The impact of a public bicycle-sharing system on urban public transport networks

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The impact of a public bicycle-sharing system on urban public transport networks

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\section*{ABSTRACT}

As a healthy and environment-friendly trip mode, public bicycle-sharing systems, which have so far been built in hundreds of cities around the world, have been developing rapidly recently. The public bicycle-sharing systems, which are usually spatially embedded where original urban bus transport networks are located, comprise the new urban public transport system together with the bus transport networks. Therefore, studying the impact of the public bicycle-sharing systems on the original urban public transport networks is an important research subject. In this study, using the real spatial location data of the public bicycle-sharing systems of Hangzhou and Ningbo in China, we propose a multi-layer coupling spatial network model that considers the geographical information on bus stations, bus routes, and public bicycle stations by studying the urban public transport networks. The spatial network model consists of bus subnets, short-distance bicycle subnets, and short-distance walk subnets which are interdependent rather than independent. We apply the model to study the influence of bicycling between the short-distance bicycle station pairs (SDB) and walking between the short-distance bus station pairs (SDW) on the performance of the urban public transport networks. Results show that SDB and SDW can significantly reduce the average transfer times, the average path length of passengers’ trips and the Gini coefficient of an urban public transport network. Therefore, the public bicycle-sharing systems can decrease the average trip time of passengers and increase the efficiency of an urban public transport network, as well as effectively improve the uneven level of traffic flow spatial distribution of an urban public transport network and will be helpful to smoothening the traffic flow and alleviating traffic congestion.

\section*{1. Introduction}

The number of public bicycle-sharing systems, which are cheap, healthy, and environment-friendly trip modes, has been increasing rapidly. Thus far, hundreds of cities around the world have built the public bicycle-sharing systems (DeMaio and Meddin, 2016). The implementation of the public bicycle-sharing systems is so flexible that it complements the original urban public transport pattern, such as the bus and subway. A passenger can borrow a bicycle from an arbitrary self-help bicycle station and then return it to another arbitrary station after the trip. Research on public bicycle-sharing systems’ performance and optimization methods have been...
drawing increased attention at present. For example, de Chardon and Caruso (2015) estimated bike-share trips using station level data. Gosse and Clarens (2014) based their estimation on sparse data in temporally and spatially continuous bicycle volumes. Winters et al. (2013) proposed a method to find the most appropriate areas for a public bicycle-sharing system through statistics. Frade and Ribeiro (2015) proposed a maximal covering location approach for a public bicycle-sharing system’s stations. Chen et al. (2015) judged the number and locations of stations and optimized route options. Chow and Sayarshad (2014) proposed a framework which is applied to formulate a symbiotic bike-sharing network design problem in the presence of a coexisting transit system as a departure-time-elastic multicommodity flow problem. We also observe that, in the public transport networks with a public bicycle-sharing system, passengers often achieve flexible transfer by way of short-distance walking. For example, de Jonge and Teunter (2013) proposed optimizing itineraries in public transportation with walks between rides. Buehler and Hamre (2015) studied American adults’ trip modes including driving, walking, bicycling, and public transportation.

A public bicycle-sharing system is usually embedded in the space of original bus public transport network and complements it to form the new urban public transport system. An urban public transport network is a type of spatial network (Barthélemy, 2011; Silva et al., 2015) that is one kind of complex networks with spatial characteristics. The networks are embedded in their specific spaces, where every node and edge has its own spatial (geographical) position whose restriction plays an important role in the network characteristic. In the real world, many networks related to geographical positions belong to spatial networks, such as the Internet (Huang and Tang, 2015; Choi et al., 2015), power grid networks (Pei et al., 2015; Dewenter and Hartmann, 2015; Bai et al., 2016), airline networks (Ryerson and Kim, 2013; Dobruszkes, 2013), and road networks (Austwick et al., 2013; Peng et al., 2014; Zheng et al., 2015; Ruan et al., 2015; Gao et al., 2016). An urban public transport network is a kind of typical spatial networks because its nodes and edges have spatial positions (Zhang et al., 2016; Louf et al., 2013). In addition, new public transport networks often consist of the public bicycle-sharing system subnets, bus subnets, and subway subnets, which are interdependent rather than independent. So they belong to typical coupling spatial networks (Yang et al., 2014; Morris and Barthelemy, 2012).

