Hindawi
Journal of Advanced Transportation
Volume 2018, Article ID 1675967, 10 pages
https://doi.org/10.1155/2018/1675967

Research Article

Planning for Operation: Can Line Extension Planning Mitigate Capacity Mismatch on an Existing Rail Network?

Yadi Zhu,[1] **Zijia Wang**,[1,2] **and Peiwen Chen**[3]

[1] *School of Civil Engineering, Beijing Jiaotong University, Beijing 100044, China*
[2] *Beijing Engineering and Technology Research Center of Rail Transit Line Safety and Disaster Prevention, Beijing Jiaotong University, Beijing 100044, China*
[3] *Comprehensive Transportation Design & Research Institute, China Urban Construction Design & Research Institute Co., Ltd., Beijing 100120, China*

Correspondence should be addressed to Zijia Wang; zjwang@bjtu.edu.cn

Received 11 April 2018; Accepted 29 May 2018; Published 27 June 2018

Academic Editor: Luigi Dell'Olio

Operational planning in China is perhaps more important today than ever before owing to the ongoing expansion of urban rail in the country. As urban rail networks increase in size and complexity, new lines added to them significantly alter both their topologies and operational characteristics. Thus, appraisal of alternative lines from the perspective of operation while planning is crucial. In this study, a method to forecast demands for new lines and obviate the effects of their addition, in terms of overcrowding in urban rail networks, was developed based on smart card data from existing networks. Using the card data and forecasted demand, transfer demand and section load can be estimated through the route choice model, and hence the influence of new lines on the operation of the network can be analyzed. The results of application of the proposed method to a case of line extension of a network in Beijing showed that it effectively prevented overcrowding by fewer interchanges on the line extension. Approximately 63% of passengers desiring an interchange on the target line altered their interchange from the station that had acted as bottleneck to the new interchange. Consequently, the headway of the feeding line was reduced from 6 min to 3.5 min. Hence, the capacity mismatch problem no longer occurred.

1. Introduction

Urban rail transit in China is experiencing unprecedented growth at present. By the end of 2016, as many as 28 cities had urban rail services operating over 3800 km, and 228 urban lines spanning 5600 km of rail were under construction in 48 cities across the country. Some of these cities were also building 300 km metro lines at the same time. Ever more lines are being planned as well. Megacities like Beijing and Shanghai have developed metro networks of more than 500 km of rail, and each network will be further expanded to 1000 km in the next decade. In such massive and complex networks, each extra line exerts a complicated influence on the existing network, especially from the perspective of the operation of the network.

Consequently, to maximize the safety, reliability, and efficiency of the transportation system, the concept of operational objective planning has been developed [1, 2]. As the first phase of implementing urban rail transit, planning is very important for a city's spatial development and the approval of rail construction by the central government in China. As the final aim of developing an urban rail, operation is always considered early in urban rail development, as early as the planning stage, to avoid serious problems later owing to flawed planning. However, this principle is seldom applied because of unreliable demand forecasts [3, 4], which is a necessity for planning, especially for operational objective planning [1]. With few operational considerations, planning of urban rail lines can generate a variety of problems in the operation stage once it is implemented. For instance, in Beijing, some metro lines starting at suburban areas end at the edge of central areas. These lines carry a large number of commuters from suburban towns to the central city, in which many companies are located. Thus, these passengers need to transfer at the terminal station to the downtown line. However, there is little remaining capacity for trains running

on the downtown lines, and the transfer passengers flood the platform immediately.

Many operational measures are consequently implemented to mitigate this problem. Passenger controls have been applied at 73 stations, which requires detaining passengers at station entrances during morning peak hours. In addition, trains on these suburban lines will run at long headways, even when the signal system allows for short headways. However, these measures limit the capacity of the network and cannot completely solve the problem. As the problem is part of planning, it should be addressed by planning, especially when the operational data are available. This means that when a new line is being planned, its impact on the existing network should be appraised from the perspective of operation—not only based on its effect on network topology, but also on demand distribution. The large amounts of smart card data (SCD) used in urban transits can aid in understanding of the real demand and can be used for such assessments.

Thus, in this study, a method to assess new line planning in a massive rail network from the perspective of operation using SCD was developed. Further, the developed method was applied to evaluate a case of urban line extension planning to determine whether it can reduce overcrowding resulting from a mismatch in capacity among lines. The remainder of this article is arranged as follows: related research is reviewed in Section 2. The proposed method is described in Section 3 and applied to the case of a line extension case in the Beijing Subway in Section 4 to determine its effectiveness in solving the capacity mismatch problem. Finally, concluding remarks are presented in Section 5.

2. Literature Review

A new line has various impacts on an existing urban rail transit network [5]; however, this work mainly focuses on ridership. Therefore, demand forecasting for a new line is the first step to analyze the ridership impacts.

To find a suitable method to forecast passenger demand for new rail lines, Preston [6] compared different models for several conditions and found that for new stations on existing rail services, a direct demand model is suitable for predicting the ridership; for new stations on a new service, disaggregate approaches are required. For the direct demand model, linear regression is the basic and normal model [7, 8]. When considering the spatial dependency of station ridership, geographically weighted regression (GWR) [8] and Kriging model [9] have been used to formulate the direct model. He et al. [10] improved the direct demand model to forecast demand for new lines based on SCD. The method categorizes existing stations using SCD and builds a linear regression model to describe the relationship between station ridership and station characteristics for every category. Based on these models, the ridership of new stations can be predicted with high accuracy. The disaggregate model is a significantly advanced and widely applied method for travel demand modeling [11]. To forecast the demand of new stations, Yao et al. [12] integrated a disaggregate model and the time series method using SCD. They considered the natural variation of passenger flow and the impact of a new line on existing stations and introduced a station accessibility index to carry out quantitative analyses of the effect of new lines on boarding and alighting demands on existing stations. The results of a case study for Beijing showed that their method can successfully estimate the impacts with high accuracy.

