Research Article

Prediction of Departure Flights’ Taxi-Out Time Based on Intelligent Algorithm Optimized BP

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Received 1 November 2021; Accepted 1 February 2022; Published 15 March 2022

Academic Editor: Rohit Salgotra

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Taxi-out time is the main performance index to evaluate the operational efficiency of major airports. Scientifically and accurately predicting the taxi-out time of departure flights is very important to improve the operational efficiency and coordination decision-making ability of airport. Firstly, the quantifiable influence factors of taxi-out time and their correlation is analyzed, including the number of departure flights, the number of arrival flights, the number of flights pushed back in the same period, the taxi-out time by half-hour in average, the taxi distance, and the number of turns, etc. And then a prediction model of departure flights’ taxi-out time based on BP is constructed. Because the traditional BP neural network is sensitive to the initial weight and threshold and has poor accuracy and stability, the taxi-out time prediction model of BP neural network optimized by intelligent algorithm is proposed. Genetic algorithm (GA) and sparrow search algorithm (SSA) are used to obtain the optimal weight and threshold of BP neural network, which is verified by the actual operation data of a major airport in central and southern China for two weeks. The results show that (1) the taxi-out time is strongly correlated with the airport surface traffic flow, moderately correlated with the average taxi-out time, and weakly correlated with the taxi distance and the number of turns. (2) The predicted outcome of the 4-element combination prediction model which considers strong correlation and medium correlation factors is the best. After adding weak correlation factors, the prediction accuracy is reduced. (3) By obtaining the local optimal weight and threshold of neural network, intelligent optimization algorithm can effectively improve the accuracy of departure flights’ taxi-out time prediction results. (4) The prediction result of BP neural network optimized based on GA is 1.79% higher than that of MAPE before optimization, MAE is reduced by 7.4 s, and RMSE is reduced by 6.93 s. The prediction result of BP neural network optimized based on SSA is 3.05% higher than that of MAPE before optimization, MAE is reduced by 16.55 s, and RMSE is reduced by 14.31 s. Therefore, Sparrow search algorithm has better optimization effect on the model than genetic algorithm.

1. Introduction

1.1. Motivation. Taxi-out time refers to the time interval between the departure flight pushing back from the stand and taxiing to the actual takeoff. With the continuous expansion of the airport and the structure, the operation modes of the runway and taxiway system are becoming more and more complex. The average taxi time at the large airports has exceeded 25 minutes; the probability of crossing and convergence, head-to-head encounters, and other unsafe events in the taxiing process is also increasing year by year, which seriously affects the safety and efficiency of airport surface operation, leading to the uncertainty and variability of the departure flights’ taxi-out time on the ground. And long taxi-out time of departure flights will lead to significant airport surface congestion, fuel burn costs, and excessive emissions of greenhouse gases. At present, most air traffic controllers calculate the taxi-out time by experience to control the process of pushback, startup, and taxi. Under the common influence of many factors such as surface traffic flow, taxi distance, and surface operational mode, the actual taxi-out time of departure flights at large airports is far from the predicted time, which directly leads to the low efficiency of airport surface operation and unnecessary congestion and
fuel consumption. Therefore, scientific and accurate prediction of the taxi-out time of departure flights is very important for improving the surface operational efficiency.

The prediction methods for taxi-out time can be roughly divided into three categories: (1) The prediction method based on queuing theory [1]: In this method, the taxi-out time is divided into two parts: barrier-free taxi-out time and the time to wait for takeoff. The barrier-free taxi-out time refers to the time required for the aircraft to taxi from the stand to the end of the runway under the ideal circumstances without congestion and bad weather, which has typical linear characteristics, while the time to wait for takeoff refers to the time from joining in the departure queue to the actual takeoff, which has typical nonlinear characteristics. The precision of the predicted results with queuing theory is about 75%. (2) The prediction method based on fast simulation [2]: This method is based on the mature simulation platforms such as Simmod and Airtop to make models about the surface operation process of departure flights. It has the disadvantages of high cost and long time to adjust the simulation model. (3) The prediction method based on the historical data mining: This method mainly uses the algorithms such as multiple linear regression [2], Bayesian network [3], support vector machine [4, 5], reinforcement learning [6–8], and deep learning [9]. At present, the highest accuracy of all the existing research prediction results is about 85%.