Studying the influence of a new public bicycle-sharing system on an urban public transport network is the topic of this paper. We propose a new multi-layer coupling spatial network model that consists of bicycle subnets, walk subnets, and bus subnets to represent the whole public transport system, where bus and bicycle-sharing stations have their geographical positions and edges are directed-weighted (weight is the path length between two stations). We studied the features of urban public transport networks with public bicycle-sharing systems on the basis of real public transport network data of Hangzhou and Ningbo in China. We discovered that bicycling between short-distance bicycle station pairs (SDB) and walking between short-distance bus station pairs (SDW) can not only significantly improve the performance of urban public transport networks but also smoothen traffic flow and alleviate traffic congestion.

This paper is organized as follows. In Section 2, we propose the multi-layer coupling spatial network model of the urban public transport system. In Section 3, we study the influence of SDB and SDW on the performance of an urban public transport network. In Section 4, we describe the performance of an urban public transport network under the conditions of feasible major short-distance bicycling and walking thresholds. In Section 5, we design a transfer algorithm on the basis of the proposed three-layer coupling spatial network model. Finally, our conclusion and discussion are given in Section 6.

2. Three-layer coupling spatial network model of urban public transport systems

A public transport network is composed of stations and routes. In recent years, researcher often used the Space-L and Space-P network models to study the network properties of urban public transport networks (Sen et al., 2002). In the Space-L network model, a node represents a bus station, there is an edge between two bus stations when they are adjacent in one bus route. In the Space-P network model, a node denotes a bus station, there exists an edge between two bus stations when they are contained in at least one common bus route. The Space-L model reflects connection status of adjacent bus stations in a bus transport network, while the Space-P model denotes the transfer topology and often is used to study the transfer feature of a bus transport network.

To represent the spatial geographic location factors of an urban public transport network, we extend the Space-L and Space-P networks and propose two new models which are named as Spatial Space-L Network Model and Spatial Space-P Network Model. For

Fig. 1. (a) A public transport network consists of two bus routes. Different edge colors represent different bus routes, and arrows denotes the bus route directions. The weights of edges represent the path length of bus routes (km). The red Station 4 represents the common station of the two bus routes. (b) represents Spatial Space-L Network Model, and (c) represents Spatial Space-P Network Model.
example, Fig. 1(a) shows the original topology structure of an urban public transport network, Fig. 1(b) shows the directed-weighted Spatial-Space-I Network Model, Fig. 1(c) shows the directed-weighted Spatial-Space-P Network Model. In the Spatial-Space-I Network Model and Spatial-Space-P Network Model, a node represents a bus station with spatial geographic position information (longitude and latitude), and a directed-weighted edge presents the corresponding bus route path between two nodes, namely, its arrow direction reflects the route direction and its weight denotes the real path length.

The short-distance spatial walk network model, which is an undirected-weighted spatial network, is proposed to study the influence of SDW on an urban public transport network. In the Short-Distance Spatial Walk Network Model, nodes are bus stations with spatial position information. Two bus stations are called a short-distance bus station pair when the path length between them is less than the short-distance walking threshold \( T_w \), that is the maximum distance of short-distance walking, e.g., 0.5 km. There exists an edge between an arbitrary short-distance bus station pair whose weight is the path length between the two nodes. In a real urban public transport network, two nodes that are very near each other but are not in the same bus route can often be found, as illustrated by nodes 3 and 5 (0.2 km away from each other) in Fig. 1(a). If a passenger wants to go to station 6 from station 1, he has to transfer at station 4, which shares two bus routes. The bus route is 1-2-4-S-6 and the total distance is 7 km. However, stations 3 and 5 are only 0.2 km away; thus, the passenger can walk to station 5 from station 3 to achieve a different station transfer. The route of bus is 1-3-5-6 and the distance is only 3.8 km, reducing the path length of the bus journey. Obviously, SDW can also reduce the transfer times for a trip in a complex urban public transport network which is helpful to improving trip efficiency.

