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Urban Rail Transit Network Planning Based on Adaptive Neural Network

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An adaptive neural network, also referred to as ANN, is an artificial neural network with adaptive learning ability. The purpose of this paper is to study an adaptive neural network-based method, and apply this algorithm to the planning of an urban rail transit network. In this paper, several important railway stations in a certain city are used as data nodes. The network planning is simulated according to these nodes, and the calculation time and energy consumption of the proposed system are compared with those using traditional calculation methods. The experimental results show that the calculation time of the ANN neural network for a certain node is about 8s, while the traditional algorithm takes more than 15s. The CPU ratio of the ANN algorithm is 35%, while the traditional algorithm CPU ratio is about 50%. By using the algorithm proposed in this paper, the CPU is reduced by 15%, which shows that the urban road traffic network planning method based on ANN is faster and consumes less power.

Keywords: adaptive neural network, urban rail, traffic planning, factors related to line network planning

1. INTRODUCTION

With the rapid construction and development of the Chinese urban rail and transportation network, urban rail transit is constantly being changed from the traditional single-track operation to a complex network and other operating forms. While providing passengers with flexible travel options, it also makes it difficult for passengers to choose a route. At present, most urban rail transits have achieved seamless transfer, and passengers only need to choose the appropriate entry and exit stations. In order to provide more intelligent and more convenient transportation services for passengers, further planning of the urban rail transit network is required.

The research on the choice of travel routes by passengers using the rail transit network is the basis for designing and planning efficient rail networks. Because of the continuous improvements being made to the rail transit network, the escalating complexity and the increasingly serious congestion caused by the large passenger flow, passengers' travel choices are diverse and uncertain. Only by accurately grasping the selection rules, the selection characteristics, and the travel needs of passengers in the road network, can the authorities responsible for transportation management carry out relevant network and operational planning. It increases the service quality of the line, meets the travel needs of passengers, and reduces the congestion of the road network traffic. The automatic rail fare collection system records a large number of passenger tickets and operation data, so as to obtain the information of passengers entering and leaving the station in the rail network. By analyzing a large amount of data, the research on passenger space-time rail transit travel route selection makes the results of passenger traffic travel route selection more objective. However, most passengers choose seamless transfer, making it difficult to plan an urban rail transit network. It is worth exploring how passenger flow data

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can be mined to provide the best traffic network information prior to planning.

The innovation of this paper lies in the pioneering design of an adaptive neural network algorithm, and the comparison of the results achieved by this algorithm in terms of speed and power consumption, and those achieved by the traditional algorithm. Results indicate that the adaptive neural network proposed in this paper can benefit rail transit network planning.

2. RELATED WORK

The urban transportation system is an important part of a city and is an interdisciplinary subject that includes traffic engineering, operations research and computer science. To provide passengers with intelligent services via the application of new technologies, it is necessary to build an optimal transportation network such as bus and rail transit. Kai et al. (2018) investigated and documented the main smart city transport models, themes and implementations as a basis for future reference and research. For the planning part, they first summarized the objectives, constraints, algorithms and implications of the currently used models, and divides the objectives and constraints into classic and new categories. Because of model updates, the Kai et al. study (2018) also summarized application trends such as integrated network design in strategic planning, synchronization, and timelines for recovery from tactical and operational planning disruptions [1]. The light rail transit network is critical to the development of urban public transport. Luan et al. (2019) proposed a new, scientific, and efficient method to measure and evaluate the strengths and weaknesses of various light rail transit (LRT) planning options. These researchers also discussed and verified the objectivity, fairness, rationality and validity of the model through a teaching case. Modelling analysis (quantitative procedure) results and survey results show that this method is reliable and suitable for evaluating and prioritizing light rail networks, avoiding decision bias due to human error or other factors. Furthermore, the proposed framework can provide urban planners, managers, and policy makers with appropriate advice and recommendations to identify better alternatives (projects) and provide guidance or a reference for other cities [2]. Zhang et al. (2021) established a general framework to capture and recognize such nonlinear dynamics. They also designed a standardized simulation model in order to understand the coordination and differences in the dynamics based on time-varying topology between the LBTN and the Urban Rail Transit Network (URTN). Furthermore, they compare the time-varying topology-based dynamics that are significantly different between LBTN and URTN. The results show that this approach gives a better understanding of topology-based dynamics from static to time-varying scales and the complexity of special nonlinear dynamical phenomena, and stimulates the application potential of complex network approaches [3]. For the rapidly developing second-tier cities, it is necessary to understand the impact of the overall planning and management of the urban transportation system. Zhao et al. (2021) applied the theory underpinning a multi-layer complex network to study this problem by comparing the characteristics of the traffic network before and after the subway construction. Calculations show that the newly-built subway network increases convenience and reduces travel costs in second-tier cities, although the vulnerability of the entire network increases, and the distribution network of key road nodes is reconfigured. For the sustainable development of urban transportation, more attention should be paid to the newly-constructed subways in second-tier cities [4]. In their study, Abutaleb et al. (2020) aimed to empirically identify key attractiveness factors in a TOSMD (transit-oriented shopping mall development) and understand their impact on passengers at TOSMD stations near the Dubai Metro Red Line. Their research helped to empirically validate the impact of TOSMD attractiveness on passenger flow at stations near TOSMD as a means of improving the economic sustainability of transportation networks. For a more comprehensive analysis, future research could replicate this study in the context of the transportation network of other cities [5]. In order to guide the expansion of the city from a single center to a multi-center and achieve sustainability, Wang (2017) conducted research on the urban rail transit design between the urban sub-center and the urban center. Wang concluded that when designing the urban rail transit between the urban sub-center and the urban center, in the planning process, the use of high-quality route resources should be prioritized, planners should determine whether the urban rail needs to be laid out according to the scale of the passenger flow network and the requirements of urban planning. These steps will provide theoretical guidance for the design of urban rail transit between urban sub-centers and urban centers [6]. Although the studies have made certain contributions to urban rail transit and achieved certain results, most of them are based on theory, and their practical application has not been tested. Therefore, further research is necessary to improve or optimize the previous urban rail transit network planning.

