Service quality evaluation of bus lines based on improved momentum back-propagation neural network model: A study of Hangzhou in China

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Abstract
This study was focused on Hangzhou in China that are undergoing large-scale subway construction, and an improved momentum back-propagation (BP) neural network model was trained. The model can analyze the complex traffic data, evaluate the service quality of bus line, and improve the estimation accuracy and convergence speed. For the same training data set, the convergence time of the BP algorithm with momentum term is reduced by 0.043 secs, the iterative convergence speed is improved by 0.66%, and the estimation accuracy is improved by 26.7% compared with the standard BP algorithm. Under similar conditions, the convergence time is 1.562 secs less than that of the standard BP algorithm, and the convergence speed was 24.1% higher than that of the standard BP algorithm, and the absolute value of the estimated error was less than 1%. Finally, a representative bus line in Hangzhou was used as an example to evaluate the model. The results showed that the improved momentum BP neural network model had a faster convergence speed and higher prediction accuracy of the comprehensive weight of bus line service quality. The prediction results of the model are consistent with the actual survey results, which indicates that the model constructed is reasonable.

1 INTRODUCTION

Urban public transportation accounts for a significant proportion of the entire transportation system. It connects various factors of the society, enhances the daily activities of urban residents, and facilitates several passenger transportation tasks in cities, which are vital for urban construction and development. The conventional bus system has good flexibility, high adaptability, and large carrying capacity, and its use has gained popularity in various countries and regions. Hence, in-depth research should be conducted on “transit priority,” which involves the systematic and in-depth evaluation of transport...
service quality, to provide a practical basis and research methods for enhancing the vitality of the public transport market, and thus, improve transport service quality continuously [1]. Experts and scholars have analysed the current problems and have proposed future research directions on the quality evaluation of the public transit service using different perspectives, indicators, and evaluation methods.

Zhang et al. [2] used three dimensions (i.e., passenger convenience perception quality, ride environmental quality, and operational service quality) to assess the quality of urban public transport services and established a model for evaluating the quality of conventional bus services using a structural equation model. Luigi and Angel [3] found the differences between the expected service quality and the perceived service quality of the public transportation system. Their results suggest that waiting time, cleanliness, and comfort are the most important variables for users of public transport services. Mohammad et al. [4] trained a multilevel framework by combining subjective and objective methods for measuring the level of public transport services. In terms of evaluation methods, Armando and Roberta [5] constructed a combined integrated-circuit evaluation model through fuzzy logic and the analytic hierarchy process (AHP). Hu [6] trained an evaluation model based on the AHP method and the back-propagation (BP) neural network. Liu et al. [30] trained an AHP-BP neural network model for evaluating the quality of bus line services from passengers’ perspectives. Based on the demand model, Rojo et al. [8] measured the improvement of service quality from the perspectives of social-passenger-operating companies and social-passengers. Gatta and Marcucci [9] used the nested logit model to quantify the service standards of the government and operators in public transportation service contracts. Currie and Delbosc [10] used multiple regression models to explore the service factors that affect the passenger flow of conventional buses and bus rapid transits. Verbich and El-Geneidy [11] used a logistic regression model to analyse the determinants of bus satisfaction among different categories of passengers. Wan et al. [12] used the least-squares regression model to quantify the impact of service attributes, sociodemographics, and external factors on the overall satisfaction of passengers. Yang et al. [13] analysed the service process of the bus system and passenger travel characteristics using statistical methods. Soza-Parra et al. [14] investigated the effect of service reliability on the service satisfaction of public transport users.

Currently, the quality of bus line services has been evaluated from different aspects using various methods. However, there is no research on the combination of AHP and improved BP neural network in the evaluation of public transport service quality. In this paper, the mean square errors (MSEs) between the actual output value and the expected output value of BP neural network is used to dynamically adjust the momentum term in each iteration process, which improves the convergence speed and estimation accuracy of BP neural network. The model is more suitable for urban traffic environment with complex data. The final prediction results showed that, compared with the standard BP neural network model, the improved model had a 24.1% faster convergence rate and the absolute value of the estimation error was less than 1%. It provides a more accurate evaluation model for the service quality evaluation of urban bus lines with large and complex data.