Based on forecasted demand, the ridership on sections of new lines can be calculated through route choice or a traffic assign model, which is an unavoidable step to evaluate the impacts of new lines. Many studies have been conducted in this area. By dividing the route choice process into two steps, a route generation step and a route selection step, Hurk et al. [13] developed a new route choice deduction model using SCD and timetables. Converting the complex rail network system into an event-activity network, passengers' routes were inferred and validated. Raveau et al. [14] proposed a novel method in which directness to destination and passengers' prior knowledge about possible routes are employed. In comparison, traditional models only consider service level and individual socioeconomic and demographic characteristics [15, 16]. These new models generate better results than traditional models.

The impacts of new lines can also be analyzed from the results of demand studies to provide suggestions for management and operation. However, most existing studies focused on postproject analysis using operation data after the new line opened. Li [17] studied the changes in the characteristics of passenger flow caused by different kinds of new lines, e.g., trunk lines, suburban lines, and loop lines in accordance with practical ridership data of Beijing. Liu et al. [18] found that new transfer stations usually induce more passengers than existing stations, and the impact of new lines normally reaches its peak a few months after commencement of operation. The types of connection formed by a new line inevitably influence the organizational mode of operation and resource allocation to the entire network, while operational strategies and other external conditions can also affect a new line's ridership. Ridership of a new line or an extension line has been stated as related to various factors, such as accessibility, bus service, and fare scheme [19, 20]. Further, Park et al. [21] evaluated the effects of a new line on the ridership of existing transfer stations using two years' SCD. The results indicated that after holiday and seasonal impacts are eliminated, new line opening has significant impacts on three stations, whereas there were no significant changes in other stations. These studies indicate that steady external conditions are important for ridership analysis of a new line, especially when analyzing the impacts on existing networks.

The studies cited above show that significant research has been deeply conducted on demand forecasting and passenger flow distribution, which are preparatory work for impact analysis on network ridership—even using SCD. However, the studies conducted on impact analysis of new lines on existing networks still aim at finding general patterns of the influence of new lines on the existing networks, rather than to guide operational organization during the planning phase. If a new line is intended to solve a specific problem in an existing

network, it is necessary to determine whether this can be accomplished in the planning stage. For the case addressed in this work, congestion and long headway occurred on the Changping Line of Beijing subway owing to the capacity-demand mismatch problem. This work investigated whether the southern extension planning of the Changping Line could solve this problem. To this end, using SCD and forecasted ridership, we evaluated the impact of the southern extension planning on the ridership of the congested sections. The results obtained can show whether and to what extent the planning scheme can solve the problem of overcrowding caused by prolonged headways. Thus, a method was developed in this study to closely consider operation in the early phase of planning to improve decision making.

3. Methodology

New rail lines change the coverage and topology of an existing network, which leads to changes in the demand distribution across the whole network, especially on lines and stations near the new line. Therefore, demand forecasting and assignment for the new line are crucial for its planning and operational management. The demand forecasting includes boarding and alighting demands for the new station and existing stations and the demand distribution of the new station.

3.1. Forecasting Demand for New Stations. The extension to the Changping Line is located in the service range of the existing network. Therefore, a direct demand model was chosen to predict the station-level demand and integrated with a geographically weighted model to consider spatial dependency. From existing studies, the built environment has verified the relationship with travel demand in urban planning [22]. Consequently, the built environment, which includes socioeconomic factors, demographic factors, and geographic factors [7, 23], was the dependent variable. Because different types of stations have diversified patterns of demand generation [10], stations were classified into different groups in accordance with passenger flow characteristics using SCD to formulate the models.

Based on previous work [24], stations were classified into four groups: office-type, residential-type, other-type, and airport terminal. However, most stations are office, residential, and other types. Therefore, a GWR model was developed for the three main station groups, respectively, as shown in

$$y_s = \beta_0(\mathbf{u}_s) + \boldsymbol{\beta}(\mathbf{u}_s)\mathbf{X}_s \tag{1}$$

where $\mathbf{u}_s(u_{xs}, u_{ys})$ is a vector of two-dimensional coordinates describing the location of station s, $\boldsymbol{\beta}(\mathbf{u}_s)$ is a vector of coefficient estimates varying with station s, $\beta_0(\mathbf{u}_s)$ is the intercept term varying with station s, y_s is the ridership of station s, $\mathbf{X}_s$ is a built environment factors' vector of station s.

On the basis of the data obtained, a population density of children (0-19), young adults (20-39), middle-aged (40-59), and seniors (>60), areas of different land use attributes, number of feeder buses, line densities of motor vehicle roads, and nonmotorized vehicle lanes were chosen as built environment factors.

The models were calibrated to forecast the ridership of new stations. For new stations, the same set of independent variables can be extracted from the feasibility study report of new lines. Substituting these variables into calibrated models, we can forecast the demand of new stations to a desirable accuracy level.

Compared with the existing methods, this study proposed a comprehensive direct model to integrate the impacts of spatial attributes and station function type on the ridership of new stations. Besides, because the proposed model is based on SCD, it allows analyzing and forecasting ridership in fine time granularity, such as ridership for each hour, which is beneficial for forecasting ridership during peak hours and for any further analysis using high time resolution demand, such as the headway evaluation in this work. Then, a GWR model for all stations is implemented by taking the ridership during 7:30 to 8:00 as an example and the local R-square range from 0.46 to 0.85, as shown in Figure 1(a). It can be seen from the figure that the stations located on the Changping Line have a lower local R-square. However, the proposed model considerably improves the fitness of the office-type station and other-type, as shown in Figure 1(b).

