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Research Article

Optimization of Airport Shuttle Bus Routes Based on Travel Time Reliability

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An optimization model of airport shuttle bus routes is constructed by taking operational reliability maximization as a main goal in this paper. Also, a hybrid genetic algorithm is designed to solve this problem. Then the theoretical method is applied to the case of Nanjing Lukou International Airport. During the research, a travel time reliability estimation method is proposed based on back propagation (BP) neural network. Absolute error and regression fitting methods are used to test the measurement results. It is proved that this method has higher accuracy and is applicable to calculate airport bus routes reliability. In algorithm design, the hill-climbing algorithm with strong local search ability is integrated into genetic algorithm. Initial solution is determined by hill-climbing algorithm so as to avoid the search process falling into a local optimal solution, which makes the accuracy of calculation result improved. However, the calculation results show that the optimization process of hybrid genetic algorithm is greatly affected by both the crossover rate and mutation rate. A higher mutation rate or lower crossover rate will decrease the stability of the optimization process. Multiple trials are required to determine the optimal crossover rate and mutation rate. The proposed method provides a scientific basis for optimizing the airport bus routes and improving the efficiency of airport's external transportation services.

1. Introduction

Air transportation is becoming an increasingly important means of transportation for residents in China. Prior to the popularization of airport rail transit, ground transportation remained the major transportation mode linked with airports, specifically airport buses. Therefore, the efficiency of airport bus routes directly determines the convenience of the access to the airport and the service quality of air transportation. Many studies have been conducted on the planning of airport bus routes. The US Federal Aviation Administration proposed five steps for the ground transportation network planning of airports in 1998 [1], which is now widely used by most scholars. Xiao et al. (1995) presented a planning method combined with quantitative and qualitative analysis for the connection of California airport traffic [2]. Li (2004) expanded the five-step planning and proposed the planning framework of the airport ground transportation network from the perspectives of prediction, evaluation, survey, scheme formulation, and optimization [3]. Based on the theory of transportation corridor planning, the studies focused on the configuration scale and suitable construction time of airport bus routes using the rolling iteration method, the node-importance evaluation, or the maximum entropy method include Li (2006) [4], Zhai (2005) [5], Yang and Zhai (2009) [6], and Lacombe (1994) [7]. However, the optimization of the route layout is less frequently addressed, and the proposed methods lack operability. With the improvement of transportation informatization in recent years, the geographic information system (GIS) and computer simulation techniques have been more frequently applied to the optimization of airport bus routes. Lu (2011) [8] managed to establish the optimization model of an airport bus route with the aim of cost minimization. The optimization model with the goal of minimizing travel time that was solved by a hybrid genetic algorithm was proposed by Zhou et al. (2012) [9]. Kivett (1996) [10], Tambi and Griebenow (2003) [11], and Chebl and Mahmassani (2003) [12] developed the organizational method for the planning of route orientation, shift arrangement, and service time for airport buses and routine bus transit. Although theoretical support for the scientific planning and design of airport bus routes can be found, the travel time reliability for passengers was barely considered and remained to be solved. There are many factors involved in route optimization. It is difficult to obtain a satisfactory optimal solution by using traditional mathematical methods. In recent years, various intelligent algorithms have been widely used, of which the genetic algorithm is the most widely used due to its good stability and easy implementation. Cipriani et al. [13] introduced the genetic algorithm and applied it to optimize the candidate bus routes. Kanoh and Hara [14] studied the problem of route planning and combined the genetic algorithm and the Dijkstra algorithm to determine the optimal route for the driver. Dinu and Bordea [15] used improved genetic algorithms in public route planning, improved the encoding accuracy of genetic algorithms based on double genotypes, and used the chromosomal fictional genes in mutation operations to improve the robustness of the results. Cipriani et al. [13] used the heuristic route generation algorithm and the genetic algorithm to obtain the second best route and jointly optimized the route. In addition, Zhao and Zeng [16], Xiong et al. [17], and Zhang et al. [18] mainly combined the simulated annealing algorithm and the genetic algorithm to reduce the number of iterations and accelerate the computation. The above studies have accumulated a great deal of experience related to the hybrid genetic algorithm design of this paper.

Despite the achievements on the improvement of airport shuttle bus routes, some deficiencies remain and mainly consist of the following two aspects. First, the optimization mainly addresses the travel time of passengers, operating costs, and network density while it barely considers the demand on travel reliability of passengers. Second, the conventional calculation methods of time reliability are more favorable for relatively stable supply-demand environments. However, when the traffic condition is seriously subject to external environments, including a broadened road, varied flow, or route adjustment, the existing method will probably fail to accurately quantify the reliability variation of the airport shuttle network.

The reliability of the access to airport has become the major consideration in airport passenger satisfaction evaluation. Airport bus routes are easily affected by ground transportation, sudden accidents, and other uncertain factors, which in turn directly affect the travel time reliability. According to incomplete statistics, the probability of traffic congestion on the Beijing Capital Airport Expressway is approximately 8.4%, which causes 10% of airport passengers to miss their flight. Therefore, based on the existing studies, this paper studies airport bus route optimization. First, the travel time reliability of passengers is introduced and reliability is regarded as the main goal of bus route optimization. These are more in line with the travel demands of airport passengers. This is the main difference between this paper and the existing studies. Second, in the design of the model's algorithm, this paper combines the hill-climbing algorithm and the genetic algorithm to make full use of the advantages of the local searching ability of the hill-climbing algorithm, avoid the search process falling into a local optimum, and improve the accuracy of calculation results. In addition, in the reliability calculation, it can quantify the impact of various factors on the reliability by using back propagation (BP) neural network method, which can measure the reliability level when the external environment changes in order to determine the passenger travel reliability under different conditions. This is also one of the main contributions of this paper.

FIGURE 1: Schematic diagram of airport bus route.