3. METHOD OF URBAN RAIL TRANSIT NETWORK PLANNING

3.1 Urban Rail Transit

(1) Development status of Chinese urban rail transit

Congested roads, environmental pollution, traffic jams, and chaotic traffic order have become common problems in the development of large and medium-sized cities in China, and hinder urban development. Since China's reform and opening up to the outside world, the Chinese urbanization process has been accelerating. The scale of urban development and the continuous improvement of urban economy has led to a surge in urban population and an increased demand for adequate public transportation within the city. The discrepancy between the supply and demand of traffic within the city is becoming increasingly wider. Like many developed cities in the world, the medium-sized and large cities in China also consider the development of rail transportation as the fundamental

Table 1 Cumulative operation volume and mileage of Chinese urban rail transit from 2017 to 2021.

Year	Operating mileage: km	Operational volume: billion
2017	4583.3	18.31
2018	5295.1	21.27
2019	6333.3	28.04
2020	7545.5	17.59
2021	8708	23.71

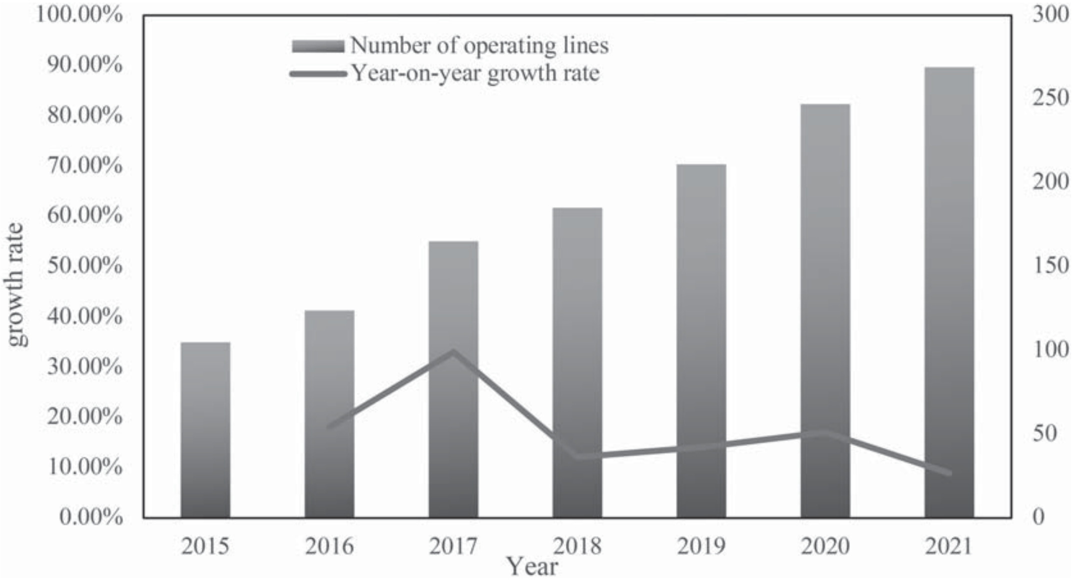

Figure 1 2015–2021 Domestic Urban Rail Transit Operation Route Map.

way to solve several problems associated with urban transportation [7–8].

With the further development of comprehensively deepening reform, local motivation and investment willingness have been continuously activated, encouraging investors such as enterprises and social organizations. Investment methods have also become diversified, which ultimately achieves the goal of making urban rail transit sustainable. Of course, in the process of development, various problems will inevitably arise. For example, there is the necessity of urban rail transit construction by local governments, blindly applying for the planning and construction of urban rail transit even if the local urban population or the economy are inadequate. However, appropriate government management, legislation and policies will ensure that the Chinese urban rail transit market will develop rapidly in a positive and healthy direction [9–10].

In recent years, the Chinese public urban rail and public transportation service industry has made admirable progress. Moreover,s the bus lines currently operating in Chinese urban rail and public transportation services are also constantly developing and expanding. According to the latest released relevant data, as shown in Table 1, the cumulative operation volume and mileage of Chinese urban rail transit have achieved rapid growth from 2017 to 2021. Although the operation volume in 2020 and 2021 will decline due to the impact of the epidemic, the overall trend is still on the rise [11].

Figure 1 shows the Chinese urban rail transit operation route map from 2015 to 2020. It can be seen from Figure 1 that the Chinese rail transit business has developed significantly, with the number of operating lines increasing from 71 in 2015 to 269 in 2021.

(2) Status quo of urban rail transit planning and development in the world

At present, China's first-tier developed cities have basically completed the construction of urban rail transit networks.

The existing scale of rail transit can adapt well to further development of the city, which means that for a long time there will be no need for other major construction. The only things that will be required are regular maintenance and the adjustment of some lines to optimize rail operations. However, in developing countries, with the increasing urbanization, the construction of urban rail transit networks is in full swing [12–13].

In addition, due to the unique public welfare and commercial nature of urban rail transit, and because of the need for huge investments in construction, only a flexible government policy and appropriate capital investment will encourage private enterprises to invest and social organizations to be involved so as to a sustainable urban rail transit network [14].

At present, the rail transit systems of most cities in first-world countries are relatively complete and mature. The rail transit volume of most cities accounts for more than

