# Design and Implementation of Urban Parking Path Planning System

Jianping Sun[1], Zhenyu Wang[1], Yun Xu[1], Xiaopeng Li[2], Zhaoping Tang[1,*]

[1] *School of Transportation and Logistics, East China Jiaotong University, Nanchang, China*
[2] *Shenhua Zhuneng Group Co., LTD., Ordos, 010300, China*
[*] *Corresponding author. Email: tzp@ecjtu.edu.cn*

**ABSTRACT**
Aiming at the problem of effective berth information prediction and driving path selection in the parking process, this paper uses BP neural network to predict the number of vacant parking stalls, establishes a multi-objective planning model for the lowest travel cost path selection, and designs an improved Dijkstra algorithm of bidirectional search based on path direction guidance. Finally, based on ArcGIS Engine's urban road network geographic information and Python's crawling Baidu map intelligent traffic information, this paper develops and designs an urban parking lot path planning system, carries out path planning and parking stall prediction for urban parking lots. Research examples show that the system developed in this paper can effectively avoid inefficient parking by drivers, and can choose three modes of distance, travel time and lowest travel cost to plan the driving route according to personal wishes. It has important reference significance to improve the efficiency of parking path planning and optimize the allocation of parking resources.

***Keywords:*** *parking problem, prediction of parking stalls, route selection, multi-objective planning, BP neural network, bidirectional Dijkstra algorithm, ArcGIS technology, system design.*

## 1. INTRODUCTION

With the improvement of national economy, the growth of urban automobile ownership has seriously exceeded the construction speed of parking infrastructure. According to data released by the Traffic Management Bureau of the Ministry of Public Security, the proportion of automobiles and parking stalls in first-tier cities in China is about 1: 0.8, and in other cities is about 1: 0.5. However, compared with the international standard of 1: 1.3, the supply of parking stalls in China is obviously insufficient, and the problem of "parking difficulty" is becoming increasingly prominent. In July 2019, The Ministry of Transport of the People’s Republic of China issued the Outline of Digital Transportation Development Plan, which pointed out that promoting "intelligent parking" and forming a modern data-driven transportation system are the major development strategies in the future [1].

Whether there is a vacant parking stall in the parking lot for parking and how to get to the parking lot or parking stall are the particular problems to which the driver should pay great attention. In terms of berth prediction, domestic and foreign scholars have proposed a variety of models and algorithms to improve the real-time and accuracy of prediction. Awan et al. evaluated parking stall prediction methods such as multi-layer perceptron, K-nearest neighbor, decision tree and random forest algorithm, and the results showed that the prediction accuracy of the decision tree, random forest and K-nearest neighbor algorithm were better than that of the multi-layer perceptron algorithm [2]. However, the multi-layer perceptron had better real-time performance. Zhang et al. proposed a Fourier transform - least squares support vector regression (FT-LSSVR) multi-step prediction algorithm, which proved that the algorithm was more accurate and real-time than the traditional LSSVR algorithm in the prediction of two typical public parking lots in Hangzhou [3]. Fan et al. proposed a support vector regression with fruit fly optimization algorithm (FOA-SVR) and proved its accuracy, however found that its real-time performance was lower than BP neural network [4]. Tang et al. used ARIMA, Kalman filtering and BP neural network to predict the number of berth, and the results showed that ARIMA and BP neural network are better than Kalman filtering, however ARIMA had poor robustness [5]. He et al. designed a prediction algorithm of parking stall occupancy rate based on BP neural network considering temporal and spatial correlation and multi-dimensional influence factors, and obtained relatively high prediction accuracy [6, 7]. Zhang et al. constructed GA-BP neural network, and the results showed the superiority of this algorithm in predicting berth accuracy in a short time [8].

In terms of optimal parking path planning, Liu et al. used adaptive genetic algorithm to induce and simulate the shortest parking path, which showed the effectiveness of the model and algorithm [9]. Du et al. carried out parking path planning for bounded rational drivers based on cooperative game, and solved it by using radial basis function, so as to realize the minimum overall driving time of road network [10]. Zhang et al. took the shortest travel time as the goal, applied MSA (Method of Successive Averages) to design the traffic flow path allocation scheme with the highest total road network efficiency, reasonably planned the travel path, and improved the parking efficiency of users [11]. Yan et al. established an adaptive parking guidance model based on improved ant colony optimization algorithm to realize optimal parking path planning in consideration of parking time and safety [12]. Yang established a reliable path model based on travel time and a solution algorithm based on reliability boundary, considered the dynamic and randomness of road network, planned a reliable stopping path for drivers [13].