2. Basic Concepts

The travel time reliability of airport bus service is defined as the probability of airport buses arriving at the destinations within the specified time threshold. Figure 1 shows an airport bus route where i and j are two adjacent bus stations, j is the next station after station i, and m is the road segment of the bus that passes between station i and station j. Normally, road segment conditions between two adjacent stations changed very little. Assuming that the road segment reliability between adjacent stations is consistent, an airport bus route with n stations can be divided into $n-1$ road segments. The travel time reliability for segment m between stations i and j is calculated as follows:

$$R_{ij}^{m} = P\left(t_{ij}^{m} \leq T_{ij}^{m}\right) \tag{1}$$

$$t_{ij}^{m} = t_m + t_i + t_j \tag{2}$$

$$T_{ij}^{m} = T_m + T_i + T_j \tag{3}$$

$$T_m = \frac{L_m}{V_m} \tag{4}$$

$$T_i = T_o + T_c + T_i^p \tag{5}$$

$$T_i^p = q_i^u \cdot T_u + q_i^d \cdot T_d, \tag{6}$$

where R_{ij}^{m} is travel time reliability of segment m between stations i and j; t_{ij}^{m} is the travel time of segment m that consists of the travel time t_m and the time of passengers getting on and off the bus t_i and t_j at stations i and j, respectively; T_{ij}^{m} is the threshold of the travel time for segment m that consists of the threshold of travel time T_m for segment m and the time threshold of passengers getting on and off the bus T_i and T_j, respectively; L_m is the length of segment m; V_m is the acceptable travel speed of the bus in segment m (80 km/h for expressway, and 40 km/h for trunk road); T_o and T_c are the opening and closing times of the bus door (3 s), respectively; T_i^p is the time that passengers get on and off the bus at station i; q_i^u and q_i^d are the number of passengers getting on and off the bus at station i, respectively; and T_u and T_d are the acceptable average time of getting on and off the bus for each passenger, respectively (2.5 s).

According to (1) and taking the flow percentage of passengers in each road segment as the weight coefficient, the travel time reliability of the airport bus route consisting of m road segments is calculated as follows:

$$R_{\text{net}} = \sum_{i\in N}\sum_{i\in N}\sum_{m=1}^{M}\alpha_{ij}^{m} \times R_{ij}^{m} \quad (7)$$

$$\alpha_{ij}^{m} = \frac{q_{ij}^{m}}{\sum_{i\in N}\sum_{j\in N}\sum_{m=1}^{M} q_{ij}^{m}}, \quad (8)$$

where R_{net} is travel time reliability of airport bus route, α_{ij}^{m} is weight coefficient, q_{ij}^{m} is number of passengers in segment m, and M is the total number of road segments in the airport bus route.

3. Model Construction

3.1. Network Optimization Model. Reliability is the primary concern for passengers transiting to the airport and the main factor in the improvement of airport bus service. By taking the maximization of travel time reliability as the goal, the optimization model airport bus route is built in the present study. The objective function is expressed as follows:

$$\begin{aligned} \max R_{\text{net}} &= \max\left(\sum_{i\in N}\sum_{j\in N}\sum_{m=1}^{M}\alpha_{ij}^{m} \times x_{ij}^{m} \times R_{ij}^{m}\right) \\ &= \max\left(\sum_{i\in N}\sum_{j\in N}\sum_{m=1}^{M}\frac{q_{ij}^{m}}{\sum_{i\in N}\sum_{j\in N}\sum_{m=1}^{M} q_{ij}^{m}} \times x_{ij}^{m} \times R_{ij}^{m}\right), \end{aligned} \quad (9)$$

where R_{net} is the reliability, α_{ij}^{m} is the weight coefficient that takes the proportion of passengers in each road segment with respect to the total passenger volume, x_{ij}^{m} is the marker variable for the bus route, (when x_{ij}^{m} is 1, it indicates that the bus route is set on the road segment m between stations i and j, and otherwise x_{ij}^{m} is 0), and R_{ij}^{m} is the travel time reliability along the road segment m between stations i and j.

If $x_{ij}^{m} = 1$, there are the following constraint conditions:

$$\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} t_{ij}^{m} \times x_{ij}^{m} \le T \quad (10)$$

$$\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} q_{ij}^{m} \times x_{ij}^{m} \le Q \quad (11)$$

$$A_{\min} \le \sum_{m\in M} x_{ij}^{m} \le A_{\max} \quad (12)$$

$$\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} l_{ij}^{m} \times x_{ij}^{m} \le L \quad (13)$$

$$\frac{\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} q_{ij}^{m} \times x_{ij}^{m} \times C}{\sum_{i\in N}\sum_{j\in N}\sum_{m\in M} l_{ij}^{m} \times x_{ij}^{m} \times S} \ge 1 + \varepsilon. \quad (14)$$

In these equations, (10) is the time constraint, which is the maximum one-way running time of the airport bus route that does not exceed T. Equation (11) is the capacity constraint, which is the total number of one-way passengers transported that does not exceed the maximum number of buses transporting passengers Q. Equation (12) is the station constraint, where $A_{\min}$ and $A_{\max}$ are the minimum and the maximum station numbers along the airport bus route. Equation (13) is the route constraint, where l_{ij}^{m} is the length (km) of the road segment m between stations i and j and L is the maximum length of the airport bus route (in km). Equation (14) is the profit constraint, where C is the ticket price, S is the operating costs of buses per unit mileage, and ε is expected profit margin.