The remainder of this paper is organized as follows. Section 2 presents the evaluation index system. Section 3 presents the process of determining the weight of evaluation index. Section 4 presents the BP neural network and its algorithm. Section 5 introduces the case study. Finally, Section 6 concludes the work.

2 | CONSTRUCTION OF EVALUATION INDEX SYSTEM OF BUS LINE SERVICE QUALITY

2.1 Principles for constructing evaluation indicators

Based on the current factors influencing Hangzhou’s public transportation system development and the ground conditions of the traffic roads, the following basic principles must be observed when selecting evaluation indicators: (1) the principle of scientificty, that is, the concept of the indicators must be clear and have a specific scientific connotation, which can measure and reflect the development characteristics of Hangzhou’s current bus lines; (2) the principle of completeness, in which the entire indicator system should reflect the developmental characteristics of Hangzhou’s bus system more comprehensively; (3) the principle of principal components, in which the comprehensive indicators that can represent the quality of public transport services are selected; and (4) the principle of independence, in which the indicators with relative independence are adopted.

2.2 Establishment of evaluation indicators

A target level, 6 criterion levels, and 16 indicators were established in the evaluation index system, as illustrated in Figure 1 [16]. This index system was based on the above scientificty, completeness, principal component, and independence principles according to the “Urban Public Transport Regulations” and “Public Metropolis Assessment and Evaluation Index System” [15], as well as the current state of Hangzhou’s public transport system, the recommendations of experts and passengers, and the AHP.

3 | METHOD FOR DETERMINING WEIGHTS OF EVALUATION INDEXES OF BUS ROUTES

3.1 Construction of judgment matrix of AHP

The pairwise judgment matrix \( A = \left[ \begin{array}{cccc} a_{11} & \cdots & a_{16} \\ \vdots & \ddots & \vdots \\ a_{16} & \cdots & a_{66} \end{array} \right] \) is constructed, where \( a_{ij} \) indicates the importance of element \( i \) relative to
**FIGURE 1** Evaluation index system of bus line service quality

**TABLE 1** Evaluation criteria

| Scaling $a_{ij}$ | Definition | Scaling | Definition |
|------------------|------------|---------|------------|
| 1                | Factor $i$ is equally important than factor $j$ | 9       | Factor $j$ is absolutely more important than factor $j$ |
| 3                | Factor $i$ is slightly important than factor $j$ | 2, 4, 6, 8 | This value is the scale value corresponding to the intermediate states between the above judgments |
| 5                | Factor $i$ is more important than factor $j$ | Reverse | $a_{ji} = \frac{1}{a_{ij}}$ |
| 7                | Factor $i$ is strongly important than factor $j$ | | |

Element $j$ when assessing the upper element in $i$ element and $j$ element at the same level. The value standards are listed in Table 1.

### 3.2 Consistency check

The matrix consistency judgment is expressed in Equations (1)–(3) [17].

\[
CR = \frac{CI}{RI}
\]  

\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1}
\]  

\[
RI = \frac{CI_1 + CI_2 + \cdots + CI_n}{n}
\]

where $CR$ is the consistency ratio, $CI$ is the consistency index, $RI$ is the random consistency index, and $\lambda_{\text{max}}$ is the maximum eigenvalue of the judgment matrix.

The random consistency index $RI$ is related to the order of the judgment matrix. Generally, the higher the matrix order, the higher the probability of consistent random deviation (Table 2).

