Optimization design of real-time scheduling scheme for city bus vehicles based on BP neural network

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ABSTRACT: Urban public transportation is inseparably related to people's travel and life. Prioritizing the development of public transportation is a major national policy proposed by the Chinese government, especially to actively promote the development of intelligent public transportation systems. Developing and building advanced intelligent public transport operation and scheduling management system, designing efficient, flexible and low-cost operation and scheduling mode, improving the management level and service quality of public transport enterprises, and thus improving the road traffic condition of the whole city, is undoubtedly the future development direction of public transport enterprises. This paper combines the problems of bus operation and scheduling in China at the present stage, and proposes the operation and scheduling model and method of the intelligent urban public transportation planning system, with a view to realizing a flexible public transportation operation model suitable for different service situations and providing systematic theoretical support for solving the imbalance between supply and demand of public transportation.

1. INTRODUCTION

As an industry development hotspot, Intelligent Network Link will drive the transformation and upgrading of the public transport industry and change the future of public transport operations and travel. Intelligent Network Connect technology provides a realistic basis for obtaining accurate bus vehicle operation data, but the operation of vehicles is subject to other factors such as the traffic environment, which is unstable and complex. Accurate prediction of bus vehicle arrival times can improve the efficiency of vehicle operations and provide a basis for decision making in vehicle command and control and management. The arrival times of bus vehicles can vary significantly at different times of the day, which increases the difficulty of prediction. By accurately predicting the arrival times of bus vehicles at different times of the day, the aim of improving transport efficiency, reducing pollution and saving energy can be achieved [1].

In a related study, Natalia et al. propose the concept of advanced management, analysis and control of intelligent transport systems for urban public passenger transport. The proposed approach uses intelligent information technologies based on neural networks (NN) and big data processing methods that allow real-time adaptation to dynamically changing conditions . Taking into account the latest research results and technologies related to the field of transport problems, a formal model describing public transport is introduced to help reveal the main issues. Using this model, a generic route network planning algorithm is proposed. Its trial and practical application results demonstrate the effectiveness of ITS applied to urban public passenger transport management. Mikhail and some others mentioned mentions that public Intelligent Transport Systems (ITS) aim to enhance the daily travel experience by providing safety, traffic efficiency and infotainment services [2].

This study is closely related to the realistic needs of China's public transport development, and investigates the models and methods that govern the flexible bus route planning, stop selection services, route length and stop selection, reasonable adjustment of the relationship between departure frequency and departure capacity, as well as how to do a good job of bus auxiliary system optimisation, i.e. the electric power replenishment of electric buses, and reasonable optimisation of energy utilisation efficiency in flexible bus system operation and scheduling. These operational models are the core issues that affect the cost-effectiveness of flexible public transport and are the key issues that limit the widespread use of flexible public transport. This paper proposes a series of flexible public transport operation and

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dispatching models and methods, and proposes corresponding solution methods for different dispatching models, in order to provide relevant optimisation models and theoretical support for flexible public transport operation and dispatching systems [3].

2. PRINCIPLE OF BP NN

Neurons are the basic processing units that make up neural nets with multiple inputs and single outputs, basic elements with non-linearity, each neuron having multiple connection channels, each corresponding to a connection authority that becomes a weight.

The network topology of a BP NN is shown in Figure 1. The neurons of a feedback NN can both output information to and receive input information from the outside world or other nodes, and the neurons can be interconnected.

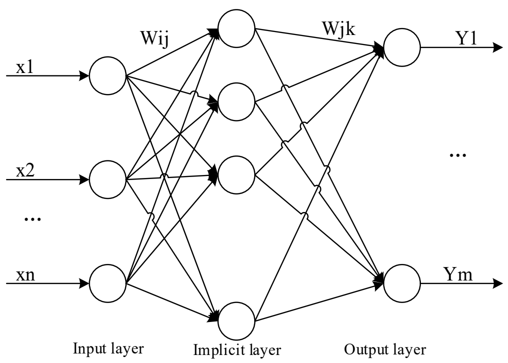

Figure 1. Network topology of BP NN

(1) NN initialization. The number of input nodes n, the number of output nodes m and the number of hidden layer nodes l. According to the order of the input X and output Y sets of the NN, determine the weights Wij for the connection between the input layer and the hidden layer and Wjk for the connection between the hidden layer and the output layer, initialize the threshold a for the hidden layer and the threshold b for the output layer, and determine the training rate and excitation function of the neurons [4].