Recently, research on the actions of people using the public bicycle-sharing systems have indicated that most bicycle trips are of short distances and short time\([14]\) (e.g., within 1.5 km). Therefore, studying the influence of SDB on an urban public transport network is the topic of the current paper. We propose the Short-Distance Spatial Bicycle Network Model which is an undirected-weighted spatial network. In Short-Distance Spatial Bicycle Network Model, nodes are bicycle stations with spatial position information. Two bicycle stations are called a short-distance bicycle station pair when the path length between them is less than short-distance bicycling threshold \( T_b \) that is the maximum path length of short-distance bicycling, e.g., 2.0 km. There exists an edge between arbitrary short-distance bicycle station pair whose weight is the path length between the two nodes.

In real public transport networks, there are only part of the bus stations near the bicycle stations, rather than there exist bicycle stations nearby every bus station. For example, Table 1 shows that there are 3261 bus stations, while there are only 626 bicycle stations in Ningbo. Namely, there are many bus stations without nearby bicycle stations. In this paper, we do not consider all bicycle-sharing stations and only concentrate on those bicycle stations near bus stations because we think that bicycle stations which are close to bus stations have greater influence on transfer performance of the whole public transport networks than those that are far away from bus stops. In light of the real distribution data of Hangzhou and Ningbo, we define the combining threshold \( C_b \) of a bus station and its nearby bicycle stations. People can arrive at bicycle (bus) station from bus (bicycle) station by walk within the combining threshold \( C_b \). The \( C_b \) is so short that we can ignore the walk cost within it. Specifically, the \( C_b \) represents the maximum distance to combine a bus station and its adjacent bicycle stations, and all the bicycle stations within the scope of \( C_b \) around a particular bus station should be combined, which means that people can transform conveniently between two trip modes of taking bus and riding at the new combined station. The new combined station are both bus stations and bicycle stations, which simplifies the complex real public transport networks and is beneficial to our study to expand. For example, in Fig. 2, the geographic locations of bicycle stations B1, B2, and B3 near bus station S1, their geographic locations are all regarded as the S1 position. In the same way, the geographic locations of bicycle stations B4, B5, and B6 near bus station S2 are all regarded as the S2 position. The path length between the bicycle stations S1 and S2 is the shortest path length between them. Bicycling between short-distance bicycle station pairs (SDB) can reduce the average bus transfer times and the trip length effectively. SDB has more influence on an urban public transport network than SDW because the SDB distance threshold is greater than that of the SDW. As shown in Fig. 1(a)’s nodes 2 and 7 (1.5 km away from each other), if a passenger wants to go to station 2 from station 7, the bus route is 7-4-2 and the total path length is 2.5 km with one transfer at station 4. However, the trip between stations 7 and 2 are only 1.5 km away by bike, which has lower cost because of free, less time and no transfer.

We think that the whole public transport system consists of the bus transport network layer, Short-Distance Spatial Bicycle Network layer, and the Short-Distance Spatial Walk Network layer, whose nodes are all bus stations, and the nodes in the Short-Distance Spatial Bicycle Network layer and the Short-Distance Spatial Walk Network layer are part of the nodes in the bus transport network layer. People can transfer freely with the help of sharing stations between two arbitrary network layers via three transfer patterns, namely, bus, bicycle, and walk. The three network layers affecting one another are coupled by sharing bus stations, building the three-layer coupling spatial network model.

<table>
<thead>
<tr>
<th>City</th>
<th>S</th>
<th>N1</th>
<th>P1 (%)</th>
<th>R</th>
<th>SD</th>
<th>BS</th>
<th>N2</th>
<th>P2 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hangzhou</td>
<td>2943</td>
<td>1350</td>
<td>46</td>
<td>890</td>
<td>0.634</td>
<td>2430</td>
<td>2056</td>
<td>85</td>
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<tr>
<td>Ningbo</td>
<td>3261</td>
<td>626</td>
<td>19</td>
<td>627</td>
<td>0.395</td>
<td>626</td>
<td>521</td>
<td>83</td>
</tr>
</tbody>
</table>
3. Influence of bicycling between the short-distance bicycle station pairs (SDB) and walking between the short-distance bus station pairs (SDW) on the performance of an urban public transport network

