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ORIGINAL RESEARCH PAPERS

What Impact Will the New-Built Metro Bring to the Transportation of Second-Tier Cities? From the Perspective of a Multilayer Complex Network

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Abstract Metro is being developed rapidly in second-tier cities. There is a need to understand the impact it brings as it relates to the planning and management of the whole urban transportation system. In this paper, we applied the multilayer complex network theory to study this problem by contrasting the characteristics of transportation networks before and after the metro is built. We focused on transportation networks in second-tier cities and (1) proposed edge functions of the road subnetwork and rail transit subnetwork with impedance as weight; (2) established an interlayer function based on the transfer behavior to couple the above subnetworks into the multilayer weighted transportation network; and (3) redefined statistical parameters, such as node strength, chessboard coefficient, and average least pass cost. At last, Hohhot, China, a typical second-tier city, was taken as a case study. Calculations show that the new-built metro network in the second-tier city increases convenience and reduces travel cost, whereas, the vulnerability of the whole network increases, and the distribution of key nodes in the road network is reconstructed. For the sustainable development of urban transportation, more attention should be paid to the new-built metro in second-tier cities.

Keywords Transportation · Multilayer complex network · Metro · Second-tier city

1 Introduction

Nowadays, metro systems are deployed worldwide. As early as 1860, London built the first metro line, and now more than 200 cities in 56 countries have a metro system. Metro is still favored by many cities suffering from traffic problems because metro is punctual, fast, and has a large capacity. In the long run, a properly planned and managed metro is conducive to the sustainable development of the city. Besides some first-tier cities, such as London, New York, Tokyo, and Beijing, many second-tier cities are planning to build a metro system for the first time [1, 2].

Both metro stations and lines should be planned scientifically, because they require substantial investment and impact the development of the whole urban transportation system. It is also important for a second-tier city that builds a metro for the first time. We studied the impacts of a new-built metro brought to a second-tier city.

It is almost impossible to take all relevant factors into account to study the impact brought by a new-built metro. Attention is focused on the transportation of a second-tier city to clarify two problems: One is whether the new-built metro will strengthen the transportation network by providing an alternative for traffic, or will weaken it by attracting too much traffic at one place. The other is whether these few new-built metro lines can change the distribution of key nodes in the road network. Therefore,

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we studied the topology and the vulnerability of the transportation network.

For the sustainable development of urban transportation in second-tier cities, the impact of a new-built metro on transportation is studied based on a multilayer complex network. Section 2 discusses the recent work about multilayer transportation networks, which involves the extraction of the network and common statistical parameters. Section 3 illustrates the details of extracting transportation networks into a multilayer weighted network and proposes the statistical parameters suitable for the transportation network in a second-tier city. Section 4 describes the case study of a typical second-tier city, Hohhot, China. Section 5 presents a comparative study of a road transportation subnetwork (ROSN) and a multilayer weighted transportation network (MWTN) by analyzing statistical parameters.

2 Literature Review

Many scholars have applied the multilayer complex network approach to explore the characteristics of transportation networks. They treated each elementary unit (intersection, station, etc.) as a network node and each group-unit interaction (transportation line, etc.) as a network link [3–5]. However, the traditional complex network approach that treats all the transportation links on an equivalent footing cannot fully capture the relationships between networks of different modes, even leading to incorrect results. The simple extraction of urban transportation networks into a single layer of nodes and links is not sufficient. In recent years, the concept of multilayer networks has been continuously improved [6, 7], for which transportation networks are natural candidates [8]. Multilayer networks offer an excellent theoretical framework for how transportation networks are interconnected, with explicit additional layer–layer interactions taken into account.

Many achievements have been made in the research of transportation networks related to multilayer networks. Cardillo et al. [9] presented a comparison between the single-plex approach and the corresponding multiplex approach to illustrate that the multiplexity strongly affects the robustness of the European air network. Gallotti et al. [10] focused on the multi-modal transportation system and built a multilayer temporal network of public transport in Great Britain. Baggag et al. [11] modeled multi-modal transportation systems of various cities as multiplex networks and addressed the problem of urban mobility, robustness, and resilience under random and targeted failures. Feng et al. [12] analyzed the weighted multilayer network of the Beijing subway system to describe the essential interactions between train flows and passenger flows. However, most of the subjects of the above work are about first-tier cities.

Urban transportation networks are composed of multiple transportation subnetworks, on which vehicles or trains run. The extraction of the transportation network into a multilayer network is a necessary and critical step before analyzing it. Commonly, there are two primary considerations; one is the relationship between the transportation network and the transportation subnetwork, and the other is relations between the transportation subnetworks [13].

For transportation subnetwork extraction, after extracting transport elements into the primary network by a primal approach [4] or dual approach [5], the network's edge weight is specially focused. The early research took it as an unweighted network and treated all edges equally [14, 15], while different edges in real transportation networks often have different properties. Some studies used real-world traffic flow data as weight. Liu et al. [16] took travel time as the weight to analyze the connectivity of the Wuhan urban rail transit network. Tak et al. [17] weighted a highway network by traffic volume and proposed an actual demands-based method to detect deviations from ideal structural configurations. However, considering second-tier cities with a new-built metro, there is barely any passenger flow data. Also, it is too expensive to conduct a comprehensive traffic volume study of the road network in a second-tier city. A new method of applying weight remains to be explored for transportation network extraction of the second-tier city.