(2) Calculate the output of the hidden layer. Based on the NN input value X and the connection weights between the input layer and the hidden layer and the specified threshold value of the hidden layer, the corresponding hidden layer output value H is calculated and the logical excitation function f is selected according to the requirements, and the output of the hidden layer is calculated as follows

$$H_j = f\left(\sum_{i=1}^{n} w_{ij}x_i - a_j\right) \qquad j = 1,2,...,l \tag{1}$$

(3) Calculate the output value of the output layer. Based on the output H of the hidden layer and the connection weight Wjk and the threshold b of the hidden and output layers, the output Ok of the BP NN is obtained as follows.

$$O_k = \sum_{j=1}^{l} H_j W_{jk} - b_k \tag{2}$$

(4) Calculate the output error of the NN. Based on the output Ok of the BP NN and the expected output Y, the prediction error of the NN is obtained as follows

$$e_k = Y_k - O_k \tag{3}$$

(5) Weights update. The connection weights of the NN are updated according to the calculated prediction error value of the NN and the set learning rate: Wij for the connection between the input layer and the hidden layer and Wjk for the connection between the hidden layer and the output layer.

$$\begin{aligned} &W_{ij} = W_{ij} + \eta H_j(1-H_j)x(i)\sum_{k=1}^{m} W_{jk}e_k \qquad i = 1,2,...,n; j = 1,2,...,l \\ &W_{jk} = W_{jk} + \eta H_j e_k \qquad j = 1,2,...,l; k = 1,2,...,m \end{aligned} \tag{4}$$

(6) Update thresholds. Update the thresholds of the network nodes a, b according to the error of the NN.

$$\begin{aligned} &a_j = a_j + \eta H_j(1-H_j)\sum_{k=1}^{m} W_{jk}e_k \qquad j = 1,2,...,l \\ &b_k = b_k + e_k \end{aligned} \tag{5}$$

(7) Determine whether the as of condition can be met based on the expected value, and if the as of condition cannot be met, return to step 2 and continue.

The design of the BP NN, the rational design of the NN structure is the basis for improving the accuracy of the algorithm.

The criteria for judging whether a BP NN design is reasonable are: firstly, whether the optimal solution is achieved and whether the accuracy of the error meets the requirements; and secondly, whether the training time is too long.

3. DESIGN OF THE MODEL

3.1. Model Design of the Dynamic Commutation Algorithm

The continued development of urbanisation and modernisation has resulted in more and more vehicles on the roads within the city and more complex road conditions. The traffic conditions of vehicles on different roads can vary considerably depending on holidays, travel times and weather conditions, and these changes affect the operation of buses. This paper uses historical bus network data as well as real-time road conditions and dynamic predictions of vehicle journey times to provide passengers with arrival predictions and dynamically adjust their travel plans, enabling the development of dynamic travel plans that provide the best interchange routes, increasing passenger trust in the intelligent bus service system and easing traffic pressure in the city [5].

Passengers select the appropriate query criteria (least interchange, shortest time, smallest walk, least cost) according to their riding preferences. The main evaluation indicators for the suitability of the ride scheme selection are the time and money spent by passengers, and the main dynamic factors affecting the ride scheme development include: stopping time, real-time road conditions and line evaluation [6]. The overall design of the interchange scheme development is shown in Figure 2.