3.2. Prediction Method of Travel Time Reliability. Two methods are commonly involved in the calculation of travel time reliability, the simulation method and analytical method. The former assumes that the road capacities and traffic demand obeying certain distribution patterns. The traffic flow assignment is repeatedly implemented using the deterministic or stochastic user equilibrium model to obtain massive amounts of sample data, based on which the Monte Carlo sampling is applied for travel time reliability estimation (e.g., Liu et al., 2004; Liu et al., 2007; Chen and Pu, 2010) [19–21]. The latter assumes that the travel time obeys a certain probability distribution, after which the mean and standard deviations of the travel time are calculated analytically using probability theory and mathematical statistics, followed by the acquisition of the travel time reliability indicator (e.g., Hou and Jiang, 2008; van Lint et al., 2008; Al-Deek and Emam, 2006) [22–24]. Although the travel time reliability under the present transportation conditions can be truly reflected by the above methods, there still are some defects. (1) The establishment and correction of the model require massive essential data and the accuracy of the model is directly related to the precision of the supply-demand function. However, it is difficult to acquire accurate data and to build a high-precision supply-demand function for an open transportation system. (2) When the transportation supply and demand change dramatically (e.g., during road widening or changes of traffic flow and travel mode), the supply-demand function needs to be rebuilt. The existing model can hardly predict the travel time reliability in an accurate way.

The back propagation (BP) neural network can automatically adjust the connection weight of the network based on sample data, thus allowing for any nonlinear connections between input variables and output variables. Moreover, the BP neural network has lower demand on the size of the sample data and exhibits the advantages in self-learning and self-organizing abilities, self-adaptability, and strong fault tolerance. Thus, it keeps adjusting the weights and thresholds of the network and further minimizes the error sum of squares. This technique has been widely used in data recognition, prediction, and classification. In this study, the travel time reliability prediction model for airport bus route is therefore established based on the BP neural network using MATLAB tool.

Table 1: List of influence factors of travel time reliability.

Influence factors	Meaning	Data type	Unit
Road grade	Four types of roads (including highways, expressways, trunk roads, and secondary trunk roads) are considered and marked as 1, 2, 3, and 4, respectively	Integer type	-
Number of driveways	Number of driveways is expressed numerically	Integer type	-
Length of road segments	Distance between two adjacent stations	Floating-point type	m
Number of intersections	Number of intersections along each road segment is expressed numerically	Integer type	-
Traffic flow	Standard traffic flow per hour along each road segment	Integer type	pcu/h
Travel time	Time taken to travel each road segment (i.e., the sum of time traveling on the road and the time of stopping at the intersections)	Floating-point type	min
Travel speed	Average travel speed on each road segment (i.e., length of road segment is divided by travel time)	Floating-point type	m/s
Percentage of cars	Number of cars traveling on each road segment per hour divided by the traffic flow	Floating-point type	-
Saturation	Actual traffic flow on each road segment per hour divided by the traffic capacity	Floating-point type	-

Step 1 (variable selection and preprocessing).

(1) Output Variable. Based on traffic survey, several sets of travel time data for each route are obtained and substituted into (1) to calculate the travel time reliability of each route as the output variable.

(2) Input Variables. The main factors that impact travel time reliability are divided into two types, the characteristics of transportation facilities and the traffic flow state. Herein, the road grade, number of driveways, length of road segments, number of intersections, traffic flow, travel time, travel speed, percentage of cars, and saturation are preliminarily selected as input variables [25], as shown in Table 1. The *SPSS* software is utilized to analyze the correlation between input and output variables and further to determine the factors affecting the travel time reliability of airport shuttle.

(3) Normalization. To eliminate the effects of different dimensions on the prediction result, the variables are normalized in advance using

$$Y = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{15}$$

$$X = X_{\min} + Y\left(X_{\max} - X_{\min}\right), \tag{16}$$

where Y is the as-normalized value, X is original data, $X_{\min}$ is the minimal value, and $X_{\max}$ is the maximum value.

Step 2 (determination of hidden layer nodes). The empirical equation for the preselected typology is $N = \sqrt{n+m} + a$. The S-type tan sig function is selected as the transfer function as $\tan\operatorname{sig}(x) = 2/(1 + e^{-2x}) - 1$, by which the nonlinear mapping capacity of the neural network can be enhanced. In the above two equations, N is the hidden layer nodes, n and m are the numbers of input and output units, respectively, a is a constant ranging from 1 to 10, and x is a transfer variable.

Step 3 (network training and testing). Four functions are used for the training (*traingdx*, *traingdm*, *traingd*, and *trainlm*) and the optimal network training function is then selected. Error analysis is presented below.

4. Algorithm Design

The genetic algorithm has been widely used in model solving. The research shows that although this algorithm is a kind of method with strong global search ability and weak local search ability, it can reach 90% of the optimal solution with extremely fast speed. However, it takes a long time to get the real optimal solution, and the precision is not high in solving small-scale optimization problems. Therefore, this paper attempts to incorporate the hill-climbing algorithm with strong local search ability into the genetic algorithm. The difference with the traditional algorithm lies in the initial stage of operation. First, the initial random station is determined, and each station uses a local hill-climbing search method to determine an initial route. If there are too many passengers in the station that is searched by previous route and it cannot deliver them all at one time, then the station is set as a new one to participate in the remaining route station search. The initial solution is thus determined to prevent the search process from falling into the local optima. Then, the chromosome coding method of the genetic algorithm is used for cross mutation after the fitness function is determined, and the optimal solution is obtained through multiple iterations of the computer. The detailed calculation procedure is as follows.

Step 4 (individual encoding). The airport bus stations are directly encoded by numbers. If there are 8 stations and 2 routes, the airport is encoded as 1, the initial and terminal stations as 2 and 3, respectively, and other stations as 4-9. For example, the two routes are encoded as 2-4-7-9-1 and 3-4-5-6-8-1, respectively.

