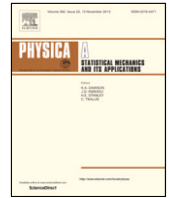




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A new global method for identifying urban rail transit key station during COVID-19: A case study of Beijing, China

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ABSTRACT

The rapid-developed COVID-19 has been defined as a global emergency by the World Health Organization. Meanwhile, various evidence indicates there is a positive correlation between the transmission and population density, especially in closed and semi-closed space. The urban rail transit, as one of the major mode choices for people to commute in big cities, carries thousands of passengers every day with relatively closed and limited space, which provides favorable conditions for the spread of the virus. If the surrounding area of any station was disrupted under COVID-19, not only the individual line but also the entire urban rail transit network will have the risk to be affected. Therefore, it is necessary to identify and explore the distribution law of key stations during the spreading process of the COVID-19 virus in the urban rail transit network during the COVID-19 pandemic. Based on the spatial distribution of epidemic area and the demand of urban rail transit passengers, we have proposed a construction method of the rail transit network and use the improved shortest path algorithm to determine the route diversity index of each station which indicates its importance in the urban rail transit network. On this basis, we identify the key stations of the Beijing rail transit network to ensure that passengers avoid high-risk stations during the epidemic. The results show that the number of reasonable routes between any two stations is **1 to 5** during the COVID-19 pandemic. Moreover, the routes diversity index of the Beijing rail transit network was **1.235** during the COVID-19 pandemic and **2.2574** in the normal period. According to the reasonable route diversity index, we have identified the key stations of the Beijing rail transit network during the COVID-19, such as Qi-Li-Zhuang station.

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1. Introduction

Urban rail transit network plays a key role in mitigating traffic congestion and pollution in many cities around the world, such as Beijing, China, and New York, USA [1–3]. Although the urban rail transit system has large capacity and high-efficiency [4,5], it is also vulnerable when an emergency arises [6]. Key stations have the largest influence on the overall urban rail transit network when they are disrupted. Therefore, an effective method to identify the key stations and guide the passengers to avoid the high-risk stations is extremely significant, especially in emergencies.

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At the end of December 2019, a novel coronavirus, 2019-nCoV, caused an outbreak and spread around the world rapidly, which has posed great threats to public health and attracted enormous attention. According to various evidence, it has been recognized that there is a positive correlation between virus transmission and population density, especially in closed and semi-closed space [7,8]. Moreover, at the end of the Spring Festival holiday, all industry sectors gradually returned to work. Urban rail transit system, as the main way for people to commute, carries thousands of passengers every day, and its space is relatively closed, which provides favorable conditions for the spread of the virus. Therefore, urban rail transit network becomes the focus of urban traffic epidemic prevention and emergency management. For the newly infected patients, it is necessary to track the spreading path of the virus and the susceptible persons. Therefore, the analysis of urban rail transit network passenger flow is of great significance to public transportation and public health safety. When emergencies (e.g., large passenger flow, the spread of the epidemic) occur at any station, it will bring inconvenience and unsafety to passengers [9,10]. When an accident occurs, urban transit operation managers need to be able to provide alternate route information to reroute passengers [11]. Thus, it is significant to know how many reasonable routes are there between any two stations in normal operation or an accident. If one or more stations were disrupted by an accident, there would be a great impact not only on individual transit lines but also on the whole network [12]. Therefore, urban transit managers should acquire the vulnerable stations (i.e., key stations which have the largest impact on the entire network when they are disrupted) in the whole network in order to protect these stations using the minimum resources.

With the rapid advance of complex network theory, it has been a useful method to evaluate the key nodes in the network. The evaluation indicators of influential nodes have degree centrality, betweenness centrality, etc. [13,14]. Sheikhahmadi et al. proposed a high degree centrality index to identify the influential nodes in large scale networks [15]. Yang et al. used degree and betweenness as a composite indicator to find the key nodes in networks [16]. However, these methods only consider the topology property, while the demand of passengers is neglected.

In recent years, the related researches of urban rail transit emergency had been studied in past decades, such as safety, reliability, robustness, and vulnerability. Zhang et al. studied the characteristics of the rail transit network and their results show that transfer stations play an important role in the whole network [17]. Mburu et al. used z-score and participation coefficient to measure the key stations in Dublin bus network [18]. Derrible and Kennedy used small-world and scale-free network to analyze the complexity and robustness of Tokyo rail transit network [19]. Recently, the vulnerability of rail transit network has been studied as a method to measure the impact of an emergency. Holmgren et al. defined the conception of vulnerability when rail transit is exposed to emergency, which can weak and limit infrastructure system [20]. In transportation network, vulnerability is counted as a complement reliability [21,22]. Deng et al. analyzed the topological vulnerability characteristics of Nanjing rail transit using the Space L model [23]. Kim and Li proposed a new survivability index to measure the vulnerability and reliability of Beijing rail transit network [24]. The new survivability index is about topological connectivity under different simulated failures.

