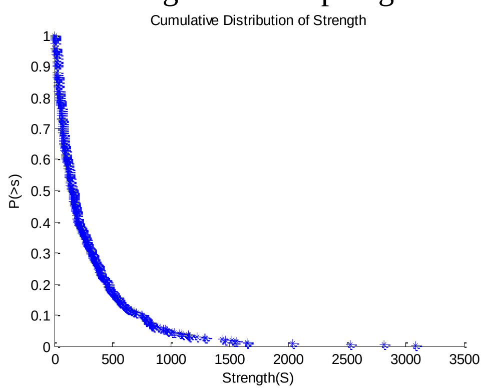

Fig.7 Cumulative distribution of SC

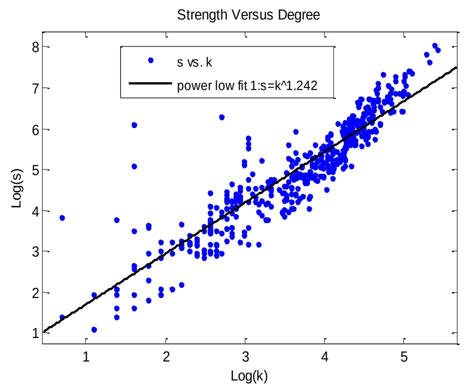

Fig.8 Distribution of DC versus SC

c. Betweenness centrality

The distribution of TBC and CBC in the TFN is shown in Table 1. Most of the stations have a very small TBC and CBC, but very few stations' BC are very large, which is 1.8% stations with the interval of 0.05730~0.06548. So these stations have very important significance in the TFN.

Table 1: The distribution of TBC and TFN

No	Interval	Probability of TBC	Probability of CBC
1	0~0.00005	0.168498	0.161172
2	0.00005~0.00030	0.131868	0.14652
3	0.00030~0.00100	0.194139	0.201465
4	0.00100~0.00307	0.197802	0.201465
5	0.00307~0.00501	0.124542	0.10989
6	0.00501~0.00603	0.03663	0.032967
7	0.00603~0.01037	0.058608	0.058608
8	0.01037~0.02206	0.040293	0.040293
9	0.02206~0.05730	0.029304	0.029304
10	0.05730~0.06548	0.018315	0.018315

d. Clustering coefficient

The average CC of the TFN is 0.697, showing high aggregation characteristics as shown in Fig. 9. While, the relationship between the CC and DC of each node is shown in Fig. 10. From the relationship graphs, it is clear that the nodes with high CC have very low DC and DC and CC show a negative correlation, which means the lower the DC of the station, the greater the CC.

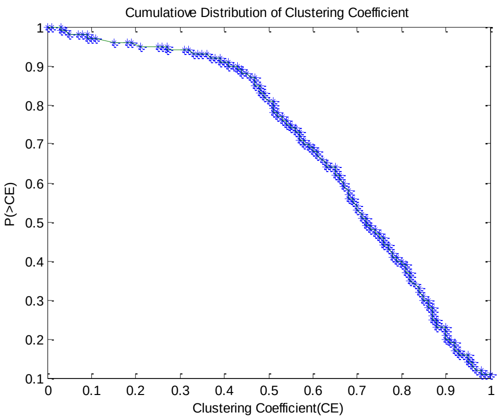

Fig.9 Cumulative distribution of CC

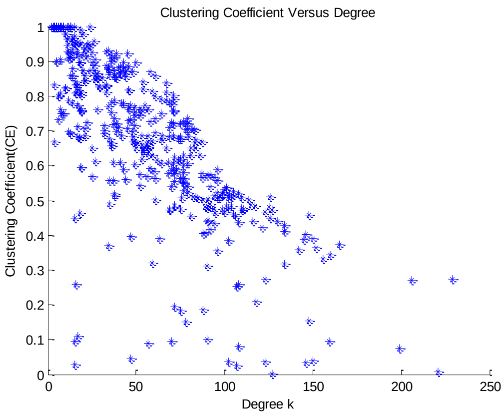

Fig.10 Distribution of CC versus DC

e. Comprehensive index

The distributions of the basic indices for the stations are different, therefore, the rank of key stations cannot be the same. Table 2 shows the top 20 stations in different indices. Whereas, the nodes with top 20 high CI are indicated with red colour in Fig. 4. Most of the high CI nodes distribute in the central and eastern regions of China, because higher economic development has higher population density and brings more transportation needs. However, not all the top 20 stations are junctions such as No.11, 40, 41, 58, 96 and 174. These nodes have higher transportation capacity, though lower physical connectivity. Thus, these stations should be given more maintenance and be more likely to be included when a new railway line is planned in the future. The stations of No. 259 and 266 in Beijing city, the capital of China, are ranked as 17 and 14, which is not the higher level in the TFN. Since there are 4 stations in Beijing to decentralize transport pressure. However, there are only 2 stations (266 and 259) in top 20 and the sum of their CI is 3.10, higher than 2.91 of the first station No. 8. Increasing some hub lines between the 4 stations can improve capacity and reliability of transportation of the whole city, which should be one direction in the future design of the railway infrastructure.