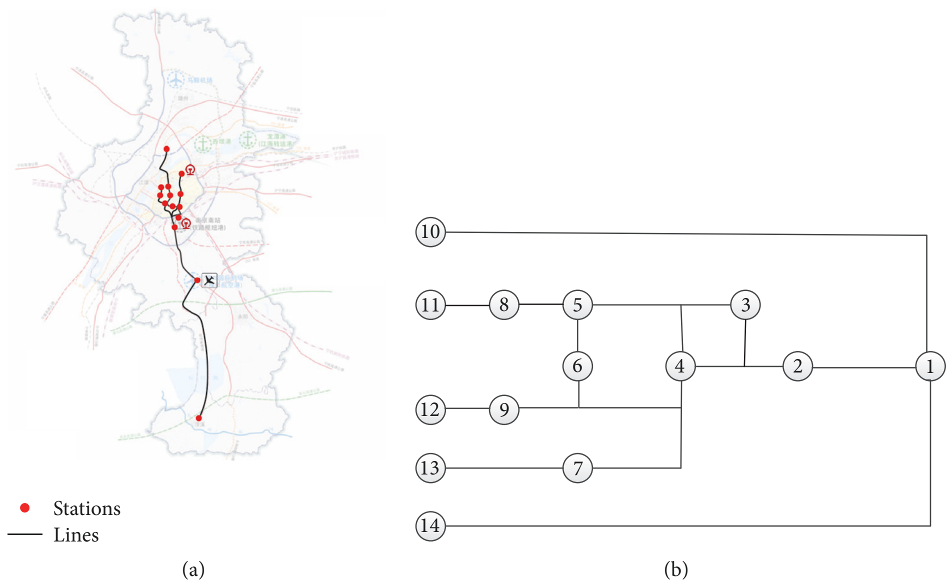


Figure 2: Bus routes distribution and typology network.

Step 5 (generation of the initial population). n initial stations are randomly selected. n initial routes are determined by the hill-climbing search algorithm, and a combination of multiple routes is encoded to form a string. Finally, N chromosomes are generated to form the initial population. The detailed calculation procedure is as follows:

(1) Let $f = f(x_i)$ and $k = 1$. n nonrepeating natural numbers x_i $(i = 1, 2, 3, \ldots, n)$ are randomly generated.

(2) P is the field of x_i. Let x_i be the incumbent solution at present. Then, $x_{\text{best}} = x_i$ such that $p = M(x_{\text{best}})$.

(3) Choose any solution y_i from p. If $f(y_i) > f(x_i)$, then let $f = f(y_i)$ and $x_i = y_i$ and return to Step (2). Otherwise, proceed to Step (4).

(4) Let $k = k + 1$. If $k < 2n$, return to Step (2). Otherwise, proceed to Step (5).

(5) Terminate the algorithm and output the incumbent solution.

$f(x)$ is estimated by the above prediction technique for travel time reliability.

Step 6 (determination of the fitness estimation method). The above constraint conditions of the initial bus route network are calculated. If one constraint condition is not met, the corresponding individuals are eliminated. The objective function value of the remaining chromosomes is Z_i $(i = 1, 2, 3, \ldots, N)$. Thus, the fitness of the individuals is $p = z_i / \sum z_i$.

Step 7 (selection operation). The roulette wheel selection combined with the strategy of keeping the best individuals is adopted. The individuals are arranged in their decreasing order of fitness. The individual ranked first is directly preserved for the next generation to ensure that the optimal individual is not disturbed by genetic operations. The remaining $N - 1$ individuals are chosen by roulette wheel selection according to fitness.

Step 8 (crossover operation). For the new population generated by selection operation, pairing and crossover are performed according to the crossover probability P_c. A break point is randomly selected. The chromosomes on the right of the break point are exchanged by the parental genetic method to generate new offspring.

Step 9 (mutation operation). An individual is randomly selected from the population and a certain gene of the individual is changed according to the mutation probability P_m.

Step 10 (termination criterion). The individual that enables the objective function to reach the minimal value is output as the optimal individual.

5. Case Study

5.1. Data Acquisition and Analysis. The Nanjing Lukou International Airport is studied in this paper and two classes of data are acquired through a traffic survey.

(1) Attributes of Airport Bus Routes. The Nanjing Lukou International Airport currently has 6 bus routes, and the bus routes distribution and topology network are clearly exhibited in Figure 2. The attributes of each route and each station can be obtained from the Administration Department of the Airport Terminal, as shown in Table 2.

(2) Operational Characteristics of Airport Bus Routes. The traffic survey covers 3 aspects: the number of passengers getting on and off the bus, the operational delay of the bus,

Table 2: List of basic attributes of airport bus route.

Route number	Station number	Distance between stations (km)	Planned travel time (min)	Route number	Station number	Distance between two adjacent stations (km)	Planned travel time (min)
I	1	-	-	IV	1	-	-
	2	26	30		3	32	40
	3	7	10		4	7	15
II	1	-	-		7	2	5
	3	32	40		13	3	8
	5	7	15	V	1	-	-
	8	3	8		14	56	60
	11	3	8	VI	1	-	-
III	1	-	-		10	55	60
	3	32	40	-	-	-	-
	6	7	15	-	-	-	-
	9	4	10	-	-	-	-
	12	2	5	-	-	-	-

Note. "Distance between stations" refers to the travel distance between two adjacent stations; "planned travel time" is the planned transit time between two adjacent stations, that is, travel time threshold.

Table 3: Average number of passengers getting on and off the bus at each station.

Station number	Number of passengers getting on and off		Station number	Number of passengers getting on and off		Station number	Number of passengers getting on and off	
1	Upward	45	6	Upward	35	11	Upward	45
	Downward	42		Downward	40		Downward	41
2	Upward	1	7	Upward	6	12	Upward	44
	Downward	4		Downward	3		Downward	35
3	Upward	39	8	Upward	4	13	Upward	32
	Downward	28		Downward	5		Downward	20
4	Upward	11	9	Upward	10	14	Upward	32
	Downward	18		Downward	18		Downward	29
5	Upward	8	10	Upward	33		-	
	Downward	12		Downward	30			

Note. Upward: with airport as the terminal station; downward: with airport as the starting station.

and the operational environment. The data on the following indicators are acquired: the length of road segments, the traffic flow of road segments, the travel time of road segments, the travel speed along the road segments, the passenger numbers in the segments, the number of passengers getting on and off the bus at the stations, and the bus dwell time. The detailed survey scheme is listed as follows:

① Number of passengers getting on and off the bus: the on-vehicle survey method is adopted. One investigator is allocated to each bus and then counts the number of passengers getting on and off the bus at each station and the total number of passengers traveling along the route.