Meanwhile, there are many researches that focus on reasonable routes set for the transportation network. At present, the popular algorithms about path searching include Dijkstra's shortest path algorithm [25], Dial's STOCH algorithm [26], and a combinatorial algorithm [27]. The shortest path algorithm aims to find the shortest route between any two nodes, which is quickly applied in the transportation network [28]. Then, various improved algorithms are proposed one after another, such as A* algorithm [29–31]. However, the passengers in real transport network may not select the shortest path in many cases due to personal preferences, a bias for or against a certain route segment and other factors [32]. Thus, the shortest path is not suitable for passengers in real transportation network especially in an emergency. Therefore, Wu et al. proposed a data-driven model for passenger route choice set in urban rail transit network. This model considered the walking time and transfer time [33]. David et al. proposed the concept of reasonable route to depict the to describe a route of an OD pair that could be used by network users with error-prone perception on the route cost [34]. Furthermore, there are many related multi-route choice algorithms [35–37]. However, these algorithms are based on assumptions and rarely involve the actual needs of passengers and traffic emergencies.

There are also many researches that focus on identifying influential nodes in the network. However, these models ignore the relationship between topology property and demand factors, especially the factors of emergency. The aim of this paper is to provide a new global method to identify the key station of rail transit network. Not only should the topology be considered, such as degree, H-index and Betweenness, but also dynamic passenger flow and the spatial distribution of epidemic area should be taken into account. Then, we propose a reasonable routes diversity index to evaluate the influence of station and solve two problems: "How many reasonable and safety routes between any two stations in rail transit network during the COVID-19?" and "Which stations are vulnerable during the COVID-19?"

The remainder of this paper is organized as follows: Section 2 gives the data description. Section 3 provides a methodology to find reasonable routes between any two stations and identify the key stations in the whole rail transit network. In Section 4, we select Beijing as a case study and analyze the routes diversity of rail transit. Then we identify the vulnerable stations of rail transit. Section 5 concludes the work of this paper and declares future work.

2. Data description

The data used in this paper included data of constructing rail transit network, passenger flow of rail transit station, OD passenger flow and the spatial distribution data of COVID-19.

Table 1
The sample data of rail transit network.

| Line number | Serial number of rail transit station |
|-------------|---------------------------------------|
| Line 1 | 1 Si-Hui East Station |
| Line 1 | 2 Si-Hui Station |
| Line 1 | ... |
| Line 2 | 23 Ping-Guo-Yuan Station |
| Line 2 | ... |
| ... | ... |
| Line 17 | Ci-Qu |

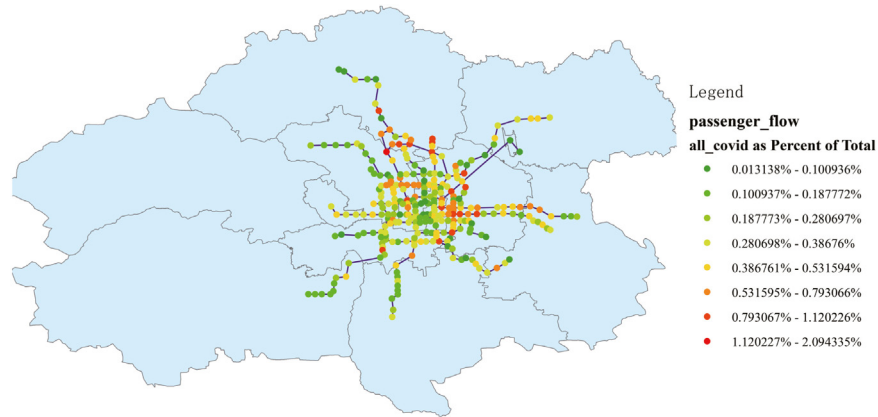


Fig. 1. Passenger flow of rail transit stations during the COVID-19 pandemic.

2.1. Data of constructing rail transit network

The construction of Beijing rail transit network needs the basic data of rail lines and stations. The Beijing rail transit network consists of 17 lines and 288 stations. The lines data includes lines number and a serial number of rail transit stations. The data are collected from the official website of the Beijing Metro Rail Operation Administration Corporation Limited. The sample of data is listed in [Table 1](#).

2.2. Passenger flow of rail transit station

Passenger flow is one of the main factors in the construction rail transit network. We obtain the statistical data regarding the passenger flow from Beijing Metro rail Operation Administration Corporation Limited. The data includes longitude, latitude, passenger flow in and out of rail transit stations. The data is from March 1 to March 6, 2020, during the COVID-19 pandemic and the same period in 2019. Statistical data of passenger flow during the morning peak (8:00–9:00) is shown in [Figs. 1](#) and [2](#). In [Figs. 1](#) and [2](#), “all_covid as Percent of Total” represents the percentage of station passenger flow in total passenger flow, respectively. The size of the passenger flow is represented by a small circle, and the color from green to red indicates the increase of the passenger flow.

2.3. The OD passenger flow of rail transit

The data of OD passenger flow can reflect the general pattern of passenger travel. In this paper, we select the OD passenger flow of Beijing rail transit network from March 3, 2019, to March 10, 2019, which contains 36,748,243 pieces of data. The data includes the latitude and longitude of departure and destination, station name, time of departure and destination, and transfer lines, etc. The specific data format of OD passenger flow data is listed in [Table 2](#).

2.4. Spatial distribution data of COVID-19

In order to obtain the relationship between the location of pandemic and rail transit stations, this paper crawled the spatial distribution data of pandemic area, which was updated by the health commission on March 2, 2020. Based on the previous studies of the attraction range of Beijing rail transit stations [[38–41](#)], we used the COVID-19 data within a 500 m range around rail transit station as our study area in this paper.