Because the traditional BP neural network is sensitive to the initial weight and threshold and has poor accuracy and stability, a taxi-out time prediction model based on intelligent algorithm is proposed. Genetic algorithm (GA) and sparrow search algorithm (SSA) are used to obtain the optimal weight and threshold of BP neural network, which is verified by the actual operation data of a major airport in central and southern China for two weeks. The research objective is to verify which intelligent optimization algorithm is more effective for the optimization of BP neural network.

1.2. Literature Review. Foreign research on the prediction of departure time began in the early 21st century. Balakrishna applied reinforcement learning algorithms for predicting aircraft taxi-out times [6]. George proposed an improved Q-learning approach for taxi-out time prediction [7]. Mayara employed a robust optimization approach for airport departure metering under uncertain taxi-out time predictions [8]. Diana compared the taxi time prediction model with integrated machine learning, ordinary least squares, and regular term algorithm in Seattle airport [9]. Herrema et al. predicted the key related factors for taxi-out time with neural network, regression tree, and reinforcement method [10]. Nan et al. proposed a spatial temporal environment deep learning model that overcomes the drawbacks of the existing machine learning methods [11, 12]. Guan et al. used least squares regression and queuing theory algorithms to calculate the taxi-out time [13, 14]. Shumsky took the traffic flow of aircraft and the number of departing flights as the main influencing factors, respectively used static and dynamic linear models to predict taxi-out time, and verified the conclusion that the prediction effect of dynamic linear model was better [1]. Idris et al. predicted taxi-out time in the case of traffic restriction by means of departure auxiliary tools based on the analysis of influencing factors of the aviation service quality performance data (ASQP) of Boston airport [2, 3]. Idris et al. constructed a multiple linear regression prediction model based on the takeoff queue length, runway, aircraft type, and other factors, wherein the length of the takeoff queue refers to the number of takeoff flights in the taxing process, which is then transformed into the prediction of flight departure time by predicting the length of the takeoff queue [4]. Simaiakis and Pyrgiotis used the independently developed queuing system to predict traffic congestion, and the prediction accuracy was very significant [5]. Elizabeth and Khan dynamically predicted the glide time of departing aircraft based on historical data of aircraft and proposed Q-learning method based on reinforcement learning, with high prediction accuracy [7]. Lee et al. used machine learning algorithm to predict the taxi time, and the prediction effect was good [15]. Herrema et al. predicted taxi-out time of single runway scene based on historical data [10].