For transportation subnetwork relations, Parshani et al. [18] introduced a conception of inter-similarity (degree–degree correlation and inter-clustering coefficient) between networks. Their studies on port networks and airport networks show that well-connected ports tend to couple with well-connected airports. However, they did not take the spatial distance between networks into consideration; Gu et al. [19] treated cooperation strength at the transition point as relations between railway and airline transportation networks in China and Europe. In contrast, there is a possibility that networks may not be connected with each other simply by a transition point. Halu et al. [20] proposed that spatial multiplex networks interact with each other by the link probability (determined by distance). Sole-Ribalta et al. [21] took the nodes with the same geographical locations as the transfer points of different modes. While the above work neglected the connect expense between subnetworks, Strano et al. [22] considered the mutually connected underground and street networks in the large metropolitan areas of London and New York. They explored how their coupling affects their global properties while they neglect inter-modal change cost. However, the inter-modal change cost is also significant [23]. Aleta et al.

[24] took the urban transportation system as a multiplex network. He connected each node between different modes as long as the distance between them was less than 100 m. However, the work did not take into account the transfer habits of travelers.

With regard to statistical parameters of transportation networks, the most frequently used are degree, betweenness [25], clustering coefficient, average shortest path [26], efficiency [27], and vulnerability [28]. Vulnerability is defined to quantify the network's performance after being attacked. Many scholars have analyzed transportation networks using these parameters and have drawn valuable conclusions. Jiang [29] illustrated further the scale-free property of urban street networks by using 40 samples of different sizes from cities in the USA and a few more from elsewhere. Results indicated that all the topologies of urban street networks demonstrate a small-world structure and a scale-free property for both street length and connectivity degree. Zhang et al. [30] conducted a comparative study on the vulnerability of metro networks in Shanghai, Beijing, and Guangzhou. Results show that the Guangzhou metro network has the best topological structure and reliability among the three metro networks. Zhang et al. [31] constructed multilayer networks of shipping lines. Results show that the topological quantities, such as average degree, average clustering coefficient, etc. increase smoothly. However, these parameters may be applicable for the transportation networks of the first-tier cities, but not suitable for transportation networks of smaller-scale and simpler structure in second-tier cities.

A preliminary conclusion can be drawn from the existing studies listed above. Multilayer networks can offer a better theoretical framework for transportation networks than traditional complex networks do. Taking additional layer–layer interactions into account, and we can obtain a more realistic extraction of the transportation network. Also, insufficient attention has been paid to the edge's weight and subnetworks' relations of transportation networks in a second-tier city. Moreover, the statistical parameters of transportation networks applied in the first-tier city did not consider the characteristics of a second-tier city. It is crucial to explore a proper extraction method and statistical parameters for transportation networks of a second-tier city. To determine the impact a new-built metro brings to the transportation of a second-tier city, edge functions, and interlayer function to extract the road transportation subnetwork (ROSN), rail transit subnetwork (RASN), and the multilayer weighted transportation network (MWTN) were proposed. Statistical parameters for the transportation network in a second-tier city were also redefined.

3 Methodology

3.1 Edge Function

The early work took transportation links as unweighted edges and treated them equally, while different links in real transportation networks have different properties. Some works weighted transportation networks by traffic flow data. Still, there is little or even no traffic data when considering second-tier cities with a new-built metro, so this method is not applicable. Therefore, to better extract the transportation network of a second-tier city, we propose an edge function considering the impedance from the perspective of travelers to express the edge's weight in the transportation subnetwork.

In the first step, we construct the transportation subnetwork by the primal approach [3]. We regard the intersection or station as nodes and the links which connect them as edges. This method retains the topological properties of the transportation network and meets the requirements of the weighted transportation network in this paper. In the second step, we construct the edge functions of the ROSN and RASN separately. From the perspective of travelers, travel time and travel expense are the most important factors, which can be regarded as the impedance.

In the ROSN, the travel time on an edge is impacted by physical properties, traffic control measures, and traffic congestion of the edge. We use length, speed limit, and peak delay index to quantify the above factors. The travel expenses are mainly vehicle fuel costs. The edge function of the ROSN is shown as Eq. (1).

$$f_{ijr} = \alpha q \frac{d_{ij}}{v_{ij}} a + \beta d_{ij} p_r \; (i, j = 1, 2, \ldots, n_r) \tag{1}$$

where f_{ijr} denotes the impedance of the edge between the station i and j in the ROSN; $i, j = 1, 2, \ldots, n_r$, and n_r represents the total number of nodes in the ROSN. The first term on the right side of Eq. (1) represents the impedance of travel time; q denotes the hourly wage; d_{ij} denotes the length of the edge ij; v_{ij} denotes the speed limit; and $a (a > 1)$ stands for the peak delay index, which is the ratio of time spent in the peak congestion period and time spent in a smooth driving period. The second term represents the impedance of travel expenses. p_r denotes fare per kilometer. Also, the adjustment parameters α and β $(\alpha + \beta = 1)$ are given according to the characteristics of travelers.

