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A Study on the Utilization of Shared Bicycles in Comprehensive Passenger Transport Hub Area Based on Neural Network Evaluation

Yunhong Shao[1,3,a*], Tao Zhang[2,b], Min Hong[2,c], Feiqiang Zhou[4,d] and Jing Zhou[2,e]

[1] *Development Planning Division, Zhejiang Institute of Communication, Hangzhou 311112, Zhejiang, China*
[2] *Rail Transit Department, Zhejiang Institute of Communication, Hangzhou 311112, Zhejiang, China*
[3] *Songyang County Digital Highway Engineering Research Institute,Songyang323400,Zhejiang, China*
[4] *Hangzhou Public Bicycle Transportation Service Development Co., Ltd, Hangzhou 311112, Zhejiang, China*

As a new mode of short-distance travel, shared bicycles play an important role in providing rapid first-/last-mile connections and have high potential for being utilized in the service areas of integrated passenger transport hubs. However, shared-bicycle use around such hubs still faces challenges, including relatively low utilization, uneven vehicle distribution, and irrational dispatching, which call for improvement and optimization. Based on the 2025 operational data of the public bicycle system in a high-speed railway hub area, this study investigates shared-bicycle utilization using big-data analytics and neural-network methods, and conducts analysis with a backpropagation (BP) neural network algorithm. The research results showed that under the same conditions, when parking points were arranged according to the conventional method, the sharing cycle utilization rates of stations and residential areas at 7–9, 11–13 and 17–19 were 92.6% and 90.4%, 88.9% and 87.6%, 89.3% and 85.5% respectively; when parking points were arranged according to big data and BP neural network algorithm, the utilization rates of shared bicycles at 7–9, 11–13 and 17–19 in stations and residential areas were 95.1% and 94.3%, 91.9% and 90.2%, 93.7% and 94.1% respectively. The utilization rate of the latter was significantly higher than that of the former, indicating that big data and neural network methods can improve the utilization rate of shared bicycles.

Keywords: Bike sharing; neural network method; big data; rail transit station

1. INTRODUCTION

Shared bicycles have been widely adopted and have become an important component of the urban integrated passenger transport system. However, in large passenger transport hub areas, shared-bicycle operations still face issues such as relatively low utilization, uneven vehicle distribution, and irrational dispatching.

This paper, based on big data and neural network methods, studies the utilization rate of shared bicycles in a large passenger transport hub area, specifically taking a high-speed rail hub as the research object. We utilize a BP (backpropagation) neural network algorithm to analyze the usage and predict demand for shared bikes around the station. By comparing the utilization rates of shared bicycles under

*Corresponding Author. [a]Email: sca717@sina.com, [b]zhangtao@zjvtit.edu.cn, [c]hm@zjvtit.edu.cn, [d]154253255@qq.com, [e]zhoujing@zjvtit.edu.cn

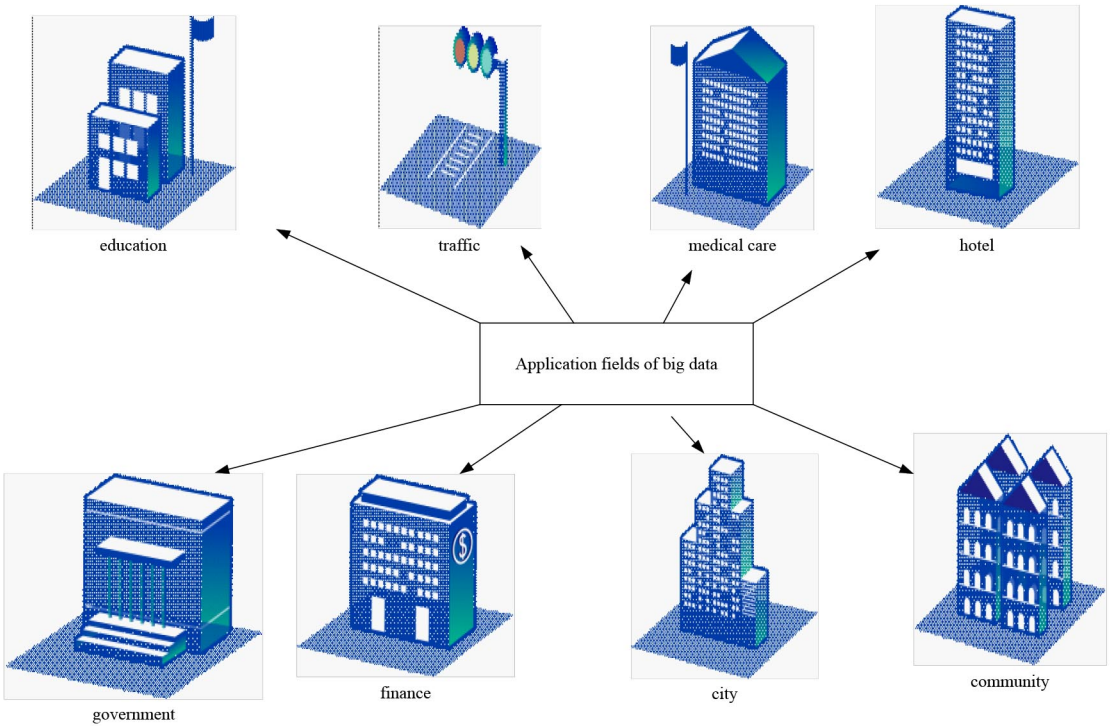


Figure 1 Application fields of big data.

different bike station layout methods (conventional vs data-optimized), we verify the effectiveness of big data and neural network approaches in improving bike utilization. The insights from this research can help to alleviate bike distribution imbalances and inform better planning and management for shared bicycles in large passenger transport hubs.

2. RELATED WORK

With the improvement of living standards of urban residents, bike sharing, as a convenient, efficient and low-carbon way of travel, has gradually entered people's lives, and a prompted a great deal of research. Chen Zheyan's research showed that the docking free design of the bike sharing system significantly improves the user's experience at the end of a bicycle trip [1]. Cheng Lu believed that planners can strengthen the resilience of the urban transport network by taking full account of the capacity and use of bike sharing terminals, as well as the consistency of subway stations and bike sharing stations in distribution and rebalancing activities [2]. Chen Wendong found that there is a substitution effect of rail transit access between the two bike sharing systems; that is, the station-based bike-sharing system may be more frequently used for commuting than the free-floating bike sharing system [3]. However, the aforementioned researches focus on the shared bicycle system, and there is no research on its utilization rate. In order to further understand the utilization rate of shared bicycles within the scope of rail transit stations, a scientific method is needed for analysis.

In view of the above research, the use of neural network method to analyze the utilization rate of shared bicycles within the rail transit station area began to be studied by scholars. Lin Lei proposed a new graph convolution neural network model with data-driven graph filter. This model can learn the correlation of hidden heterogeneous pairs between stations to predict the hourly demand at the station in the large-scale shared bicycles network [4]. Ashqar Huthaifa developed a model for modeling the availability of bicycles in the San Francisco Bay Area bike-sharing system, and applied neural networks-networks and sites at two levels [5]. This research showed the applicability of the neural network method in the shared bicycles scheme, and laid a foundation for its application in analyzing the utilization rate of shared bicycles within the rail transit station area.