3.2. Forecasting Demand for Existing Stations. The influence of new line demands on an existing station can be divided into induced demand and diverted demand [3, 12, 18]. In this work, induced demand derives from newly generated or shifted travel demand from other modes because of lower generalized travel cost and higher accessibility of rail transit [12, 18]. Diverted passenger flow demand refers to passengers diverted from existing rail stations to the new one owing to overlapping station catchment areas or more convenient route choices.

Regarding induced demand, we chose indicator of accessibility to describe the impact. Accessibility of an existing station i is formulated by average distance and transfer times of the shortest path from other existing stations to this station [12] with the betweenness. Accessibility indicators are calculated before and after the new line is added to the network. Integrating with average riding distance, which is formulated using SCD, the proportion of induced the demand of existing station i, p_i, is determined.

Accordingly, the induced demand of existing station i can be calculated using

$$Q_i^{ind} = Q_i \cdot p_i \tag{2}$$

where Q_i is the original boarding demand at existing station i.

As for the diverted demand of existing station i, it is mainly affected by the distance between this station and the new station [12, 18]. From our previous work [25], the average access distances for walking and cycling to the metro station are 0.43 km and 1.45 km, respectively. Therefore, this work assumes that when the distance between new stations and an existing station i is less than 3 km, the new stations will divert the ridership of station i. This effect is described using

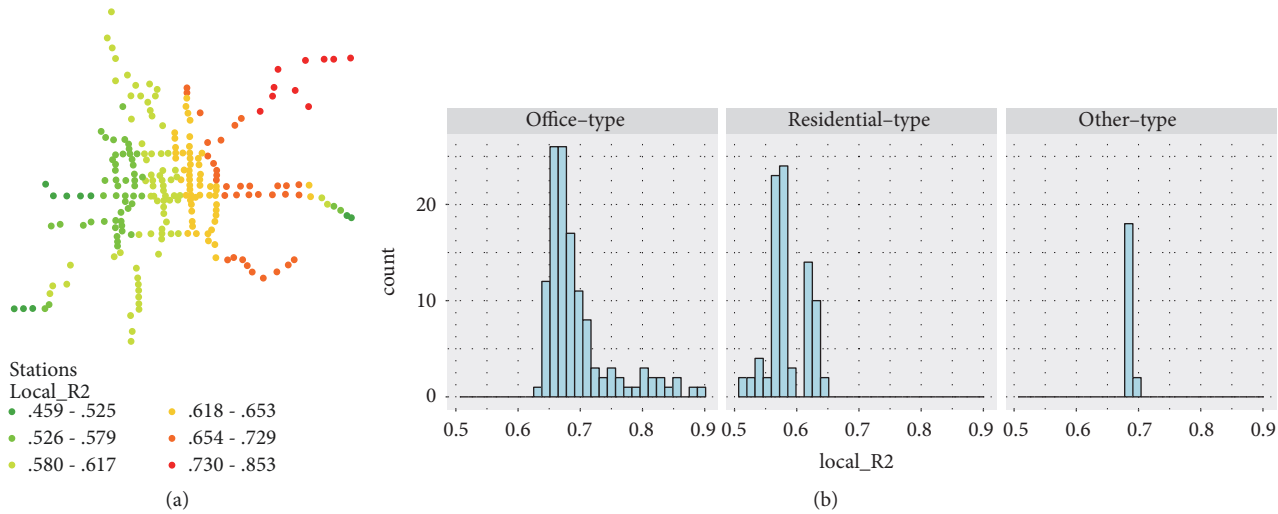


Figure 1: Comparison of existing model and proposed model.

a diverted factor β_i, and hence, the diverted demand can be calculated using

$$Q_i^{div} = Q_i \cdot \beta_i \tag{3}$$

The alighting demand at the existing station generated by the new one is calculated in a similar manner to boarding demand.

Finally, the demand of existing station i after the new line is added can be calculated using (4), where Q_i^{ori} is the ridership of station i in the existing network. This method makes full use of existing ridership data, which is different from the method of new station. It considers the effects of new line on the accessibility of existing stations to calculate the induced demand, and the diverted demand is considered in the access range of nonmotor vehicles.

$$Q_i = Q_i^{ori} + Q_i^{ind} - Q_i^{dvi} \tag{4}$$

3.3. Demand Distribution for New Stations. Stations can be classified into different groups based on land use types, where boarding and alighting demands in the same group follow the same pattern. This assumption is also applied to demand distribution for new stations. Thus, we can calculate the demand distribution of each new station according to the attraction pattern of each group. The factors influencing demand distribution are the number of stations along the shortest path between stations, transfer times, and the total daily alighting demand of the destination station. Supposing that station i and station j belong to groups m and n, respectively, fitting a linear equation as shown in (5) indicates the proportion of demand from station i to j to the total alighting demand at station i:

$$P_{ij} = b_0^{mn} + b_1^{mn} x_{ij}^{dis} + b_2^{mn} x_{ij}^{trans} + b_3^{mn} x_{ij}^{out} \tag{5}$$

where x_{ij}^{dis} and x_{ij}^{trans} are the number of stations and transfer times along the shortest path from i to j, respectively. x_j^{out} is the total daily alighting demand at station i; b_0^{mn},b_1^{mn},b_2^{mn}, and b_3^{mn} are the fitting parameters of the proportion of distribution from group m to n.

The origin-destination (OD) demand between new stations can be obtained after normalizing the distribution proportion using

$$a_{ij} = O_i \cdot \frac{P_{ij}}{\sum_{j=1}^{n} P_{ij}} \tag{6}$$

where $a_{ij}$is the OD from station i to station j after the introduction of a new line and O_i is the boarding demand at station i.