In the RASN, the travel time is impacted by its physical structure and operational management factors, and we quantify the above factors by length, running speed, and extra time spent at metro stations. The travel expenses are mainly ticket price. The edge function of the RASN is shown as Eq. (2).

$$f_{ijm} = \alpha q\left(\frac{d_{ij}}{v_{ij}} + T_{ije}\right) + \beta d_{ij} p_m (i,j = 1,2,\ldots,n_m) \quad (2)$$

f_{ijm} denotes the impedance of the edge between the station i and j in the RASN; $i,j = 1,2,\ldots,n_m$, and n_m represents the total number of nodes in the RASN. The first term on the right side of Eq. (2) represents the impedance of travel time; T_{ije} denotes the extra time, and it consists of arrival time, departure time, ticket-buying time, and waiting time. The second term represents the impedance of travel expenses; p_m denotes the ticket price per kilometer. The other notations are the same as above.

3.2 Interlayer Function

Transportation subnetworks are connected directly by transfer nodes. Transfer node refers to a geographical location that can connect multiple modes of transportation. In fact, from the perspective of travelers, whether a transportation node can perform as a transfer station depends on the transfer behavior that occurs at it or not. On the one side, travelers' transfer behavior may not just happen in these transfer stations, since a considerable number of travelers walk or ride a distance to transfer; on the other hand, it is worth noting that travelers will not neglect the cost during the transfer. Thus, based on the transfer behavior, this part proposes an interlayer function to express the connections between the transportation subnetwork of second-tier cities.

The transfer behavior (only walking and riding between intersections and metro stations are considered) can be analyzed based on resident trip investigation data, so that the transfer habits and transfer cost for the interlayer function can be obtained.

Given the trip survey data (D, T, P), where D, T and P represent the vector of transfer distance, time, and cost, respectively. Firstly, considering that there are no clear criteria for "long-distance," "long time," or "high expense," the fuzzy flustering method is applied to classify the samples based on the characteristics of transfer behavior. Secondly, a proper value from the sample set m is selected as the range of D_m. $D_m \rightarrow (T_m, P_m)$ means within a specific distance range D_m, the transfer time and expense are T_m and P_m. Then, the distance ρ_{ij} between the intersections and metro stations is calculated. Travelers can travel freely between residential areas and buildings, so the distance between intersection $i(x_i, y_i)$(x_i and y_i represent geographical coordinates of node i separately) and metro station $j(x_j, y_j)$ can be measured by Euclidean distance shown as Eq. (3). Finally, the interlayer function is shown as Eq. (4).

$$\rho_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, (i,j = 1,2\ldots n) \quad (3)$$

$$f_{rsm} = \begin{cases} \alpha q T_m + \beta P_m, & (\rho_{ij} \in D_m) \\ \infty, & (\rho_{ij} \notin D_m) \end{cases} \quad (4)$$

The interlayer function expresses the relationship of the subnetworks by the transfer behavior, which is consistent with a real transportation network. Besides, the difference in transfer links can also be described. The ROSN and RASN can be coupled into the MWTN by the interlayer function.

3.3 Statistical Parameters for the Transportation Network in a Second-Tier City

Degree, clustering coefficient, average shortest path, betweenness, and efficiency are the statistical parameters used the most. However, some of the parameters are not applicable to the transportation network (neither subnetwork nor multilayer network) in second-tier cities. Therefore, considering the small-scale, simple, and square format structure of the transportation network in second-tier cities, we redefine the node strength, chessboard coefficient, and average least pass cost based on the existing parameters in this part. These efforts capture more features of the transportation network in a second-tier city than before and lay a foundation for further research.

3.3.1 Node Strength

The transportation network in most second-tier cities includes a road transportation network with a square format structure, so an integer sequence between 1 and 4 can describe its node degree. Worse still, the degree of a large number of nodes is equal to 4, which makes statistical results challenging to reflect the complexity of the transportation network accurately. So the degree is not suitable for the study of the transportation network in second-tier cities. In this paper, we propose node strength as a substitute. Similar to the concept of degree, a node with a large node strength means it has good ability. Since we define edge function with impedance in this paper, the larger the sum of edge impedance connected by the node, the more difficult to access the node, and the worse the node's ability is. To better express this relationship, we define the node strength as the reciprocal of the sum of edge impedance connected by the node. The node strength of i is shown in Eq. (5).

$$s_i = 1/\sum_{j=1}^{n} f_{ij}, (i,j = 1,2\ldots n) \quad (5)$$

where f_{ij} denotes the impedance of edge that directly connects to i. $p(s) = P\{x_1 \leq s \leq x_2\}$ can be defined as the probability distribution function of node strength, and it reflects the statistical macro-characteristics of the network's structure. When taking the travel cost as the edge impedance, larger node strength means smaller travel costs.

3.3.2 Chessboard Coefficient

The clustering coefficient is applied mainly in the social network. It describes the aggregation of nodes. It may not be applicable for nodes in the transportation network, for they are sparser. We focus on the characteristics of the transportation networks in second-tier cities and develop a new parameter. The transportation networks in second-tier cities look like a chessboard, so we define the chessboard coefficient of a node i, shown as Eq. (6):

$$c_i = \frac{\sum_{j=1}^{n} A_{xj}A_{jy} - 1}{C_{d_i}^2}, (i,j = 1,2\ldots n) \quad (6)$$

where A_{xj} and A_{jy} are elements in the adjacent matrix A of a transportation network, $A_{xj} = 1$ denotes that node x has a neighbor j, and so does A_{jy}. Only when both node x and node y are neighbors to node j, $A_{xj}A_{jy} = 1$. $C_{d_i}^2$ is the total number of neighbors of the node i, and d_i is the number of the nodes that link to the node i. Note that the chessboard coefficient is defined for nodes with more than two neighbors.