Domestic research on the prediction of departure flights’ taxi-out time is still in its infancy and only a few of scholars have done some research on the prediction of taxi-out time at single runway airport. Zhao and Tang have made a quantitative analysis of airport operation efficiency indicators including the number of takeoff queues and the number of aircraft entering ports and established a multiple linear regression model to predict the barrier-free taxi-out time [16]. Yang et al. analyzed the influencing factors of taxi-out time by establishing a traffic flow transmission model based on cellular transmission machine theory and deduced the influencing mechanism of these characteristic factors [17]. lv analyzed the taxiing state of aircraft scene based on monitoring data and predicted taxi-out time with multiple linear regression method [18]. Meng established a taxi-out time prediction model based on queuing theory for airport collaborative decision system and used static and real-time methods to predict taxi-out time, respectively [19]. Xia and Meng divided the flight departure process into two stages of barrier-free taxiing to the runway end and queuing for takeoff at the runway end according to the problem attribute of flight departure process and taxi-out time prediction. The influence of inbound and outbound flights on taxiway time is analyzed, and a measuring index of scene traffic condition and a calculating model of barrier-free taxiway time based on this index are proposed [20]. Xia and Meng established a high-precision taxi-out time prediction model of departing aircraft for large hub airports based on k-nearest neighbor and support vector machine [21]. Li established a ground taxing simulation model for inbound and outbound flights and used adaptive ant colony algorithm to design a taxing routing algorithm for flights to predict and evaluate taxi-out time [22]. Xing et al. used the incremental learning characteristics of Bayesian networks to dynamically adjust the prediction model, so that the model could dynamically estimate the taxi-out time of departing aircraft [23]. Liu et al.
proposed a prediction model of departure taxi-out time based on SVR and BP neural network and applied the prediction results to the A-CDM system, which effectively improved the operation efficiency of airport scenes [24]. Nan et al. used cluster analysis algorithm to classify airport operation periods according to hourly flight flow. A multivariate regression model was established according to the classification results, and traditional statistics and machine learning (Lasso regression) were used to predict the departure flights’ taxi-out time [12]. Chen et al. proposed a method to improve the prediction model of taxi-out time from the perspective of feature selection in order to improve the accuracy of taxi-out time prediction [25]. Liu et al. proposed the autoregressive integrated moving average and support vector regression combined model for departure flight taxi-out time prediction [26]. Huang and Xia proposed the prediction model of departure flights’ taxi-out time based on backpropagation (BP) [27].

In summary, the existing research results have analyzed the main influencing factors of departure flights’ taxi-out time, including the length of departure queue, taxi distance, the number of departure and arrival flights in the same period, runway operation mode, and adverse weather conditions such as low visibility. Although machine learning algorithm has been widely used in the prediction of departure flight taxi-out time, the best reported accuracy of the predicted results is about 85%. Meanwhile, the existing researches are not considering the characteristics of multirunway traffic flow and the influence of airport surface operation mode, and the correlation of influencing factors was not analyzed. Moreover, due to the different structure and traffic flow characteristics of the runway and taxiway systems, the foreign existing research results cannot be directly applied to the prediction of departure flights’ taxi-out time of domestic large hub airports. Therefore, it is urgent to establish a more accurate and stable prediction model of departure flights’ taxi-out time, so as to improve airport surface operation efficiency and reduce fuel consumption and emissions.

1.3. Contribution. Our contributions in this study are as follows: (1) The correlation of quantifiable influencing factors of departure flights’ taxi-out time is analyzed. Taxi-out time is strongly correlated with the airport surface traffic flow, moderately correlated with the average taxi-out time, and weakly correlated with the taxi distance and the number of turns. (2) Taxi-out time prediction model of BP neural network optimized by intelligent algorithm is proposed in this paper; genetic algorithm (GA) and sparrow search algorithm (SSA) are used to obtain the optimal weight and threshold of BP neural network. By obtaining the local optimal weight and threshold of neural network, intelligent optimization algorithm can effectively improve the accuracy of departure flights’ taxi-out time prediction results. (3) The predicted outcome of the 4-element combination prediction model which considers strong correlation and medium correlation factors is the best. After adding weak correlation factors, the prediction accuracy is reduced. (4) By comparing the optimization degree of BP neural network prediction results between genetic algorithm and sparrow search algorithm, it can be seen that sparrow search algorithm has better performance.

2. Materials and Methods

2.1. Factors for Departure Flights’ Taxi-Out Time. The control process of departure flights in large hub airports is as follows: Firstly, the delivery issues ATC (air traffic control) clearance to the departure flights according to the expected departure time, and then the ground controller issues the clearance for pushback and startup, records the actual off-block time (AOBT), and gives the taxi route to the departure flights to the holding point of runway. If there is taxi conflict during taxiing, the conflict should be cleared at first. Finally, the tower controller issues the clearance to enter onto the runway and to take off and records the actual takeoff time (ATOT). Therefore, the taxi-out time (TOT) of the departure flights is equal to the difference between the actual departure time and the actual off-block time [11, 28].

\[ TOT = ATOT - AOBT. \]  