Compared with the traditional gravity model, the proposed model is a direct method to calculate demand distribution, which is easy to conduct without fitness reduction. Furthermore, the proposed model can make full use of existing OD distribution data and is suitable for demand prediction of fine time granularity using SCD. Besides, as an impact factor of station demand, land usage type is incorporated into the model to improve the model's performance. Then, we take 70% ridership data during 7:30 to 8:00 as training data and 30% as predicting data, and a dual-constrained gravity model and the proposed model are conducted. The Pearson correlation coefficients (PCC) of predicted results and real OD demand are calculated. For the gravity model, the PCC is 0.639, and the PCCs calculated by the proposed model range from 0.592 to 0.751 for the nine group pairs. These results indicate that the performance of the proposed model is as good as the dual-constrained gravity model, while being easier to conduct.

3.4. Trip Assignment. Based on forecasted boarding and alighting demand as well as the demand distribution of new stations, OD matrix for new lines at different periods can be obtained. With regard to passengers' choice of paths and the final section load distribution, it is necessary to create a trip assignment model to simulate a passenger's path choice

behaviors to infer the spatiotemporal distribution of network demand.

The main factors influencing a passenger's route choice are travel time, transfer convenience, level of service, and random factors [26]. Considering these factors, the generalized travel cost function, which describes passengers' travel impedance, can be defined by

$$C_{r-s}^{w} = \left(\sum_{e \in R_{r-s}^{w}} t_e + \sum_{s \in R_{r-s}^{w}} t_s \right) + \sum_{t \in R_{r-s}^{w}} \alpha \cdot \left(e_{t,w}^{r-s} \right)^{\beta} \cdot \left(t_{t,walk}^{m,n} + 0.5 \cdot f_n \right) + \varepsilon_{r-s}^{w} \tag{7}$$

where R_{r-s}^{w} is the route w between OD pair r-s, C_{r-s}^{w} is the generalized cost of R_{r-s}^{w}, t_e denotes the in-vehicle travel time on section e, t_s represents the train's dwell time at station s, $t_{t,walk}^{m,n}$ is the walking time during transfer time from line m to n, f_n is the scheduled headway of line n, and $0.5 \cdot f_n$ represents the average transfer waiting time. $e_{t,w}^{r-s}$ denotes the accumulated transfer count at transfer station t along path w between OD pair r-s, β represents the exponential increase in the additional penalty (time) incurred by increased transfer times, α represents the transfer sensitivity of passengers, considering passenger transfer times and convenience, and can be estimated by survey data, and ε_{r-s}^{w} is the random error term.

The shortest path is not suitable here on the complex network, and thus, we choose the k-shortest paths algorithm to search all valid paths in the threshold of each OD pair. If there are multiple paths between two stations, the probability of passengers choosing the one that costs the lowest is higher. An improved logit model was used to calculate the probability of passengers choosing different paths as shown in (8). From this equation, the probability of choosing a specific path is calculated by using the relative travel cost rather than the absolute travel cost that is used in the traditional logit model [26]. This improvement is suitable for trip assignment based on the k-shortest paths.

$$P_{r-s}^{w} = \frac{e^{-\theta C_{r-s}^{w} / C_{r-s}^{\min}}}{\sum_{w=1}^{n} e^{-\theta C_{r-s}^{w} / C_{r-s}^{\min}}} \tag{8}$$

where P_{r-s}^{w} is the proportion of choosing the valid path w for an OD pair r-s, n is the total valid path for an OD, and θ is generally taken to represent a passenger's familiarity with the urban rail network, which is estimated by survey data.

4. Case Study

In December 2016, the Beijing subway network consisted of 18 lines covering major travel corridors, with a total length of 574 km over 345 stations, as shown in Figure 2. Changping line (in pink) serves central city and suburban towns and solves the commuting demand of residents in Changping district. Owing to the problems in planning, it ends at large passenger load sections on the trunk line (Line 13 in green) in urban areas, where Xierqi (red dot) is the interchange station.

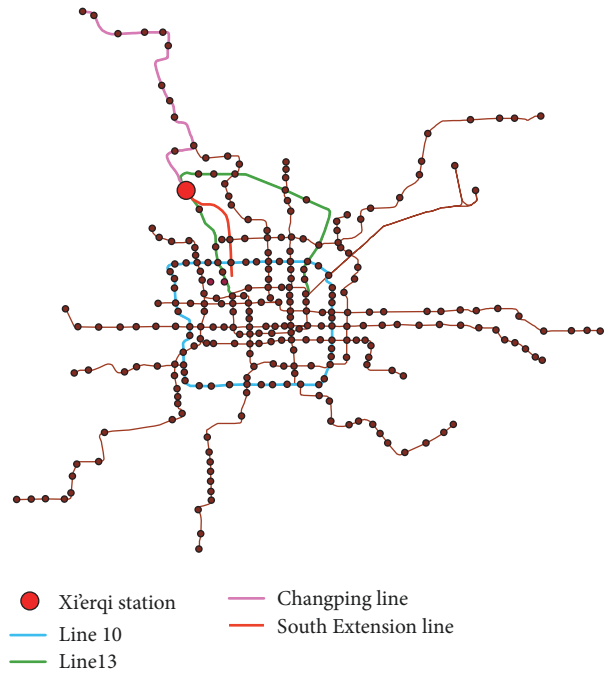


Figure 2: Southern extension planning of the Changping Line.

Before Changping Line opened, trains running on the two sections connected to the Xierqi station were full during morning peak with little surplus capacity. Once it opened, although many operation strategies including regular passenger controls for five stations of Changping Line and minimum headway of 2.5 min for Line 13 are conducted simultaneously, Line 13 still cannot cope with transferring the ridership from Changping Line. Hence, Changping Line is forced to run with 6 min headway, while the minimum headway is 2 min. Some sections of this suburban line became the most crowded sections of the network. For Changping Line, a paradox is that overcrowding occurred with available capacity. To solve this problem, the planners wanted to extend Changping Line to the central city and connect it to Line 10 (in blue), to reduce the load of Line 13 and decrease the headway on the Changping Line. Could this goal be achieved? Would the same problem occur in Line 10? The case study answers these questions.