Using the ArcMap, the relationship between urban rail transit stations and the pandemic area was established with the station as the center of the circle and the radius of 500 m. The coupling results between station and the pandemic are shown in [Fig. 3](#).

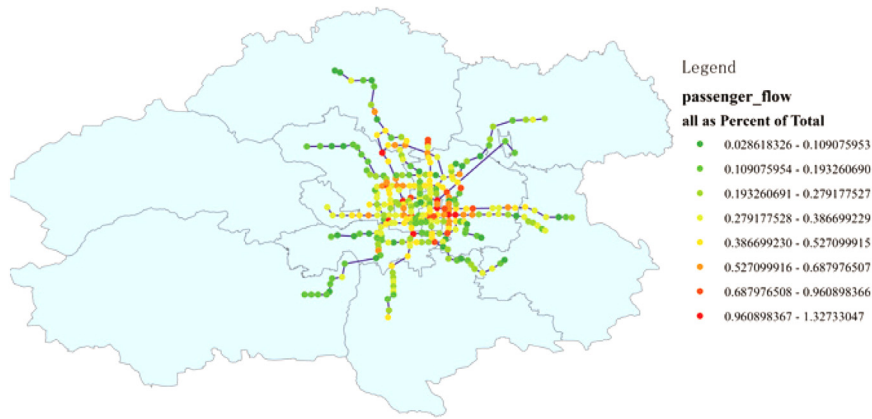


Fig. 2. Passenger flow of rail transit stations during the same period in 2019.

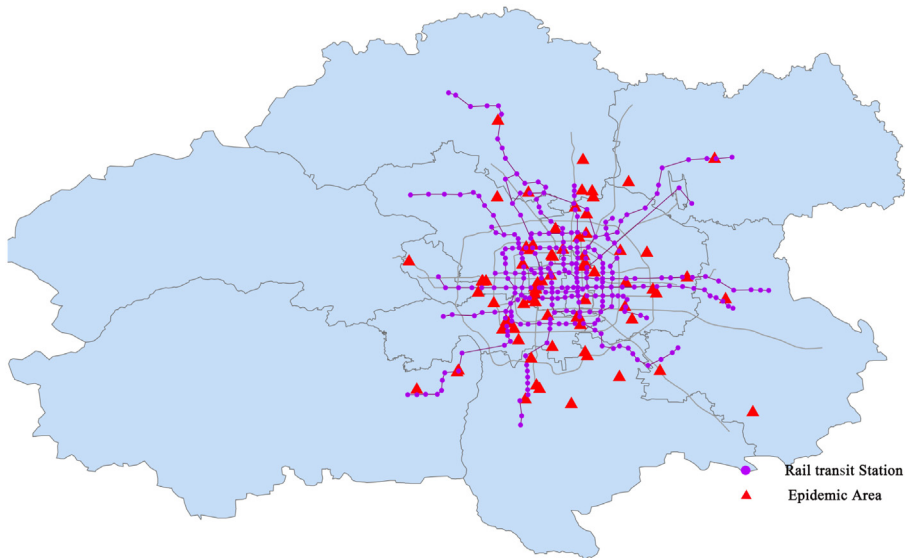


Fig. 3. The epidemic area distribution of COVID-19 around the rail transit stations.

Table 2
The sample data of passenger OD pairs.

| Filed | Sample | Filed | Sample |
|-----------------|------------------|------------------|------------------|
| Trip ID | 107 213 | Off station name | Si-Hui |
| On line name | Line 1 | Off station time | 2019/03/03 21:08 |
| On station name | Da-Wang-Lu | On latitude | 39.9073211 |
| On station ID | 23 | On longitude | 116.4707213 |
| On station time | 2019/03/03 20:08 | Off latitude | 39.9188711 |
| Off line | Line 1 | Off longitude | 116.4707204 |
| Off station ID | 28 | Transfer lines | Line 2 |

3. Methodology

There are numerous routes between any two stations in the large-scale rail transit network. However, most of them are not applicable to passengers in consideration of travel time, money cost, and safety, especially during the COVID-19 pandemic. Therefore, in this section, some conceptions of reasonable routes and reasonable routes diversity index are raised. Then we provide the method for identifying key rail transit stations and the solution algorithm.



Fig. 4. The rail transit network of Beijing.

3.1. Method for constructing the rail transit network

In this paper, a rail transit network can be represented as a graph $G = (V, E)$. V is the set of rail transit stations. E is the set of links of the rail transit network. G can be represented by $N \times N$ the adjacency matrix $e_{i,j}$. If two stations have a link, $e_{i,j} = 1$; otherwise, $e_{i,j} = 0$. N is the number of rail transit stations. Using the theory of complex networks, we construct the rail transit network as shown in Fig. 4.