② Operational delay: GPS equipment and a vehicle traveling data recorder are installed on each bus to record the entire operational process, including the travel time along each road segment, the travel speed along the road segment, and the bus dwell time.

③ Operational environment: a field survey is performed with one investigator allocated to each road segment. The grade of the road, the number of driveways, the number of intersections, the traffic flow, and the percentage of cars are recorded.

The survey is performed during a week between December 5 and December 11 in 2016. The peak hour (7:00–8:00) and the nonpeak hour (14:00–15:00) in each day are investigated. The average number of passengers getting on and off the bus at the 14 stations is 392 sets, while the passengers of 13 segments were 338 sets. The statistical results are presented in Tables 3 and 4, respectively. Meanwhile, a total of 364 sets of characteristic data of all segments are acquired, and part of the survey results are exhibited in Table 5.

Table 4: Average number of passengers traveling along each road segment.

Road segment number	Number of passengers	Road segment name	Number of passengers	Road segment name	Number of passengers
1-2	42	3-6	35	4-7	28
2-3	40	6-9	27	7-13	33
3-5	31	9-12	29	1-14	30
5-8	34	3-4	30	1-10	32
8-11	44		-		

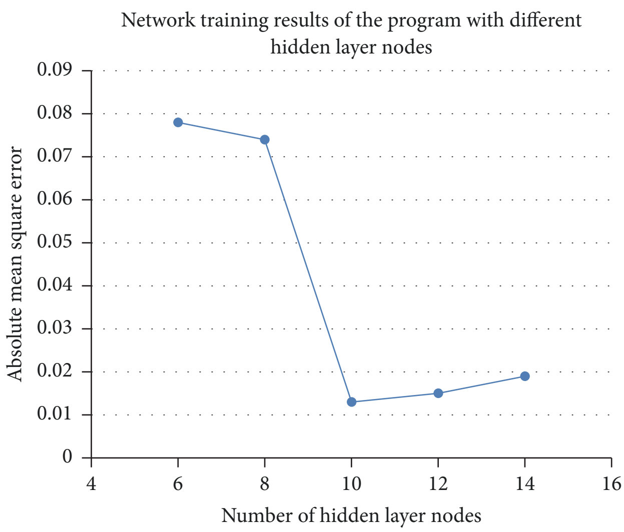


Figure 3: Absolute mean square errors at different node numbers of the hidden layer.

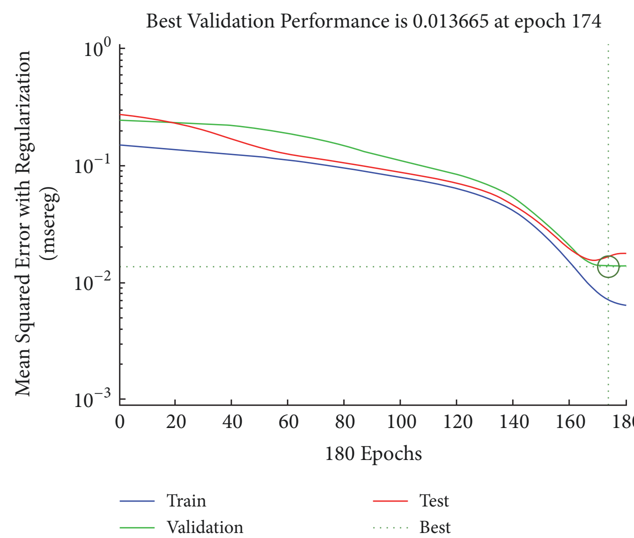


Figure 4: Mean square errors of network training.

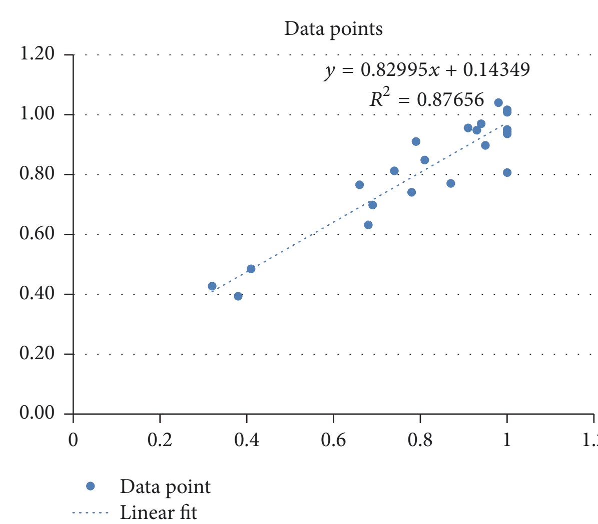


Figure 5: Predicted value versus observed value regression.

5.2. Prediction Result of Reliability. According to the prediction model of reliability in Section 3.1, the input and output variables are first determined, from which the reliability of the output variables of each segment is presented in Table 5. The correlations between the input and output variables are analyzed by SPSS software, with the results shown in Table 6. A correlation coefficient above 0.8 is considered as a strong correlation of the two factors, based on which of the influential factors of travel time reliability, including the road grade, the length of road segments, the traffic flow, the travel speed, the percentage of cars, and the saturation, have been selected. Different hidden layer nodes (6, 8, 10, 12, and 14) are used for the test of the 364 sets of data. According to the training results, the absolute mean square error of the samples is the smallest when the node number is 10. Therefore, the node number of the hidden layers is determined to be 10, as presented in Figure 3.