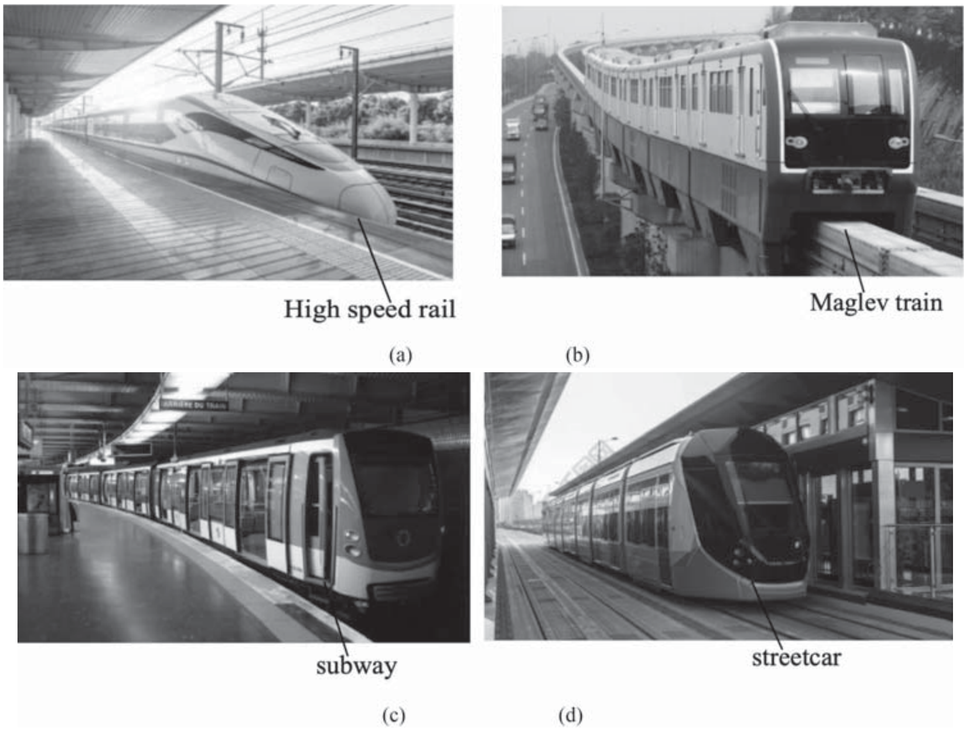

Figure 2 Types of urban rail transit.

50% of the volume of urban public transportation, and some cities even reach 70%. At the same time, many large cities such as Paris, Tokyo, New York and Seoul, have also developed regional rapid rail transit systems, which are highly efficient and model examples of systems that integrate urban and regional networks [15].

(3) Classification of urban rail transit

Figure 2 shows several of the current urban rail transit modes.

(4) AFC system

The AFC system integrates a number of cutting-edge technologies such as big data, intelligent control, and computer communication, and offers a variety of automated service functions such as ticket sales, ticket checking, clearing and ticketing statistics. ACC is the data management center of AFC, which is responsible for collecting information such as passenger flow and financial status, and transmitting the data to the corresponding ticketing management center. The terminal ticket checking equipment SLE of the station is usually installed at the ticket gate of the hall of the station. Passengers can directly obtain ticket checking services from the device, including automatic ticket checking, automatic ticketing, automatic recharge, etc. A ticket card enables travelers to make a payment before either entering or leaving the station, and it is also the data source of the AFC system. The ticket is bought by the traveler before entering the station, paid for in advance according to the terminal selected by the traveler, and swiped before the traveler enters the station. It needs to be recycled when the traveler leaves the station. The ticket is issued internally by the urban rail transit company and can be used only within the urban rail transit system. The one-card is used for settlement before leaving the station, which is a non-contact IC card [16–17].

The AFC system has three economic operation management modes: normal operation mode, lift operation mode and emergency release operation. Under the normal operation mode, when passengers enter or exit the station in the urban rail transit network, the automatic ticket gate reads and records the travel information of the passenger who owns the ticket. When abnormal conditions occur, the AFC system will start the degraded operation mode. One such abnormal condition may be when a technical fault occurs in the train or at a station. This prevents the equipment from reading passengers' ticket, and passengers cannot leave the station as they would normally. Passengers can exit only at other stations, and the new information is recorded on the passenger's ticket. This data is held in a temporary archive. The other is that due to the failure of the exit ticket checking equipment at the station, or the overload of the ticket checking equipment caused by the concentrated exit of the large passenger flow, the passengers have to congregate in a large area. This occurs when a certain situation may threatenthe safety of the passengers themselves. In this case, the mode of downgraded operation of outbound ticket gates and emergency release indicates that the ticketing equipment is automatically turned off when a serious failure may endanger the lives of passengers. For example, when a fire or explosion occurs in the ticket checking equipment at a station or on a train, all ticket checking devices will stop reading all tickets [18].

When passengers travel by rail, the AFC system will automatically collect the relevant information about the traveler such as subway card information and travel information. The

Table 2 AFC Data Sheet.

Data naming	Example
DATE	20181218
CARDCODE	S0100000001001245367852
ENTERTIME	10:35:00
INL INECODE	45
OUTTIME	10:55:42
OUTLINECODE	45
OUTSTATICODE	2610

subway card information includes fare, ticket type, and ticket number. The bus information includes the time when a passenger swipes the card when entering and when leaving the station, the line number of their train, and the location of the station. The AFC data format is shown in Table 2. According to the AFC data style, the relevant traffic route information can be learned [19].

3.2 Traffic Line Network Planning

The construction of urban rail transit projects is of great significance, affecting the social, environmental and economic elements of a city. Therefore, how to reasonably calculate the reasonable scale of an urban rail network is a complex overarching problem.

(1) Principles of rail network planning

The planning of a transportation network must be comprehensive, representative, operable (feasible), and scientific.

Comprehensiveness is required because the traffic network planning as an organic whole must be able to reflect all features and functions of the system from all perspectives. Representativeness must be considered because there are many factors that can affect the reasonable scale of urban rail transit, and it is not feasible to take all of them into account when planning a transportation network. Hence, only representative and important indicators can be selected from various aspects. The principle of operability must be applied to ensure that the rail transit network is both scientific and feasible in terms of practical application. Since it is difficult to estimate accurately many relevant influencing factors, it is necessary to consider whether there are relevant statistical data when selecting indicators, or whether the indicators can be obtained directly from government work reports and other data, that is, whether the indicators are realistically operable. The scientific principle is applied because the indicators (influencing factors) that affect the reasonable scale of urban rail transit must be clearly defined. It can reflect the relationship between various influencing factors and the reasonable scale of urban rail transit, and can comprehensively and objectively reflect the actual situation of urban rail transit construction [20].

(2) Factors influencing rail network planning

Generally speaking, the rational planning of an urban rail transit network takes into account relevant qualitative and quantitative influencing factors. These are interrelated and influence each other, as shown in Figure 3.

(3) Selection of relevant indicators

1) Relevant indicators involved: these can be divided into qualitative and quantitative indicators, as shown in Table 3.