We can also define the average of all c_i as the chessboard coefficient of the whole network. It is easy to know that the minimum chessboard coefficient is zero. We can define the maximum chessboard coefficient based on the standard grid network, that is $\max C = \lim_{n\to\infty}(\sum_{i=1}^{n} c_i)/n$. Given the standard grid network G, shown as Fig. 1, node i has four neighbors ($d_i = 4$), and these neighbors share four neighbors (node 6, 7, 8, 5), so $c_i = 4/C_4^2 = 2/3$. Similarly, almost all the chessboard coefficients of nodes in G are $2/3$. When the network becomes large enough that nodes at network boundaries are negligible, $\max C = C_G = 2/3$ can be obtained. Therefore, the chessboard coefficient range is $0 \leq C \leq 2/3$. $C = 0$ if and only if all nodes do not form a grid structure; $C = 2/3$ if and only if all nodes in the network form a grid structure and the network is large enough. The chessboard coefficient is a measure of nodes' local aggregation. The larger chessboard coefficient implies the higher aggregation.

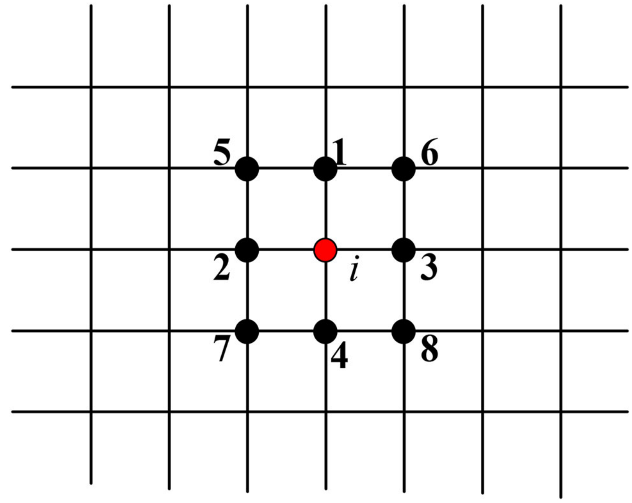


Fig. 1 Standard grid network

3.3.3 Average Least Pass Cost

In a weightless network, the shortest path between two nodes is the least number of edges connecting them, and the average shortest path of a node refers to the mean of all shortest paths starting from it. Correspondingly, in a transportation network weighted by impedance, the least pass cost between i and j can be defined as the least cost (written as l_{ij}) taken to connect them. The average least pass cost of the transportation network is the mean of all least pass cost of node pairs, which can be formulated as Eq. (7).

$$L_i = \frac{\sum_{j=1}^{n} l_{ij}}{n(n-1)}, (i,j = 1,2\ldots n) \quad (7)$$

The average least pass cost of a node reflects the difficulty in reaching it, so a node with a smaller average least pass cost implies that arriving at it takes less effort. The diameter of the network is the maximum cost. It can reflect the scale of the transportation network.

3.3.4 Betweenness

We can define the betweenness in the weighted network according to the least pass cost. The betweenness of node t written as B_t can be formulated as Eq. (8).

$$B_t = \sum_{i<j}^{n} g_{ij,t}, \ (i,j = 1,2\ldots n) \quad (8)$$

When the shortest path between i and j passes t, $g_{ij,t} = 1$. Otherwise, $g_{ij,t} = 0$. A large betweenness reflects that the node is badly needed for origin–destination (OD) pair travel, which implies that the node plays an essential role in the network. The network betweenness is the mean of betweenness of all nodes.

3.3.5 Vulnerability

It is assumed that all travelers choose routes according to the least-cost path, and there is no limit of network capacity. The network efficiency E represents the accessibility of the whole network. E is described in Eq. (9).

$$E = \frac{2}{n(n-1)} \sum_{i \neq j} \frac{1}{l_{ij}}, (i,j = 1,2...n) \quad (9)$$

A node with high efficiency means little cost is necessary to access it. V_i is the vulnerability of node i, shown as Eq. (10).

$$V_i = (E - E_i)/E, (i,j = 1,2...n) \quad (10)$$

E_i is the network efficiency without node i. The vulnerability of a node can also reflect its importance in the whole network.

We analyze the network vulnerability by observing the change of efficiency after the network has been attacked. There are two kinds of attacks, including random attacks and deliberate attacks. The random attack mostly comes from natural disasters or some random events, such as damage to intersections or metro stations caused by earthquakes. That is to say, every node is attacked by the same probability until all nodes have been attacked. Deliberate attacks are caused by human-made factors such as terrorist attacks. That is to say, nodes are attacked according to particular purposes until all nodes have been attacked.