3. CONSTRUCTION OF BIG DATA AND NEURAL NETWORK METHODS

3.1 Overview of Big Data

Big data refers to an enormous amount of data, which is a relatively new concept. Big data analytics can process large volumes of data and mine them to derive significant patterns and information. With the rapid development of big data, its application fields are also expanding, and have become a part of most individuals' daily lives. The various application fields are shown in Figure 1.

IBM (International Business Machines Corporation) was the first to describe the characteristics of big data. After years of development and evolution, the term "five V" is now widely used in the industry to construct the basic concept of big data, which is shown in Figure 2. It can be concluded that

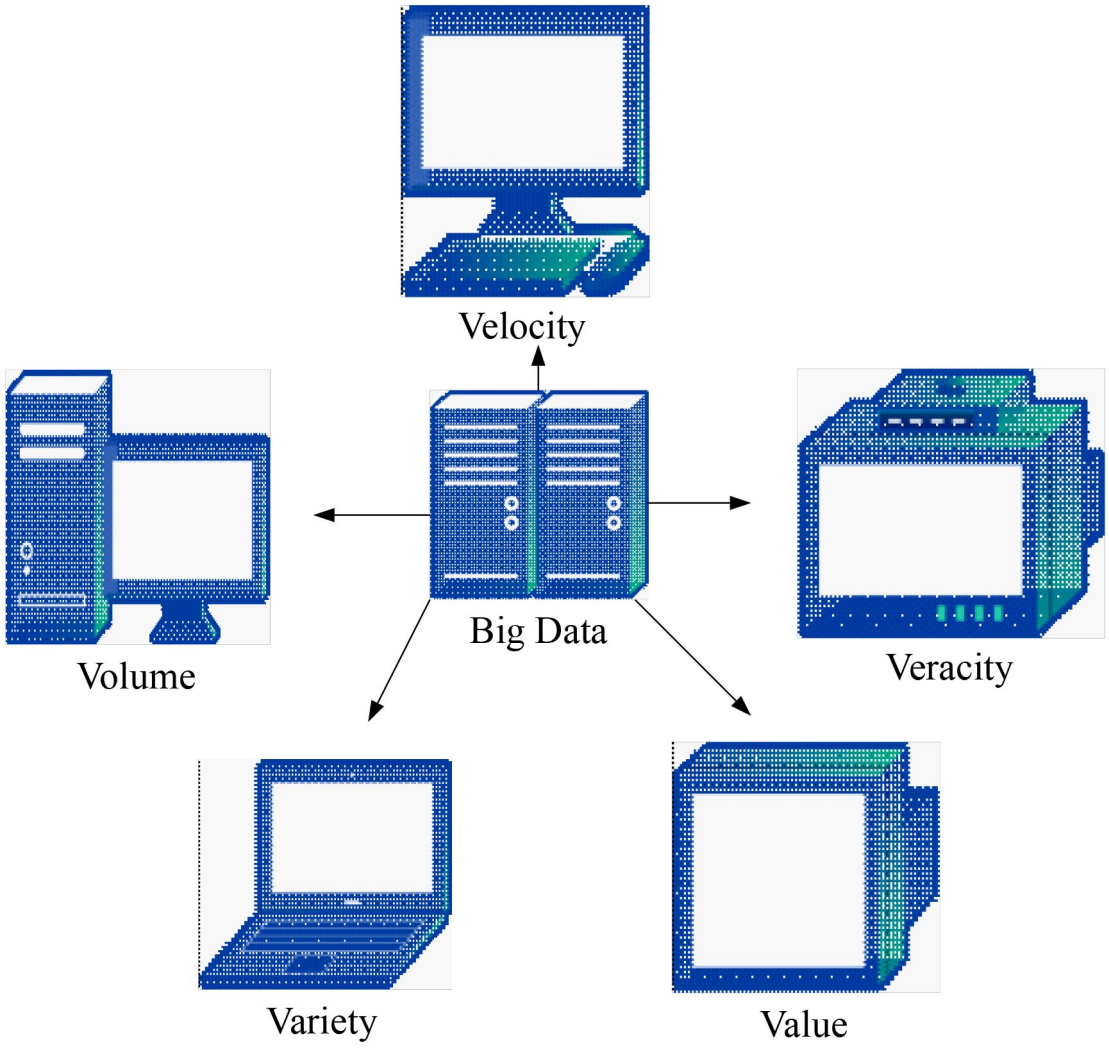


Figure 2 Big data concept.

big data is not a simple big data set, but a complex and huge data system.

Big data can help this study to better understand the current situation and use of shared bicycles, thereby validating the data. In practice, data mining techniques are essential for extracting meaningful patterns from massive and complex datasets [6].

3.2 Establishment of Shared Bicycle Optimization Model Based on BP Neural Network

Generally, shared bicycles are equipped with GPS, which can monitor and record vehicle location, driving distance, borrowing and returning range, borrowing and returning time, location and other information in real time. As a result, the leased vehicles in various regions and time periods can be predicted so as to achieve the optimal allocation [7–8]. Similar neural-network-based prediction models have been successfully applied in other domains, further supporting the applicability of BP neural networks to nonlinear prediction problems [9]. First, a certain region is selected. The number of shared bicycles during a certain period of time is counted and compared with the actual demand in the region. By predicting the historical loan and return data of shared bicycles, it is possible to make a separate prediction of the rental and return demand of shared bicycles, so that the difference in the number of rented bicycles between regions is the number of bicycles required to be dispatched [10–11].

By using BP neural network method, the demand for shared bicycles in various regions can be predicted [12]. If A represents input, B represents output and E represents weight. The output of the first neuron in layer l can be obtained by the input of the neuron through the activation function:

$$B_o^l = g(A_o^l) \tag{1}$$

The output of the o neuron in layer l is equal to the inner product of the output and weight vector of the $l-1$ neuron:

$$A_o^l = \sum E_{ok} B_k^{l-1} \tag{2}$$

If the output layer is layer n, LMS (Least Mean Square) algorithm is used to find the wrong expression of the o neuron in layer n:

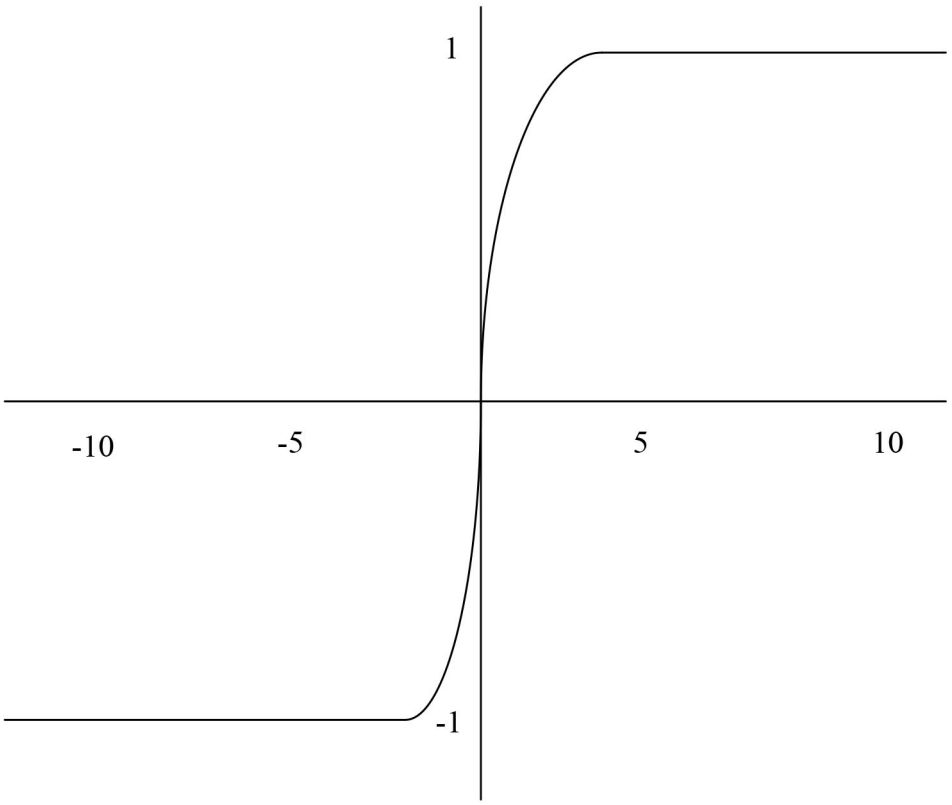


Figure 3 A-Sigmoid function image.