In the present work, 364 sets of samples are randomly divided into two groups. One that consists of 344 samples is taken as the training sample set, while the other one that consists of 20 samples is taken as the testing sample set. The four training functions of *traingdx*, *traingdm*, *traingd*, and *trainlm* have been employed. The error analysis is presented in Table 7. It can be easily found that the *traingdx* function has a relatively higher prediction accuracy, and the best absolute error of 0.06 is achieved for the tested samples after the 174th epoch of training, as shown in Figure 4. Regression fitting is performed on the predicted and observed values and the result is demonstrated in Figure 5. R^2 is 0.8766, indicating a high accuracy of the model, which is appropriate for the travel time reliability estimation of the airport bus route.

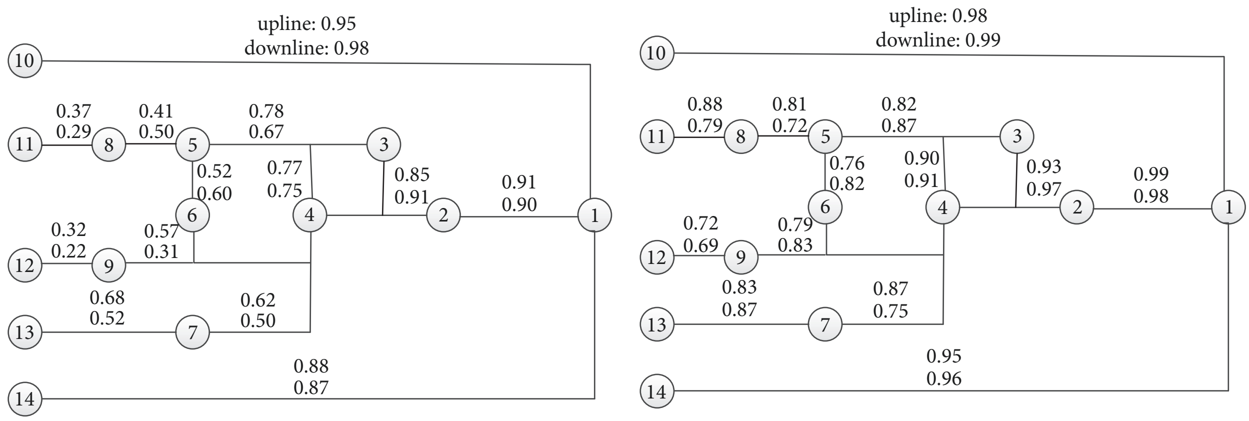
Table 5: List of operational attribute data.

Road segment	Grade of road	Number of driveways	Length of road segment (km)	Traffic flow (pcu/h)	Travel time (min)	Travel speed (km/h)	Percentage of cars	Saturation	Reliability
1-2	1	4	26	857	28	93	0.92	0.33	1.0
1-2	1	4	26	637	29	96	0.85	0.31	1.0
1-2	1	4	26	1102	31	87	0.95	0.36	1.0
…	…	…	…	…	…	…	…	…	…
2-3	3	3	7	1256	18	45	0.84	0.62	0.79
2-3	3	3	7	702	11	61	0.87	0.42	0.98
2-3	3	3	7	905	12	47	0.91	0.57	0.82
…	…	…	…	…	…	…	…	…	…
3-5	2	3	4	2108	12	35	0.71	0.89	0.68
3-5	2	3	4	1135	5	65	0.75	0.52	1.0
3-5	2	3	4	1536	8	52	0.73	0.70	0.81
3-5	…	…	…	…	…	…	…	…	…
5-8	3	1	7	1675	28	22	0.72	0.93	046
5-8	3	1	7	2640	18	19	0.70	0.98	0.32
5-8	3	1	7	1722	25	21	0.73	0.96	0.29
…	…	…	…	…	…	…	…	…	…
8-11	4	3	3	2408	17	25	0.69	0.92	0.41
8-11	4	3	3	2862	14	31	0.68	0.93	0.38
8-11	4	3	3	2911	19	22	0.71	0.95	0.33
…	…	…	…	…	…	…	…	…	…
3-6	2	4	32	1022	42	65	0.90	0.44	0.91
3-6	2	4	32	859	37	71	0.86	0.41	0.88
3-6	2	4	32	773	36	73	0.86	0.41	0.87
…	…	…	…	…	…	…	…	…	…
6-9	3	3	7	1435	12	68	0.73	0.62	1.0
6-9	3	3	7	1662	13	61	0.69	0.63	0.9
6-9	3	3	7	870	7	75	0.71	0.35	1.0
…	…	…	…	…	…	…	…	…	…
9-12	3	3	2	1304	6	20	0.77	0.83	0.65
9-12	3	3	2	1892	8	16	0.74	0.89	0.59
9-12	3	3	2	1911	8	15	0.77	0.90	0.55
…	…	…	…	…	…	…	…	…	…
3-4	2	3	7	1231	12	28	0.72	0.88	0.81
3-4	2	3	7	1645	15	27	0.73	0.85	0.78
3-4	2	3	7	1857	21	37	0.80	0.90	0.69
…	…	…	…	…	…	…	…	…	…
4-7	4	3	2	984	5	38	0.72	0.71	0.94
4-7	4	3	2	1175	5	46	0.80	0.71	1.0
4-7	4	3	2	1576	8	27	0.76	0.92	0.72
…	…	…	…	…	…	…	…	…	…
7-13	2	2	3	1385	9	38	0.79	0.73	1.0
7-13	2	2	3	1435	9	37	0.73	0.62	1.0
7-13	2	2	3	992	6	44	0.74	0.51	1.0
…	…	…	…	…	…	…	…	…	…
1-14	2	3	56	1744	64	62	0.82	0.77	0.87
1-14	2	3	56	650	52	75	0.81	0.46	1.0
1-14	2	3	56	1674	61	60	0.80	0.80	0.91

Table 5: Continued.