In this section, the three-layer coupling spatial network model is applied in urban public transport networks to study the influence of SDB and SDW on urban public transport networks based on the public transport system data (AMAP, 2016) of Hangzhou and Ningbo in China. The basic public transport system data of Hangzhou and Ningbo are listed in Table 1, and the distributions of bus routes and bicycle stations are shown in Fig. 3. In Hangzhou and Ningbo, the proportion of the number of bicycle stations within 300 m of bus stations in the total number of bicycle stations is 85% and 83% respectively, namely, most bicycle stations are located within 300 m of the bus stations. So we set the value of Cb (the combining threshold of a bus station and its nearby bicycle stations) to 300 m.

3.1. Influence of the short-distance bicycling threshold \( T_b \) and the short-distance walking threshold \( T_w \) on the average number of bus routes of a trip in an urban public transport network

In our network model, \( T_b \) is the maximal path length of SDB and \( T_w \) is the maximal distance of SDW. The different values of \( T_b \) and \( T_w \) make up the different scales of Short-Distance Spatial Bicycle Network Model and the Short-Distance Spatial Walk Network Model, and thus have different influences on the performance of an urban public transport network. In an urban public transport network, the number of bus routes from arbitrary node I to j is the number of bus routes of the shortest paths of this trip, the average number of bus routes denotes the average number of bus routes between any two different stations, namely the transfer times of the trip plus 1, which is an important indicator in evaluating the transfer performance of an urban public transport network. That is, in an urban public transport network, low average number of bus routes means a passenger will have low average transfer times to finish a trip between two arbitrary stations, namely, the lower the average number of bus routes the better the transfer performance of an urban public transport network.

Fig. 4 presents three-dimensional relationship diagram of \( T_b \), \( T_w \), and the average number of bus routes. The scopes of thresholds are \( T_b \in [0.0,3.8] \) and \( T_w \in [0.0,1.0] \) respectively. When \( T_b = 0 \) and \( T_w = 0 \), the condition does not consider bicycling and walking, while...
When the bicycling and walking thresholds are both zero, the average number of bus routes is the highest. As the thresholds gradually increase, both of the average number of bus routes of the two cities present a declining trend, where they decline sharply when $T_b$ and $T_w$ are small values and decrease slowly when $T_b$ and $T_w$ are big values. The result indicates that, instead of the bigger the better, large values of $T_b$ and $T_w$ are less meaningful, which is in accordance with people's trip habits because people usually use bicycles and walk as trip modes within short distance rather than long distance.

Therefore, there should be a suitable threshold which we call feasible major threshold. Within the feasible major threshold, the increments of $T_b$ and $T_w$ have obvious influence on the average number of bus routes of a trip; whereas outside the scope of the threshold, the increments of $T_b$ and $T_w$ have little effect on the average number of bus routes of a trip.

The steps of solving the feasible major threshold are as follows.

1. Fitting the 3D curved surface in Fig. 4(a), we can get its function expression which can be supposed to be $f(x,y,z) = 0$.

2. At arbitrary point $(x,y,z)$ of the curved surface, using the fitting function $f(x,y,z) = 0$ to obtain the tangent plane equation $z = tp(x,y)$.

3. Using the tangent plane equation $z = tp(x,y)$ to get the partial derivative $\frac{\partial p(x,y)}{\partial x}$ and $\frac{\partial p(x,y)}{\partial y}$, which indicate the change rates of $z$ for $x$ and $y$ respectively in the tangent plane. When both change rates are less than a certain fluctuation threshold $\tau$, the change of $x$ and $y$ have little impact on $z$, namely, the change of $T_b$ and $T_w$ have little impact on the average number of bus routes of a trip. The minimum values of $T_b$ and $T_w$ which satisfy above conditions are feasible major thresholds.

We set the fluctuation threshold $\tau = 0.4$ (average number of bus routes of a trip/km) and get the feasible major thresholds as $T_b = 2.2$ km and $T_w = 0.5$ km according to the above three steps.