$$r = \frac{1}{2}\sum_{o}\left(B_o^n - \hat{b'}_o\right)^2 \tag{3}$$

According to formulas (1), (2) and (3), the reverse propagation algorithm is derived by using the fastest descent method in nonlinear programming. According to the negative gradient of the error function, the weight coefficient is modified to obtain:

$$\nabla E_{ok} = -\iota\frac{\alpha r}{\alpha E_{ok}}(0 < \iota < 1) \tag{4}$$

$$\frac{\alpha r}{\alpha E_{ok}} = \frac{\alpha r}{\alpha A_o^l}\cdot\frac{\alpha A_o^l}{\alpha E_{ok}} = \frac{\alpha r}{\alpha A_o^l}\cdot B_k^{l-1} = f_o^l \cdot B_k^{l-1} \tag{5}$$

It should be pointed out here that in Formula (6), the function defined is:

$$\frac{\alpha r}{\alpha A_o^l} = f_o^l \tag{6}$$

Thus, it is possible to continue to take the error gradient of the o unit of layer l:

$$f_o^l = \frac{\alpha r}{\alpha A_o^l} = \frac{\alpha r}{\alpha B_o^l}\cdot\frac{\alpha B_o^l}{\alpha A_o^l} = \frac{\alpha r}{\alpha B_o^l}\cdot f'\left(A_o^l\right) \tag{7}$$

Formulas (4) and (5) are applied to obtain:

$$\nabla E_{ok} = -\iota \cdot f_o^l \cdot B_k^{l-1} \tag{8}$$

The program described above is cycled, and the training algorithm is completed when the error signal reaches the expectation.

(1) Design input and output

This study needs to design input and output variables. The number of shared bicycles rented in a working day in a region is taken as the output variable. In the same region, the shared bicycle rental demand to be predicted is related to the number of shared bicycles rented in this period, and the historical shared bicycle rental usage in this period can be selected as input variables.

(2) Activation function

Due to the nonlinear change in the number of shared bicycles, it is necessary to select an appropriate excitation function between neurons and output layer neurons so as to achieve nonlinear mapping [13–14]. The output of the Sigmoid function is positive, which has an impact on the convergence, so this study uses an improved A-Sigmoid function of the Sigmoid function as its starting function. The expression is:

$$g\,(a) = \frac{1 - r^{-a}}{1 + r^{-a}} \tag{9}$$

where, a is the output of upper-level neurons. The A-Sigmaid function is an S-type saturation function with zero as the center. Its value range is (-1, 1), which has good convergence and good differentiability. Its function is shown in Figure 3.

(3) Performance function

Performance function is used to measure the error of output and expectation, which can directly indicate the accuracy of prediction. Common methods include root mean square error (RMSE), mean square error (MSE), and mean absolute error (MAE).

RMSE is used to measure the estimation of a parameter and a true value, shown in Formula (10):

Table 1 Average Daily Rentals per Station in 2025.

Station ID	Avg Daily Rentals
30217	210.5
3528	112.3
3507	41.2
30479	39.4
3526	31.0
30425	24.0

$$RMSE = \sqrt{\frac{\sum_{o=1}^{m} a'_o - a_o}{m}} \tag{10}$$

MSE refers to an expected value, which is the square between a parameter estimate and the true value of a parameter. The expression is shown in Formula (11):

$$MSE = \frac{1}{M} \sum_{o=1}^{m} |(a'_o - a_o)| \tag{11}$$

MAE is used to represent the average value of absolute error, shown in Formula (12):

$$MAE = \frac{1}{m} \sum_{o=1}^{m} |(a'_o - a_o)| \tag{12}$$

Compared with MSE and MAE, RMSE can more accurately indicate the accuracy of measurement. The smaller the RMSE, the more accurate the prediction results would be. On this basis, a prediction model of shared bicycle backlog value is established to predict the demand of the region during the same period, and the corresponding prediction results are given.

4. EXPERIMENTAL EXPLORATION OF SHARED BICYCLE UTILIZATION RATE IN COMPREHENSIVE PASSENGER TRANSPORTATION HUB BASED ON BIG DATA AND BP NEURAL NETWORK ALGORITHM

4.1 Station Profile and Data Description

This study obtained detailed 2025 data from a public bike-sharing rental system in a high-speed rail hub area. Six rental stations were selected for the analysis of the daily bike pick-up and return patterns during different time periods. Meanwhile, a sample survey was conducted on bike-sharing usage along the main dispersal directions of the hub area (the east, north, and west sides). The high-speed rail hub integrates high-speed rail, metro, and bus services, and its surrounding area is dominated by residential and commercial land uses. Users have strong demand for short-distance first/last-mile connections, making it well-suited as a case study for research on bike-sharing usage rates. Hereafter, this high-speed rail hub is referred to as Station A.

(1) Basic Information

The dataset includes records of every rental and return at the public bike docking stations within the vicinity of the station, timestamped to the hour. The six public bike rental stations (docked bike-sharing stations) we selected are denoted by station ID numbers: 30425, 3528, 30217, 3507, 30479, and 3526.

Table 1 lists each docking station and its average daily usage (total rentals and returns) in 2025. It can be seen that station ID 30217 has the highest daily average usage ($\sim$ 210 bike rentals/returns per day), indicating a major bike-sharing demand point (likely a primary exit or a nearby high-demand location). In contrast, station ID 30425 shows a much lower daily usage ($\sim$ 24 per day), possibly due to its location being less frequented by commuters. Overall, about 458 bike rental/return transactions occur per day on average across all six points combined, indicating a significant volume of bike-share usage in this hub area.

(2) Usage Patterns and Tidal Analysis of Public Bicycles

Using the hourly usage data, we first examined the intraday cycle of public bicycle demand in the station area. The findings reveal a pronounced bimodal pattern on weekdays: a morning peak during roughly 7:00–9:00 and an evening peak around 17:00–19:00. The usage surges sharply during these periods, reaching a maximum around 8 a.m. in the morning and around 6 p.m. in the evening. Conversely, usage during midday and late night is relatively low.