3.2. Reasonable routes of rail transit during the COVID-19 pandemic

Reasonable routes between the origin and destination are the set of routes that are safe and reliable during the pandemic period. Moreover, the travel time of these routes is within the acceptable range of passengers. The influence of reasonable routes includes the topological structure, pandemic near the stations, passenger flow of stations during the pandemic, and travel time between two adjacent stations. In this section, we use the PageRank [42] of the topology property for rail transit, the importance of COVID-19 distribution, passenger flow of stations, and the travel time of two adjacent stations as the weight of link i . In the choice passenger route, these factors are interrelated. For example, in case of emergency, passengers will choose the route with less passenger flow, less epidemic, shorter travel time, and convenient transfer. Therefore, based on the theory of multiplicative interaction, the influence factors of weight are multiplied [43]. The route weight model between two stations is as follows.

$$E_i = \prod_{m,n} SPR_{pagerank} \times \prod_{m,n} \Lambda_{COVID-19} \times \prod_{m,n} P_{COVID-19} \times E_0 \quad (1)$$

where $\prod_{m,n} SPR_{pagerank}$ represents the topological importance between station m and station n . $\prod_{m,n} \Lambda_{COVID-19}$ is the distribution of novel coronavirus between station m and station n . $\prod_{m,n} P_{COVID-19}$ is the passenger flow of station m and station n . E_0 is the initial weight.

3.2.1. Topology influence of station in rail transit network

SPR algorithm is in fact an expansion of PageRank, which originated from Google's search technology. To calculate the influence of each station in the urban rail transit network, the model is as follows.

$$SPR(m) = \frac{1-d}{N} + d \sum_{i \in N} \frac{SPR(n)}{L(n)} \quad (2)$$

where m, n is the origin and destination of adjacent links. N is the number of rail transit stations. d is the damping factor. The value of the damping factor ranges between 0 and 1 and it is usually taken as 0.85 [44]. $L(n)$ is the number of adjacent stations. SPR is the topology influence of rail transit station. The value of SPR can be represented by the eigenvector of a

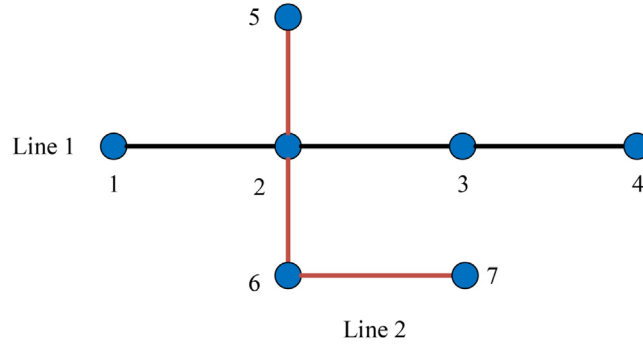


Fig. 5. The illustration of distance between two adjacent stations.

special adjacency matrix. The eigenvector R is expressed as formula (3) and (4).

$$R = \begin{bmatrix} SPR(P_1) \\ SPR(P_2) \\ \dots \\ SPR(P_N) \end{bmatrix} \tag{3}$$

$$R = \begin{bmatrix} (1-d) \times N \\ (1-d) \times N \\ \dots \\ (1-d) \times N \end{bmatrix} + d \begin{bmatrix} l(p_1, p_1) & l(p_1, p_2) & \dots & l(p_1, p_n) \\ l(p_2, p_1) & l(p_2, p_2) & \dots & l(p_2, p_n) \\ \dots & \dots & \dots & \dots \\ l(p_n, p_1) & l(p_n, p_2) & \dots & l(p_n, p_n) \end{bmatrix} \times R \tag{4}$$

If there is a link connecting station i to station j .

$$\sum_{i=1}^N l(p_i, p_j) = 1 \tag{5}$$

Otherwise

$$\sum_{i=1}^N l(p_i, p_j) = 0 \tag{6}$$

3.2.2. Influence of COVID-19 on rail transit stations

3.2.2.1. **Influence of epidemic.** The influence of COVID-19 on rail transit stations can be dealt with a buffer. The weight of rail transit station during the COVID-19 pandemic is the number of all epidemic areas in the buffer zone around the station. The calculation method as follows.

$$\Lambda_{COVID-19} = \{x \mid D(x, A) \leq r\} \tag{7}$$

where $\Lambda_{COVID-19}$ represents the influence of rail transit station. x is the number of epidemic areas in the station buffer. A represents the station of rail transit station. r is the distance threshold.

3.2.2.2. **Passenger flow of station during the COVID-19 pandemic.** The influence of demand for passengers can be reflected by the normalized station volume. Therefore, we use the normalized March 2020 data during 2020 COVID-19 and the same period during 2019 as the weight of stations.

3.2.3. Initial weight of links between two stations

In this paper, we use the travel time as the initial weight which can be calculated by the distance and travel speed between two adjacent stations. The distance used in this paper is the Euclidean distance, which represented the straight-line distance between two adjacent stations. (i.e., the distance of non-adjacent stations is not calculated.) To illustrate the distance more visually, we used Fig. 5 to represent the distance. For example, in Fig. 5, the distance of adjacent stations we need to calculate is (1, 2), (2, 3), (2, 5), (2, 6), (3, 4), (6, 7). Meanwhile, the straight-line distance between two adjacent stations can be calculated by the longitude and latitude of stations. Therefore, the distance used in this paper is very close to the real physical distance.