4 Case study

Hohhot, China, a typical second-tier city, started operating its first metro line in 2019. This paper takes this city as a case study. We obtain the ROSN and the MWTN of Hohhot transportation networks by the edge function and interlayer function proposed in Sects. 3.1 and 3.2, respectively. The details can be described as follows:

- Firstly, a primal approach is applied to obtain the unweighted networks of the ROSN and RASN. The unweighted network of the ROSN includes the expressway, main road, and secondary road within the second ring road, as these roads carry the main traffic of Hohhot. The unweighted network of the RASN includes metro line 1 and line 2.
- Secondly, edge functions are built to obtain a weighted network. We obtain the data from the database of Hohhot Planning and Design Institute, including the length d_{ij}, the speed v_{ij}(metro 80 km/h, expressway 80 km/h, main road 60 km/h, and secondary road 40 km/h), and peak delay index ($a = 1.863$) in pratical traffic. The taxi fare ($p_r = 5$ CNY/km), average extra time ($T_{ije} = 5$ min), ticket price ($p_m = 3$ CNY/km), mean hourly wage ($q = 20$ CNY/h), and adjustment parameters ($\alpha = 0.6, \beta = 0.4$) are retrieved based on the trip survey. So we can obtain two weighted subnetworks (ROSN and RASN) following the methodology described in Sect. 3.1. The ROSN consists of 169 nodes and 297 edges, and the RASN consists of 27 nodes and 25 edges.
- Finally, the interlayer function is proposed to obtain the MWTN. We apply the fuzzy clustering method to obtain (D, T, P) (data standardized by min-max transformation, the fuzzy similarity matrix established by the angle cosine method, clustered by the transfer closure method, $m = 4$ is more reasonable). Additionally, the latitude and longitude of the intersections and the metro stations are accessed by Amap. The interlayer function of the MWTN is obtained according to Eq. (11), and following the process shown in Fig. 2 the MWTN of Hohhot is extracted (see Fig. 3). There are 196 nodes and 348 edges in the MWTN.

$$f_{rsm} \begin{cases} = 1.3, & (\rho_{ij} \in (0, 0.8]) \\ = 2.1, & (\rho_{ij} \in (0.8, 1.3]) \\ = 2.9, & \rho_{ij} \in (1.3, 2.0]) \\ = 3.3, & (\rho_{ij} \in (2.0, 3.0]) \\ = \infty, & (\rho_{ij} > 3) \end{cases}, (i,j = 1,2...n) \quad (11)$$

We calculate the statistical parameters of these networks by MATLAB programming, and the trip survey is made

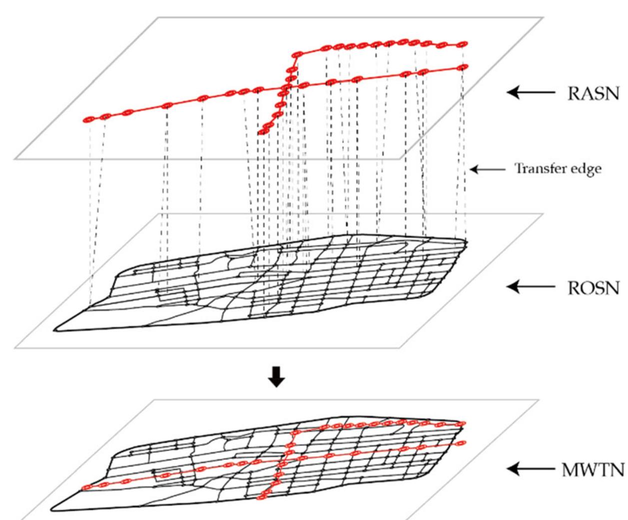


Fig. 2 Extraction process of the MWTN of Hohhot

using the random sampling method. Eight hundred seventy-three questionnaires were collected, among which 866 were valid for analysis.

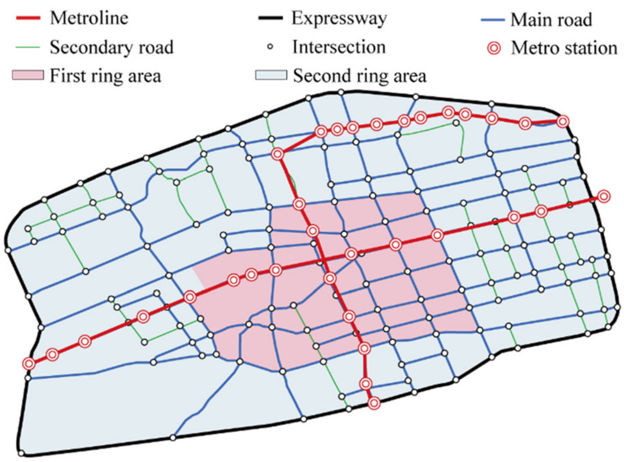


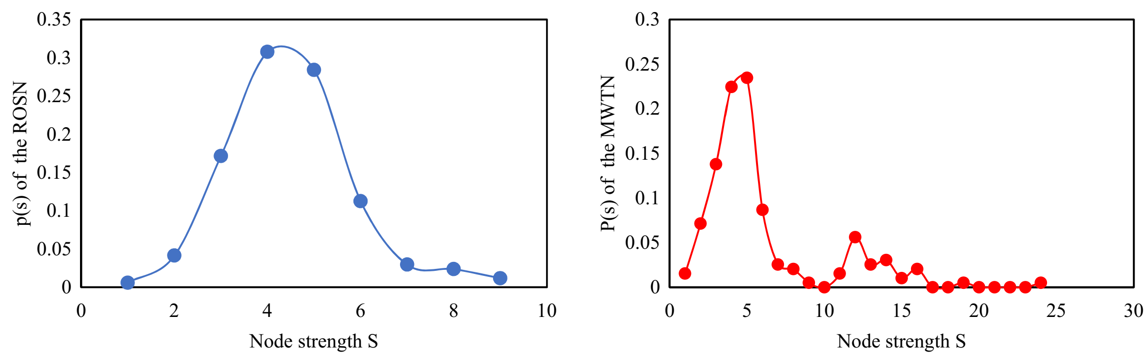
Fig. 3 MWTN of Hohhot

5 Results and Discussion

In this section, we analyze the statistical parameters and conduct comparative studies of the ROSN and the MWTN.