Figure 4 shows the average hourly usage curve for weekdays compared with weekends. The weekday curve exhibits two prominent spikes corresponding to commute hours, whereas the weekend usage is much flatter throughout the day. Specifically, on workdays, the system handles on average about 60 rentals per hour at the 8:00 and 18:00 peaks, whereas on weekends the busiest hour (typically midday) sees only about 20 rentals. This pattern aligns with typical commuting behavior: many commuters cycle to the high-speed rail hub in the morning to catch high-speed trains or transfer to the metro, and in the evening they take a shared bicycle from the station to return home, leading to heavy bicycle turnover during rush hours.

A pronounced tidal flow phenomenon is observed, where different stations experience directional imbalances between morning and evening. The stations around the hub can be broadly classified into two types: (a) Origin-type stations, which see far more bikes being rented out in the morning than returned, and conversely more returns in the evening. These are typically located near residential areas. In the morning, residents check out bikes to ride toward the station (draining bikes from the station), and in the evening they return the bikes to the station (filling up docks). (b) Destination-type stations, which serve as sinks in the morning (many incoming returns) and sources in the evening (many rentals), are often situated directly at the railway station exits or

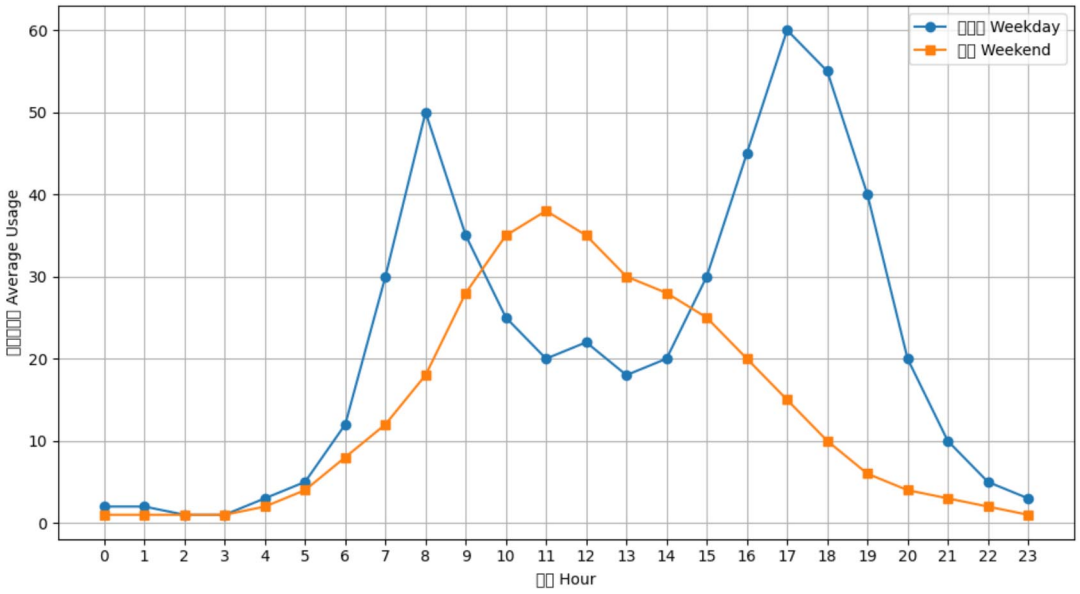


Figure 4 Average hourly public bicycle usage on weekdays and weekends.

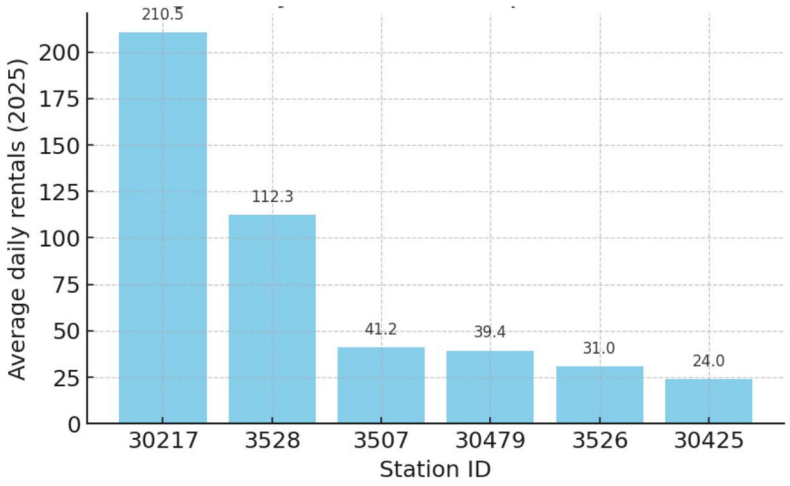
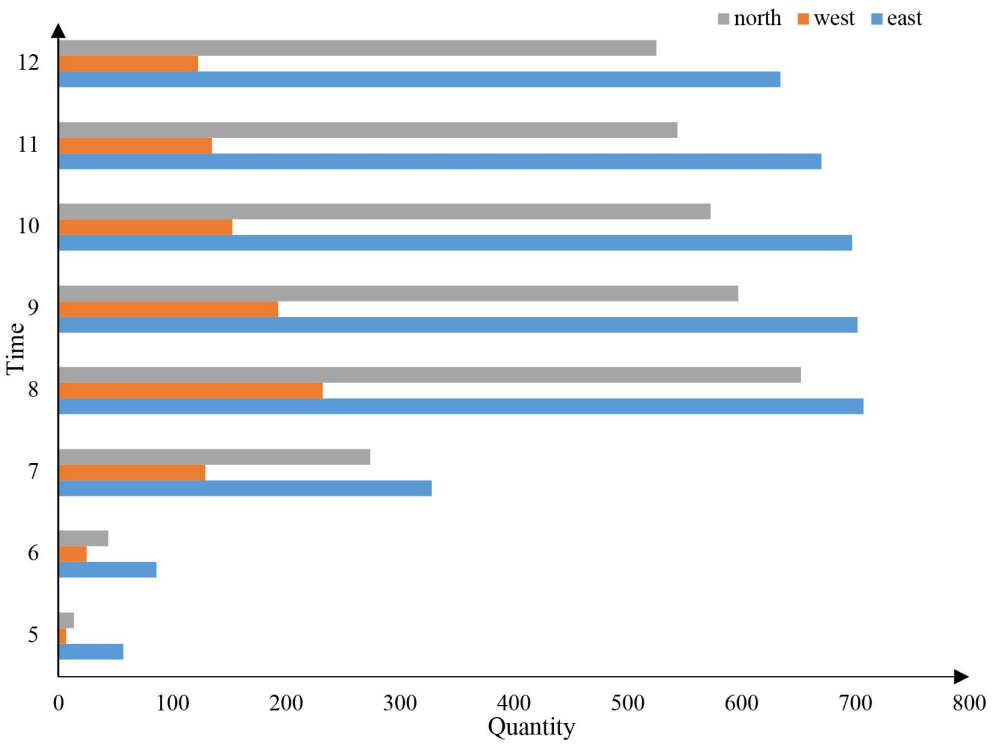


Figure 5 Average daily rental count per station in 2025.