### 3.2. Influence of the short-distance bicycling threshold $T_b$ and the short-distance walking threshold $T_w$ on the average path length of an urban public transport network

In an urban public transport network, the path length between two random nodes $i$ and $j$ is the shortest path length between them. In the three-layer coupling spatial network model of an urban public transport network, a transfer may occur between arbitrary two of three network layers during a trip from random node $i$ to $j$. Therefore, the path length is the sum of all the lengths of paths that pass through the whole network layers. For example, if a passenger starts from bus station $i$ to $j$, whose trip consists of bus routes’ length of bus trip $L_{bus}$, SDB path length $L_{bik}$, and SDW distance $L_{wal}$, then the path length of the trip is $L_{bus} + L_{bik} + L_{wal}$. The average path length is the average value of the path lengths among all station pairs.

Fig. 5 presents 3D relationship diagram of $T_b$, $T_w$, and the average path length. The scopes of thresholds are $T_b \in [0.0,3.8]$ and $T_w \in [0.0,1.0]$ respectively. When $T_b = 0$ and $T_w = 0$, the condition does not consider bicycling and walking, while $T_b > 0$ and $T_w > 0$ consider otherwise. As $T_b = 0$ and $T_w = 0$, the average path length is the highest. As the thresholds gradually increase, both of the average path lengths of the two cities present a declining trend, where they decline sharply when $T_b$ and $T_w$ are small values and
decrease slowly when $T_b$ and $T_w$ are big values. The result indicates that instead of the bigger the better, large values of $T_b$ and $T_w$ are less meaningful, in accordance with people’s trip habits. From the Fig. 5, according to the steps in Section 3.1 of this paper, we get the feasible major thresholds are $T_b = T_{2k}$ and $T_w = T_{0.5k}$ respectively. The feasible major threshold value of $T_b$ of Fig. 5 is different from that of Fig. 4, but we can see that the two figures have similar evolutionary trend.

Fig. 5 also shows that SDB and SDW can significantly reduce the average path length in an urban public transport network. Considering bicycling and walking are both short-distance, in fact the average bus path length of a trip is also drastically reduced, that is, the same departure frequency bus can load more passengers or the lower departure frequency bus can carry the same number of passengers, which would increase the operation efficiency of an urban public transport network, reduce fuel consumption, improve the efficiency of whole city road networks.

3.3. Influence of short-distance bicycling the threshold $T_b$ and the short-distance walking threshold $T_w$ on the Gini coefficient of an urban public transport network

The initial definition of the Gini coefficient is as an analysis index used in economics to inspect the income difference of residents in a country. Reference Morris and Barthelemy (2012) applies the principle of the Gini coefficient in networks with the betweenness centrality to describe the edges’ flow distribution in a complex network. In the present paper, we use the Gini coefficient in an urban public transport network to describe the traffic flow allocation of edges. The definition of Gini coefficient is

$$G = \frac{1}{2E^2X} \sum_p \sum_q |x_p - x_q|$$

(1)

where subscripts $p$ and $q$ are edges in a network, $E$ represents the total number of edges, $x_p$ indicates the betweenness centrality of edge $p$, that is, the number of shortest paths that pass this edge, and $\bar{X} = \sum_p x_p/E$ is the average flow of all the edges. $G \in [0,1]$. The Gini coefficient can describe the smoothness of the flow distribution of edges in the urban public transport network. When network flows are distributed unevenly, they centralize a few edges and the flows of the other edges are less; thus, the value of $G$ is relatively big. Otherwise, the flow difference between edges is not large, and the value of $G$ is relatively small. For example, a Gini coefficient of one indicates that all flows only pass one edge; a zero coefficient indicates that the traffic flow is allocated at every edge homogeneously.

In the three-layer coupling spatial network model, we assume that the flow of every edge in three network layer is zero at first. For a path between random nodes $i$ and $j$, the flow of an edge in every network layer passing through the shortest path between $i$ and $j$ plus one. We compute all shortest paths between every node pairs. Then we get the flow of every edge. According to formula (1), we can obtain the Gini coefficient. In particular, we only use the flow of edges of bus network layer in Spatial Space-L Network Model to compute the Gini coefficient of an urban public transport network.