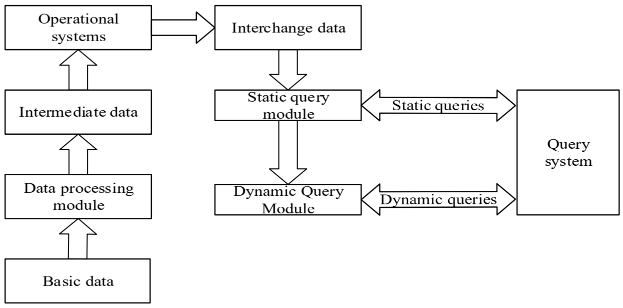

Figure 2. general design of interchange scheme development

NNs have excellent robustness, memory, non-linear mapping and self-learning capabilities, and are capable of mapping arbitrarily complex non-linear relationships, making them suitable for dealing with the optimisation of dynamic interchange schemes. In this paper, a BP NN is used to build a dynamic optimisation system for passenger travel schemes. The inputs to the BP NN for travel schemes are: arrival time prediction, real-time road conditions and route evaluation, and the output is the dynamic scheme evaluation for travel schemes. The structure of the BP NN is shown in Figure 3 and the flow chart of the algorithm is shown in Figure 4.

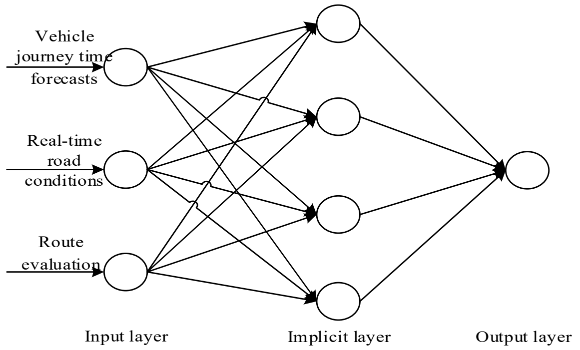

Figure 3. Structural design of the BP NN

There are three input nodes to the NN. The prediction of vehicle journey times has been described in detail in the previous section, and the predicted journey times of bus vehicle sections are used as inputs to this network; the real-time road conditions are based on the road information collected from the vehicles for structured data processing, and the evaluation is made by combining the historical data of road traffic; the evaluation of the routes is based on the frequency of departures and punctuality, and the bus vehicles are evaluated according to these two indicators [7]. The evaluation of routes is based on frequency and punctuality.

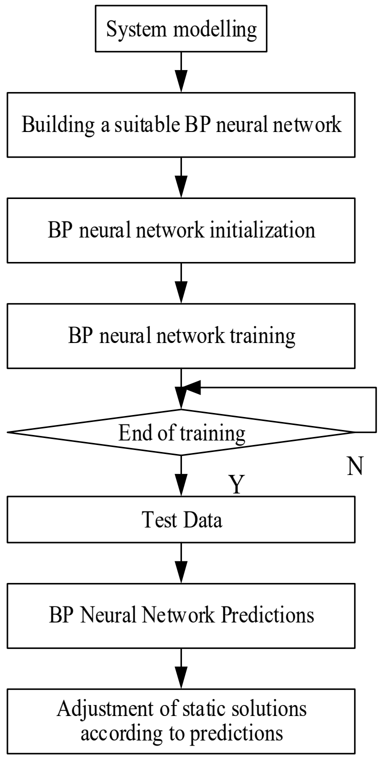

Figure 4. Algorithm flow

3.2. Real-Time Bus Vehicle Scheduling Scheme Design

The smart bus real-time dispatching module solves different dispatching problems based on the different dispatching algorithms obtained from the bus operation data. The key link of the smart bus dispatching sub-system is the intelligent real-time dispatching system. Based on the scheme design and actual demand analysis of the smart bus real-time dispatching system, the smart bus dispatching model is functionally subdivided and the module function of the real-time dispatching system is divided as shown in Figure 5.