Through literature review, it can be seen that there are many factors affecting the taxi-out time of departure flights. Affected by the airport surface traffic flow, flights will compete for runway and taxiway resources, which will inevitably lead to the waiting of a flight, resulting in a large deviation between its taxi-out time and its barrier-free taxi-out time. At the same time, the taxi-out time is also affected by flow control, bad weather, airlines, controllers, passengers, number of turns, and other factors, but these factors are not quantifiable or small, so they will not be considered in this paper. Therefore, the main quantifiable factors of departure flight taxi-out time include the number of departure flights launched in the same period, the number of takeoff flights taxiing in the same period, the number of landing flights taxiing in the same period, taxi distance, and the number of turns. Considering that the airport ground traffic flow has obvious hourly variation characteristics, the half-hour average taxi-out time was introduced in this paper innovatively to reflect the busy degree of the scene.

2.2. Definitions

(1) The number of departing flights taxiing at the same time is \( x_1 \), unit sorties [11]. It indicates the number of all departing flights whose actual departure time \((t_{ATOT}(j))\) of flight \( j \) just falls between the actual departure time \((t_{AOBT}(i))\) and the actual departure time \((t_{ATOT}(i))\) of flight \( i \).

\[ x_{1j} = \sum_{j=1}^{n} \text{num}(j), \ t_{AOBT}(i) < t_{ATOT}(j) \]

(2) The number of inbound flights taxiing at the same time is \( x_2 \), unit sorties [11]. It indicates the number of all departing flights whose actual landing time \((t_{ALDT}(j))\) of flight \( j \) just falls between the actual
departure time \(t_{\text{AOBT}(i)}\) and the actual departure time \(t_{\text{ATOT}(i)}\) of flight \(i\).

\[
x_{2,i} = \sum_{j=1}^{n} \text{num}(j), \quad t_{\text{AOBT}(i)} < t_{\text{ALDT}(j)} < t_{\text{ATOT}(i)}.
\]  

(3) The number of departing flights launched in the same period is \(x_3\), unit sorties \([11]\). It indicates the number of all departing flights whose actual launch departure time \(t_{\text{AOBT}(i)}\) of flight \(i\) just falls between the actual launch departure time \(t_{\text{TOBT}(j)}\) and the actual departure time \(t_{\text{ATOT}(j)}\) of flight \(j\).

\[
x_{3,i} = \sum_{j=1}^{n} \text{num}(j), \quad t_{\text{TOBT}(j)} < t_{\text{AOBT}(i)} < t_{\text{ATOT}(j)}.
\]  

(4) The average taxi-out time is \(x_4\) in half an hour, in seconds (s). Since the average taxi-out time at this airport is about 16 minutes, the average taxi-out time by half an hour will become an important variable to explain the departure flights’ taxi-out time.

\[
x_{4,i} = \frac{1}{n} \sum_{i=1}^{n} t_{\text{TOBT}(i)}
\]  

where \(t_{\text{TOBT}(i)}\) represents the taxi-out time of departing flight \(i\), and \(n\) represents the number of departing flights in half an hour.

(5) Taxi distance of departure flight is \(x_5\), unit: meters. If the parking bays of the departure flights are different, the taxi distance will be different, and the length of taxi-out time will be different too.

\[
x_{5,i} = \frac{d_{ai}}{d_b} \times 3600.
\]  

\(d_{ai}\) represents the length of taxiing path for flight \(i\), \(d_b\) represents the measured length of runway, and 3600 represents the runway length in meters.

(6) Number of turns is \(x_6\). There is a great difference between the straight-line taxiing speed and the turning taxiing speed of the aircraft. Therefore, if the departing aircraft experiences more turns in the process of taxiing out, its taxi-out time will increase.