Road segment	Grade of road	Number of driveways	Length of road segment (km)	Traffic flow (pcu/h)	Travel time (min)	Travel speed (km/h)	Percentage of cars	Saturation	Reliability
...	...	...	...	...	...	...	...	...	...
1-10	2	3	55	963	52	68	0.90	0.53	0.93
1-10	2	3	55	1336	61	57	0.85	0.71	0.87
1-10	2	3	55	820	48	66	0.88	0.50	0.95
...	...	...	...	...	...	...	...	...	...

Note. "Reliability" is calculated by substituting the survey data into (1). Only three sets of survey data in each segment are listed in consideration of limited space.



(a) Peak hour

(b) Nonpeak hour

Figure 6: Travel time reliability for each road segment of each route.

Table 6: Correlation coefficients between input and output variables.

Input variables	Correlation coefficient
Road grade	0.982
Number of driveways	0.591
Length of road segment	0.808
Number of intersections	0.755
Traffic flow	0.896
Travel time	0.629
Travel speed	0.903
Percentage of cars	0.881
Saturation	0.923

The parameters obtained by the traffic survey are substituted into the above prediction model. The travel time reliability for each road segment is then obtained and clearly distributed in Figure 6 and Table 8. According to (4), the travel time reliability of the airport bus route is 0.57 in the peak hour and 0.88 in the nonpeak hour. The average travel time reliability of each road segment is only approximately 0.6 in the peak hour, which means that 40% of the passengers cannot arrive at the airport within the time threshold. The travel time reliability in the peak hour is 26.4% lower than that of the nonpeak hour. Meanwhile, the value in the downtown area is obviously lower than that of the suburban area. Approximately 80% of the road segments in the downtown area have a travel time reliability lower than 0.68, and this percentage is approximately 25% lower than that of the suburban area. The travel time reliability also varies with the travel direction of bus, even along the same road segment. The travel time reliability along the downward direction in the downtown area is much lower due to the cars that enter into city during the peak hour, and the value is 10% lower than that of the upward direction. It is thus deemed that the travel time reliability of the airport bus is greatly affected by traffic conditions in peak hours and the airport bus routes should be optimized to improve the reliability of the access to airport.

5.3. Optimization Result of Routes. According to the current distribution of the bus stations and roads of the Nanjing Lukou International Airport, the existing bus route network is optimized and the one established for the algorithm testing is shown in Figure 7. The network has 14 stations and 18 routes. The data of the grade, length, peak hour traffic flow, travel speed, percentage of cars, and saturation for each road segment are shown in Tables 1 and 5. The average values of other roads of the same grade are adopted for the road segments not surveyed. Thus, 6 routes are included for optimization with 2-6 stations on each route (including the airport station). The maximum operating time of the route is 90 min, and each station is covered by 3 routes at the most. The profitability of the airport bus is 25%, the ticket price is 25

Table 7: Error analysis for different training functions.

Node number of hidden layers	$m = 6$		$m = 8$		$m = 10$		$m = 12$		$m = 14$	
Error analysis	Absolute error	Relative error%	Absolute error	Relative error%	Absolute error	Relative error%	Absolute error	Relative error%	Absolute error	Relative error%
traingdx	0.12	0.15	0.13	0.16	0.06	0.07	0.06	0.07	0.06	0.07
traingdm	0.25	0.31	0.10	0.12	0.23	0.29	0.27	0.33	0.18	0.22
traingd	0.10	0.12	0.18	0.22	0.17	0.20	0.32	0.39	0.12	0.15
trainglm	0.23	0.28	0.15	0.19	0.14	0.18	0.02	0.03	0.19	0.23

Table 8: Result of travel time reliability for each road segment.

Time period	Direction	Maximum	Minimum	Squared error	Mean squared error	Mean	Difference (%)	
Travel time reliability in peak hour	Upward	0.95	0.37	0.045	0.213	0.68	10.2	26.4
	Downward	0.99	0.22	0.064	0.254	0.61		
Travel time reliability in nonpeak hour	Upward	0.99	0.72	0.007	0.102	0.86	0	
	Downward	0.99	0.72	0.084	0.101	0.86		

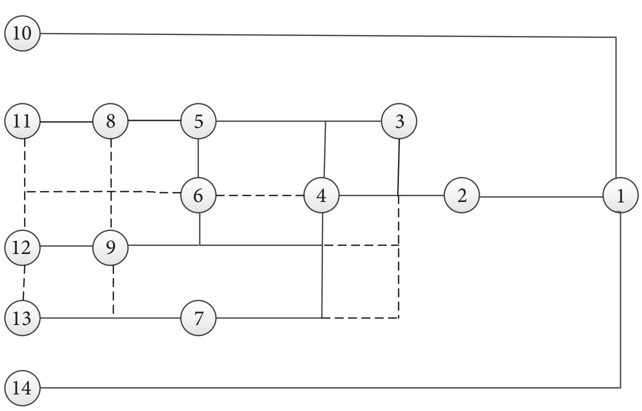


Figure 7: Typology of optimized airport bus route network.

yuan per person, and operating costs are 8 yuan per kilometer. The above information can be expressed as follows:

$M = (1, 2, 3, 4, 5, 6)$, $N = (1, 2, 3, \ldots, 14)$, $T = 90$ min, $A_{\min} = 2$, $A_{\max} = 6$, $\varepsilon = 25\%$, $d = 3$, $S = 8$, and $C = 25$.

Using MATLAB software, the simulation calculation is performed iteratively with the proposed genetic algorithm at different mutation rates and crossover rates. The results show that the instability of optimizing increases at a lower crossover rate (Figure 8(a)) and a higher mutation rate (Figure 8(b)). Therefore, after calculating the crossover rate and mutation rate, the crossover rate of 0.9 and the mutation rate of 0.05 are determined as the test results according to the stability and convergence of the calculation results, as shown in Figure 8(c). The optimization results of the bus route are given in Table 9. The objective function value of the model is 0.79, thus indicating that the travel time reliability is 0.79 in the peak hour after optimization. This is an 11.5% increase compared with that before optimization, thus demonstrating a remarkable optimization effect.