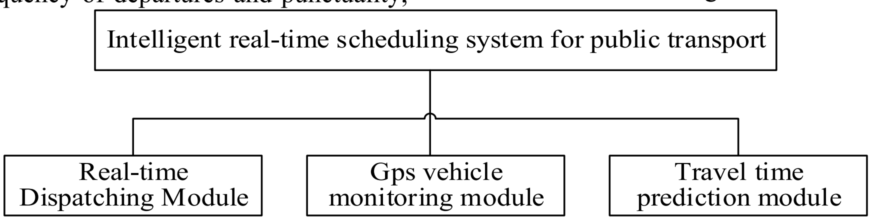

Figure 5. Functional division of the real-time scheduling system

4. EXPERIMENTAL

4.1. Analysis of the Results of the Dynamic Permutation Algorithm

The dynamic interchange algorithm introduces real-time road conditions compared to the static algorithm, and will give different interchange options depending on the time of day the bus is running. The static algorithm gives the same result for each query, while the dynamic algorithm's will vary depending on the time of day. According to the different modes of bus operation given in Chapter 4, the bus is in different scenarios depending on the time of day, and the road conditions are different, thus making the interchange scheme change accordingly [8], and thus affecting the overall journey time. In this paper, we use bus route 3/9 at four different points in time to examine the impact of different time points on the travel scheme and to verify the effectiveness of the dynamic algorithm. The results of the dynamic interchange algorithm are shown in Table 1.

Table 1. Comparison of dynamic interchange algorithm and Baidu query bus vehicle running time

Travel options	Point in time	Baidu programme	Dynamic Solutions
Route 3	10:00	39	37
	12:00	39	42
	17:00	39	45
	21:00	39	35
Route 9	10:00	37	35
	12:00	37	38
	17:00	37	41
	21:00	37	35

According to the comparison results, the solution given by Baidu for bus travel is a static solution, the dynamic interchange algorithm for bus vehicles proposed in this paper will change according to the vehicle running time, and the change pattern of the running time given by the dynamic algorithm is in line with the actual situation [9].

4.2. Testing of the predicted Departure Interval Algorithm

Table 2 gives the one-way running time of bus route 3 at different moments of a day in a certain place and the reasonable departure interval at this time. The departure interval is recalculated using the combination of NN and equipartition method proposed in this paper and compared with the reasonable departure interval, see Figure 6.

Table 2. Comparison table of departure intervals

Time taken one way (minutes)	Reasonable interval (min)	Predicted interval (min)
83.11	10	9.59
84.16	9	9.71
70.97	8	8.18
63.24	8	7.30
66.24	9	7.64
74.25	9	8.57
72.78	8	8.40
67.32	7	7.77
84.71	10	9.78