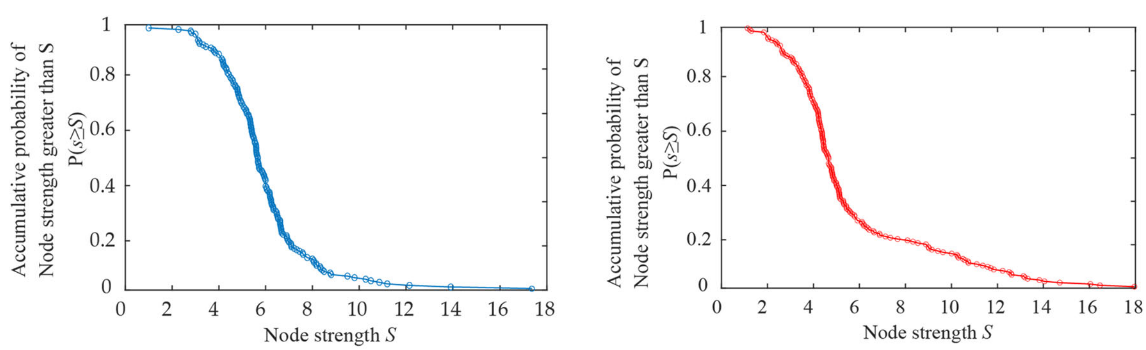
5.1 Node Strength

In the ROSN, the node strength $s_i \in [1, 17]$, and the average node strength $S \approx 5.920$, while in the MWTN, the node strength $s_i \in [1, 25]$, and the average node strength $S \approx 7.365$. The average node strength of the MWTN increases by 24.41% compared with that of the ROSN. The Kolmogorov–Smirnov test shows that the probability distribution function $(p(s > S) = P\{s > x\})$ in the ROSN follows a normal distribution, and that of MWTN does not (seen in Fig. 4), which shows that with the new metro, significant changes in the structure of the whole transportation network take place in Hohhot. By the way, Fig. 5 shows that both networks do not exhibit obvious scale-free or small-world characteristics as a transportation network in a first-tier city does.



(a) $p(s)$ of the ROSN (b) $p(s)$ of the MWTN

Fig. 4 Probability distribution function $p(s)$ in the ROSN and MWTN



(a) Accumulative probability of $p(s)$ in the ROSN (b) Accumulative probability of $p(s)$ in the MWTN

Fig. 5 Accumulative probability of $p(s)$ in the ROSN and MWTN

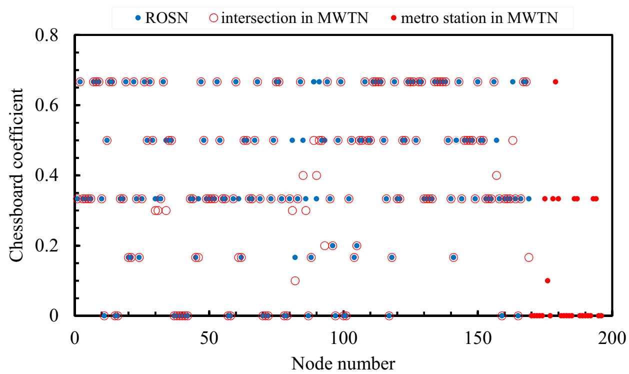


Fig. 6 Chessboard coefficient of ROSN and MWTN

5.2 Chessboard Coefficient

Compared with the ROSN ($C = 0.398$), the average chessboard coefficient of the MWTN ($C = 0.349$) decreases by 12.37%. Results show that the metro network makes a more aggregated transportation network than before. In Fig. 6, metro stations are numbered from 170 to 196, and they are marked with solid red dots. As shown in Fig. 6, most metro stations have a small chessboard coefficient, and the chessboard coefficients of intersections in the ROSN obviously decrease. From a geometric point of view, in Hohhot, transportation inconvenience caused by the square format network is reduced, while traffic congestion caused by this may be relieved.

5.3 Average Least Pass Cost

We calculated the least pass cost of the ROSN and MWTN. As the results show in Table 1, the network diameter and average least pass cost decrease by 29.61% and 27.60%, respectively. On average, it takes at most 37.141 minutes and 8.254 CNY to arrive at any intersection or metro station in the MWTN. But in the ROSN, it takes 52.790 minutes and 11.731 CNY. As shown in Fig. 7, the average least pass cost of OD pairs in the MWTN is less than that of OD pairs in the ROSN. The further calculation shows that travelers can save 5.845 minutes and 1.299 CNY on average on each trip. All these statistics demonstrate that the new-built metro saves transportation costs in Hohhot by nearly 30%.