6. Conclusions and Discussions

First, the influential factors of the travel time reliability of airport bus routes are analyzed and the prediction model of travel time reliability is thereafter built based on the BP neural network. The model established for Nanjing Lukou International Airport is verified to have high accuracy. It is found that the travel time reliability in the peak hour is greatly affected by the road conditions. Its value is only 0.62, which means that 40% of the passengers cannot arrive at the airport within the time threshold. The travel time reliability of the urban road segments is generally below 0.68 in the peak hour, which is 25% lower than that of suburban road segments. The proposed method is believed to provide a theoretical basis for the optimization of airport bus routes.

Second, the optimization model of the airport shuttle bus route is determined by taking reliability maximization as the goal and synthetically considering the constraint conditions including time, station, and service. After this, the hill-climbing algorithm is utilized to acquire the initial solution of the route, the fitness function is established in terms of reliability, and the hybrid genetic algorithm is designed using different mutation rates and crossover rates. The results show that instability of optimizing increases at lower crossover rates and higher mutation rates. The objective function value is determined to be 0.79 under a crossover rate of 0.9 and a mutation rate of 0.05, which is accompanied by an 11.5% increase in reliability when compared with that before optimization. This demonstrates a prominent optimization effect.

The proposed method is of certain theoretical significance and can be applied to airport bus route optimization. Moreover, it provides a new approach for the improvement of travel time reliability and airport bus service efficiency. An in-depth investigation on the algorithm of the optimization model of airport bus routes shall be involved in further work. The focus will be placed on the determination of the initial

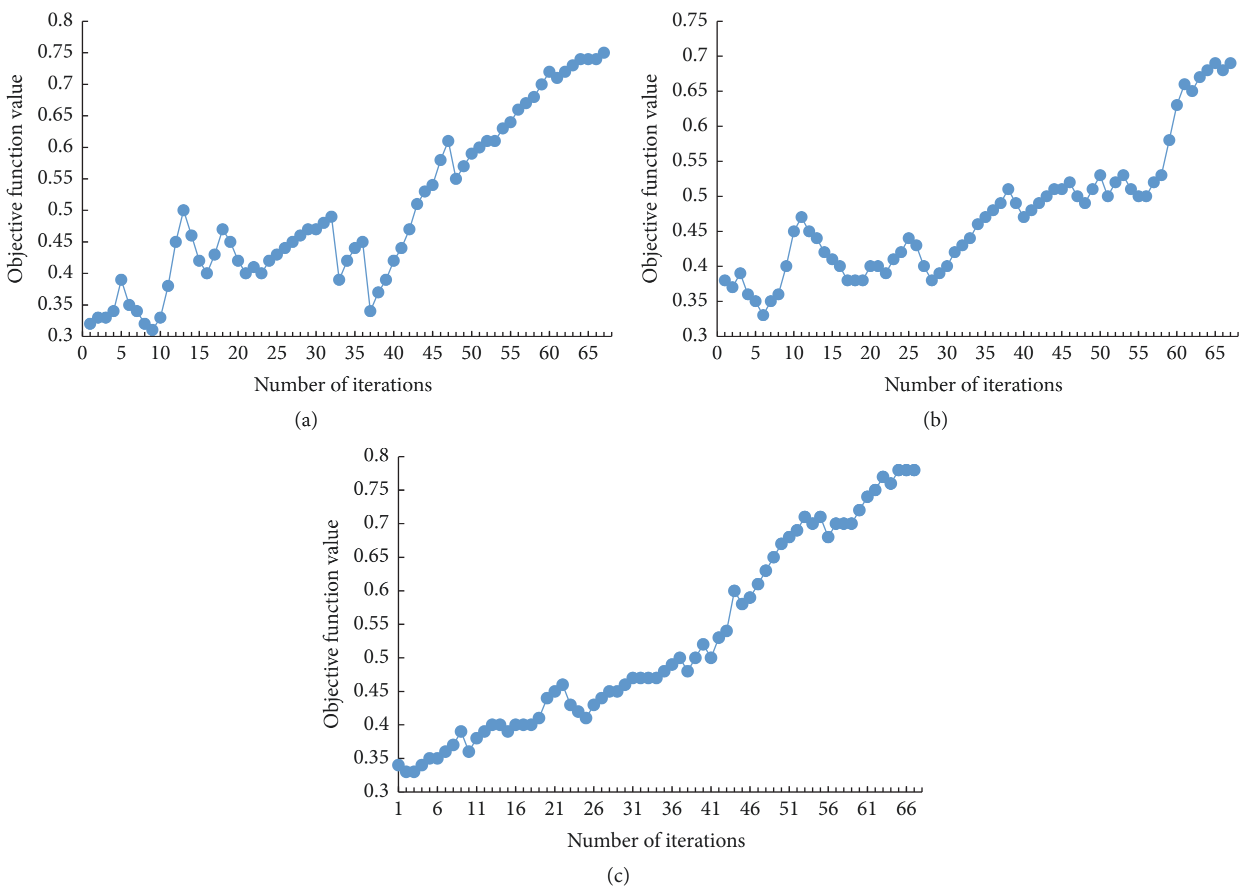


Figure 8: Testing result of the algorithm: (a) $P_c = 0.85$, $P_m = 0.05$; (b) $P_c = 0.90$, $P_m = 0.1$; (c) $P_c = 0.90$, $P_m = 0.05$.

Table 9: Results of bus route optimization.

Route	Optimized route	Terminal station	Objective function value
1	1-3-8-11	11	0.86
2	1-2-4-6	6	0.74
3	1-3-5-6-9	9	0.69
4	1-2-9-12-13	12	0.70
5	1-3-4-7	7	0.75
6	1-14	14	0.92

population of routes and the optimization process with the goal of improving the accuracy of the established model.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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