Intelligent parking system can effectively provide users with intelligent and efficient parking guidance services in real time. Safi et al. proposed a new cloud intelligent vehicle parking system based on VANET, which can provide real-time vacant parking stall information, reservation and recommendation functions [14]. Kizilkaya et al. proposed an IoT intelligent parking system based on binary search tree stratification method, which showed superior performance in terms of search time and fuel consumption [15]. Zhou established a smart parking platform based on static traffic big data and applied it in Minhang District, Shanghai, which improved the parking efficiency [16]. Dai et al. established a parking inducing cloud platform based on mobile Agent technology, optimized the allocation of parking lot resources, significantly reduced the time for users to find berths, and provided convenience for travel [17].

Numerous berth prediction algorithms play an important role in revealing the changing trend of parking stalls and berth prediction. When describing the time series of available vacant berths, each method has advantages and disadvantages, and its adaptability is different. Most of the optimal parking paths are single-objective planning, in the current study, the shortest distance, minimum travel time and travel cost minimum target together into planning, and consider the real-time traffic information and traffic impact on the optimal path is lacking. This paper considers urban real-time road conditions and traffic information, by using the BP neural network, established user intention optional (shortest distance, minimum travel time and travel cost minimum) goal programming model, design an improved Dijkstra algorithm for bidirectional search based on path direction guidance [18]. Moreover the urban parking lot path planning system is developed based on ArcGIS Engine urban road network geographic information, crawl intelligent transportation information of Baidu Map through Python, by Visual Studio2010 as the platform, ArcGIS Engine software and C# language as tools [19]. The research in this paper is of great practical value in alleviating traffic congestion caused by berth searching and guiding the parking path planning for users' individual needs.

## 2. MODEL BUILDING

### 2.1. Construct the Optimal Path Planning Model

Supposing the network graph connecting node and road $G=(V,E,W)$, Where $V=\{1,2,\ldots,n\}$ is the set of nodes, $E$ is the path set and $W$ is the weight set of paths. The optimal path selection model of the lowest travel cost considering the time cost and fuel consumption cost is established.

Transportation travel cost is composed of travel time cost and fuel consumption cost. In order to achieve the user's desired goal is optional (the shortest driving distance, the shortest travelling time or the lowest driving cost ), the 0-1 logical variables $y_o$, $y_k$ and $y_l$ are introduced (when the user chooses the shortest driving distance, $y_o=1$, $y_k=0$, $y_l=0$; When the user chooses the shortest travel time, $y_o=0$, $y_k=1$, $y_l=0$; When the user chooses the lowest travel cost, $y_o=0$, $y_k=1$, $y_l=1$), the optimal path planning model of user intention considering traffic congestion delay index $\gamma$ is established as follows:

$$\min Z = y_o \sum d_{ij} x_{ij} + y_k \sum \gamma (\frac{d_{ij}}{v_{ij}}) VOTx_{ij} + y_l \sum CB_{ij} x_{ij} \quad (1)$$

$$s.t. \quad x_{ij}, y_o, y_k, y_l \in \{0,1\} \quad i,j \in V \quad (i,j) \in E \quad (2)$$

Equation. (1) represents an optional objective function of the user's intention, where the average travel time value of the driver $VOT = I_p / H_p$, $\sum t_{ij} VOTx_{ij}$ represents the total travel time cost, the fuel consumption $B_{ij} = \gamma d_{ij} Q$ of section $(i,j)$, and $\sum CB_{ij} x_{ij}$ represents the total travel fuel consumption cost; In Equation. (2) $x_{ij} \in \{0,1\}$, $x_{ij}=1$ means that this path is selected, otherwise $x_{ij}=0$ ; $i, j \in V$ means $i, j$ chooses the two points to be located in the node set $V$ ; $(i, j) \in E$ means that the line segment between the two points is located in the path set $E$ . The meaning of the related parameters as shown in the Table 1.

**Table 1.** The meaning of model related parameters

| Parameters | Meaning |
|---|---|
| $d_{ij}$ | The distance weight of the path between $i, j$ |
| $v_{ij}$ | The passage speed between $i, j$ |
| $C$ | The unit price |
| $x_{ij}$ | Whether the section is selected |
| $\gamma$ | Traffic congestion delay index |
| $H_p$ | Per capita annual working hours |
| $B$ | Fuel consumption |
| $Q$ | fuel consumption of automobile |
| $I_p$ | annual per capita income |

## 2.2 Forecast Number of Vacant Parking Stalls

In this paper, BP neural network is used to predict the number of vacant berths in parking lots. $t-40$ , $t-30$ , $t-20$ , $t-10$ and $t$ are selected to predict the number of vacant berths at time $t$+10 , so the number of nodes at the input layer and output layer are 5 and 1 respectively. Using a single hidden layer, then gradually increase the number of nodes, test the learning error, and the learning error is tested to make the learning error less than the given threshold value. Finally, the number of neurons in the hidden layer is determined to be 5.