When $CR < 0.1$, the judgment matrix meets the consistency requirement, which indicates that the constructed judgment matrix is reasonable and feasible. When $CR > 0.1$, the judgment

**TABLE 2** Standard values of average random consistency index RI

| $n$ | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 |
|-----|----|----|----|----|----|----|----|----|----|----|
| $RI$ | 0  | 0  | 0.58 | 0.89 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |
4 | ESTABLISHMENT OF THE BACK-PROPAGATION NEURAL NETWORK MODEL

4.1 | Principle of the BP neural network

The BP neural network is a multilayer feed-forward neural network that propagates backward according to errors. Generally, a three-layered structure (an input layer, a hidden side, and an output layer) is adopted for the BP neural network. The algorithm consists of the forward transmission of the input signal and the backward propagation of the error. The three-layered BP neural network can be used to approximate any non-linear function [18]. Compared with other neural networks, it has the advantages of simple structure, strong applicability and high fault tolerance. At present, many scholars have applied it to the research of bus line service quality evaluation [19–21].

The weight between the input node $x_j$ point and the hidden node $y_i$ point is $\omega_{ij}$, and the connection weight between the $y_i$ point of the hidden node and the $Y_l$ point of the output node is $\omega_{li}$. The calculation formula used for the BP model is expressed as follows.

$$\mu_i = \sum_j \omega_{ij} x_j$$

(4)

Similarly, the output of the hidden layer node is expressed in Equation (5).

$$y_i = f \left( \sum_j \omega_{ij} x_j - \theta_i \right)$$

(5)

Here, $y_i$ is the output value of $i$ neuron in the hidden layer, $f$ is the activation function of the hidden layer, $x_j$ is the $j$ input of the input layer, and $\theta_i$ is the threshold of the hidden layer [22].

The input and output of the neurons in the output layer are expressed in Equations (6) and (7), respectively.

$$v_j = \sum_j \omega_{j2} y_i$$

(6)

$$Y_l = g \left( \sum_j \omega_{j1} y_i - \theta_j \right)$$

(7)

where $Y_l$ is the output value of the $l$ neuron in the output layer, $g$ is the activation function of the output layer, and $\theta_j$ is the threshold of the output layer.

The error formula of the output layer (between the hidden and output nodes) is described as follows:

1. The expected output of the output node is $t_l$.
2. The error of the error control unit $k$ is expressed in Equation (8).

$$e_k = t_l^{(k)} - Y_l^{(k)}$$

(8)

Next, the total square error function at the output is established, as expressed in Equations (9) and (10).

$$E = \frac{1}{2} \sum_l (t_l - Y_l)^2$$

(9)

$$E = \frac{1}{2} \sum_l \left( t_l - g \left( \sum_j \omega_{jl} \left( \sum_i \omega_{ij} x_j - \theta_j \right) - \theta_j \right) \right)^2$$

(10)

4.2 | Standard BP neural network algorithm

The standard BP neural network uses the gradient descent method as its main algorithm. The weight coefficient is adjusted along the reverse direction of the gradient change of the error function such that the error decreases along the gradient direction. Continuous iterative training is carried out until the error satisfies the training accuracy set by the system [23].

During the weight adjustment stage, adjustment is successively performed in reverse for each layer across the network.

First, the weight $\omega_{jl}$ existing between the hidden layer and the output layer is adjusted. By using the gradient descent method, the gradient $\frac{\partial E(k)}{\partial \omega_{jl}}$ of the error $\omega_{jl}$ is calculated and then adjusted along this direction using Equations (11) and (12).

$$\nabla \omega_{jl} (k) = -\eta \frac{\partial E(k)}{\partial \omega_{jl} (k)}$$

(11)

$$\omega_{jl} (k + 1) = \omega_{jl} (k) + \nabla \omega_{jl} (k)$$

(12)

However, each search is carried out along the gradient direction of the point using the gradient descent method. The search path is zigzag, the convergence speed is slow, the accuracy is not high, and it is easy to fall into the local minimum [25, 26]. Thus, the following BP algorithm is used to increase the momentum, which helps overcome the shortcomings of the BP algorithm [27].