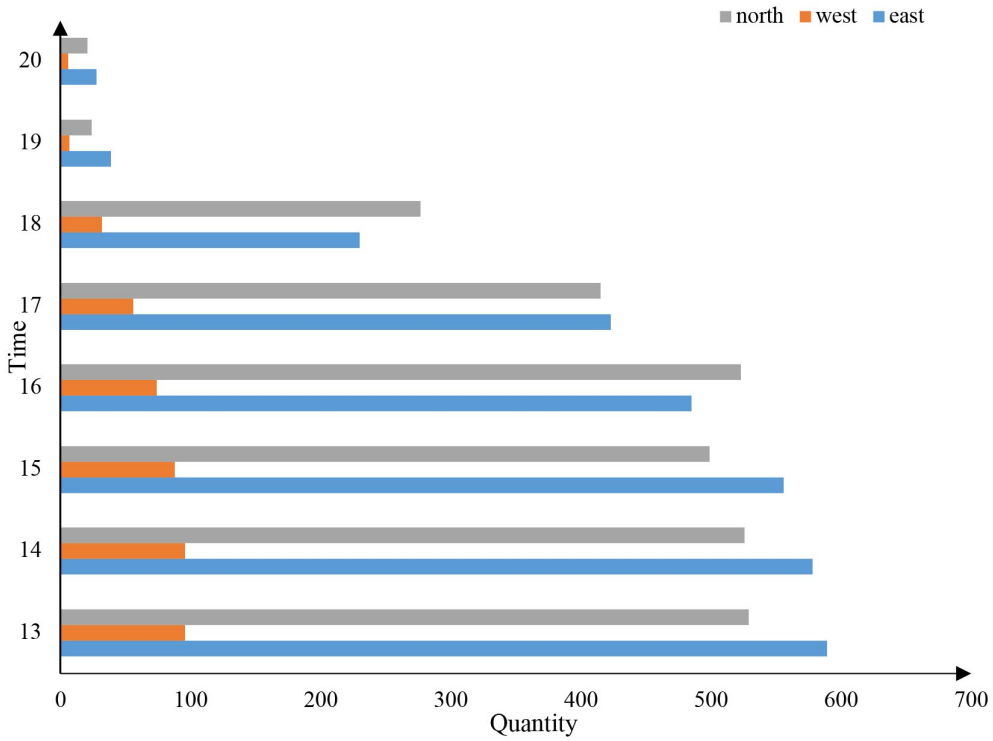
transit interchange points. For example, Station 30217 (close to a main entrance) handled about 20% more usage events during the 7–9 a.m. window than during 5–7 p.m., suggesting it primarily receives inbound bikes in the morning as commuters arrive at the station. In contrast, Station 30479 recorded higher activity in the 17–19 p.m. slot than in the morning rush, indicating more bikes are taken from that station in the evening (likely by commuters leaving the station). In general, during the morning peak, bicycles flow from peripheral neighborhood stations toward the central station area; during the evening peak, the flow reverses. This tidal pattern causes the well-known imbalances: core area docks tend to fill up in the morning (no free docks to return bikes), and core stations run empty in the evening (no bikes available to rent). By quantifying each station's usage at different times of day, our analysis confirms the existence of strong tidal flows, which will inform targeted redistribution strategies.

(3) Annual Usage and Station-Level Variance of Public Bicycles

Building on the intraday analysis, we next consider the broader usage over the entire year of 2025 to capture total demand and inter-station variance. Collectively, the six stations facilitated approximately 167,000 rental transactions over the year, equating to a combined average of about 458 rentals per day across the hub area. Notably, usage was highly concentrated at a few key locations: the busiest station, 30217, accounted for roughly 46% of the total annual transactions (about 76,800 events), underlining its critical role in the system. The second-busiest, station 3528, contributed around 24% (41,000 events). In contrast, station 30425 handled only $\sim$ 5% of annual transactions (8,800 events), indicating significantly lower utilization. The remaining stations (3507, 30479, 3526) each carried about 7–10% of the yearly load. To visualize the disparity, Figure 5 presents a bar chart of the average daily rental count for each station in 2025.



(a) Shared bicycle parking data from 5:00 to 12:00



(b) Shared bicycle parking data from 13:00 to 20:00

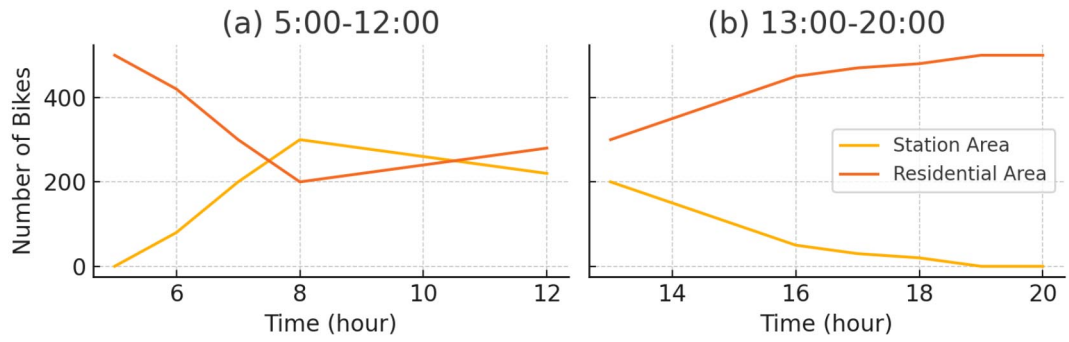
Figure 6 Backlog of shared bicycles in each area from 5:00 to 20:00.

(4) Investigation of the backlog of shared bicycles on working days

First of all, the parking situation in regard to shared bicycles at Station A was investigated thoroughly.

The shuttle bicycle parking space at Station A was divided into three areas: north, east and west. The recording time was from 5:00 to 20:00, and every hour, the number of different types of shared bicycles was recorded [15–16]. The survey was conducted on Monday, June 20, 2022, with sunny weather and moderate temperature. The results are shown in Figure 6.

Figure 6(a) shows the shared bicycle backlog in each region from 5:00 to 12:00. Figure 6 (b) shows the shared bicycle backlog in each region from 13:00 to 20:00. Figure 6



(a) 5:00–12:00 (b) 13:00–20:00.

Figure 7 Backlog of public bicycles in each area over time on a typical work day.

shows that the backlog of shared bicycles at Station A can be divided into four stages [17]. The first stage is from 5:00 to 8:00, and the backlog of shared bicycles increases rapidly. This is why residents near Station A use shared bicycles and stop near Station A during the morning rush hour. The second stage is from 9:00 to 14:00, when the backlog of shared bicycles gradually decreases. This is because the shared bicycles in the residential area near Station A are concentrated near the station, and there are no vehicles in the residential area, so the number of shared bicycles in Station A is becoming increasingly less. The third stage was from 15:00 to 18:00, when the backlog of shared bicycles decreases rapidly. This is because there were some bicycles available in the community, and the shared bicycles at Station A had also been returned. Later, with the evening peak, a large flow of people leaves the station, and the shared bicycles at Station A are quickly ridden away. The fourth stage is from 19:00 to evening when there is no backlog of shared bicycles at Station A. This is due to the high demand for shared bicycles during the traffic rush hours. By 19:00, the remaining dozen bicycles had been ridden away, leaving Station A with an insufficient supply of shared bicycles. At 20:00, the only shared bicycles remaining at Station A were either inferior or damaged, so no shared bicycles were available.

In addition, the bike sharing staff released 20 new bike sharing vehicles in the evening, and took away 19 broken bikes at around 21:00.

The study found that A had a serious backlog of shared bicycles, with 1591 bikes accumulated at 8:00 in peak hours; by 19:00, the number of shared bicycles on site A was running low, which meant that the supply and demand were unbalanced. Although the user's requirements had not been met, there had been a large backlog at some stage.