The transfer function selected by the hidden layer is the Log-Sigmoid function:

$$Logsig(n)=\frac{1}{1+e^{-n}} \tag{3}$$

The purelin function of the output layer:

$$y=x \tag{4}$$

Analyze and predict the parking data of Diwang Plaza from November 4 to November 17, 2019 from 11: 00 to 16: 00, select 420 sets of data as training samples, and compare the test sample data on November 16, 2019 (Table 2) Perform predictive analysis.

**Table 2.** Partial parking stall data of Diwang Plaza parking lot

| t/min | 11: 00-12: 00 | 12: 00-13: 00 | 13: 00-14: 00 | 14: 00-15: 00 | 15: 00-16: 00 |
|---|---|---|---|---|---|
| 00~10 | 43 | 61 | 52 | 15 | 11 |
| 10~20 | 42 | 64 | 43 | 13 | 8 |
| 20~30 | 49 | 59 | 32 | 11 | 15 |
| 30~40 | 48 | 56 | 28 | 10 | 20 |
| 40~50 | 54 | 56 | 21 | 7 | 18 |
| 50~60 | 56 | 53 | 24 | 11 | 25 |

The prediction results and the absolute error of the prediction are shown in Fig. 1 and Fig. 2 respectively. It can be seen from Fig. 1 that curve fit of the predicted value is distinctly accurate and the predicted value is close to the actual value. It can be seen from Fig. 2 that the maximum error is 3.7017%. In general, when predicting changes in the number of berths, the prediction results are considered to be accurate if the theoretical average error is less than 5%. The average error of this method for forecasting empty berths in parking lots is 1.98%, indicating that the prediction results of this method are relatively accurate.

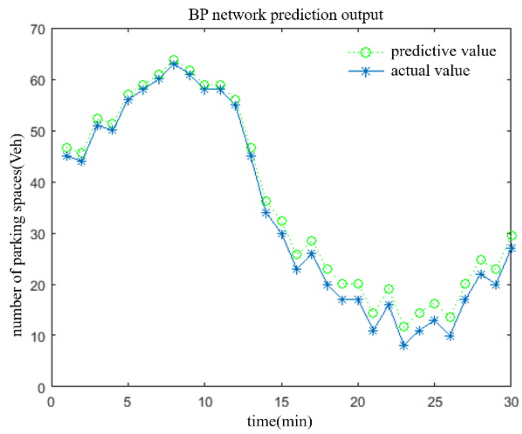


**Figure 1** The results of BP neural network predicted

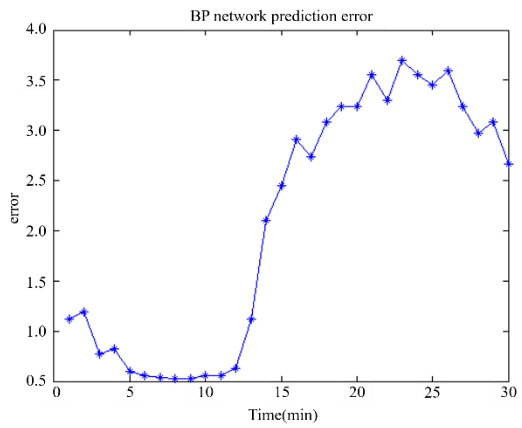


**Figure 2** BP neural network predicts absolute error results

# 3. SOLVING ALGORITHM

## 3.1 The Improved Dijkstra Algorithm of Bidirectional Search Based on Path Direction Guidance

Considering the spatial distribution characteristics of urban road network nodes and the need of traditional Dijkstra algorithm to traverse all node sets, the algorithm is inefficient, especially when the number of nodes is large and time consuming, this paper presents an improved Dijkstra algorithm of bidirectional search based on path direction guidance. The improved algorithm decompositions the shortest path into several sub-problems for solving, minimizes the triangle area formed by the starting point, the ending point and the searching node in the path as the judgment criterion, holds the general direction of the optimal path, and searches from the starting point and the ending point by binary tree according to its directionality. Specific ideas are as follows:

Supposing $O$ and $D$ is any given starting point and end point in the traffic network, to find the optimal path from $O$ to $D$, it is the most common and simplest case that all sections of roads constituting $OD$ are basically in the same or similar direction with $OD$, however in most cases, the optimal path of $OD$ is not a straight path, however its general direction should be from $O$ to $D$. If there are multiple other nodes in the $OD$ optimal path, the shortest path from $O$ to $D$ can be divided into multiple sub-problems for solving. The shortest path from $O$ to $D$ can be finally determined by bidirectional search for the shortest path from $O$ to $D$ and $D$ to $O$. The algorithm is as follows:

**Step 1:** Calculating the straight line distance between $O$ and $D$. If $OD$ has only one straight line, then this path is the shortest path of $OD$. If there is a side chain composed of several road along the $OD$ line direction between $OD$, then the path composed of all sections on the side chain is the shortest path from $O$ to $D$, then the nodes and distance that the path passes through are recorded. Otherwise, it is turned into Step 2.