The calculation of initial weight is as follows.

$$E_0 = \frac{D(s, t)}{V(s, t)} \tag{8}$$

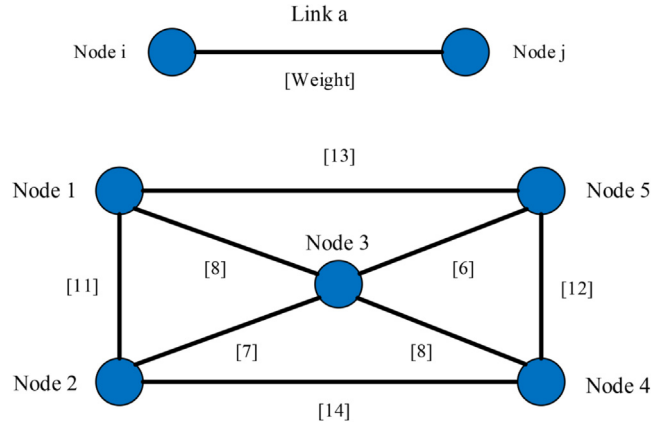


Fig. 6. Simple network.

where E_0 represents the initial weight. $D(s, t)$ is the distance, which can be calculated by the longitude and latitude of two adjacent stations. s, t is the adjacent stations. $V(s, t)$ is the expected speed of rail transit.

3.2.4. Reasonable routes constraint λ

In real transit network, there may exist thousands of different routes between stations with long distance. However, most of routes are unreasonable for passengers because of taking much time and money. Meanwhile, the reasonable routes also play the role in safe evacuation under emergencies, especially during the COVID-19. Therefore, the constraint parameter is of great significance for constructing reasonable routes set of passengers. In order to establish a reasonable route set, we use a parameter λ to constrain. In addition, the shortest path between two stations is needed as a basis. The model of the constraint is as follows.

$$L(s, k) < \lambda L(s, 0) \tag{9}$$

where $L(s, 0)$ represents the generalized cost of shortest path between two stations, which includes the influence of topology, passenger flow of stations, area of COVID-19 and travel time. λ is the parameter of reasonable routes constraint. $L(s, k)$ is the reasonable route set.

3.3. Identification of key station method of rail transit network

Through the path search algorithm, the reasonable path between the origin and destination stations is calculated. Then an index is constructed to measure the routes diversity of the whole rail transit network. The new index is given as follows.

$$\Gamma = \frac{\sum_{s=1}^N (\sum_{t=1}^{s-1} m(s, t) + \sum_{t=s+1}^N m(s, t))}{N \times (N - 1)} \tag{10}$$

where Γ is the index of route diversity. N is the number of rail transit stations. s, t is the origin and destination station of rail transit. $m(s, t)$ is the number of reasonable routes between origin station and destination station.

The remaining network routes diversity is calculated by node removal. The station which is removed out, the urban rail transit station with the largest change of route diversity is called the key station in the network.

In order to illustrate the reasonable routes and routes diversity, we use a simple network as an example. The simple network can be represented as Fig. 6. This simple network has 5 nodes, 8 links, 20 OD pairs. In this simple work, we assumed that the constraint parameter is 2 (i.e., any routes within 2 times the shortest route is the reasonable routes). For example, the reasonable routes from node 2 to node 5 are $(2 \rightarrow 3 \rightarrow 5)$, $(2 \rightarrow 1 \rightarrow 5)$. Moreover, we obtain the number of reasonable routes between two nodes presented in Table 3. The route diversity of simple network is 2.4 indicating that there exist 2.4 reasonable routes on average between each O-D pair. We assume that the node is failed in turn. The route diversity of nodes is shown in Table 4.

3.4. Solution algorithm

In order to solve the above problems, we propose a novel algorithm based on Yen's shortest path [45]. In this section, we give the detailed procedure of the algorithm for calculating the number of reasonable routes between any two stations and routes diversity for the rail transit network. The algorithm includes three parts:

Table 3
The reasonable routes between two nodes in the simple network.

| Nodes | 1 | 2 | 3 | 4 | 5 |
|-------|---|---|---|---|---|
| 1 | 0 | 2 | 1 | 7 | 3 |
| 2 | 2 | 0 | 1 | 4 | 2 |
| 3 | 1 | 1 | 0 | 1 | 1 |
| 5 | 3 | 2 | 1 | 2 | 0 |

Table 4
The route diversity of nodes in the simple network.

| Nodes | 1 | 2 | 3 | 4 | 5 |
|-----------------|-----|-----|-----|-----|-----|
| Route diversity | 0.9 | 1.1 | 0.8 | 1.0 | 1.1 |

- (1) Firstly, based on the spatial distribution data of the COVID-19 pandemic and the passenger flow of rail transit stations during the pandemic, we constructed the rail transit network;
 - (2) Based on improved shortest path algorithm, we get the reasonable routes between any two stations;
 - (3) Finally, we calculate the reasonable routes diversity index of the whole rail transit network.
- The detailed procedure of algorithm is summarized in Algorithm 1.

Algorithm 1 Route diversity and key stations indentation algorithm.

Input: Input all sorted stations of rail transit network $\{n \in N \mid n = 1, 2, 3, \dots, N\}$, all sorted links $\{a \in A \mid a = 1, 2, 3, \dots, A\}$, and the adjacent matrix of nodes. The initial alternate routes set $S_n = \emptyset$.

Output: The reasonable routes, the diversity of reasonable routes for the whole network.