4.1. Current Scenario Analysis. Implementing the trip assignment model with the SCD for a Monday in March 2016, the section load distribution of the network from 7:30 a.m. to 8:00 a.m. was estimated, as shown in Figure 3. The most heavily loaded section on the Changping Line, Life Science Park-Xierqi, had a demand of 9,954 (19,908 persons/h), with a load factor of 136.4%. As many as 71.6% of the passengers on it transferred to the in-bound train of Line 13. The section load of Xierqi-Shangdi on Line 13 was 19,744 (39,488 persons/h) with a load factor of 112.7%.

Figure 4 shows the destinations of the passengers boarding at the Changping Line from 7:30 a.m. to 8:00 a.m. The green dot indicates the destinations of passengers in the most congested section (in black). These passengers are mainly

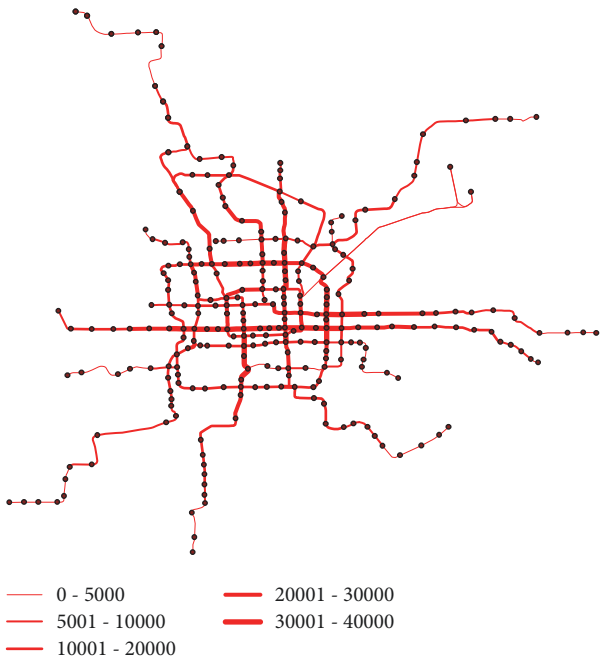


Figure 3: Section load distribution for the period 7:30 a.m. to 8:00 a.m.

Figure 4: Destination distribution of boarding passengers.

classified into two groups. Some passengers alighted at each station along sections of Line 13 from Xierqi to Xizhimen, while others went to stations located on the northwest of Line 10 near Zhongguancun, China's Silicon Valley. Therefore, if Changping Line is extended to Line 10, passengers heading to Zhongguancun would choose the extended line with only one

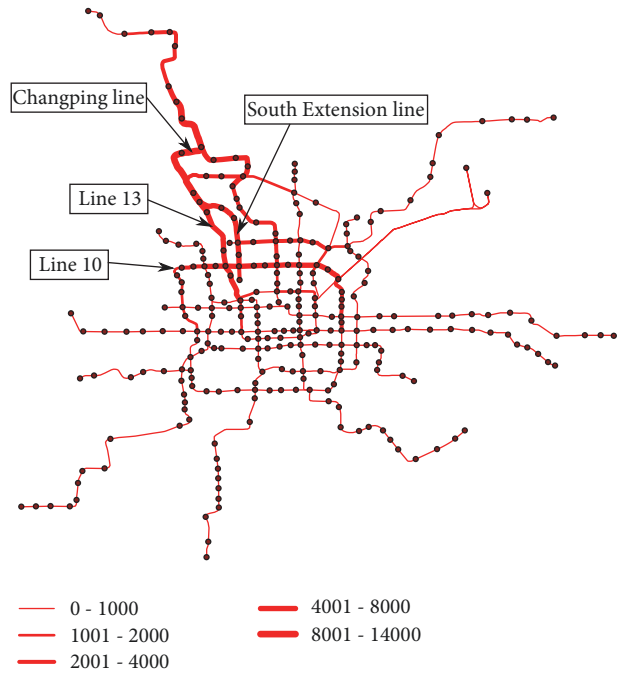


Figure 5: Demand distribution on extended Changping Line and part of Lines 10 and 13.

interchange, rather than two transfers on the original route, and these passengers would be diverted from Line 13.

4.2. Planning Impacts Analysis

4.2.1. Impact on Section Load. Figure 5 shows that the extension line significantly reduces the load on Line 13. The section load of Xierqi-Qinghe decreases by 4,590 (9,180 persons/h) or 23.3%. The reduced load can be regarded as the remaining capacity when a train passes Xierqi station; hence, the headway of Changping Line can be decreased.

The boarding ridership and section load of the extended Changping Line are shown in Figure 6. Transfer stations are marked with cycling symbols with letter 'T'. Section load represents increasing followed by decreasing, and reaching the maximum at the Xierqi-Qinghe section. The reduction in a section of the Zhuxinzhuang-Life Science Park is due to the diversion of Line 8 at Zhuxinzhuang station, but it is not obvious. The section load of Xierqi-Qinghe does not decrease compared with the upstream section because many passengers from the Changping Line did not change to Line 13, as they had in the past. Conversely, some passengers boarding at the upstream stations of Xierqi on Line 13 changed to the Changping Line. The extension clearly diverts the demand at Line 13.