2) Indicator selection method: This is an investigation and research method. First, the process involves investigating, researching, and collecting a large number of optional impact indicators. Then, through a questionnaire survey, all impact indicators are listed on a form and sent to scholars and experts in related fields. It invites scholars and experts to select the impact indicators that should be included in the indicator system, and then integrates all expert opinions for statistical analysis, and feeds the results back to experts for revision opinions, and finally determines the indicator system. Statistical analyses (e.g., cluster analysis and factor analysis) are conducted to summarize and categorise a large number of existing indicators that will constitute a well-organized and well-structured indicator system. Specifically, the initially formulated indicators are clustered first, and the associated indicators are grouped under different categories. Then principal component analysis is carried out on various indicators, the key indicators are screened out and, finally, various indicators are integrated to form an indicator system that shows the scientific impact. The frequency analysis method refers to the frequency statistics of the current reports and papers on the construction of the index system. In order to ensure comprehensiveness, it selects the most frequent, representative indicators that have a greater impact on the analysis of the reasonable scale of urban rail transit. The index attribute grouping method is applied to construct the composition of each index in the evaluation system from the perspective of the attribute of the index. Specifically, the indicators can be divided into two categories: "quantitative" and "qualitative", and then further subdivided into "city scale-related indicators" and "economic development scale-related indicators".

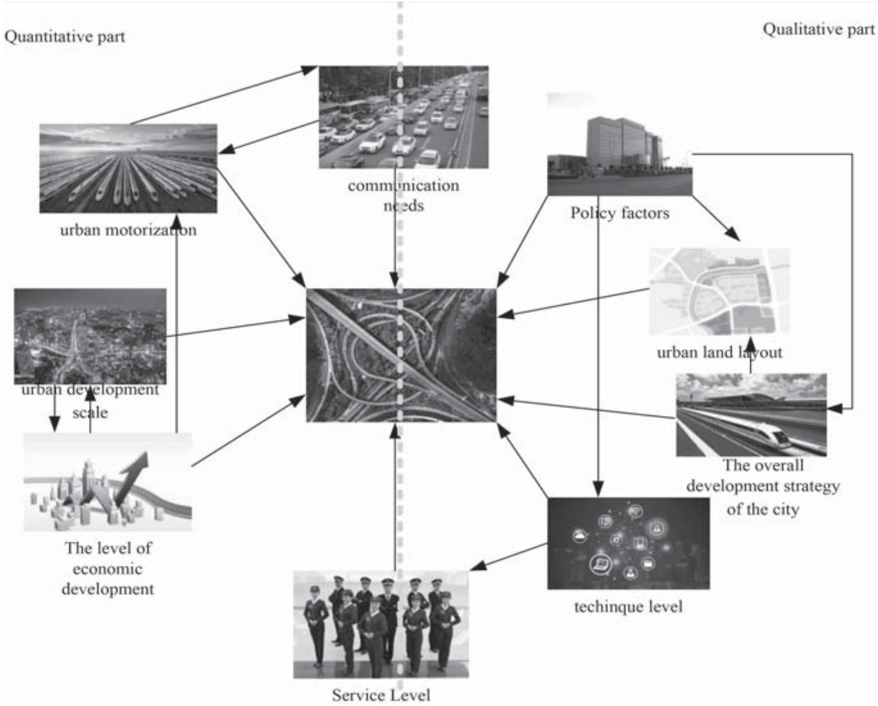

Figure 3 Factors affecting the rational planning of urban rail transit.

Indicators	Factor	Classification
Qualitative Indicators	Policy factors	traffic policy, development policy
	Urban form and land use layout	city geometry, urban land layout
	techinque level	Signal technology, equipment technology, quality of transport
	Service Level	Comfort, safety, Line identification
Quantitative indicators	urban development scale	population size, size of urban land
	The level of economic development	GDP, Revenue, The proportion of the tertiary industry
	transportation needs	The total number of trips by residents, Travel intensity per capita, Passenger flow
	Urban motorization level	car ownership, Public transport to private car ratio
	other	operating cost, Operational efficiency

3) The indicators selected for this study are shown in Figure 4.

3.3 Neural Networks

(1) Classification of neural networks

1) Feedforward neural network: this is a common perceptron and BP neural network. Its three-layer structureal model is shown in Figure 5. It consists of an input layer, hidden layer and output layer.
2) Feedback neural network: Elman network and Hopfield network are common, and their structural model is shown in Figure 6.
3) Adaptive Neural Network

Self-organizing neural networks can automatically search for various regularities and essential properties in samples. It can adaptively change the parameters and structure of the neural network according to the actual situation. Similar to its human counterpart, the supervised or unsupervised learning instructs the network on how to interpret and interact with various inputs, such neural networks can learn online or offline. Its structural model is shown in Figure 7.

(2) ANN network planning algorithm

An adaptive neural network is used to generate a nonlinear function model for analyzing and researching an example, and to describe a very complex nonlinear system. This process is essentially a quantitative description of the objective phenomenon, and on this basis, the prediction problem is solved [21–22].

The processing of data via an adaptive neural network simulates the processing of information in a biological neural network. The neuron is the basic unit of neural network processing information. Its specific structure and information processing model are shown in Figure 8.

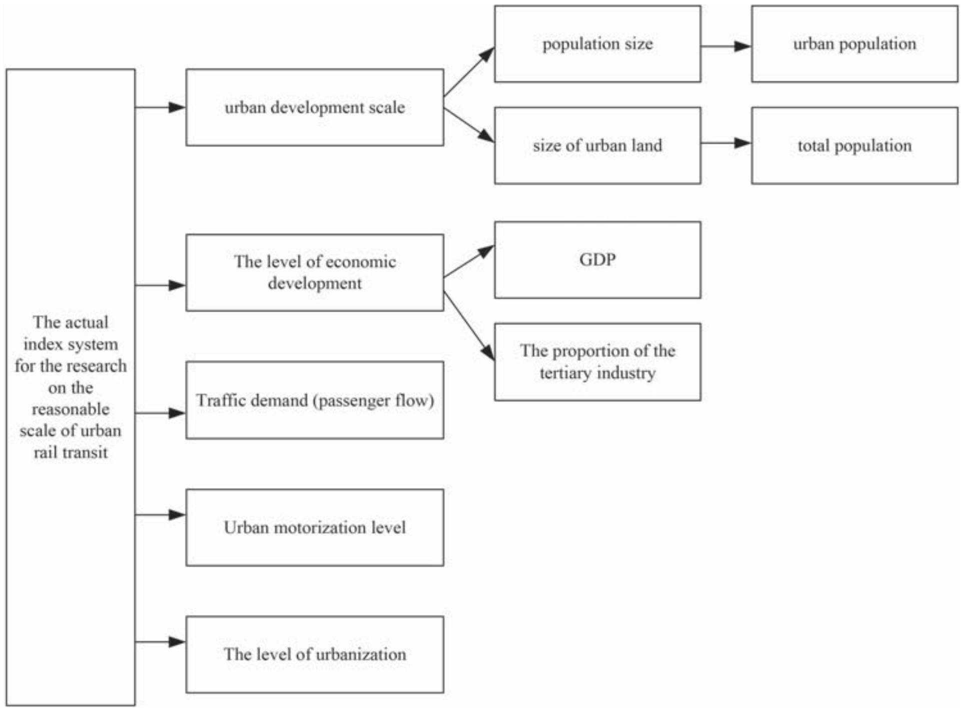

Figure 4 Selection of indicators for rational planning of urban rail transit offline network.