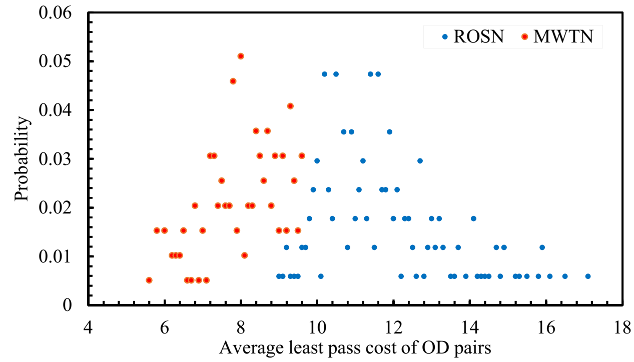


Fig. 7 Average least pass cost of the ROSN and MWTN

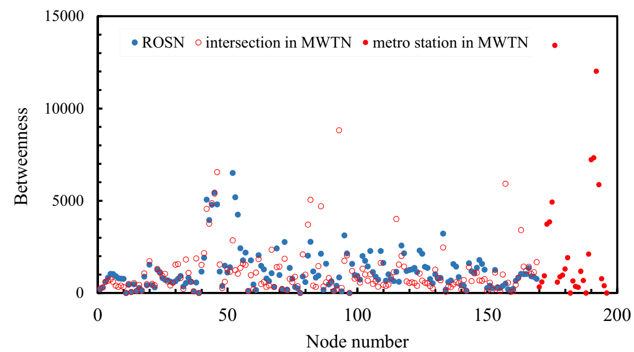


Fig. 8 Betweenness of the ROSN and MWTN

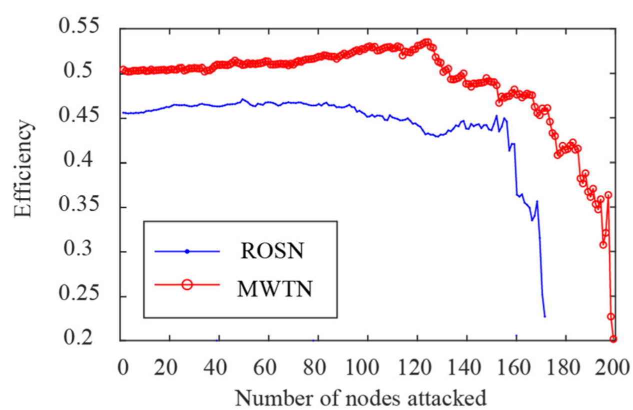


Fig. 9 Network efficiency of the ROSN and MWTN under random attacks

Table 1 Results of the least pass cost

	Network diameter (time, expense)	Average least pass cost (time, expense)
ROSN	29.328 (52.790 min, 11.731 CNY)	11.766 (21.178 min, 4.706 CNY)
MWTN	20.634 (37.141 min, 8.254 CNY)	8.518 (15.333 min, 3.407 CNY)

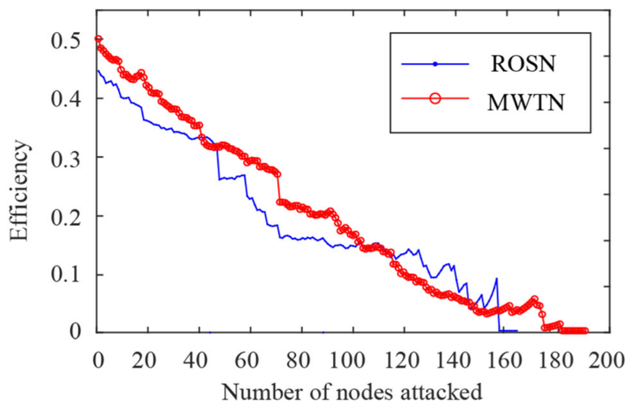


Fig. 10 Network efficiency of the ROSN and MWTN under deliberate attacks

5.4 Betweenness

The average betweenness of the ROSN is 1157, and the maximum is 6505 (node 52, intersection near Hohhot Railway station), while the MWTN's average betweenness is 1317, and the maximum is 13,416 (node 176, Hailiang Square station). The intersection in the MWTN has an average betweenness of 1099, which is 5% lower than it is in the ROSN, although the MWTN has an increased average betweenness by 13.83%. The much higher betweenness of metro stations (nodes numbered from 170 to 196 in the MWTN) is responsible for this. As shown in Fig. 8, several metro stations have much higher betweenness than others. Statistics indicate that the metro network shares a considerable amount of traffic with the road network, which is conducive to alleviating the traffic pressure of the road network.