4.3 | Momentum-term BP neural network algorithm

The momentum BP method is used to introduce the momentum factor $\alpha \ (0 < \alpha < 1)$ during the weight update stage of the standard BP algorithm so that the weight correction will have desirable inertia.
\(\nabla \omega(k)\) in Equation (11) is redefined as expressed in Equation (13).

\[
\nabla \omega(k) = \alpha \nabla \omega(k-1) - \eta \frac{\partial E(k)}{\partial \omega(k)}
\]

(13)

Let \(\nabla \omega'(k)\) be expressed, as shown in Equation (14).

\[
\nabla \omega'(k) = -\eta \frac{\partial E(k)}{\partial \omega(k)}
\]

(14)

Therefore, the weight update equation of the BP neural network algorithm with the momentum terms can be obtained, as expressed in Equation (15).

\[
\omega(k + 1) = \omega(k) + \alpha \nabla \omega(k-1) + \nabla \omega'(k)
\]

(15)

Compared with Equations (11) and (13) shows that when the weight is updated, an additional factor \(\alpha \nabla \omega(k-1)\) exists in the above equation. This additional factor indicates that the update direction and amplitude of the weights are not only related to the gradient calculated within this time but also related to the direction and amplitude of the last update. The addition of this factor improves the antishock and accelerated convergence abilities of the weight update [28]. The principle is described as follows.

From Equations (13)–(15), the BP neural network algorithm containing the momentum term memorizes the modification direction of the model weights at time \((k-1)\). Additionally, the modification amount of the connection weight of the error function \(E\) at time \((k+1)\) is the sum of the modification amounts at times \((k-1)\) and \(k\). If the current \(\nabla \omega'(k)\) has the same sign as \(\nabla \omega(k-1)\) at the previous time, the vector directions of the current negative gradient and last weight modification amount are almost the same, which indicates that the last weight modification amount has a more significant impact on the current weight modification amount. Thus, the weight modification amount at time \((k+1)\) increases, and the update speed of the weight is accelerated. In contrast, for the same reason, the update speed of the weight slows down, which is beneficial for the convergence of the algorithm [7, 29].

4.4 Improved momentum BP neural network algorithm

The momentum-term BP algorithm accelerates the convergence of the algorithm by introducing the last weight update amount in the current weight update process. With the continuous iteration of the algorithm, if the error curve continues to decline, it implies that the direction of the negative gradient is almost the same as that of the last weight change. Hence, the momentum factor \(\alpha\) should be increased slowly. If the error curve oscillates, it signifies that the direction of the negative gradient is opposite to that of the last weight change. The momentum factor \(\alpha\) should then be reduced to minimize the effect of the last weight change on the weight update until the error curve no longer shocks. When the error curve tends to be stable, the addition of the momentum term increases the learning rate of the algorithm. A high learning rate may significantly increase the amount of the model weight or even cause the algorithm not to converge.

The magnitude of the momentum factor is dynamically adjusted using the MSE of the actual and expected output values of the model, where the MSE is defined as expressed in Equation (16) [31].

\[
Mse(k) = E[(t_j - Y_j)^2]
\]

(16)

The momentum factor \(\lambda\) is dynamically adjusted, and the momentum term function is defined as expressed in Equation (17).

\[
a(k) = \lambda[1 - \rho^{-Mse(k)}]
\]

(17)

where \(\lambda\) is a constant that indicates the speed at which the adjustment curve rises and \(\rho\) is a constant that defines the range of the control function variations.