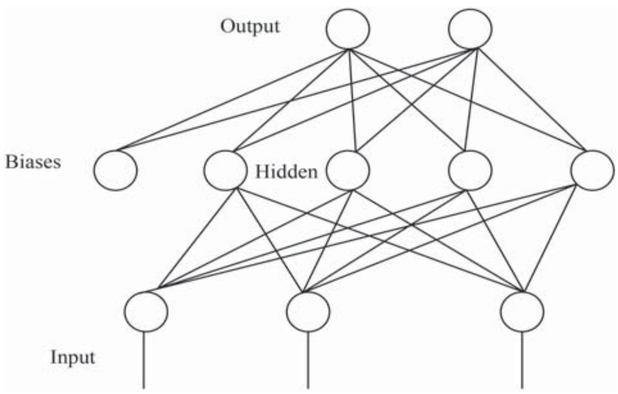

Figure 5 Feedforward neural network model.

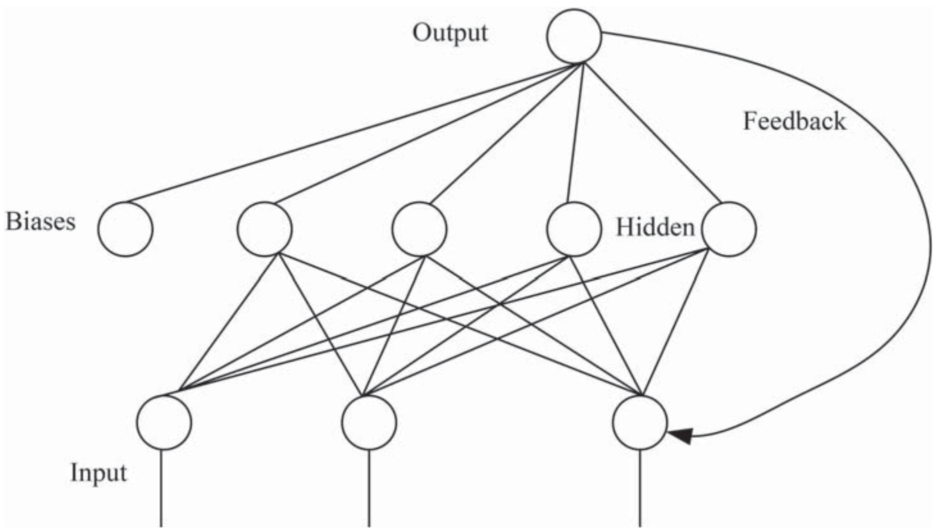

Figure 6 Feedback neural network.

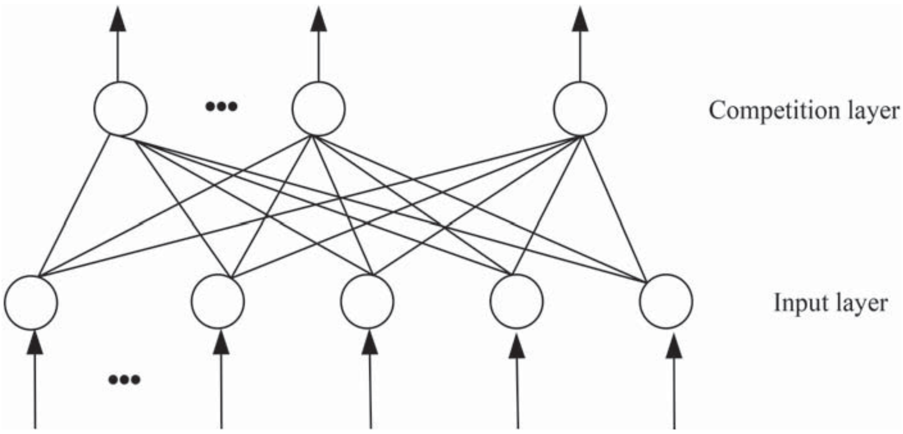

Figure 7 Adaptive neural network structure model.