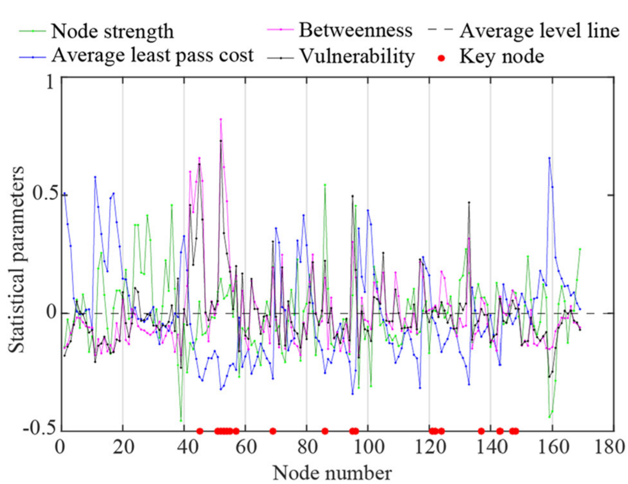


Fig. 11 Key nodes in the ROSN

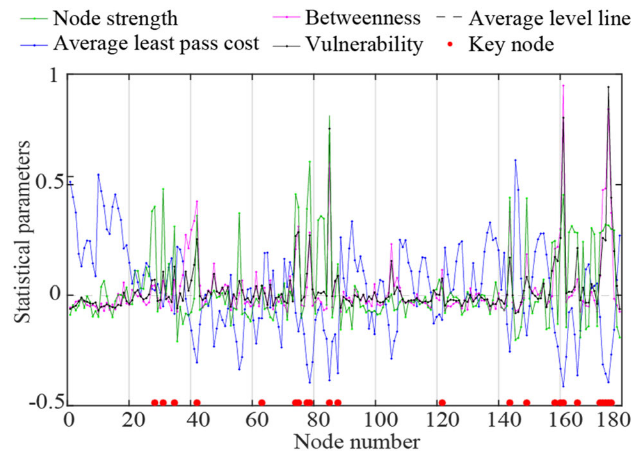


Fig. 12 Key nodes in the MWTN

5.5 Vulnerability

The network average efficiency of the ROSN is 0.453, and that of the MWTN is 0.532, which shows that the metro network increases traffic transmission efficiency in the second-tier city by 17.46%.

We then conduct random attacks by deleting a node randomly and calculating the efficiency of the network until all nodes are removed. As Fig. 9 shows, in the beginning, both the ROSN and MWTN show high robustness, and they are not vulnerable. When the number of damaged nodes is more than 150, the ROSN experiences a rapid decline in efficiency, as did the MWTN after only 120 nodes being attacked. The efficiency of the MWTN declines earlier than it does for the ROSN, which shows that the metro network makes the transportation network in Hohhot more vulnerable to random attacks.

We conduct deliberate attacks by deleting the node with the maximum betweenness and calculate the efficiency of the network until all nodes are deleted. As shown in Fig. 10, both the ROSN and MWTN experience a rapid decline in efficiency. However, the MWTN declines faster on average.

Both results show that the metro network increases the vulnerability of the transportation network in Hohhot.

5.6 Key Nodes Analysis

According to statistical parameter definitions, nodes with high node strength, small average least pass cost, large betweenness, and high vulnerability tend to carry more traffic. So they often play essential roles in the whole network, known as key nodes. In this section, we analyze the parameters of nodes comprehensively to figure out what kind of changes the metro network brings to nodes in the transportation network. We use the average level line as a benchmark, and take nodes with the higher parameters as key nodes. However, we take nodes with lower average least pass cost. As shown in Fig. 11, there are 19 key nodes in the ROSN, among which nodes numbered 51, 52, 53, 54, and 55 form a large key nodes group. In the MWTN, shown in Fig. 12, there are 26 key nodes, of which 34.62% are metro stations. Nearly 80% of former intersections are no longer key nodes, while other intersections, such as the node numbered 83, form its new key nodes group, including nodes 82, 85, and 86 in the MWTN. The above analyses demonstrate that the new-built metro network reconstructs the distribution of key nodes in the road network.

6 Conclusions

With the trend in metro construction in second-tier cities, the impacts of new-built metro networks have raised questions related to transportation planning and management. In this research, to better understand the transportation network of second-tier cities with a new-built metro network, a study based on the multilayer complex network is conducted. From the perspective of multilayer networks, the ROSN and MWTN of the typical second-tier city of Hohhot, China, are extracted, and a comparative analysis between them is presented. The empirical studies show that:

- The new-built metro network changes the distribution of node strength significantly, which means that the essential topological characteristics of the transportation network's structure are different. More attention should be paid to transportation management of second-tier cities with a new-built metro.
- With the metro network, node strength, betweenness, and efficiency of the transportation network increased by 24.41%, 13.83%, and 17.46%, respectively. Besides, the chessboard coefficient and average least pass cost decreased by 12.37% and 27.60%. All these data show that the metro network increases convenience and efficiency while reducing the cost of transportation in second-tier cities. However, the increased vulnerability it brings also cannot be ignored. More emphasis should be placed on the planning and management of key transportation nodes.
- The new-built metro network reconstructs the distribution of key nodes in the road network. Nearly 80% of the former intersections are no longer key nodes, and new key intersections come into being. However, among all new key nodes, 34.62% are metro stations. This result suggests that the formulation of metro planning requires overall consideration of the whole transportation network.

In conclusion, analysis of the impacts that a new-built metro bring to the transportation of second-tier cities will be essential, for more and more second-tier cities resort to the metro to alleviate traffic congestion. Besides, the network extraction method and statistical parameters proposed by this paper are also the foundation for further research on the transportation networks in second-tier cities. However, we did not consider the impact of the new-built metro on the traffic flow as Chodrow et al. [32] did, which is a limit of our work.

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