Fig. 6 presents the 3D relationship diagram of $T_b$, $T_w$ and the Gini coefficient of the urban public transport networks in Hangzhou and Ningbo, where $T_b \in [0.0,3.8]$ and $T_w \in [0.0,1.0]$, respectively. When $T_b = 0$ and $T_w = 0$, the Gini coefficients are the highest. As $T_b$ and $T_w$ gradually increase, the Gini coefficients of the two cities show declining trends, where Gini coefficients decline sharply when $T_b$ and $T_w$ are small values, Gini coefficients decrease slowly when $T_b$ and $T_w$ are big values. The result indicates that, instead of the
bigger the better, large values of \( T_b \) and \( T_w \) are less meaningful. From Fig. 6, according to the steps in Section 3.1 of this paper, we get the feasible major thresholds \( T_b = 2.2 \text{ km} \), \( T_w = 0.5 \text{ km} \).

From Fig. 6, we can see the Gini coefficients decline with the increasement of \( T_b \) and \( T_w \), which means that SDB and SDW can effectively improve the uneven level of flow distribution of an urban public transport network, so they will be helpful to smoothening the traffic flow and alleviating traffic jams.

4. Analysis of property and performance of an urban public transport network on the feasible major thresholds of short-distance bicycling and walking

We got the feasible major short-distance bicycling threshold \( T_b \) and walking threshold \( T_w \) of Figs. 4–6 respectively in the last section. We use the maximum value of them as the feasible major thresholds, namely, \( T_b = 2.2 \text{ km} \) and \( T_w = 0.5 \text{ km} \). In this section, the properties and performance of an urban public transport network on the feasible major bicycling and walking thresholds are analyzed to study the influence of SDB and SDW on an urban public transport network.

4.1. Degree distribution

The degree of a node in the network is the number of edges connected to the node directly. Degree distribution, which describes the distribution sequence of a network degree, plays an important role in evaluating network performance. We analyze the degree distributions of Spatial Space-L Network Model, Spatial Space-P Network Model, Short-Distance Spatial Bicycle Network Model, and Short-Distance Spatial Walk Network Model. The network is processed using the smooth method in actual condition to eliminate errors from the noise disturbance, that is, by drawing its cumulative degree distribution \( P_k \), which is the proportion of nodes whose degrees are not less than \( k \) in the whole network, as shown below:

\[
P_k = \sum_{k' = k}^{\infty} P(k')
\]

(2)

Specifically, the degree distributions of the Spatial Space-L Network Model and the Spatial Space-P Network Model are represented by the semi-log form. However, the Short-Distance Spatial Bicycle Network Model and Short-Distance Spatial Walk Network Models are represented by the degree distribution form. They are shown in Fig. 7.

In Fig. 7(a) and (b), we can see that most of the data fall on linear lines on the single-logarithmic plane, which means the cumulative distributions of Spatial Space-L Network Model and Spatial Space-P Network Model in two figures can be presented as two exponential functions [form \( p(x) \sim e^{-ax} \)] respectively, indicating that an urban public transport network is a kind of growth network with random attachment mechanism (Barabási and Albert, 1999). In Fig. 7(c), the cumulative degree distribution of the Short-Distance Spatial Bicycle Network Model is similar to the uniform distribution [form \( p(x) \sim kx + b \)]. Because each edge’s length is less than \( T_b \) [the maximal path length of SDB (bicycling between the short-distance bicycle station pairs)], the Short-Distance Spatial Bicycle Network Model is a kind of spatial distributed set of networks with short edges. The reason for the uniform distributions is that, for the Short-Distance Spatial Bicycle Network Model, its degree distribution accords with random distribution, namely, bicycle.
stations with many neighbor nodes is less, and the number of neighbor nodes of most stations satisfies even distribution. In Fig. 7(d), the degree distribution of the Short-Distance Spatial Walk Network Model is similar to the Gaussian distribution \[ p(x) \sim e^{-\left(\frac{(x-\mu)^2}{2\sigma^2}\right)} \]. These results show that Short-Distance Spatial Bicycle Network Model and Short-Distance Spatial Walk Network Model are both random networks whose degree distributions are random distributions without preference.