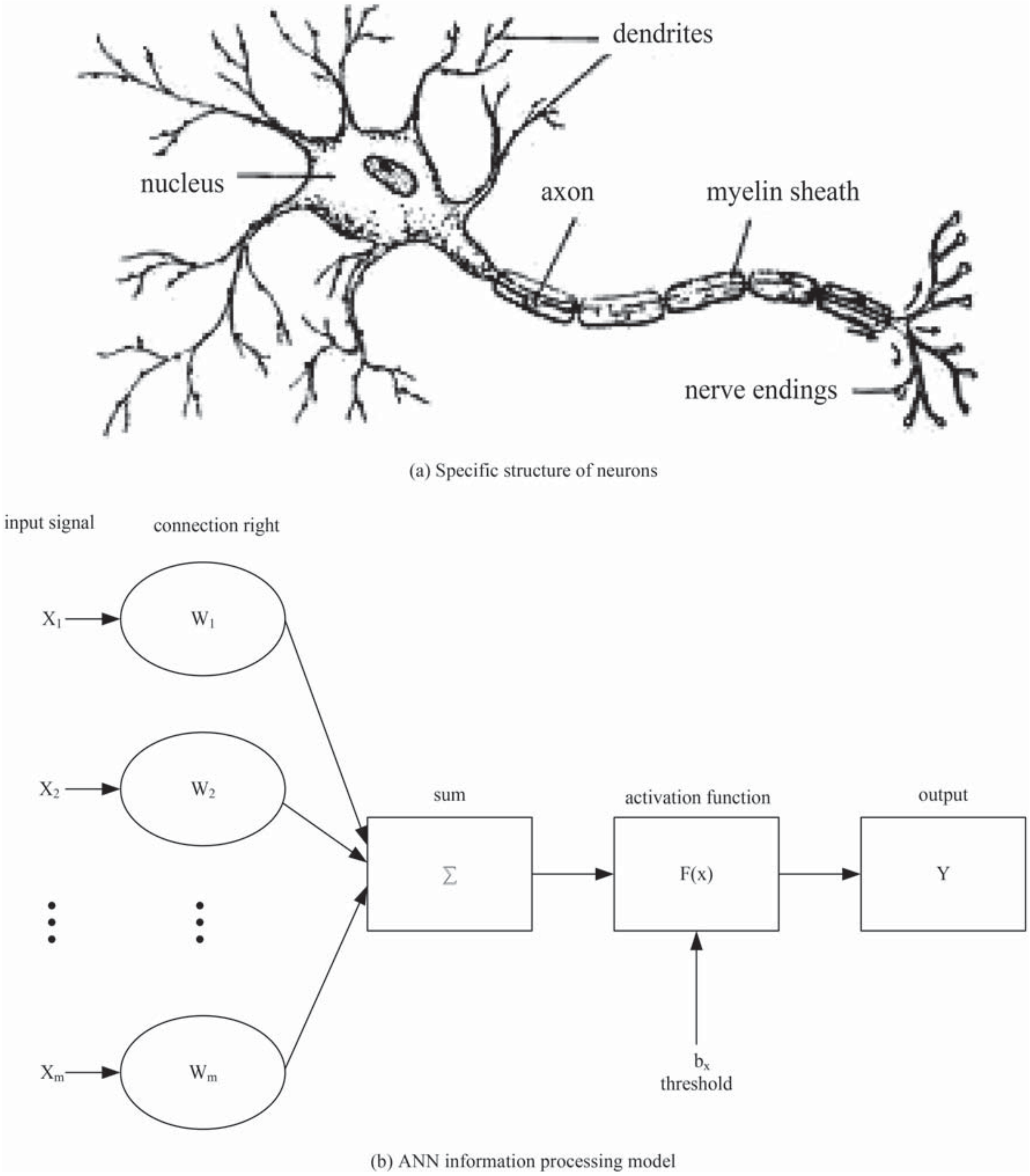

Figure 8 ANN structure and information processing model.

Neurons usually consist of connections (weights), signal combiners, and activation functions. Assuming that the traffic flow is q, then:

$$q = \frac{N}{T} \tag{1}$$

where: N is the number of vehicles in the observation period, T is the length of the observation period.

$$u = \frac{dx}{dt} = \lim_{t_1 \to t_2 \to \infty} \frac{x_2 - x_1}{t_2 - t_1} \tag{2}$$

where: x_2 and x_1 are the positions of the vehicle at time t_2 and t_1, respectively.

For linear formulas:

$$f(x) = (\omega \cdot x) + b \tag{3}$$

where the variables ω and b have the optimization formula:

$$\omega' = min \frac{\|\omega\|^2}{2} + c \sum_{i=1}^{n} (\xi + \xi^*) \tag{4}$$

$$y_1(\omega \cdot x_i) + b \geq 1 \tag{5}$$

Among them: ξ represents the Lagrangian coefficient, and the smaller the value of $\|\omega\|^2$ the more accurate is the classification of the influencing factor indicators of the transportation network planning is. The Lagrange formula is:

$$\begin{aligned} l(\omega, \xi, \xi^*) = \frac{\|\omega\|^2}{2} + C \sum_{i=1}^{n} (\xi + \xi^*) \\ - \sum_{i}^{\infty} \alpha_i (\varepsilon + \xi_i - y_i + (\omega \cdot x) + b) \end{aligned} \tag{6}$$

The partial derivatives of the variables should satisfy:

$$\frac{\partial l}{\partial \omega} = \omega - \sum_{i=1}^{m} (\alpha_i - \alpha_i{}^*) x_i = 0 \tag{7}$$

$$\frac{\partial l}{\partial b} = \sum_{i=1}^{m} (\alpha_i - \alpha_i{}^*) = 0 \tag{8}$$

$$\frac{\partial l}{\partial \xi} = C - \alpha_i - \eta_i = 0 \tag{9}$$

$$\frac{\partial l}{\partial \xi^*} = C - \alpha_i{}^* - \eta_i{}^* = 0 \tag{10}$$

This leads to the dual optimization formula:

$$min \frac{1}{2} \sum_{i,j=1}^{m} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) + \sum_{i=1}^{m} \alpha_i (\varepsilon - y_i) + \sum_{i=1}^{m} \alpha_i^* (\varepsilon - y_i) \tag{11}$$

solved to obtain:

$$\omega = \sum_{i=1}^{N} (\alpha_i + \alpha_i{}^*) x_i \tag{12}$$

In the optimal solution, there are:

$$\alpha_i (\varepsilon + \xi_i - y_i + (\omega \cdot x) + b) = 0 \tag{13}$$

$$\alpha_i{}^* (\varepsilon + \xi^* - y_i + (\omega \cdot x) + b) = 0 \tag{14}$$

$$\xi_i (C - \alpha_i) = 0 \tag{15}$$

$$\xi_i (C - \alpha_i{}^*) = 0 \tag{16}$$

to obtain

$$\omega = \sum_{i=1}^{m} (\alpha_i - \alpha_i{}^*) x_i \tag{17}$$

It can be seen that the function expression is:

$$f(x) = (\alpha_i - \alpha_i{}^*) \langle x_i \cdot x \rangle + b \tag{18}$$

This formula is based on an ideal state. For the actual traffic network, there are a large number of influencing indicators, and a kernel function needs to be applied to perform multi-dimensional calculations. Therefore, the formula is optimized as:

$$\begin{aligned} \omega(\alpha_i, \alpha_i{}^*) = \frac{1}{2} \sum_{i,j=1}^{m} (\alpha_i - \alpha_i{}^*)(\alpha_j - \alpha_j{}^*) K(x_i, x_j) \\ + \sum_{i=1}^{N} (\alpha_i - \alpha_i{}^*) y_i - \sum_{i=1}^{N} (\alpha_i + \alpha_i{}^*) \varepsilon \end{aligned} \tag{19}$$

to obtain:

$$\omega = \sum_{i=1}^{N} (\alpha_i + \alpha_i{}^*) \Phi(x_i) \tag{20}$$

$$b = y_i - \sum_{i=1}^{N} (\alpha_i - \alpha_i{}^*) K(x_i, x_j) - \varepsilon \tag{21}$$

and the final objective function:

$$f(x) = (\alpha_i - \alpha_i{}^*) K \langle x_i \cdot x \rangle + b \tag{22}$$

4. ANN-BASED NETWORK PLANNING TEST

4.1 Design of the Model

The design of the rail transit network planning model proposed in this paper is mainly derived from the requirements of the function of the model, as shown in Figure 9.