4.2.2. Impact on Interchange Nodes. Capacity-demand imbalance occurred at transfer station Xierqi, and the interchange demand during a given time is shown in Figure 7. Prior to the extension, most passengers passing through Life Science Park station on Changping Line headed to Shangdi station on Line 13 (as many as 7,125 passengers (14,250 persons/h)). After the

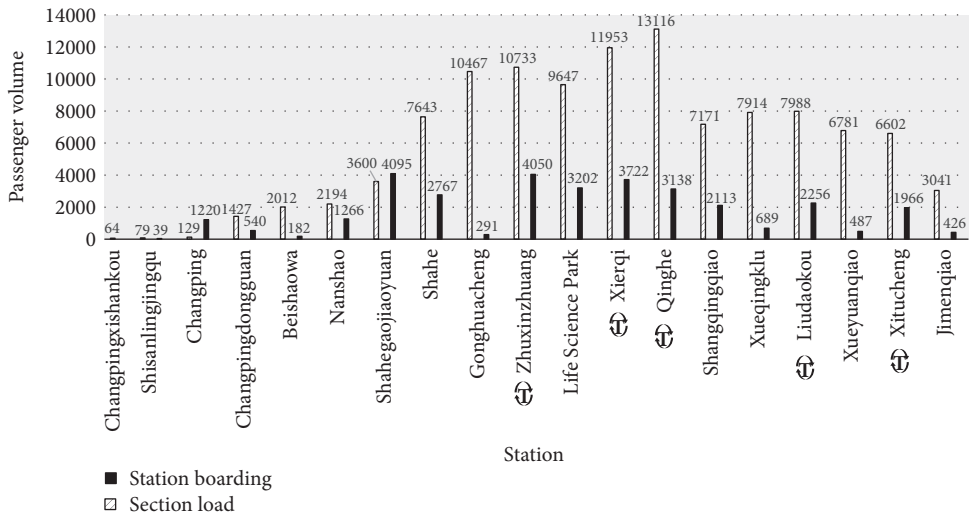
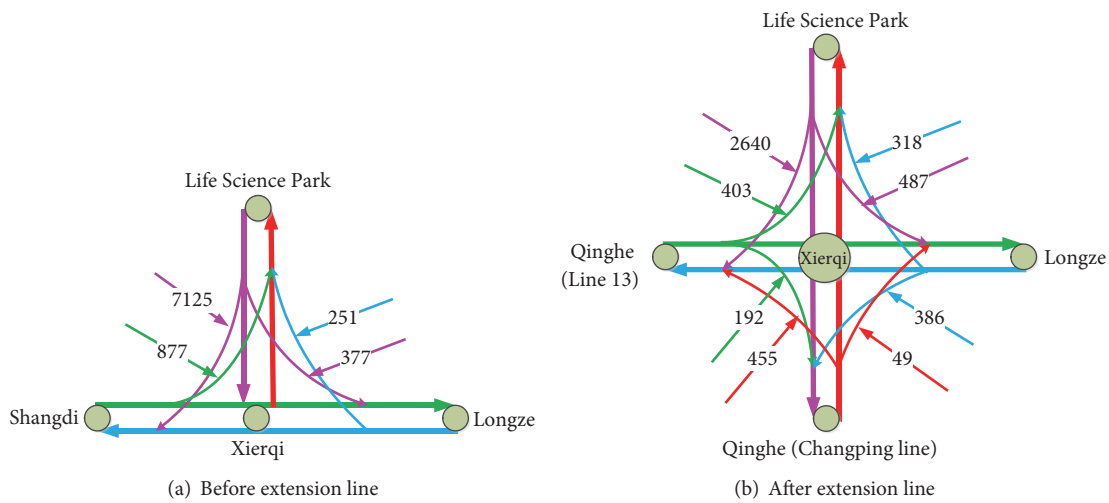


FIGURE 6: Section load along the Changping Line and the south extension line.



(a) Before extension line

(b) After extension line

FIGURE 7: Transfer passenger flow at Xierqi station for the period 7:30 a.m. to 8:00 a.m.

extension, this demand decreased to 2,640, by 62.9%, which significantly reduces the transfer pressure on Xierqi station.

Xitucheng becomes a transfer station after the extension, and Figure 8 shows the interchange demand during 7:30 a.m.–8:00 a.m. The interchange ridership is 10,062 (20,124 persons/h). 48.6% of them passing through Xueyuanqiao station on the extension line transfer to Zhichunlu station on Line 10. This demand exerts tremendous pressure on Xitucheng station and increases the load factor of the two sections on Line 10 connected to it—from 65.5% to 83.4%, and from 43.9% to 53.9%, respectively. However, the 2 min headway of Line 10 could handle the capacity. If the south extension could extend farther into the city center, the problem would be resolved better.

4.2.3. Decreased Headway. As shown in Figure 9, the total boarding demand of Zhuxinzhuang and upstream stations on Changping Line is 14,514 (29,028 persons/h) from 7:30 a.m. to 8:00 a.m. The load of the section down to Xierqi station is 11,387 (22,774 persons/h). The extension line diverts 5,419 (10,838 persons/h) passengers, 40.9% ridership of the most congestion section, which was originally served by Line 13. Assuming that other operational conditions remain unchanged, there will be surplus capacity when inbound trains pass through Xierqi station on Line 13 because numerous passengers are diverted to the extension line, which means that Line 13 can serve a greater number of passengers from Changping Line. Thus, passenger control can be removed and the headway of Changping Line can be shortened to serve more passengers. At present, Changping Line runs B-type trains with six carriages and the capacity is 1,460 passengers per train. According to the diverted ridership, 3.71 trains can be added during the period 7:30 a.m. to 8:00 a.m., and the headway during the morning peak can be reduced to 3.5 min. Furthermore, the average load factor of Life Science Park-Xierqi section on Changping Line and Xierqi-Shangdi section on Line 13 can be reduced to 71.5% and 94.9%, respectively.