4.2. Edge length distribution

The edge length in the urban public transport network model is the actual path length (including bus, bicycle and walk path length) of a trip between arbitrary two stations, which plays an important role in the computation of the bus trip cost and transfer scheme. Fig. 8 shows the edge length distributions of Spatial Space-L Network Model, Spatial Space-P Network Model, Short-Distance Spatial Bicycle Network Model, and Short-Distance Spatial Walk Network Model, where the Spatial Space-L Network Model and Spatial Space-P Network Model are represented by cumulative length distribution.

As shown in Fig. 8(a), the cumulative edge length distributions of the Spatial Space-L Network Models resemble the power-law distribution \[ p(x) \sim x^{-\beta} \], which indicates that the setting distance between the two adjacent stations prefers short distances rather than few stations that are far away from each other. In Fig. 8(b), the cumulative edge length distributions of the Spatial Space-P Network Model resemble the exponential distribution \[ p(x) \sim e^{-x} \], which indicates that the total setting path length between two stations has no specific preference based on random demand. The edge length distributions of Short-Distance Spatial Bicycle Network Model and Short-Distance Spatial Walk Network Model also resemble the linear distribution \[ p(x) \sim x\gamma \]. The distributions show that bicycling and walking networks have similar edge characteristics, that is, network edge length is proportional to the network scale i.e., the larger the network scale, the higher the probability of long edges.
4.3. Transfer performance

The average number of bus routes of a trip and the average path length of an urban public transport network are two important indicators in evaluating the transfer performance of an urban public transport network. We calculate the average number of bus routes and the average path length of the two cities and list them in Table 2.

Table 2 indicates that SDB and SDW cause the sharp decrease of the average number of bus routes of urban public transport networks, which reduces Hangzhou to 58% and Ningbo to 66%, the sharp decrease of the average path length that reduce Hangzhou to 40% and Ningbo to 49%. Passengers will spend less time and path length on a trip with the bicycle and walk pattern. So the transfer performance was clearly improved.

Table 2

Statistical data on transfer performance of the urban public transport networks of Hangzhou and Ningbo. \(\text{ANR}_1\) denotes the average number of bus routes of a trip considering only the bus pattern. \(\text{ANR}_2\) denotes the average number of bus routes of a trip considering the bus, bicycle and walk pattern. \(\text{APL}_1\) is the average path lengths considering only the bus pattern, and \(\text{APL}_2\) is the average path lengths considering the bus, bicycle and walk pattern.

<table>
<thead>
<tr>
<th>City</th>
<th>(\text{ANR}_1)</th>
<th>(\text{ANR}_2)</th>
<th>(\text{ANR}_2/\text{ANR}_1)</th>
<th>(\text{APL}_1) (km)</th>
<th>(\text{APL}_2) (km)</th>
<th>(\text{APL}_2/\text{APL}_1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hangzhou</td>
<td>3.20</td>
<td>1.88</td>
<td>0.58</td>
<td>23.62</td>
<td>9.44</td>
<td>0.40</td>
</tr>
<tr>
<td>Ningbo</td>
<td>3.14</td>
<td>2.06</td>
<td>0.66</td>
<td>22.12</td>
<td>10.83</td>
<td>0.49</td>
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</table>
4.4. Bus average path length distribution

A bus path length of a trip is the marched route length of a passenger taking the bus between two random nodes $i$ and $j$ without including the bicycling and walking path lengths. The bus average path length (km) is the average value of bus path lengths among all station node pairs.

Fig. 9 shows the bus average path length distribution considering and without considering the SDB and SDW. We can see that the bus average path length considering the SDB and SDW is located below the bus average path length curves without considering the SDB and SDW. This result indicates that SDB and SDW can effectively reduce the bus average path length so that loading the same number of passengers only need buses with less departure frequency. It is beneficial to the improvement of the operating efficiency of an urban public transport network and the reduction of fuel consumption.

5. An application of the three-layer coupling spatial network model: transfer algorithm design

A new improved public transport network transfer algorithm based on the three-layer coupling spatial network model is designed in the light of the Dijkstra algorithm. The new algorithm can find the transfer route of the minimum travel cost between arbitrary two stations in the proposed three-layer weighted directed network, which can be used to plan passengers’ travel route.