Therefore, the weight update equation of the improved adaptive momentum-term BP neural network algorithm can be obtained using Equation (18).

\[
\omega(k + 1) = \omega(k) + \lambda[1 - \rho^{-Mse(k)}] \nabla \omega(k-1) - \eta \frac{\partial E(k)}{\partial \omega(k)}
\]

(18)

5 VERIFICATION EXAMPLE

5.1 Background of passenger satisfaction survey

During the construction of the Hangzhou Metro, subway lines were laid along the main roads, and the occupied main roads were generally the main lines used for traveling from Hangzhou. Enclosed construction was carried out on the roads, resulting in different degrees of impact traffic on the ground. This study primarily aims to investigate the adverse impact on the quality of public transport services in the context of several subways in Hangzhou. The impact of subway construction on bus vehicles mainly includes the reduction of the number of dedicated lanes, the partial enclosing of parking platforms, and the reduction of road capacity. These factors may easily cause problems such as traffic congestion for bus travel, which adversely affects service satisfaction when using bus vehicles. As shown in Figure 2, the bus station platform is partially enclosed by the subway construction, resulting in low efficiency at the entrance and exit stations, and the bus is becoming train.

The most significant impact of subway construction on road traffic is changing the original traffic route. As shown in Figure 3, due to on-going construction, the original bus lanes...
were blocked, and the straight-line roads were diverted through large-angle turns, which affected the speed and load factor of the buses, resulting in reduced service quality and lower satisfaction [32].

5.2 Process of passenger satisfaction survey

Paper questionnaires were used in this study. The researchers randomly selected passengers at the bus stations in the main urban area of Hangzhou; they covered different characteristics of the population, such as gender, age, and number of bus rides. The results demonstrate that, through final processing and verification, a small part of the answer logic was found to be a significant problem, and the questionnaire could not be completed. The actual sample size of the bus satisfaction survey was 13,992, and the completion rate was 99.94%. Figure 4 shows the scene of the investigation.

5.3 Analysis of passenger satisfaction survey results

After the data were collected and sample data recovery and processing were performed, the results were analysed based on the evaluation index scores and related evaluation methods presented in Table 3. The bus passenger satisfaction score in the main urban area was 83.67 points.
Based on the results of the service quality satisfaction survey, we specifically analysed the West Lake District and Gongshu District, where Hangzhou has a large public traffic volume. The average scores of the questionnaires for each station in the Xihu District and Gongshu District were calculated and graphically presented on a geographic information system map (Figures 5 and 6). The larger the dots in each figure, the higher the average score of the survey site. The red dots indicate the substandard scores, and the average satisfaction for each site was less than 60 to observe the areas with lower satisfaction scores.

From the score analysis, the main reasons for the areas with lower satisfaction were as follows: (1) Metro construction led to the relative weakening and lagging of bus facilities. (2) Metro construction occupied the roads, and road flatness affected passengers’ overall attitude toward taking bus rides.

Based on the assessment method, the assessment indicators were divided into six categories [33]. Assuming that the full score of each category was 100 points, the conversion result of the average score for each category was obtained (Figure 7). Among the categories, bus information service had the highest satisfaction score, and service reliability had the lowest satisfaction score.

Assuming that the total score of a single indicator was 100 points, the conversion results of the average scores of the 16 question-related indicators used in the questionnaire were obtained (Figure 8). The top three rankings of satisfaction were service reliability, information normalization, and docking normalization (Figure 8). In contrast, the bottom three positions went to the crowding degree in the bus, waiting time, and waiting time for transfer.

The 16 individual evaluation indicators were selected to collect “unsatisfied” and “very dissatisfied” samples for a separate analysis (Figure 9). The “dissatisfied” sample of the indicator of crowding degree in the bus had the highest proportion and reached 11.44%, followed by the unsatisfactory rate of waiting time (9.85%). These results indicate that the Hangzhou bus system still has much room for improvement in these two areas.

According to the score map of each evaluation index of the ground bus system and the ranking chart of the proportion of the “unsatisfactory” sample size of the single index, the questionnaire survey processing results showed that the degree of crowding in the bus and the waiting time were the worst indicators of passenger satisfaction. The results provided a reference standard for the model prediction.