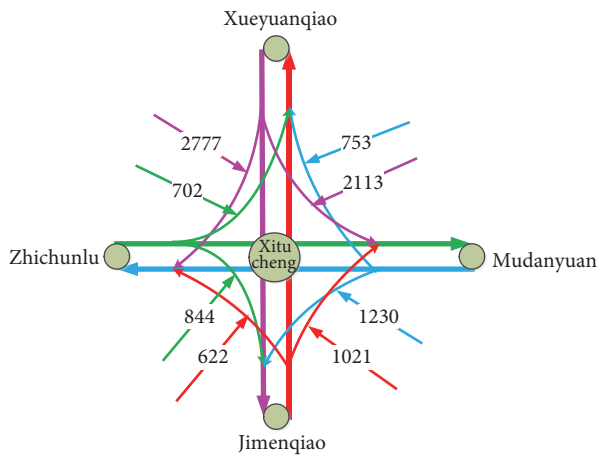


Figure 8: Interchange demand after the extension.

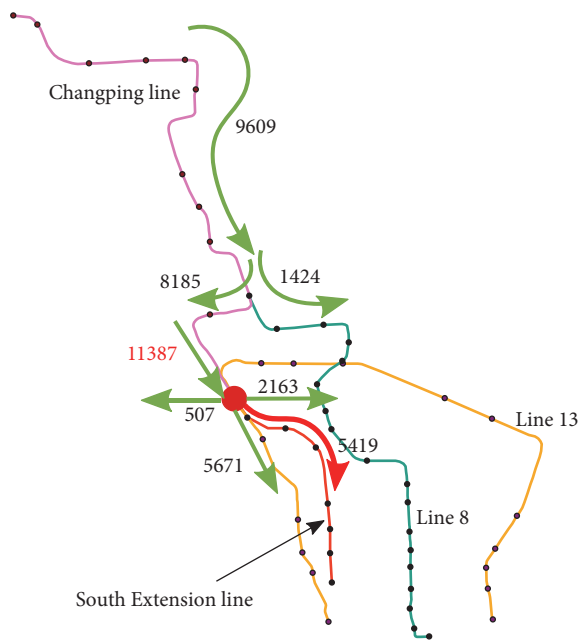


Figure 9: Section load on Changping Line.

5. Conclusions

Urban rail transit as a capital-intensive project remains virtually unchangeable once built. Therefore, it is crucial to know in advance whether the aims of planning transit routes can be successfully achieved. This is the philosophy of planning for operation, which is more important for new lines added to a large and complex rail network. In such a circumstance, the objects of the planned lines are specific, while the unreliability of demand is limited. In this study, the authors developed a method based on demand forecasting and the route assignment model to provide an ex-ante appraisal of a case of line extension to the Beijing subway. Using SCD from the existing network in combination with the forecasted demand for the new line extension, the proposed method was applied to distinguish and quantify the reasons for overcrowding on the line before it was extended and to assess the effect of the extension from the perspective of operation. The results revealed the conclusions below.

An analysis of the pre-extension scenario showed that Changping Line ended at a high-occupancy station, Xierqi on Line 13, and brought 72% of trains filled with passengers looking to change to the in-bound direction of Line 13 during morning peak hours. The spatial distribution of these passengers showed this pattern clearly. But when in-bound trains on Line 13 arrived at Xierqi station, they were overloaded with a load factor of 113%. Although the interchange passengers had been squeezed into these trains, more passengers had been left stranded on the platform. To prevent this state of affairs, Changping Line was run with a headway of 6 min, although its actual line capacity was a 2 min headway. This extended headway in turn aggravated the overcrowding on the Changping Line, making some of its sections the most crowded in the entire network. This is instructive for urban rail network planning in general.

When extended to the circle line in more central areas, Changping Line could run more trains per hour, which reduced crowding on both Changping Line and Line 13. The new line increased the connectivity of the network and provided more choices of routes to passengers. Residents could go directly to central areas with fewer interchanges. In this case, the interchange demand from Changping Line in the in-bound direction at Xierqi station was reduced by 63% with the extension. The saved capacity resulted in more passengers being accepted from Changping Line in the same time span, and more trains could run on it. Thus, the headway could be safely reduced to 3.5 min, and the average load factor during peak hours was reduced to 70% for the most crowded section on Changping Line and 95% for Line 13. This line extension planning hence was effective. It increased interchange demand and section load at the cross-section with Line 10, but the overall occupancy was acceptable, and the capacity mismatch problem did not occur at the new crossing. The extension only went one station after crossing Line 10. Thus, a real concern was whether the original problem at the old end crossing will be brought to the new crossing by the extension. According to the results, the remaining capacity on the train on Line 10 was sufficient to cater to interchange demand from Changping south extension.

Operational objective planning is important for new line design, especially for solving existing operational issues in a complex network. The models proposed in this study provide a valid method to evaluate a line design scheme from an operational perspective using SCD, which is helpful for policy making. According to the results of this case study, passenger control measurement for the stations on the Changping Line can be canceled after the extension. Besides, the findings stated above show that the suburban line should terminate on the downtown loop line, and this connection pattern has been used in several urban rail transit systems, such as in Tokyo and London, or even pass through the downtown area in New York. Consequently, for the design of a suburban line that mainly serve commuting trips, it should terminate in or pass through the downtown area in practice.

The main limitation of this work is that the trains' timetables were not considered in the demand assignment model. This affects the accuracy of the calculation of section load and the load factor of the trains. Moreover, the forecasting and distribution of the demand induced by the extension were relatively simple and did not refer to the integrated transport model. The third weakness of this work is that the SCD used was influenced by passenger control measures, and the entry time recorded by the card was not the actual boarding time of the passengers. This also influenced the estimation of the train load factor. These limitations will be addressed in subsequent research.

Data Availability

The smart card data (SCD) used to support the findings of this study were supplied by Beijing Transportation Information Center under license and so cannot be made freely available. Requests for access to these data should be made to Beijing Transportation Information Center ((+86) 010-57079655).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the Beijing Municipal Science & Technology Commission, Special Program for Cultivation and Development of Innovation Base in 2017 [Grant no. Z171100002217011] and the Natural Science Foundation of Beijing Municipality [Grant no. 17H10148].