**Step 2:** Starting from $O$ and $D$ respectively, find the node with the smallest triangle area, and set it as A and B. i.e.

$$S_{\Delta OAD} = \min_{A_i \in V_1}(S_{\Delta OA_iD}) \tag{5}$$

In Eq. (5), $V_1$ is the set of all nodes connected with $D$ in the road network.

$$S_{\Delta DAO} = \min_{B_i \in V_2}(S_{\Delta DB_iO}) \tag{6}$$

In Eq. (6), $V_2$ is the set of all nodes connected with $O$ in the road network.

If $A$ is the selected node in the search from $O$ to $D$, $A$ is taken as the current node, and $A$ is used as the starting point to find the node which form the minimum triangular area with $AD$, and this is repeated until the currently selected point coincides with the target end point $D$. In this way, chain obtained by the search is feasible solution of the shortest path from $O$ to $D$. When the selected node is the termination point and this point does not coincide with the target endpoint $D$, the chain search ends at this point, then the search process continues with the previous node of the selected node as the current node, and so on.

Similarly, the process and algorithm of searching another chain from $D$ is the same as the searching from $O$. In this way, the final result of the shortest path between any given starting and ending point in the traffic network may be two or one, and the nodes passed by the path are recorded. The shortest path obtained in this process is basically the same or similar to $OD$ line direction. However, the condition is simple, so it is necessary to verify by subsequent Step 3 to determine whether the chosen path is the shortest path.

**Step 3:** Similarly $O$, $D$ as a root nodes, and then the binary tree method is used to search from $O$ to $D$ and from $D$ to $O$ respectively. The above process and algorithm are repeated to add the node and its line which can form the smallest area of the triangle with $O$ and $D$, the two active nodes of the binary tree are marked until the selected node coincides with either $O$ or $D$. In this way, the shortest path between any given starting and ending $OD$ in the road network has at most 4 results. In order to reduce the time cost and minimize the structure of the binary tree, the following two measures should be adopted: Firstly, the breadth first method should be adopted to minimize the number of nodes traversed in the binary tree during the search process; Secondly, it is necessary to judge in advance whether path nodes and chains should be added to child nodes and their lines. If it is the search target node $O$ (or $D$), path nodes and chains should not be added, but the corresponding cumulative length marks of nodes and child nodes affected by them should be changed accordingly.

### *3.2 Algorithm Verification*

Establishment of a road network diagram with software ArcGIS shown in Fig. 3, the black number represents the vertex in the picture, and the red number represents the distance between the vertices (Unit: km).

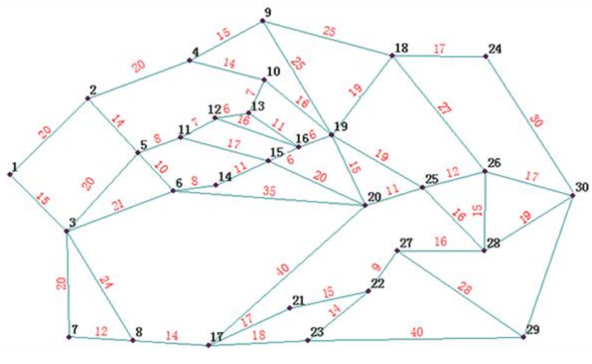

**Figure 3** Road network diagram

After many experiments, the relevant parameters of path optimization results between two points are obtained, as shown in Table 3.

**Table 3.** The search results of Dijkstra algorithm are compared with those of this paper

| Algorithm | *OD* point | The optimal path | Distance (km) | Number of search nodes | Number of passing nodes | Algorithm running time (ms) |
|---|---|---|---|---|---|---|
| Dijkstra algorithm | 1~16 | 1→3→6→14→15→16 | 61 | 10 | 6 | 235 |
| | 1~30 | 1→3→6→20→25→26→30 | 113 | 30 | 7 | 455 |
| | 8~18 | 8→17→20→19→18 | 88 | 27 | 5 | 334 |
| Algorithm of this paper | 1~16 | 1→3→6→14→15→16 | 61 | 10 | 6 | 189 |
| | 1~30 | 1→3→6→20→25→26→30 | 113 | 27 | 7 | 412 |
| | 8~18 | 8→17→20→19→18 | 88 | 24 | 5 | 270 |

It can be seen from Table 3 that the optimal path finally obtained by the two algorithms is consistent, however in terms of running time, the algorithm presented in this paper has advantages. With the increase of road nodes, the complexity of road increases, the advantages of this algorithm in running time reduction will be considerable.