5.4 Establishment of BP neural network topology

The BP neural network can have multiple input variables as the prediction conditions. Based on the above analysis and calculation, the AHP weights of the 16 evaluation indicators that affected the quality of bus line services in this study were used as the neural network input, and the integrated weights were
TABLE 3  Scores of various evaluation indexes of bus lines

| Index category (Index)                      | Index definition and content                                      | Score |
|--------------------------------------------|------------------------------------------------------------------|-------|
| Bus service convenience (26)                | Walking time by bus (6) 5 min, the score is 6; 8 min, the score is 4; 10 min, the score is 0. | 5.03  |
|                                            | Transfer convenience (3) Number of transfer lines in station ≥ 8, the score is 3; 5, the score is 2; 2, the score is 1; 0, the score is 0. | 2.46  |
|                                            | Waiting time for transfer (3) Peak period/flat hump period transfer time ≤ 3 min/5 min, the score is 3; 5 min, the score is 2; 7 min, the score is 1; 10 min, the score is 0. | 2.38  |
|                                            | Operation time (6) The published time of the first and last buses on the bus line is consistent with the actual time, the score is 3; 2; 1; 0. | 5.00  |
|                                            | Running speed (8) Peak period average speed ≥ 15 km/h, the score is 4; 13 km/h, the score is 2; 10 km/h, the score is 0. | 6.53  |
|                                            | Flat hump period average speed ≥ 28 km/h, the score is 4; 23 km/h, the score is 2; 18 km/h, the score is 0. | 6.63  |
|                                            | Crowding degree in the bus (8) Full load rate ≤ 50%, the score is 8; 60%, the score is 6; 80%, the score is 4; 100%, the score is 2; 110%, the score is 0. | 6.01  |
|                                            | Interior environment (6) The appearance of the vehicle is clean and tidy, and the logo is clearly visible, the score is 3; 2; 1; 0. | 5.08  |
|                                            | Platform facilities environment (6) The sanitation environment of the bus station is clean and tidy, and the signs are clearly readable, the score is 6; 5; 4; 3; 2; 1; 0. | 5.13  |
|                                            | Staff service attitude (6) The service attitude of the staff, the score is 6; General service attitude of the staff, the score is 3; The others, the score is 0. | 5.17  |
| Bus service reliability (10)               | Waiting time (10) Waiting time during peak period ≤ 5 min, the score is 5; 10 min, the score is 3; 15 min, the score is 1; 20 min, the score is 0. | 3.90  |
|                                            | Waiting time during flat period ≤ 10 min, the score is 5; 15 min, the score is 3; 20 min, the score is 1; 30 min, the score is 0. | 4.16  |
|                                            | Line driving standardization (6) The bus runs according to the established route and stops normally, the score is 6; 4; 2; 0. | 4.41  |
|                                            | Docking normalization (6) The bus stops at the designated station, the score is 6; The others, the score is 0. | 5.18  | (Continues)
TABLE 3 (Continued)

| Index category                  | Index                                      | Index definition and content                                                                 | Score |
|---------------------------------|--------------------------------------------|---------------------------------------------------------------------------------------------|-------|
| Information normalization (6′)  | Clear specification of the line and station information posted on the platform and bus, and report station in advance correctly; the score is 6; The others, the score is 0. | 5.26  |
| Bus service safety (8′)         | Driving safety (8′)                        | The bus obeys the traffic regulations and runs smoothly; the score is 8; The others, the score is 0. | 7.52  |
| Bus information service (12′)   | Availability of Information (6′)           | Passengers can access travel information online and offline; the score is 6; Passengers can access travel information online or offline; the score is 3; The others, the score is 0. | 5.18  |
| Service reliability (6′)        | The information the passenger gets is consistent with the actual travel experience; the score is 6; The information the passengers get is basically the same as the actual travel experience, the score is 3; The others, the score is 0. | 5.28  |

Total score 83.68

used as the output. The hidden layer activation function selected the sigmoid function, and the output layer activation function selected the tanh(x) function. The algorithm was based on three gradient descent methods. The number of hidden layer nodes was calculated using Equation (19) [34]:

$$L = \sqrt{m + n + a}$$  \hspace{1cm} (19)

where $L$ is the number of hidden layer nodes, $m$ is the number of input layer nodes, $n$ is the number of output layer nodes, and $a$ is a constant ranging between 0 and 10.