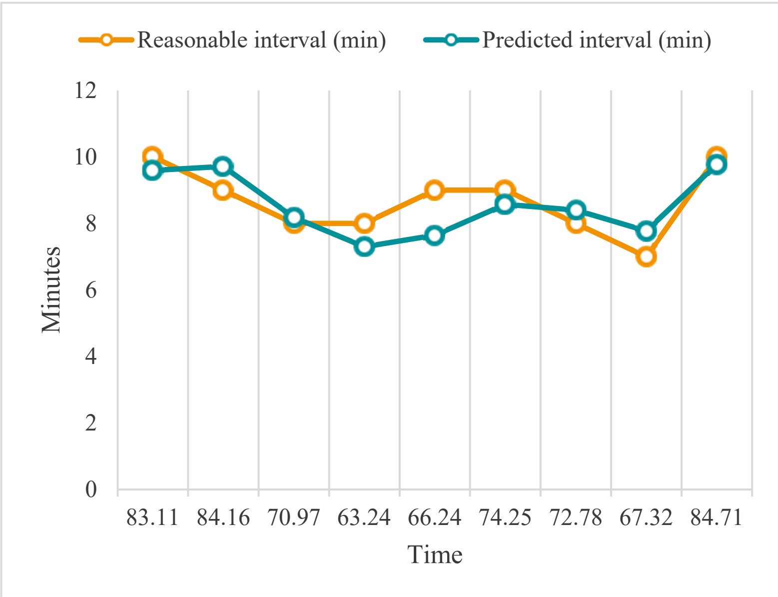

Figure 6. Analysis of the departure interval

The reasonable interval is the interval between departures that is manually adjusted in real time by the excellent dispatcher at Route 11 dispatch based on the number of vehicles allocated, road conditions and the number of people waiting for trains. The predicted interval is the interval that the program has calculated and recommended to the dispatcher. The predicted interval, after rounding, basically matches the manually adjusted departure interval, with the biggest difference being between 10:54 and 11:57, where the manual dispatching interval is 9 minutes and the predicted interval is 7.64 minutes. After simulating the two departure intervals against the original data, a comparative analysis revealed that the predicted interval was more in line with the road conditions and passenger flow at the time. From the prediction results, it can be seen that the recalculated departure interval algorithm is reliable and effective [10].

5. CONCLUSIONS

This paper focuses on the design of a smart bus service system, which is based on the existing bus system and introduces modern, intelligent and informative means to promote positive interaction between users, bus vehicles and bus operating companies. This paper aims to save emissions, increase efficiency and improve service levels by establishing a more intelligent, efficient and comprehensive information system that maximises the superiority of the bus network and the carrying capacity of bus transport by integrating the functions of intelligent bus scheduling. In this paper, based on the analysis of bus data collection and pre-processing, a BP NN-based vehicle travel time prediction model is established, and the improvement measures of scene adaption and learning rate adaptive adjustment are proposed to improve the prediction accuracy of the proposed model to a certain extent.

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REFERENCES

1. Jezabel Molina-Gil, Pino Caballero-Gil, Alexis Quesada-Arencibia, Gabriele Salvatore de Blasio: Application of Fuzzy Logic in a Secure Beacon-Based Guidance System for Public Transportation. Int. J. Appl. Math. Comput. Sci. 32(3): 371-387 (2022).
2. Juan Godfrid, Pablo Radnic, Alejandro A. Vaisman, Esteban Zimányi: Analyzing public transport in the city of Buenos Aires with MobilityDB.J. Public Transp. 14(2): 287-321 (2022).
3. Jesper Bláfoss Ingvardson, Otto Anker Nielsen: The influence of vicinity to stations, station characteristics and perceived safety on public transport mode choice: a case study from Copenhagen.J. Public Transp. 14(2): 459-480 (2022).
4. Hailong Huang, Andrey V. Savkin, Chao Huang: Reliable Path Planning for Drone Delivery Using a Stochastic Time-Dependent Public Transportation Network.C. IEEE Trans. Intell. Transp. Syst. 22(8): 4941-4950 (2021).
5. Mikhail Y. Kovalyov, Boris Rozin, N. N. Guschinsky: Mathematical Model and Random Search Algorithm for the Optimal Planning Problem of Replacing Traditional Public Transport with Electric.J. Autom. Remote. Control. 81(5): 803-818 (2020).
6. Mohammad Wazid, Basudeb Bera, Ashok Kumar Das, Saraju P. Mohanty, Minho Jo: Fortifying Smart Transportation Security Through Public Blockchain.C. IEEE Internet Things J. 9(17): 16532-16545 (2022).
7. Nieves R. Brisaboa, Antonio Fariña, Daniil Galaktionov, Tirso V. Rodeiro, M. Andrea Rodríguez: Improved structures to solve aggregated queries for trips over public transportation networks.J. Inf. Sci. 584: 752-783 (2022).
8. Nils Olsen, Natalia Kliewer, Lena Wolbeck: A study on flow decomposition methods for scheduling of electric buses in public transport based on aggregated time-space network models. Central Eur. J. Oper. Res. 30(3): 883-919 (2022).
9. Natalia Selini Hadjidimitriou, Marco Lippi, Marco Mamei: A Data Driven Approach to Match Demand and Supply for Public Transport Planning.C. IEEE Trans. Intell. Transp. Syst. 22(10): 6384-6394 (2021).
10. Sajikumar S, Bijulal D . Zero bunching solution for a local public transport system with multiple-origins bus operation.J. Public Transport,14(3): 655-681 (2022).