## 4. INSTANCE ANALYSIS

### *4.1 Design of Urban Parking Path Planning System*

The urban parking lot path planning system is developed by Visual Studio2010 as the platform, ArcGIS Engine software and C# language as tools. It consists of three parts: front-end display interface design, system programming design and system database design. The operation and development environment of the entire system is covered by the overall framework. Among them, the front-end display interface mainly serves urban drivers with parking needs and provides real-time map, optimal path and target cost result display interface for drivers, which is mainly completed by the secondary development software of ArcGIS Engine. Background programming is written in C# language for user operation and access to database and other functional modules with the help of Visual Studio (VS) 2010 platform. The system database uses the Geodatabase provided by ArcGIS to create a geographic database, which is used to store data sets, attribute object elements, geometric network, topological relations and spatial reference.

The road network data set is created in Shapefile format with the road information of Nanchang metro, urban expressway, freeway, national trunk highway, provincial trunk highway, county road, township road, pedestrian way, nine-grade road and other road information as the original data. On this basis, network data set is constructed, section impedance is set, topological processing of geographic data is done, functions are added to ArcGIS points, new analysis layer is created, and network analysis function is added. Part of road information network of Nanchang city and the main interface of system is shown in Fig 4.

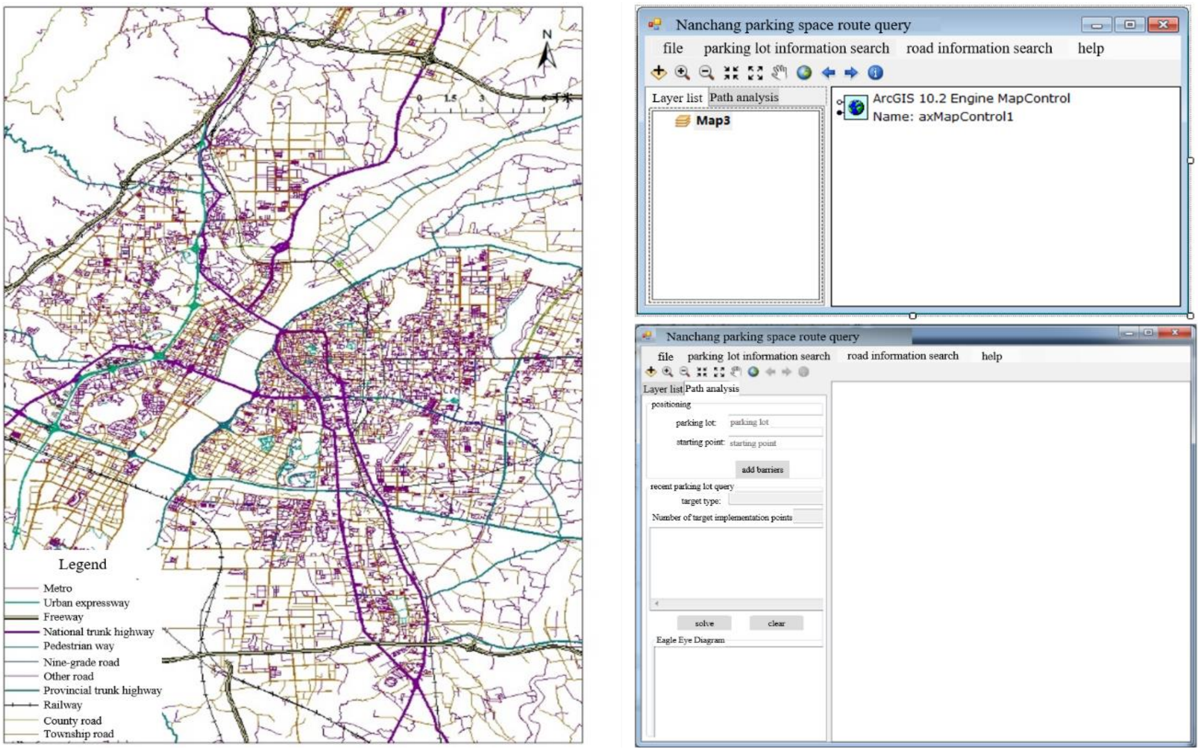


**Figure 4** Road information network map of Nanchang city and the main interface of system

Using ArcGIS network analysis function of the shortest path analysis function, the relevant parameters (such as annual per capita income $I_p$, per capita annual working hours $H_p$, unit fuel price $C$, vehicle fuel consumption $Q$, etc.) of the model under three different targets (the shortest distance, the shortest travel time and the lowest travel cost) are imported through the field evaluator, to complete the assignment of model parameters. Complex parameters are imported in the form of constructing functional relations to achieve the solution of the optimal path of the model under different objectives (e.g., the shortest travel distance, the shortest travel time and the lowest travel cost), and the visualization is presented.