(5) Analysis of the parking capacity for shared bicycles

Given the parking width of 0.6m required for each bicycle, about 1300 bicycles can be parked in the available parking area of Station A.

According to the statistics, at 9:00 on the survey day, there were 400 private and 100 public bicycle parking spaces in this area.

Based on the above analysis, under reasonable parking conditions, the parking capacity of shared bicycles at Station A can reach about 800. This was far from the peak of 1591 shared bicycles; that is, the parking capacity was far from meeting the needs of commuters.

4.2 Backlog of Public Bicycles and Staging Analysis

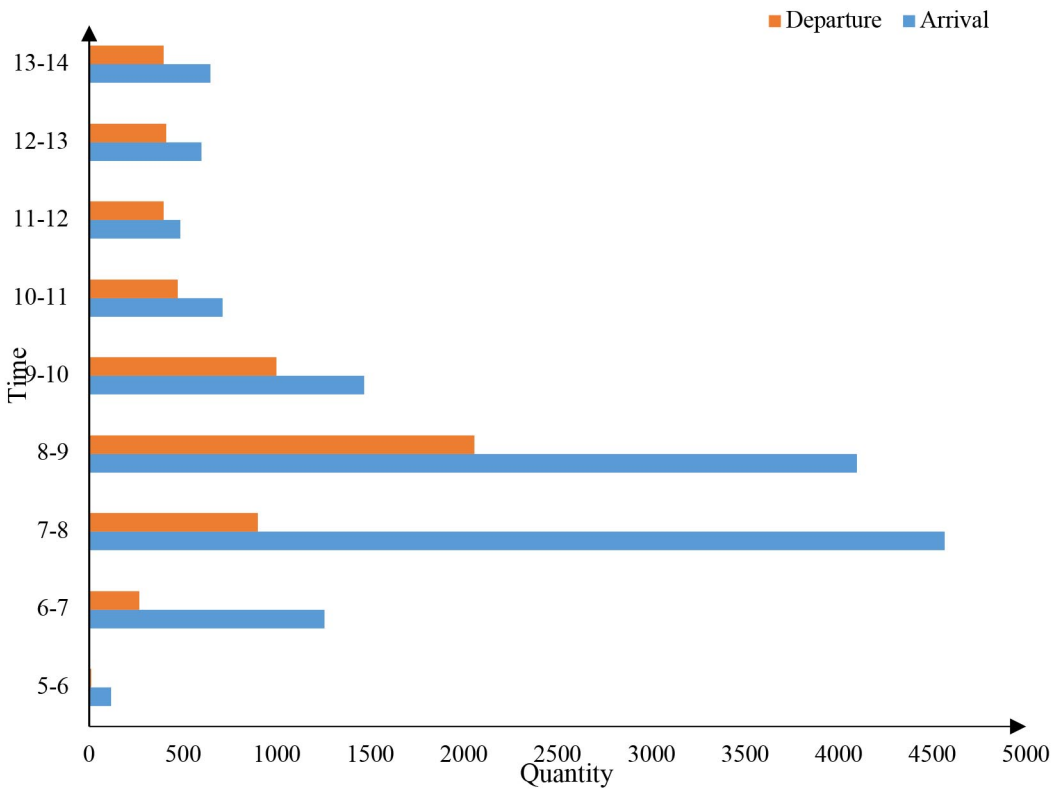
A noteworthy phenomenon at large stations is the"backlog"of public bicycles that accumulates at certain times of the day. A bike backlog refers to a buildup of idle bicycles at particular locations when many bikes are ridden there and not immediately taken out again. At the high-speed rail hub area, this typically occurs during the morning rush: commuters ride bikes from surrounding residential areas to the station, leaving them there, which causes a pile-up of bikes at the station entrance areas. Conversely, by the evening rush, the backlog at the station tends to disappear as people exiting the station take those bikes to ride back to their neighborhoods. To analyze this, we divide the station area into two broad regions: station area (the vicinity of the station exits where bikes accumulate) and the residential areas (the surrounding neighborhoods where bikes originate or end up). We then examine how the number of available bikes in each region changes over the course of a workday. Figure 7 tracks the modeled bike backlog at the station vs. residential areas from early morning (5 a.m.) to evening(8 p.m.).

4.3 Evaluation of Shared Bicycles Carrying Capacity of Station A

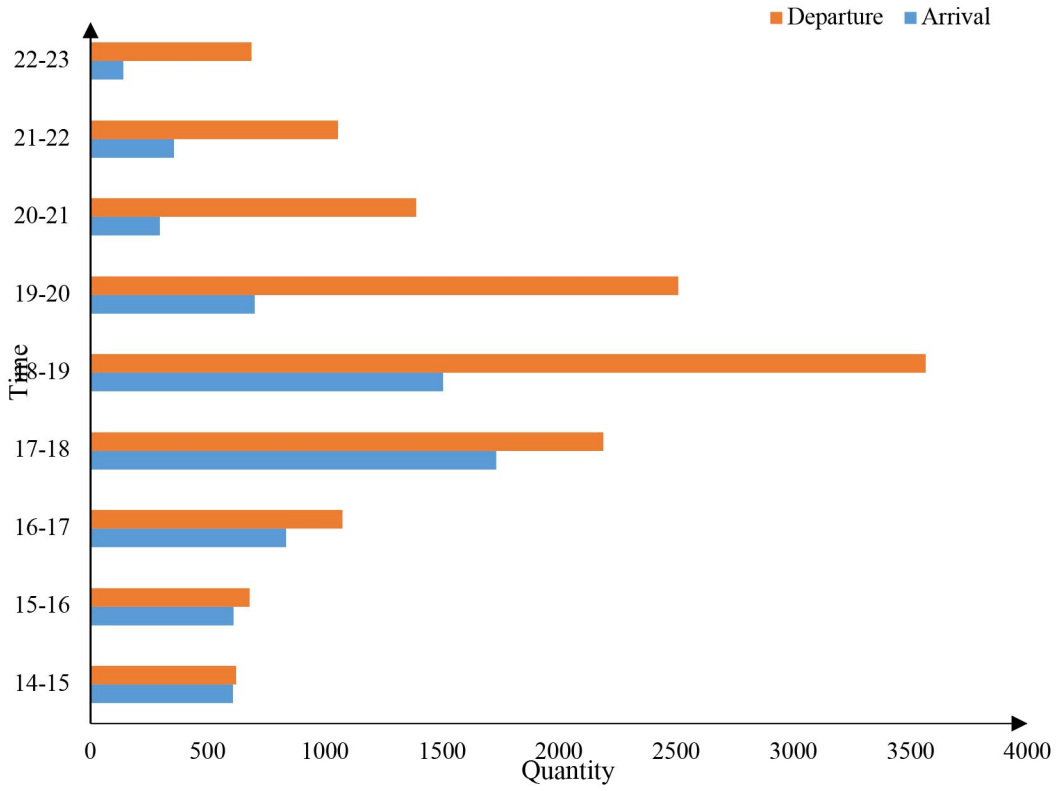
Inbound and outbound passenger flow

The problem of shared bicycle backlog in Station A is closely related to the passenger flow in and out of that station, so the passenger flow in and out of Station A on weekdays was analyzed. The results are shown in Figure 8.