5.5 | Algorithm verification

In the questionnaire data, 500 groups of sample data with representative lines were randomly selected, and the index weight and

![FIGURE 5](image-url) Satisfaction score map of West Lake subsites
comprehensive weight were calculated using the above equations. Among the 500 sets, 450 were used as training samples, and 50 were used as test samples after model training. The MATLAB neural network toolbox was used to design, train, test, and inspect the BP neural network. Based on the actual model of the urban bus line service quality and sample data collected in this study, the numbers of nodes in the input and output layers of the neural network were set to $m=16$ and $n=1$, respectively. By using Equation (15) and performing an error analysis, the number of hidden layer nodes was obtained as $L = 11$. The
The trained BP neural network model was used to estimate the comprehensive weight of the bus line service quality. The estimated errors of the three algorithm estimates were compared (Figure 11), and the number of iterations and the average squared error of the estimated results were obtained (Table 4).

As shown in Figures 10 and 11, and Table 4, for the same training data set, the number of iterations of the BP algorithm with momentum terms is 320, the number of iterations is reduced by 36.6% compared with that of the standard BP algorithm, the convergence time is reduced by 0.043 seconds.
compared with the standard BP algorithm, the convergence speed increases by 0.66% compared with that of the standard BP algorithm, and the estimation accuracy improves by 26.7%. The improved momentum term BP algorithm was used for estimation. The algorithm converged rapidly only after 120 iterations. The number of iterations is reduced by 76.2% compared with that of the standard BP algorithm, the convergence time is 1.562 s less than that of the standard BP algorithm, the convergence speed was 24.1% higher than that of the standard BP algorithm, and the absolute value of the estimated error was less than 1%. These results showed that the improved momentum BP neural network algorithm trained in this study had a faster convergence speed and a higher estimation accuracy for predicting the comprehensive weight of the bus line service quality. The trained algorithm is useful for the evaluation and optimization of the service quality of the commuter lines.

5.6 Empirical results of service quality evaluation of Hangzhou bus lines

The data for the representative bus line questionnaire survey of Hangzhou bus line services were randomly selected, the AHP weight value of the index system was computed, and the average value of the AHP weight of each line was selected. The calculated AHP weight of each index was utilized as the input of
TABLE 4  Estimation results of different algorithms

| Algorithm                      | The number of iterations | The average time per iteration | The total time to convergence | Average error |
|-------------------------------|--------------------------|-------------------------------|-------------------------------|---------------|
| Standard BP algorithm         | 505                      | 0.009                         | 6.480                         | $9.90 	imes 10^{-3}$ |
| Momentum BP algorithm         | 320                      | 0.014                         | 6.437                         | $7.25 	imes 10^{-3}$ |
| Improved momentum BP algorithm | 120                      | 0.025                         | 4.918                         | $4.25 	imes 10^{-4}$ |

FIGURE 12  Evaluation index comprehensive weights and various index values

the neural network. The BP neural network of the momentum term was improved, and the comprehensive weight vector of the index system was obtained as follows:

$$W^c = [0.028, 0.032, 0.101, 0.065, 0.102, 0.110, 0.031, 0.043, 0.089, 0.108, 0.010, 0.023, 0.058, 0.039, 0.107]^T$$

5.6.1  Data collection and preprocessing

From the questionnaire survey results, after normalizing data using Equation (20), the data index vector after the original data processing of the representative bus line were processed is denoted by $X$.

$$x' = (x - x_{\text{min}})/(x_{\text{max}} - x_{\text{min}})$$

$$X = [0.794, 0.769, 0.810, 0.834, 0.846, 0.791, 0.871, 0.848, 0.847, 0.805, 0.756, 0.732, 0.879, 0.884, 0.890, 0.859]$$

5.6.2  Calculation of satisfaction for evaluation of bus routes

The satisfaction for the bus line can be determined according to the comprehensive weight of the indicators in the bus line evaluation system and the specific index value of the line [6]. The satisfaction for the bus line was calculated using Equation (21):

$$A = XW^c$$

where $A$ is the line satisfaction, $X$ is the index data vector after the original data processing of the line, and $W^c$ is the comprehensive weight vector of the index system. The satisfaction for the Hangzhou bus line was obtained using Equation (21), as $A = XW^c = 0.8315$.