**Table 4.** Partial crawl data of traffic congestion delay index

| Road name | Traffic congestion delay index $\gamma$ | Traffic congestion level |
|---|---|---|
| Beijing west road | 2.34 | Very severe |
| Qingshan south road | 2.17 | Very severe |
| Meilin avenue | 1.93 | Severe |
| Ganjiang north avenue | 1.9 | Severe |
| Zhuqiao east road | 1.9 | Severe |
| Jinggangshan avenue | 1.76 | Moderate |
| Nanjing east road | 1.66 | Moderate |
| Changnan avenue auxiliary road | 1.57 | Moderate |
| Jingdong south avenue | 1.57 | Moderate |
| Jiangling west second road | 1.32 | Mild |
| Sandian west road | 1.28 | Mild |
| Jinta east street | 1.21 | Mild |

### *4.2 Parameter Assignment Overview*

This paper selects the road network of East Lake District, West Lake District and Qingshan Lake District in Nanchang city as the research area. The traffic congestion delay index data in the region is obtained through the interface of China Urban Congestion Index Platform provided by Baidu Map intelligent transportation, and the refresh frequency is every 5 minutes. The road congestion status, longitude and latitude and real-time traffic congestion delay index within the query range can be obtained by crawling data through Python. The data was crawled on November 12, 2019, and some data are shown in Table 4.

According to the Urban Road Traffic Operation Evaluation Index System, the speed value of national trunk highway, provincial trunk highway and other trunk roads is limited to 45km/h, and the speed value of county road, township road and other secondary trunk roads is limited to 35km/h. The data of traffic congestion delay index is the data at 16: 00 on November 12, 2019. The vehicle with 1.6L displacement is the standard model, and its fuel consumption is 9L/100km, and unit oil price is 6.78 ¥/L. In 2019, the average annual salary of Nanchang city is 40,844 ¥, and the average annual working time is 2,000 hours. Based on the existing traffic information data of Nanchang urban road network, the weight value of Nanchang city traffic network data set created in ArcGIS software is granted.

### 4.3 Instance Result Display

This paper takes the parking demand of the users driving to the employment building in Nanchang city as an example to illustrate.

#### *4.3.1 Parking Lot Selection and Driving Path Planning Without Considering The Number Of Vacant Berths*

The paths planned by the system for users under different targets are shown in Figure 5. Figure 5(a) is the path planning of the parking lot under the target of the shortest travel distance. Tianhong Shopping Mall parking lot on Zhongshan Road, Nanchang is selected by the system with a driving distance of 2472.32m. Figure 5(b) shows the parking lot path planning under the goal of the shortest travel time. The parking lot in Nanchang Times Plaza is selected by the system, and the driving time is 5.40 minutes. Figure 5(c) shows the parking lot path planning under the target of the lowest travel cost (time cost and fuel consumption cost). Tianhong Shopping Mall parking lot in Zhongshan Road, Nanchang is selected by the system, and the travel cost is ¥3.40.

(a)The shortest distance path

(b) The shortest travel time path

(c) The minimum travel cost path

**Figure 5** Optimal path planning

#### *4.3.2 Parking Lot Selection and Driving Path Planning Considering The Number Of Vacant Berths*

The BP neural network prediction method proposed in this paper is used to predict the vacant berths by using the original detection device of parking lot to obtain the parking stall data. Set iteration times as 100, learning step size as 0.1, convergence accuracy as $4\times10^{-5}$, and predict the number of vacant parking stall after 10min in the parking lot. The results are shown in Table 5. The system automatically eliminates the unreliable parking lots with 5 or less vacant parking stalls (Tianhong Shopping Mall parking lot in Zhongshan Road, Jinguan Food Court parking lot and Nanchang Times Plaza parking lot) for users, and the remaining 12 parking lots are used as new available parking lots to choose from.