- 1: for $1 < n < N$ do
- 2: for $1 < a < A$ do
- 3: Calculate the weight of links with COVID-19, the demand of passengers and topology.
- 4: Calculate the shortest path from the origin s to the destination t using the Yen algorithm. The shortest path is $P_{s,0}$, and the cost of shortest path is $L_{s,0}$. We save the shortest path to the alternate routes set S_n as the first reasonable route.
- 5: end if
- 6: end for
- 7: for $1 < s < N$ do
- 8: for $1 < k < N$ do
- 9: for $1 < a < A$ do
- 10: if $L(s, k) < \lambda L(s, 0)$
- 11: Calculate the new shortest path from the origin s to the destination k using the Yen algorithm. We save the shortest path to the alternate routes set S_n as the second reasonable route.
- 12: $S_n = n + 1$
- 13: else
- 14: break
- 15: end if
- 16: end if
- 17: end for
- 18: end for
- 19: Calculate the diversity of reasonable routes for the whole network Γ .
- 20: The routes diversity of the rail transit network is calculated again when station is removed.

4. Case study

In this section, we selected Beijing, China as our case study to illustrate the application of the route reasonable diversity index to a real-world network. By comparing the difference of routes reasonable diversity during the COVID-19 and normal operation period, we analyzed the impact of the COVID-19 on Beijing rail transit network. Then, we analyzed the vulnerability of the rail transit network and identified the key stations during the COVID-19.

4.1. Topology properties of rail transit network

Based on the complex network theory, the basic characteristics of the Beijing rail transit network are calculated, such as Degree Centrality (DC), K-shell, Betweenness Centrality (BC), Clustering Coefficient (CC), Eigenvector Centrality (EC), and PageRank (PR). The results of rail transit network statistical indicators are shown in Fig. 7. The indicators of topology

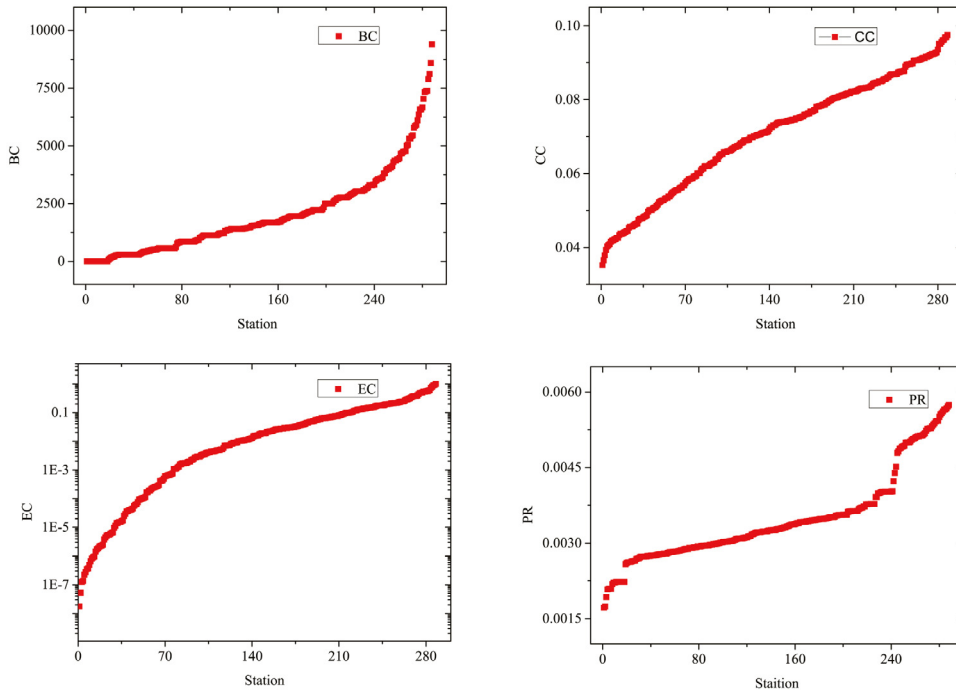


Fig. 7. The topology of Beijing rail transit network.

Table 5
The ranking of Beijing transit stations depends on the network topology.

| Ranking | Station | Ranking | Station |
|---------|---------------|---------|-----------------------|
| 1 | Ci-Shou-Si | 6 | Hai-Dian-Huang-Zhuang |
| 2 | Jiao-Men-Xi | 7 | Song-Jia-Zhuang |
| 3 | Olympic Park | 8 | Xi-Zhi-Men |
| 4 | Wang-Jing | 9 | Bei-Tu-Cheng |
| 5 | Gu-Lou-Da-Jie | 10 | Dong-Zhi-Men |

Table 6
The reasonable routes between any two stations during the COVID-19.

| Reasonable routes | 1 | 2 | 3 | 4 | 5 |
|-------------------|-------|------|-----|-----|---|
| Number | 32961 | 7361 | 677 | 321 | 8 |

can reflect the importance of stations. According to the results, we use the PageRank (PR) as the basis for the importance of stations to identify the key stations. The top stations of importance are shown in Table 5

However, it is inaccurate to identify the key station in the rail transit network only based on the topological structure in large passenger flows and emergencies such as COVID-19. The combination of epidemic data and station passenger flow data can better reflect the key stations of the rail transit network.