Table 2: Comparison of top 20 statioins in different indexes

Rank	**Station (DC)**	**Station (SC)**	**Station (TBC)**	**Station (CBC)**	**Station (CC)**	**Station (CI)**	**CI**
1	8	8	5	29	215	8	2.909347
2	10	10	69	48	217	10	2.856245
3	38	38	55	10	219	5	2.594738
4	48	29	45	8	187	69	2.51187
5	85	40	96	256	246	48	2.282593
6	5	81	266	69	234	29	2.281926
7	29	85	259	58	89	38	2.179361
8	40	48	19	67	90	45	1.962085
9	11	174	22	38	258	55	1.914219
10	41	25	61	11	259	96	1.842426
11	81	5	232	85	260	85	1.718422
12	2	11	30	81	88	11	1.69267
13	43	12	24	5	250	40	1.651933
14	13	248	7	2	257	266	1.626548
15	12	67	4	25	261	58	1.615441
16	39	2	58	18	272	81	1.60119
17	83	13	254	13	235	259	1.473424
18	67	41	46	40	266	67	1.467032
19	160	126	208	27	267	41	1.460257
20	69	44	56	41	209	174	1.423473

3.3. Network Efficiency Analysis

The efficiency of TFN is 2.10, much higher than 0.06 of RPN, which means the physical connectivity of the high-speed railway network in China is not very dense, but it has a very high service capacity and convenient transportation services. Distributions of R under different failure modes are shown in Fig.11. The relative network efficiency is declined sharply in the beginning of the selective mode, however, is relatively flat in the random mode. The failure of the top 20 stations, 4% of the total nodes shows a higher loss of efficiency in the both modes, which are close to 70% and 40% respectively. Furthermore, the top 40% failure makes the network efficiency loss to nearly 0 in selective mode, while in random mode, 80% failure dropped the efficiency to almost 0. Therefore, the key stations that are identified in section 2.2 should be given more attention in the future development of the railway network.

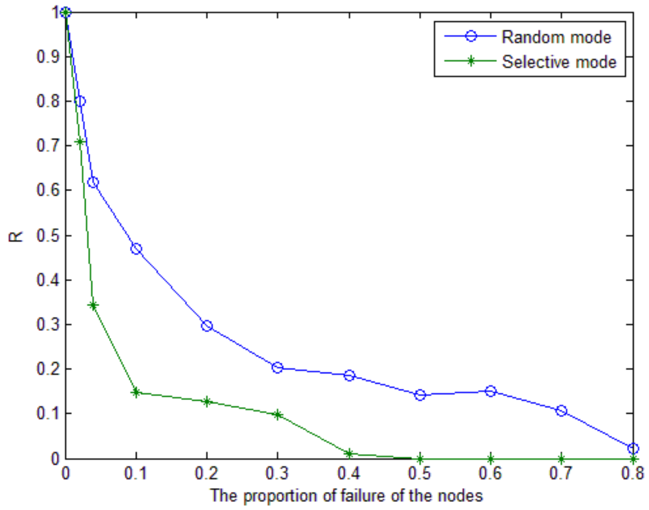

Figure.11 Distribution of R under different failure modes

4. RECOMMENDATIONS TO IMPROVE RAILWAY NETWORK

Based on the reliability analysis of the railway network, the optimised suggestions of improving the network considering in the following two terms.

a. Railway Network Infrastructure Planning

- The reliability of the network should be considered in the future infrastructure planning, in addition to the economic and demographic factors. Some high-CI stations have only one railway line passing through should be included when a new rail line is planned, which will not only balance the distribution of the key stations in the network and relieves the transportation pressure but also help to improve the network reliability.
- The combination of the topology of RPN indicates that some stations are located in the same city, for instance, 4 in Beijing and 3 in Shanghai. Some hub links between these stations should be allocated in the future, which will not only be able to improve the physical connectivity and transportation service of stations but also improve the reliability of the whole network in different failure modes.

b. Railway Transportation Operation

According to the reliability analysis of the railway network, once the key stations are failed or lost capacity, the connectivity and efficiency of the overall network would drop rapidly. To ensure the normal operation of the railway, it is recommended to strengthen the protection of the key stations, for example, protection strategies in advance to reduce the impact of disaster weather, organizing extra trains to improve transportation capacity etc. Furthermore, service capacity can be improved by optimising operation scheme with the constraints of the existing RPN. Therefore, higher k power means higher service capacity as shown in Eq. 11, which means a better operation scheme. Nevertheless, all these principles should be considered in the future to improve the stability of the high-speed railway Network.

5. CONCLUSIONS

The paper presented a new method to analyse the reliability of the railway network by identification of the key stations based on the two network models of RPN and TFN. In addition, both physical network topology and dynamic operation strategies are considered in this method. Considering the key stations, railway network efficiency is analysed under selective and random failure modes. A real-world case study of the high-speed railway network in China is presented to demonstrate that the cumulative distribution of DC is exponential and the relationship between DC and SC follows power distribution. Furthermore, the key stations were obtained by the CI by considering all the factors of topological connectivity, transportation capacity and local influence. Therefore, maintenance of these key stations can ensure a higher reliability of the whole network. In the end, some recommendations are given in terms of infrastructure planning and transportation operation of the railway network in order to improve the network development.

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