**Table 5.** Information table of the number of parking spaces in the parking

| Parking lot name | Number of parking stalls | Predicted number after 10min |
|---|---|---|
| Diwang Plaza parking lot | 100 | 30 |
| Yuanzhong Building parking lot | 150 | 56 |
| Zhongshan City parking lot | 46 | 13 |
| Tianhong Shopping Mall parking lot | 32 | 4 |
| Jinguan Food Court parking lot | 28 | 3 |
| Dazhong shopping center parking lot | 37 | 10 |
| Nanchang Times Plaza parking lot | 30 | 5 |
| Shunfeng convenient parking lot | 30 | 20 |
| Blue Ocean Shopping Plaza parking lot | 132 | 47 |
| Xianshi Lake Park parking lot | 50 | 30 |
| Walmart parking lot | 96 | 39 |
| Gaoxin Avenue parking lot | 60 | 14 |
| Danxia Road parking lot | 54 | 21 |
| Ruzi Park parking lot | 106 | 46 |
| Xincheng Wuyue Plaza parking lot | 338 | 134 |

After considering the impact of the number of vacant parking stalls on the parking reliability, the routes planned by the system for users under different targets are shown in Figure 6. In this case, it is coincidental that under the three targets of the shortest distance, the shortest travel time and the lowest travel cost (time cost and fuel consumption cost), the system selects the parking lot of Diwang Plaza for users, with a driving distance of 2780.27m, a driving time of 6.43 minutes and a travel cost of ¥3.88.

The comparison of the optimal path planning of the parking lot with and without considering the number of vacant berths is shown in Table 6.

According to Table 6, Figure 5 and Figure 6, it can be seen that the path planning methods (the shortest distance, the shortest travel time and the lowest travel cost) under the three targets have been realized. Users can choose the planning path according to their own needs to improve parking efficiency and avoid invalid berth searching.

(a)The shortest distance path (b) The shortest travel time path (c) The minimum travel cost path

**Figure 6** Optimal path after prediction

**Table 6.** The optimal path planning of the parking lot in two situations

| | Leave out the number of available parking stalls | Consider the number of available parking stalls |
|---|---|---|
| The shortest distance | Tianhong Shopping Mall parking lot, Zhongshan road, Nanchang, distance 2472.32m | Diwang Plaza parking lot, distance 2780.27m |
| The shortest travel time | Times Plaza parking lot, Nanchang, 5.40min | Diwang Plaza parking lot, 6.43min |
| The minimum travel cost | Tianhong Shopping Mall parking lot, Zhongshan road, Nanchang, cost ¥3.40 | Diwang Plaza parking lot, cost ¥3.88 |

## 5. CONCLUSION

Aiming at the "difficult parking" problem that often troubles people's daily travel, this paper uses ArcGIS software to develop and design urban parking path planning system, introducing 0-1 logical variables, and constructs the user intention target the optional (including the shortest distance, the shortest travel time or the minimum travel cost) route planning model of the parking lot, the bidirectional search Dijkstra improved algorithm based on path direction guidance was designed. Traffic congestion delay index was considered in this model, it can reflect the real-time road condition information accurately, thus realizing the intelligent parking induction of driving path planning and parking under the real-time road condition, it saves time and cost while completing parking tasks safely and quickly, and improves economic efficiency.

## AUTHORS' CONTRIBUTIONS

Jianping Sun, conceived the idea, designed the study, performed the research, analysed data, and wrote the paper; Zhenyu Wang and Yun Xu participated in the paper revision. Xiaopeng Li and Zhaoping Tang provided the data.

## ACKNOWLEDGMENTS

This project was supported by the key research and development project of Jiangxi Science and Technology Department (No.20192BBE50006) and the Social Science Planning Project of Jiangxi Province (No.19YJ20).

## REFERENCES

[1] Liang Jin. Ministry of Transport: Implementation of Digital Transportation Network Integrating Heaven and Earth in 2035[J]. China Tendering

Weekly, 2019, (31): 6-6. “in Chinese” DOI: CNKI:SUN:ZBZG.0.2019-31-003

[2] Awan F M, SALEEM Y, MINERVA R, et al. A Comparative Analysis of Machine/deep Learning Models for Parking Space Availability Prediction[J]. Sensors, 2020, 20(1): 322-322. DOI: 10.3390/s20010322

[3] Mei Z, Zhang W, Zhang L, et al. Real-time Multistep Prediction of Public Parking Spaces Based on Fourier Transform–least Squares Support Vector Regression[J]. Journal of Intelligent Transportation Systems, 2020, 24(1): 68-80. DOI: 10.1080/15472450.2019.1579092

[4] Fan J, Hu Q, Tang Z. Predicting Vacant Parking Space Availability: a Support Vector Regression Method with Fruit Fly Optimization[J]. IET Intelligent Transport Systems, 2018, 12(10): 1414-1420. DOI: 10.1049/iet-its.2018.5031