5.6.3  Error analysis

$$\epsilon = \frac{|\hat{y} - Y|}{Y}$$

where $\epsilon$ is the error rate, $\hat{y}$ is the predicted value, $Y$ is the actual value.

Based on the evaluation results of the improved momentum-item BP neural network model, the satisfaction score for the service quality of the Hangzhou bus line was 0.8315 points, which...
was replaced by a percentage system of 83.15 points. The error rate was obtained using Equation (22), as \( e = 0.6\% < 1\% \).

The predicted results were within the allowable range of error. This indicates that the improved momentum-item BP neural network model was accurate and realistic. The comprehensive weight of the predicted indicators and the value of each indicator were obtained (Figure 12) to investigate the specific conditions of the predicted and actual indicators more intuitively.

As shown in Figure 12, series 1 represents the comprehensive weight value of the bus line service quality, whereas series 2 represents each index value. From the comprehensive weight values in series 1, the third transfer waiting time, fifth running speed, sixth in-vehicle congestion degree, tenth waiting time, and sixteenth reliable information service indicators all exceeded 0.1. Therefore, these five indicators were considered more important by passengers. The corresponding values of the five indicators for representative bus lines in Hangzhou surveyed in this study were 0.810, 0.846, 0.791, 0.805, and 0.859, respectively. Among these indicators, the third index transfer waiting time, sixth index in-vehicle congestion level, and tenth index waiting time were all lower than the comprehensive score of the bus line, suggesting that these indicators enhanced passenger satisfaction. The lowest three indicators were consistent with the results presented in Figures 8 and 9, which further showed that the prediction results of the improved momentum BP neural network model were consistent with the actual questionnaire survey results [35]. The model construction was reasonably accurate and could be applied to Hangzhou bus routes. The quality evaluation trained in this study provides practical guidance on the evaluation of bus routes.

6 CONCLUSIONS

In this study, we evaluated passengers’ satisfaction with public transport service quality in the context of large-scale construction of subway transportation systems in Hangzhou. First, we obtained the satisfaction score of the service quality of bus lines through a questionnaire survey. Second, we predicted the comprehensive weight of the service quality of the Hangzhou bus line by improving the BP neural network model of the momentum item. Finally, we verified the model using an example of the representative line of Hangzhou City. Based on the findings of this study, the following conclusions are drawn:

1. This paper presents the establishment of a new BP neural network model that uses the MSE of the actual output and the expected output of the model to adjust the size of the momentum factor dynamically. The standard BP neural network improved the evaluation of bus line service quality and overcame the drawbacks of the standard BP. The neural network has the disadvantages of slow convergence speed and low accuracy. Nevertheless, the results showed that the improved momentum BP neural network increased the convergence speed by 24.1% compared with the standard BP network, and the absolute value of the estimation error was less than 1%. The improved momentum BP neural network can accurately and swiftly predict the weight value of the comprehensive indexes of the bus line service quality and lays the foundation for accurately obtaining the satisfaction for the bus line.

2. In this study, a representative bus line in Hangzhou was used as an example to verify the feasibility and accuracy of the model. The results showed that the passenger satisfaction for the Hangzhou bus line was 0.8315, but the degree of crowding in the bus, the waiting time, and the transfer waiting time were the indicators with the lowest satisfaction. The actual questionnaire survey results were consistent with the predicted results, indicating that the trained model conforms to Hangzhou’s current bus operation background. This study provides new techniques for evaluating the service quality of new first-tier city bus lines exposed to large-scale subway construction.

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