4.2 Simulation Experiment

In this paper, the simulated experimental data are selected from the database, and then the adaptive neural network is trained and learned for multiple traffic network paths. Then the neural network model is applied to multiple nodes randomly selected by distribution (i.e., multiple rail transit stations) to simulate the network. The optimal planning traffic track route is obtained. The so-called optimal planning route should include as many stations as possible and the track route should be as short as possible.

The test system environment is shown in Table 4.

For the data training, this paper selected 800 sets of data, and the training was divided into two groups. The results of the two groups of training fitting errors are shown in Figure 10.

It can be seen from Figure 9 that after 800 sets of data training, the final error for the first set of training is 0.021, and

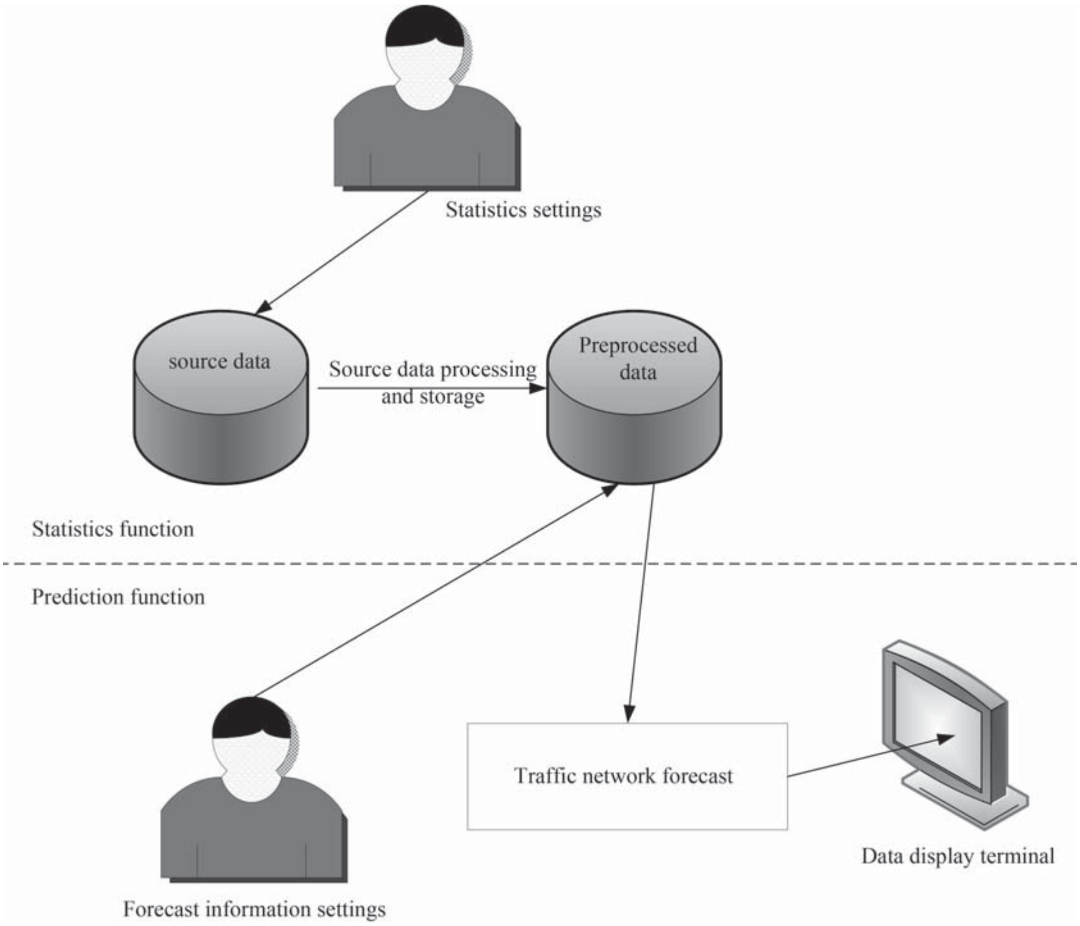

Figure 9 Design framework for the model.

Table 3 Test system environment.

System parameters	Detail
CPU	Intel Core,i7-9770
CPU frequency	4.20GHz
RAM	6.00GB
Hard disk	1T
Development environment	Java,JDK,IDEA

the final error for the second set is 0.0064. The error values of the neural network are all lower than the target error value of 0.03, thereby achieving the required test accuracy.

4.3 Experimental Results

After the neural network is trained with the data, it has sufficient accuracy and can then be used for simulation tests of urban rail network planning. In this paper, several major railway stations are selected as the data nodes. The network planning is simulated according to these nodes, and the results are compared with those obtained by the traditional calculation method in terms of time and energy consumption by the system. The results are shown in Figure 11.

As can be seen from Figure 11, the calculation time of the ANN neural network is about 8s, while the traditional algorithm takes more than 15s, which is 7s faster, and nearly half the speed. The CPU ratio of the ANN algorithm is 35%, while the CPU ratio of the traditional algorithm is about 50%, which is 15% lower. This shows that the ANN neural network algorithm proposed in this paper in terms of speed and lower power consumption.

5. DISCUSSION

In this paper, the problem of selecting an adaptive neural network in an urban rail transit network is studied, and specific nodes are analyzed in detail. However, further research is required to address the issues below.

(1) The values of some parameters in the model are drawn from the existing research results and have not been estimated. For example, the algorithm for the node transformation and adaptive neural network is taken from the literature, and the accuracy of the parameter estimates in this regard needs to be verified.