4.2. Reasonable routes between any two rail transit stations

Beijing rail transit network has 288 nodes and 82656 OD pairs. Based on the new algorithm, we obtain the number of reasonable routes between each OD pairs. In order to obtain the parameter of reasonable routes constraint λ , we select the actual OD data of passenger travel based on IC card data and calculate the parameter which is 1.36. The results of reasonable routes between any two stations during the COVID-19 are shown in Table 6. The routes of the whole rail transit network are 41328 and the reasonable routes are 51038. All OD pairs have at least 1 reasonable route and at most 5 reasonable routes. The maximum number of reasonable routes between any two stations is 1, which indicates that there is 1 reasonable route between most stations during the COVID-19. The variation trend of reasonable routes distribution is shown in Fig. 8. From Fig. 8(a), there is a linear relationship between the number of reasonable routes and the reasonable routes in logarithmic coordinates. With the reasonable routes between any two stations increasing, the number of OD pairs decreases sharply, as shown in Fig. 8(b).

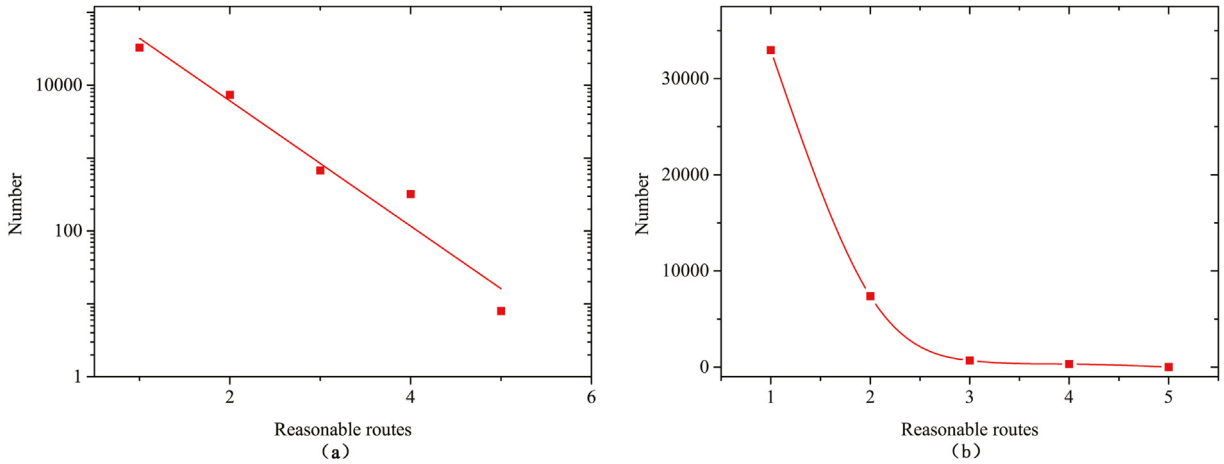


Fig. 8. The number distribution of reasonable routes during the COVID-19. (a) is the relationship between reasonable routes and the number of reasonable routes under logarithmic coordinate. (b) is under the linear coordinate.

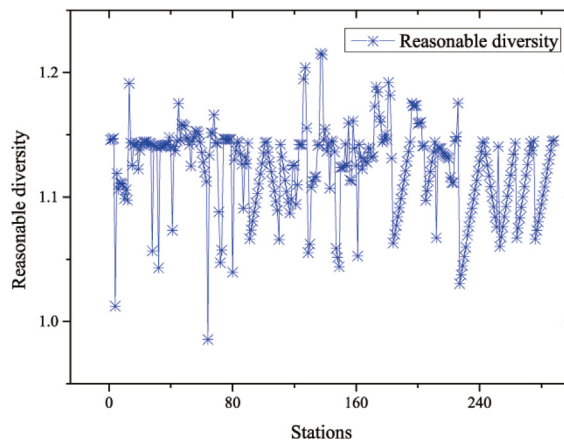


Fig. 9. The reasonable route diversity of Beijing transit network during the COVID-19 pandemic.

The route diversity of the Beijing rail transit network is **2.2574** during the normal operation times. However, the reasonable diversity of the Beijing rail transit network is **1.235** during the COVID-19. The results show that the novel coronavirus has a great influence on people’s use of rail transit.

4.3. Distribution of key rail transit stations during the COVID-19 pandemic

There are 288 stations in the Beijing rail transit network and we number the stations according to the routes, such as {1, 2, 3, . . . , 288}. We remove the stations in turns to calculate the reasonable route diversity and the results are shown in Fig. 9. In the path search algorithm, we use station passenger flow and epidemic distribution data as station weight, which will avoid stations with large weight. By removing the stations, the reasonable routes diversity index of the Beijing transit network decreasing the fastest is Qi-Li-Zhuang station, which indicates that Qi-Li-Zhuang station is the key station during the COVID-19 pandemic. The reasonable route diversity value of Qi-Li-Zhuang station is **0.986** during the COVID-19. The main reasons are the existence of large farmers’ markets such as Xin-Fa-Di and large passenger transport hubs such as Liu-Li-Qiao Passenger transport Center, which near the Qi-Li-Zhuang Station. During the epidemic, in order to meet the needs of travel and living materials (vegetables, fruits, meat, etc.), Qi-Li-Zhuang station becomes the passenger gathering center and the most vulnerable node of the rail transit network. Compared with the identification method of topology structure, the new method combined with the pandemic, passenger flow, and other factors can better reflect the reality.