Assuming there is a transfer route $P$ in which the transfer times is $T$, the distances of taking bus, bicycling and walking are $s_1$, $s_2$, and $s_3$, respectively. The average speeds of taking bus, bicycling and walking are $v_1$, $v_2$ and $v_3$ respectively.

The transfer cost function of transfer route $P$ is defined as

$$CT(P) = T^2 + \alpha s_1 + \beta s_2 + \gamma s_3$$

(3)

where $\alpha = 1/(2v_1), \beta = 1/(2v_2), \gamma = 1/(2v_3)$. Here we use empirical data: $v_1 = 20,000$ m/h, $v_2 = 1250$ m/h, $v_3 = 5000$ m/h, and correspondingly $\alpha = 0.000025, \beta = 0.00004, \gamma = 0.001$.

On the basis of the cost function, taking an example of a node $v_0$, let $Phs$ be the set of the optimal paths of $v_0$ to all other nodes. The new algorithm is detailed as follows.

1. Initialization: Let $v_0$ be the initial node, and add $v_0$ into the $Phs$, namely, $Phs = \{v_0\}$. Initialize a stack $H$ to store nodes, and add the initial node $v_0$ into $H$ at first. Then define a data structure $(v_i, CT(v_i \rightarrow v_0))$ where $v_i$ represents the node which has been searched and $CT(v_i \rightarrow v_0)$ is the value of the cost function traveling from $v_i$ to $v_0$. Let $seen$ be the set of $(v_i, CT(v_i \rightarrow v_0))$, and its initial value be $(v_0, 0)$. If the initial state node $v_0$ is not connected with other nodes, it is defined as $CT(v_i \rightarrow v_0) = \infty$.

2. Pop the top node in the stack $H$, which is defined as $v$. Traverse all neighbors of the node $v$ in Spatial Space-L Network, Spatial Space-P Network, Short-Distance Spatial Walk Network and Short-Distance Spatial Bicycle Network, respectively, and then store them into the variable array $N$.

3. After getting a node $w$ in array $N$, judge whether the node $v$ and node $w$ exist an edge in Spatial Space-L Network or Spatial Space-P Network at first. If edges exist, add 1 at $T[w]$, record the distance between $v$ and $w$ in $S_1[w]$ and calculate the value of trip cost $CP$ based on the formula (3). Secondly, judge whether the node $v$ and node $w$ exist an edge in Short-Distance Spatial bicycle.
Network. If edges exist, record the distance between v and w in S2 [w] and calculate the cost value. In a similar way, judge whether the node v and node w exist an edge in Short-Distance Spatial Walk Network. If edges exist, get the distance and the cost value in S1 at last. After calculating values of the trip cost CP of four networks above respectively, namely, the minimum value of CP, judge whether w exists in seen. If it doesn’t exist in the array seen, add it in seen and push w in stack H. Otherwise if w existed in seen and the calculated value of CP is less than the corresponding recorded value in seen, update the node and its value of CP in seen and Phs, mark the specific type of trip mode (by bus, by bicycle or walking) and update values in arrays of T, S1, S2 and S3.

(4) Acquire the next node in N, repeat the step (3) until traverse all nodes in N. Then we get next node of v with the minimum cost.

(5) Repeat the step (2) until the stack H is empty. We get the Phs which is the set of optimal routes from v0 to all other nodes.

6. Conclusion and discussion

In this paper, according to the actual spatial location data of the public bicycle-sharing systems of two cities in China, we propose a multi-layer coupling spatial network model that considers the spatial geographic location information of bus stations, bus routes, and bicycle stations to study the influence of the public bicycle-sharing systems on an urban public transport network, with special concentration on the influence of SDB and SDW. We find that SDB and SDW can reduce the number of transfer times and the travel time of passengers’ trip effectively, improving the operation efficiency. Therefore the public bicycle-sharing systems can smoothen the traffic flow, alleviate traffic jams, save energy and protect the environment.

A public bicycle-sharing system that is usually embedded in the original space of a bus transport network composes the new urban public transport system together with the bus transport network. Configuring the optimal number and location of bicycle stations in a public bicycle-sharing system and achieving the optimal performance with minimum cost of deploying a public bicycle-sharing system in an urban public transport network will be our future major subject.

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