References

[1] A. Ceder, "Operational objective functions in designing public transport routes," *Journal of Advanced Transportation*, vol. 35, no. 2, pp. 125–144, 2001.

[2] J. Atkinson, J. Bauer, and K. Hunt, *Designing for Transportation Management and Operations: A Primer*, US Department of Transportation, Federal Highway Administration, 2013.

[3] L. He, Q. Liang, and S. Fang, "Challenges and Innovative Solutions in Urban Rail Transit Network Operations and Management: China's Guangzhou Metro Experience," *Urban Rail Transit*, vol. 2, no. 1, pp. 33–45, 2016.

[4] K. C. Sinha, S. Labi, and Q. Bai, "Uncertainties in Transportation Infrastructure Development and Management," in *Proceedings of the International Symposium on Engineering Under Uncertainty: Safety Assessment & Management*, Management., S. Chakraborty and, and G. Bhattacharya, Eds., pp. 55–71, Springer, India, 2013.

[5] H. S. Martínez Sanchez-Mateos and M. Givoni, "The accessibility impact of a new High-Speed Rail line in the UK - a preliminary analysis of winners and losers," *Journal of Transport Geography*, vol. 25, pp. 105–114, 2012.

[6] J. M. Preston, "Passenger Demand Forecasting for New Rail Services - Manual of Advice," *University of Leeds*, pp. 1–89, 1991.

[7] B. D. Taylor, D. Miller, H. Iseki, and C. Fink, "Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas," *Transportation Research Part A: Policy and Practice*, vol. 43, no. 1, pp. 60–77, 2009.

[8] M.-J. Jun, K. Choi, J.-E. Jeong, K.-H. Kwon, and H.-J. Kim, "Land use characteristics of subway catchment areas and their influence on subway ridership in Seoul," *Journal of Transport Geography*, vol. 48, pp. 30–40, 2015.

[9] D. Zhang and X. C. Wang, "Transit ridership estimation with network Kriging: A case study of Second Avenue Subway, NYC," *Journal of Transport Geography*, vol. 41, pp. 107–115, 2014.

[10] Z. He, B. Wang, and J. Huang, *A Demand Forecast Method for Urban Rail Transit New Line Based on Historic Data*, State Intellectual Property Office of the People's Republic of China, 2014.

[11] J. L. Bowman and M. E. Ben-Akiva, "Activity-based disaggregate travel demand model system with activity schedules," *Transportation Research Part A: Policy and Practice*, vol. 35, no. 1, pp. 1–28, 2001.

[12] E. Yao, X. Cheng, S. Liu, and R. Zhang, "Accessibility-based forecast on passenger flow entering and departing existing urban railway stations," *Tiedao Xuebao/Journal of the China Railway Society*, vol. 38, no. 1, pp. 1–7, 2016.

[13] E. Van Der Hurk, L. Kroon, G. Maróti, and P. Vervest, "Deduction of passengers' route choices from smart card data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 1, pp. 430–440, 2015.

[14] S. Raveau, J. C. Muñoz, and L. de Grange, "A topological route choice model for metro," *Transportation Research Part A: Policy and Practice*, vol. 45, no. 2, pp. 138–147, 2011.

[15] J. N. Prashker and S. Bekhor, "Route choice models used in the stochastic user equilibrium problem: a review," *Transport Reviews*, vol. 24, no. 4, pp. 437–463, 2004.

[16] M. S. Ramming, *Network knowledge and route choice*, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, 2001.

[17] S. Li, "Influence of a New Subway Line's Opening on Passenger Flow Characteristics of an Urban Rail Transit Network," in *Proceedings of the 15th COTA International Conference of Transportation Professionals*, pp. 1756–1769, Beijing, China.

[18] S. Liu, E. Yao, X. Cheng, and Y. Zhang, "Evaluating the impact of new lines on entrance/exit passenger flow of adjacent existing stations in urban rail transit system," *Transportation Research Procedia*, vol. 25, pp. 2629–2642, 2017.

[19] J. Lee, M. Boarnet, D. Houston, H. Nixon, and S. Spears, "Changes in service and associated ridership impacts near a new light rail transit line," *Sustainability*, vol. 9, no. 10, 2017.

[20] N. Baum-Snow and M. E. Kahn, "The effects of new public projects to expand urban rail transit," *Journal of Public Economics*, vol. 77, no. 2, pp. 241–263, 2000.

[21] M. S. Park, J. K. Eom, T.-Y. Heo, and J. Song, "Intervention analysis of the impact of opening a new railway line on passenger ridership in Seoul," *KSCE Journal of Civil Engineering*, vol. 20, no. 6, pp. 2524–2534, 2016.

[22] R. Cervero and K. Kockelman, "Travel demand and the 3Ds: density, diversity, and design," *Transportation Research Part D: Transport and Environment*, vol. 2, no. 3, pp. 199–219, 1997.

[23] G. L. Thompson and J. R. Brown, "Explaining variation in transit ridership in U.S. metropolitan areas between 1990 and 2000: Multivariate analysis," *Transportation Research Record*, no. 1986, pp. 172–181, 2006.

[24] Z. Yue, F. Chen, Z. wang et al., "Classifications of Metro Stations by Clustering Smart Card Data Using the Gaussian Mixture Model," *Urban Rapid Rail Transit*, vol. 30, no. 2, pp. 48–51, 2017.

[25] Z. Wang, F. Chen, and T. Xu, "Interchange between Metro and Other Modes: Access Distance and Catchment Area," *Journal of Urban Planning and Development*, vol. 142, no. 4, p. 04016012, 2016.

[26] B. Si, L. Fu, J. Liu, S. Shiravi, and Z. Gao, "A multi-class transit assignment model for estimating transit passenger flows - A case study of Beijing subway network," *Journal of Advanced Transportation*, vol. 50, no. 1, pp. 50–68, 2016.