Figure 8(a) shows the flow data from 5:00 to 14:00, and Figure 8(b) shows the flow data from 14:00 to 23:00. It can be seen from Figure 8 that the inbound traffic of Station A was significantly higher than the outbound traffic at the morning peak, while the outbound traffic at the evening peak was significantly higher than the inbound traffic, which is a typical



(a) Data of inbound and outbound passenger flow from 5:00 to 13:00 on working days



(b) Data of inbound and outbound passenger flow from 14:00 to 23:00 working days

(b) Data of inbound and outbound passenger flow from 14:00 to 23:00 working days

Figure 8 Passenger flow in and out of Station A on working days.

Table 2 The cumulative difference between the inbound and outbound stations of Station A

time	5–6	6–7	7–8	8–9	9–10	10–11	11–12	12–13	13–14
differential value	105	1094	4760	5902	7270	7509	7598	7786	8038
time	14-15	15-16	16-17	17-18	18-19	19-20	20-21	21-22	22-33
differential value	8025	7956	7716	7258	5199	4309	2296	1597	1050

Table 3 Raw data fitting for the first period.

Time value	Metro cumulative difference	Actual backlog value for removing damaged vehicles and replacement
5	0	0
6	105	82
7	1094	658
8	4760	1518

Table 4 Raw data fitting for the second period.

Time value	Actual backlog value for removing damaged vehicles and replacement
9	1419
10	1369
11	1295
12	1228
13	1160

suburban residential station. Since most users store their shared bicycles at Station A, the cumulative difference in the flow of entering and exiting the station is the main reason for the backlog of shared bicycles. It can be concluded that there is a large correlation between the cumulative difference between the inbound and outbound stations and the backlog of shared bicycles. Therefore, the cumulative difference between the inbound and outbound stations from Station A (that is, the difference between the inbound and outbound stations) was calculated. The results are shown in Table 2.

It can be seen from Table 2 that from 5:00 to 15:00, the cumulative difference between inbound and outbound stations shows an upward trend. The peak is from 6:00 to 9:00 in the morning, with the largest increase; from 15:00 to 23:00, the cumulative difference between inbound and outbound stations shows a significant downward trend, the greatest decline being from 18:00 to 21:00. It is worth mentioning that the train operation had been completed by 23:00, and the cumulative difference between the final arrival to and departure from the station is 1050.

4.4 Calculation of Shared Bicycle Backlog Based on BP Neural Network Algorithm Prediction Model

(1) Overview of piecewise fitting methods

Through the quantitative analysis of the backlog of shared bicycles and the number of entrances and exits, the issue of urban bicycle backlog can be better understood, and the theoretical maximum backlog value can be obtained, thereby providing a basis for solving the problem of urban parking backlog.

The BP neural network is a new method for the comprehensive optimization analysis of nonlinear curve fitting. The model has good application prospects in nonlinear regression, curve fitting, nonlinear, parameter estimation for complex engineering models, etc. This method has unique global optimization performance and is not affected by the initial conditions, which not only reduces the application requirements, but also greatly improves the success rate of the solution. Based on the prediction model of BP neural network, the relationship between the backlog of urban shared bicycles and the difference between subway entrances and exits and the time was fitted.

(2) Piecewise fitting function construction

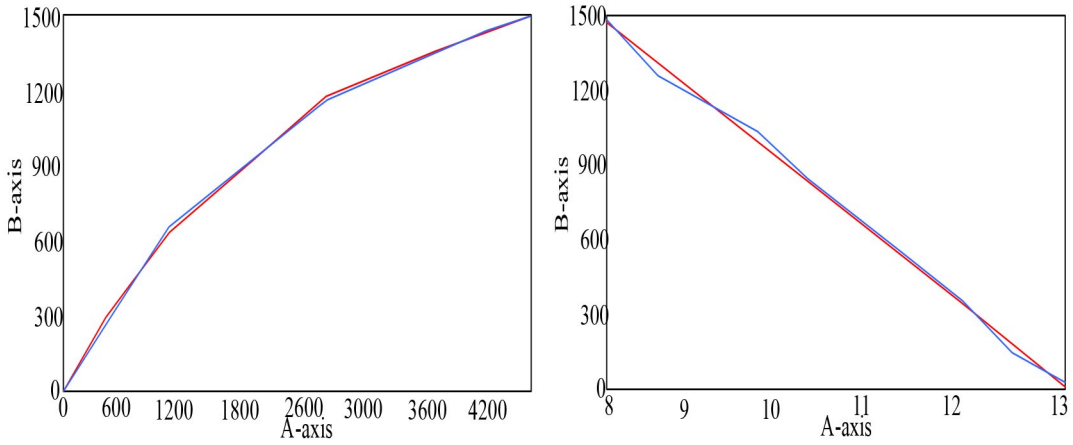
First, after excluding the effects of damaged or faulty bicycles and dispatching activities, the original data of the difference between the shared bicycle backlog value and the subway between 5:00 and 8:00, the shared bicycle backlog value between 9:00 and 13:00, and the shared bicycle backlog value between 14:00 and 18:00 were obtained. The data results for the three periods are shown in Table 3, Table 4 and Table 5, respectively.

The fitting results were obtained by using the fast formula fitting function of BP neural network algorithm prediction model to fit the data in Tables 3, 4 and 5. The results are shown in Figure 9.

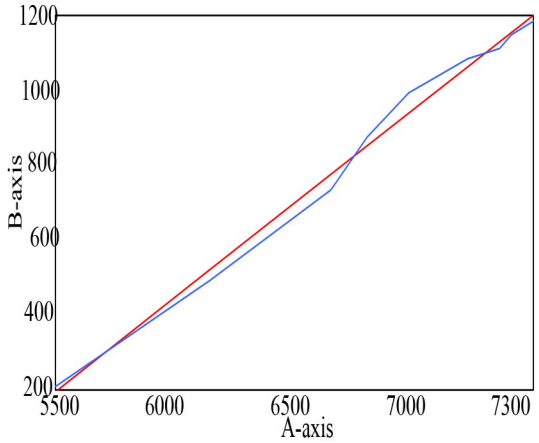
Figure 9 (a) shows that from 5:00 to 8:00, the ratio between the total number of shared bicycles and the subway access continued to decrease. This is because the number of shared bicycles in the community was gradually decreasing; some users cannot find them and need to walk or use other means of transportation. Figure 9 (b) shows that from 8:00 to 13:00, the total number of shared bicycles is not clearly related to the difference between subway station entries and

Table 5 Raw data fitting for the third period.

Time value	Actual backlog value for removing damaged vehicles and replacement
14	8038
15	8025
16	7956
17	7716
18	7258



(a) First segment fitting result (b) Second segment fitting result



(c) Third segment fitting result

Figure 9 Fitting results of BP neural network algorithm prediction model.

exits; instead, it decreases gradually over time. This was because at 8:00, there were few shared bicycles left in the community, most of which were near the subway station. In the vicinity of the subway station, the number of shared bicycles was also decreasing due to the fact that they can only enter and exit. Therefore, when public bicycles gather at subway stations, the backlog value would naturally decrease. It can be seen from Figure 9 (c) that the backlog value of shared bicycles has been zero for a long time, and the supply exceeds the demand. Figure 9 shows that during the first and second periods, shared bicycles mainly flow from the surrounding residential areas to Station A (the high-speed rail hub), corresponding to the morning commute; during the third period, the flow reverses, with shared bicycles moving from Station A back to the surrounding residential areas during the evening peak. Here, "residential areas" refers to the residential neighborhoods adjacent to Station A, rather than suburbs in general.