The values of routes diversity for the top 10 stations are shown in Table 7. Meanwhile, we list the key stations of the top ten in Fig. 10. Key stations carry the larger passenger flows during the COVID-19. Identifying and protecting the key stations in the rail transit network can effectively inhibit the spread of the virus and protect the safety of passengers.

Table 7
The ranking of Beijing transit stations during the COVID-19.

| Ranking | Station | Diversity | Ranking | Station | Diversity |
|---------|-----------------------|-----------|---------|------------------------|-----------|
| 1 | Qi-Li-Zhuang | 0.986 | 6 | Jiao-Men-Xi | 1.043 |
| 2 | Hai-Dian-Huang-Zhuang | 1.012 | 7 | Zhong-Guan-Cun | 1.044 |
| 3 | Feng-Tai-Dong-Da-Jie | 1.030 | 8 | Ke-Yi-Lu | 1.045 |
| 4 | Feng-Tai-Nan-Lu | 1.038 | 9 | Da-Wang-Lu | 1.047 |
| 5 | Wang-Jing | 1.040 | 10 | Peking-University-East | 1.051 |

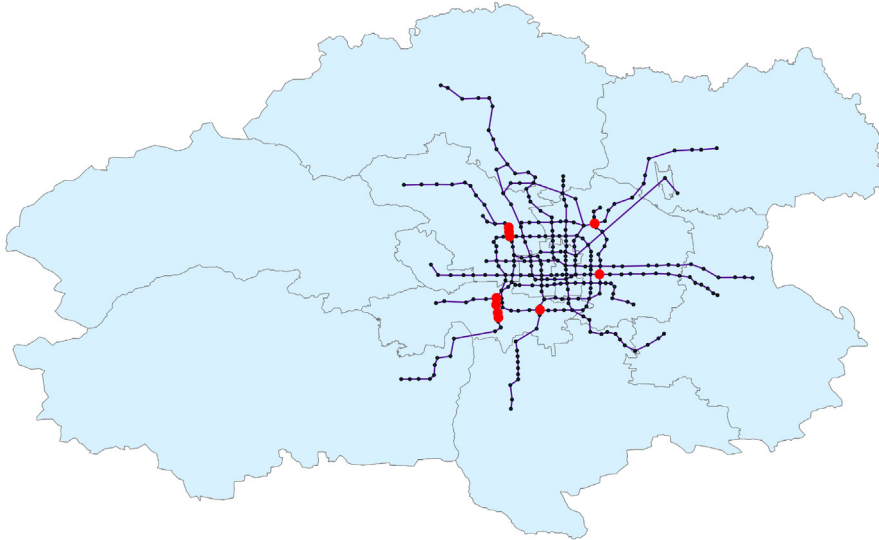


Fig. 10. The vulnerable stations of Beijing transit network during the COVID-19 pandemic.

5. Conclusions

The rail transit carries a large number of passengers, and the space is relatively closed, which provides favorable conditions for the spread of the virus. Meanwhile, the key stations of the rail transit network are the vulnerable stations, which have the largest impacts on the overall rail transit network, i.e., the station will decrease the routes diversity the most when it is failed. Identifying and protecting the vulnerable stations in the rail transit network can effectively inhibit the spread of the virus and protect the safety of passengers. The main contribution of this paper is to propose a new algorithm for measuring the route diversity and identifying key stations of the rail transit network during the COVID-19. The case study based on the Beijing transit network with the real world infrastructure data and epidemic data is conducted, which can answer two questions for passengers and rail transit managers: “How many reasonable routes between any two stations?” and “Which stations are vulnerable in whole rail transit network?” The results of this paper can be summarized as follows:

(I) Based on the topology and passenger flow of stations, we calculated the reasonable routes between any two stations in Beijing rail transit network during the COVID-19. The maximum reasonable route between any two stations is **5** and the minimum is **1**. By calculating the reasonable route between any two stations, passengers can travel safely during the COVID-19.

(II) Using the diversity of the reasonable routes, we calculated the vulnerable stations of the Beijing rail transit network based on the reasonable number between any two stations. The most vulnerable station is Qi-Li-Zhuang station during the COVID-19. The other vulnerable stations are Hai-Dian-Huang-Zhuang station, Feng-Tai-Dong-Da-Jie station, Feng-Tai-Nan-Lu station, Wang-Jing station, etc. Compared with the method of topology structure, the results in this paper can provide management strategies for rail transit managers to ensure the safety of passengers during the COVID-19.

For the future, we will consider the load factor to analyze the key stations and reasonable routes of the rail transit network, which more accurately represent the demand for passengers. In addition, it should be tested the new algorithm in other large-scale rail transit networks such as America, Tokyo, New York, and London rail transit network.

CRedit authorship contribution statement

Jianlin Jia: Data curation, Writing - original draft. **Yanyan Chen:** Writing - review & editing. **Yang Wang:** Conceptualization, Methodology. **Tongfei Li:** Visualization, Investigation. **Yongxing Li:** Routes diversity index of rail transit network calculation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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