[5] TANG Keshuang, HAO Zhaokang, YI Xiebowen, et al. Evaluation of Prediction Methods for Parking Occupancy Rate[J]. Journal of Tongji University (Natural Science), 2017, 45(04): 533-543. “in Chinese” DOI: 10.11908/j.issn.0253-374x.2017.04.011

[6] HE Jian, Zhu Zhe, Wang Weidong, et al. Prediction Technology for Parking Occupancy Rate Based on Multidimensional Spatial-temporal Causality Learning[J]. Journal of Beijing University of Technology, 2020, 46(01): 17-23. “in Chinese” DOI: 10.11936/bjutxb2018100025

[7] Liang Ma,Feng Liu,Liangliang Chen,Ming Hong. Simulation of Crop Evaportranspiration Based on BP Neural Network Model and Grey Relational Analysis[J]. International Journal of Information Technology and Computer Science, 2012, 02(29): 15-21. DOI: 10.5815/ijem.2012.01.03

[7] ZHANG Jinmeng, LIU Huijun. Prediction of Spare Parking Spaces Based on Bp Neural Network Optimized by Genetic Algorithm[J]. Journal of Chongqing University, 2018, 41(03): 76-81. “in Chinese” DOI: 10.11835/j.issn.1000-582X.2018.03. 009

[8] Jingyu Liu, Jing Wu, Linan Sun. Control Method of Urban Intelligent Parking Guidance System Based on Internet of Things[J]. Computer Communications, 2020, (153): 279-285. DOI: 10.1016/j.comcom.2020.01.063

[9] Yuchuan Du, Shanchuan Yu, Qiang Meng, et al. Allocation of Street Parking Facilities in a Capacitated Network with Equilibrium Constraints on Drivers' Traveling and Cruising for Parking[J]. Transportation Research, 2019, 101(4): 181-207. DOI: 10.1016/j.trc.2019.02.015

[10] Zhang Yue, Kong Dewen, SUN Lishan, et al. Curb Parking Resource Allocation Method Based on Optimal Road Network Traffic Efficiency[J]. Transport Research, 2020, 6(03): 64-73. “in Chinese” DOI: 10.16503/j.cnki.2095-9931.2020.03.008

[11] YAN Yong, LEI Hang, LIANG Pan. Design of Adaptive Parking Guidance System Based on Improved Ant Colony Algorithm[J]. Experimental Technology and Management, 2020, 37(03): 80-82+138. “in Chinese” DOI: 10.16791/j.cnki.sjg.2020.03.018

[12] Yang Zhenzhen. Data-driven Dynamic Path Optimization and Parking Guidance Models and Algorithms [D]. Beijing: Beijing Jiaotong University, 2019, 91-105. “in Chinese”

[13] Safi Q G K, Luo S, Pan L, et al. SVPS: Cloud-based Smart Vehicle Parking System over Ubiquitous Vanets[J]. Computer Networks, 2018, 138(JUN.19): 18-30. DOI: 10.1016/j.comnet.2018.03.034

[14] Kizilkaya B, Caglar M, Al-Turjman F, et al. Binary Search Tree Based Hierarchical Placement Algorithm for IoT Based Smart Parking Applications[J]. Internet of Things, 2019, 5: 71-83. DOI: 10.1016/j.iot.2018.12.001

[15] Zhou Chizhong. Innovation and Application of Smart Parking Platform Based on Static Traffic Big Data System[J]. Computer Applications and Software, 2018, 35(02): 330-333. “in Chinese” DOI: 10.3969/j.issn.1000-386x.2018.02.060

[16] Dai Dadong, Wu Hongjie, Lu You, et al. Research and Application of Parking Guidance Cloud Platform Based on Mobile Agent[J]. Computer Applications and Software, 2018, 35(07): 142-147. “in Chinese” DOI: 10.3969/j.issn.1000-386x.2018.07.025

[17] Deqiang Zhou. A New Hybrid Grey Neural Network Based on Grey Verhulst Model and BP Neural Network for Time Series Forecasting[J]. International Journal of Information Technology and Computer Science, 2013, 09(01): 114-120. DOI: 10.5815/ijitcs.2013.10.12

[18] Md. Saef Ullah Miah, Md. Masuduzzaman, Williyam Sarkar, H M Mohidul Islam, Faisal Porag, Sajjad Hossain . Intelligent Tour Planning System using Crowd Sourced Data[J]. International Journal of Education and Management Engineering, 2018, 01(08): 22-29. DOI: 10.5815/ijeme.2018.01.03