4.5 Layout of Shared Bicycle Parking Points Based on Big Data and BP Neural Network Algorithm

After the station entrance parking area is determined, the station entrance parking and resident parking is established in the area. The setting of parking points close to stations and

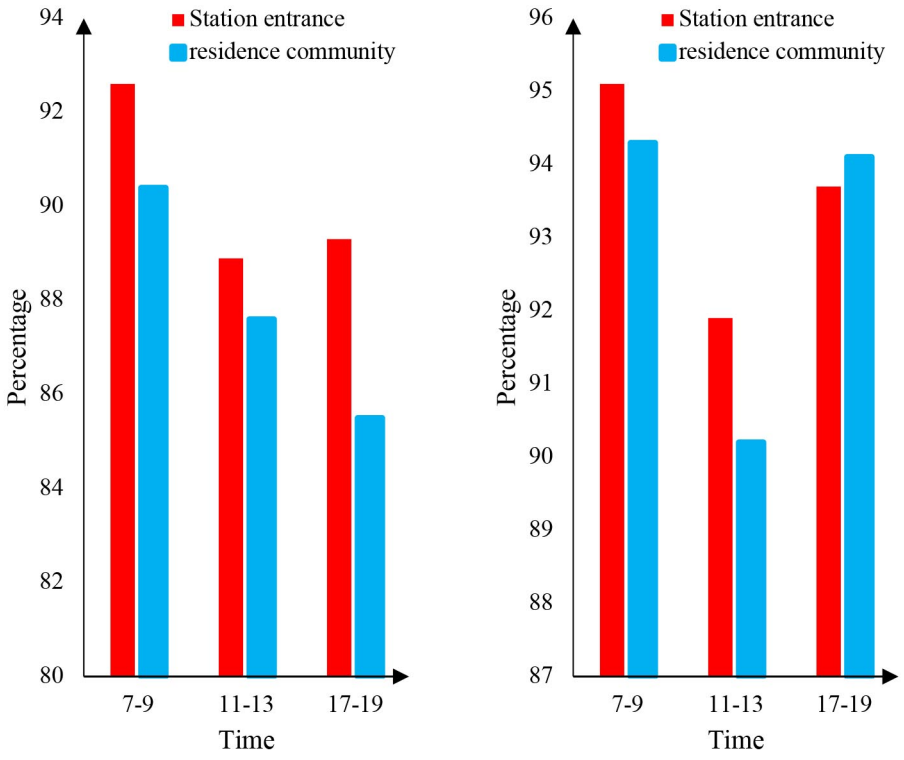


Figure 10 Usage rate of shared bicycles for each of the two parking spots. (a) Parking point layout after applying the conventional method. (b) Parking point layout after applying big data and BP neural network algorithm.

residential areas not only facilitates the efficient dispatching of public bicycles: it also standardizes the parking behavior in the community and avoids the parking of vehicles. At present, most of the shared bicycles in the community are scattered, which often occurs in the rush hours. As a result, a large number of travelers cannot find bicycles to use, so they have to give up. However, once the parking point is set, users can find a large number of bicycles at the designated location, which is very convenient.

In a word, when setting bike sharing parking spots, the key is not the cost, but the residents' travel and the ease of dispatching. For residents, the greater the number of parking spots, the better. It is more desirable to have parking spaces at the entrance of each community. However, if there are too many parking spaces, this is obviously not conducive to scheduling. Therefore, it is necessary to classify according to the entrances and exits of the community, which not only meets the need for residents to walk to the parking place, but also facilitates management. In the adjacent cells, it is not necessary to set up multiple bays—only one bay is needed to meet the access of the surrounding cells.

In order to better understand the role of shared bicycle parking point layout based on big data and BP neural network algorithm, it was compared with conventional parking point layout. The times were 7–9, 11–13 and 17–19 respectively. The results are shown in Figure 10.

It can be seen from Figure 10 (a) that when the parking points were arranged according to the conventional method, the use rates of shared bicycles at 7–9, 11–13 and 17–19 in the station and residential area were 92.6% and 90.4%, 88.9% and 87.6%, 89.3% and 85.5% respectively. It can be seen from Figure 10 (b) that when conventional parking points were arranged according to big data and the BP neural network algorithm, the utilization rates of shared bicycles at 7–9, 11–13 and 17–19 in stations and residential areas were 95.1% and 94.3%, 91.9% and 90.2%, 93.7% and 94.1% respectively. Figure 7 shows that when parking points were arranged according to big data and BP neural network algorithm, the utilization rate of shared bicycles was significantly higher than when parking points were arranged by conventional methods.

5. CONCLUSIONS

According to analytical results obtained for each city, from 2020 to 2022, bike sharing in China has increased rapidly. The scope of urban rail transit stations has become a key area for the development of bike sharing. At the same time, as an increasing number of businesses have been established in the region, there are many problems facing these businesses, such as nonstandard vehicle parking. Therefore, it is very important to improve the parking management of enterprises and standardize the parking of shared bicycles. Applying the neural network method, this study analyzed the use rate of shared bicycles and verified the effectiveness of the model by using the BP neural network prediction model. To improve the efficiency of the transportation department, it is necessary to address the issue of standardizes disorderly parking and the placing of shared bicycles within the immediate vicinity of rail transit stations. Shared bicycles not only facilitate people's travel—they also have a positive impact on the

development of the city. However, with the increase in the number of people wanting to share bicycles but low rate of actual utilization, the department responsible for managing this scheme needs to strengthen its supervision of shared bicycles and formulate corresponding rules to improve the operation of shared bicycles.

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Yunhong Shao was born in Qujing, Yunnan Province, China, in 1978. She is a Professor in Zhejiang Institute of Communications. She received the bachelor’s degree and master’s degree from Chongqing Jiaotong University, and her PhD from Southeast University. Her research interests include transportation planning, transportation management, and transportation planning and management.
E-mail: shaoyh@zjvtit.edu.cn

Tao Zhang was born in Jining, Shandong Province, China, in 1980. He is an Associate Professor at Zhejiang Institute of Communications and holds a master’s degree. He received the bachelor’s degree from Shandong University and his master’s degree from Zhejiang University. His research interests include rail transit electrical control technology, electrical control systems for rail transit, and rail transit electrical control engineering.
E-mail: zhangtao@zjvtit.edu.cn

Min Hong was born in Tiantai, Zhejiang Province, China, in 1988. She is a lecturer at Zhejiang Institute of Communications and holds a master’s degree. She received the bachelor’s degree from Zhejiang Normal University and her master’s degree from Beijing Jiaotong University. Her research interests include urban rail transit operations management, rail transit operations and management, and urban rail transit management.
E-mail: hm@zjvtit.edu.cn

Feiqiang Zhou was born in Hangzhou, Zhejiang Province, China, in 1976. He is the Deputy General Manager of Hangzhou Public Bicycle Transportation Service Development Co., Ltd. and an economist, primarily engaged in the

operation and management of urban public transportation.
E-mail: 154253255@qq.com

Jing Zhou was born in Lishui, Zhejiang Province, China, in 1988. She is an Associate Professor at Zhejiang Institute of Communications. She received the bachelor's degree from Zhejiang Normal University and her master's degree from Southwest Jiaotong University. Her research interests include transportation planning, transportation management, and transportation planning and management.
E-mail: zhoujing@zjvtit.edu.cn