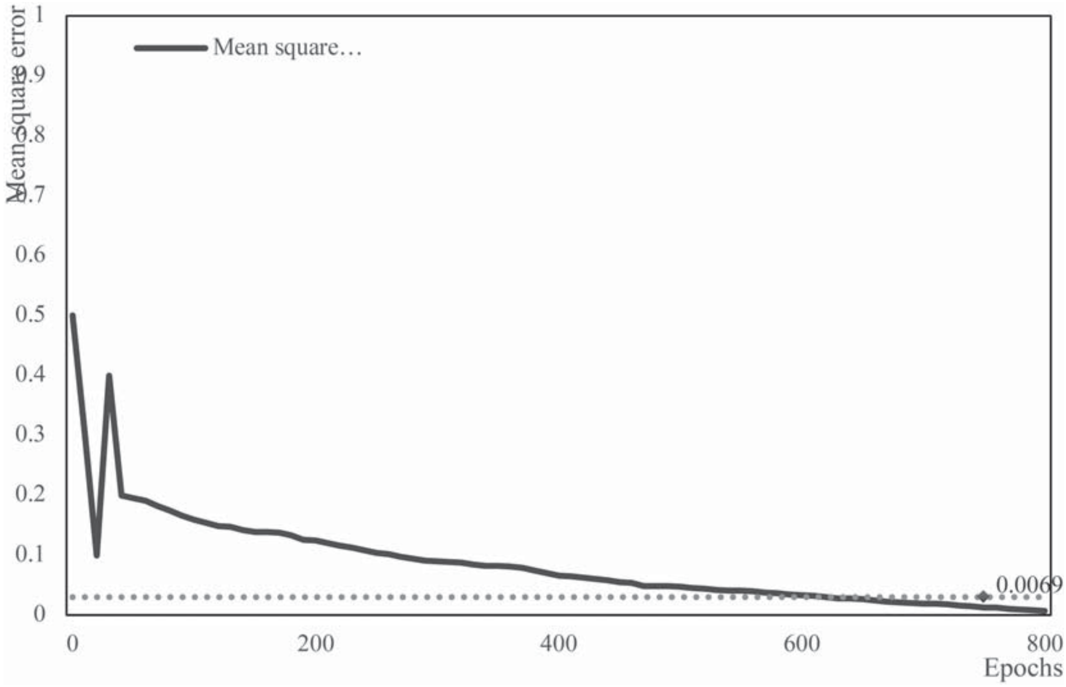

Figure 10 Adaptive neural network training results.

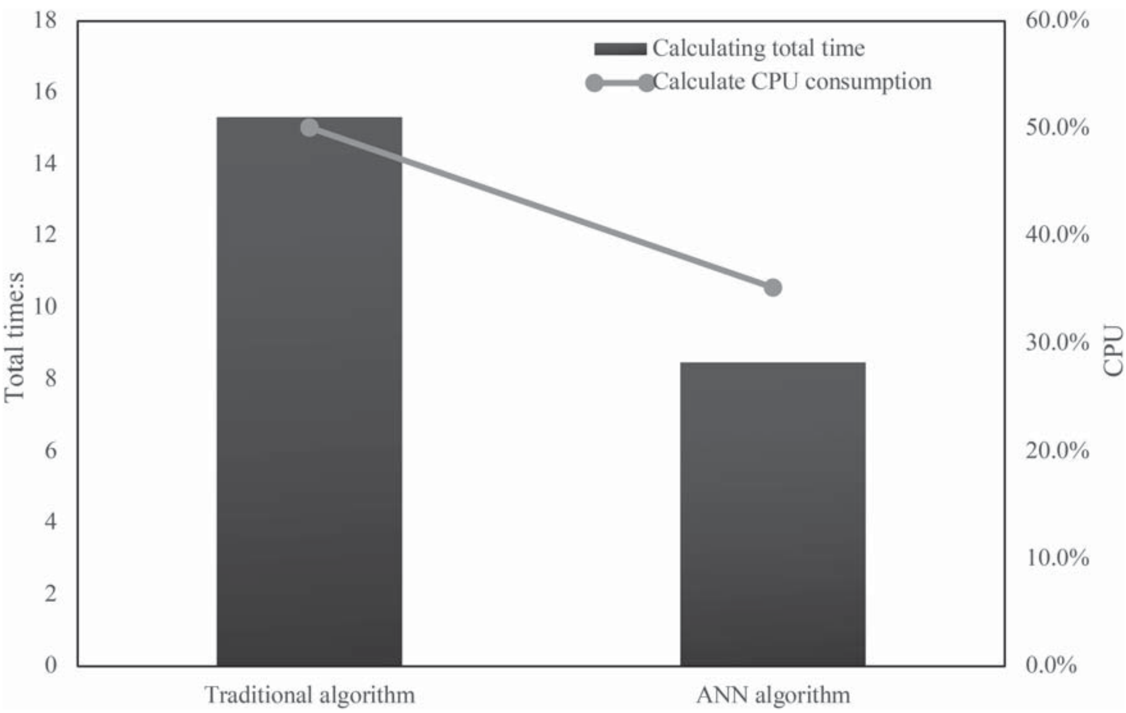

Figure 11 Comparison of adaptive neural network algorithms and traditional algorithms.

(2) The particularity of the site should be considered when choosing the starting and ending points and pick-up points of different routes. This paper does not consider in detail the passenger's choice of ride and travel route. The factors that affect the actual travel decisions of passengers are very complex and will be affected by subjective and objective attributes. Also, further research is needed on the travel behavior of passengers.

(3) The crowding degree of passengers during the ride needs to be considered when constructing the planning path of the rail network. However, during the rush hour, the management of commuter movements involves more than just the ride. Other factors must be taken into account such as the choice of stairs or escalators, the amount of time that passengers are waiting on platforms, transfers etc. – all of which are associated with passenger movement and speed. Hence, a comprehensive quantification of the network planning is required.

6. CONCLUSION

In the theoretical research, firstly, this paper explains the main content of the urban rail transit system, including its current status, classification and so on. This paper then introduces network planning, including its planning principles, influencing factors, and index selection. Secondly, this paper explains the neural network, including its classification and the adaptive neural network algorithm. In the experimental part, the design model of this paper is first introduced, and then the simulation experiment is carried out. The experiment is based on the selected data node as the simulation site to carry out the network planning, and the final result is displayed together with the data chart. The ANN neural network algorithm designed in this paper is faster and consumes less power, which should be considered when planning an urban rail transit network.

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