2.3. Correlation Analysis. The data used in this paper comes from the actual operation data of a hub airport in Central South China from May 26 to June 8, 2019. The data set has 12323 records, including 5747 departure flights and 6576 inbound flights. Each record consists of key information such as aircraft call sign, aircraft type, actual takeoff time, actual gear removal time, actual landing time, runway number, parking position, etc. By sorting out the data, delete the duplicate and abnormal data, and obtain the number of departure flights taxiing at the same time, the number of inbound flights taxiing at the same time, the number of departure flights launched at the same time, the half-hour average taxi-out time, taxi distance, the number of turns, and the actual taxi-out time according to formulas (2)–(6). Through the correlation analysis of the sample data, Figure 1 can be obtained.

Figure 1(a) analyzes the correlation between the taxi-out time of departure flights and the number of departure flights taxiing at the same time. The correlation coefficient is \(r = 0.7084\), indicating that the number of departure flights taxiing at the same time is strongly correlated with the variable taxi-out time \((r > 0.6)\). Figures 1(b) and 1(c), respectively, show the departure flight taxi-out time and the number of all landing flights taxiing at the same time and the number of departure flights launched at the same time. The correlation coefficients are \(r = 0.6595\) and \(r = 0.6122\), respectively, indicating that the above two factors are strongly correlated with the taxi-out time. Figure 1(d) shows the correlation between the average sliding time and sliding time in half an hour, with a correlation coefficient \(r = 0.5842\), indicating a moderate correlation \(0.3 < R < 0.6\). Figure 1(e) shows the correlation between taxi distance and taxi-out time, \(r = 0.1852\), indicating that the correlation between them is weak \((r < 0.3)\). Figure 1(f) shows the correlation between the number of turns and the taxi-out time, \(r = 0.052\), indicating that the correlation between the two is weak \((r < 0.3)\). According to the correlation analysis, there is a strong correlation between the taxi-out time and the airport surface traffic flow, because inbound and outbound flights will compete for runway and taxiway resources.

2.4. Taxi-Out Time Prediction Model Based on BP. BP neural network is the most widely used neural network structure at present. It has the ability of arbitrary complex pattern classification and multidimensional function mapping. It is widely used in pattern recognition, classification, prediction, and other fields. In order to further analyze and discuss the impact of different correlation factors on the taxi-out time, this paper constructs a departure flight taxi-out time prediction model based on the correlation analysis results. According to the results, the factors \(x_1\), \(x_2\), and \(x_3\) are strongly correlated with the taxi-out time, \(x_4\) is moderately correlated with the taxi-out time, and \(x_5\) and \(x_6\) are weakly correlated with the taxi-out time. So, the inputs of the model are divided into three cases, as shown in Table 1.

Among them, the 3-element combination prediction model only considers the influence of strongly related factors on the taxi-out time; the 4-element combination prediction model only considers the influencing factors of strong correlation and medium correlation; the 6-element combination prediction model will comprehensively consider all quantifiable factors. The number of hidden layer nodes can determine an initial value according to the number of nodes in the input layer and output layer and then gradually increase on the basis of this value. Compare the prediction performance of each network, and select the corresponding number of nodes with the best performance as the number of hidden layer neuron nodes. As a result, the hidden layer of BP neural network adopts 10 neurons, and the output is the prediction result of taxi-out time. Then, the departure flight
A taxi-out time prediction model based on BP neural network is constructed, as shown in Figure 2.

### 2.5. Taxi-Out Time Prediction Model Based on GA-BP

Genetic algorithm (GA) is a parallel random search optimization method simulating the law of biological evolution. It is widely used in the fields of function optimization, automatic control, data mining, and so on. The characteristic of genetic algorithm is that it takes the value of objective function as search information and has the characteristics of population search. Based on probability rules, the search of the algorithm is more flexible, and the parameters have little influence on the search effect.

In view of the shortcomings of traditional BP neural network, such as sensitivity to initial weight and threshold, poor accuracy, and stability, in the prediction of departure flights’ taxi-out time, the fitness of future generations is continuously updated by using the selection, crossover, and mutation operations of legacy algorithm, and then the optimal weight and threshold parameters of BP neural network are obtained by decoding, and then training and simulation prediction are carried out. The algorithm flowchart is shown in Figure 3 as follows.

Firstly, the sample data is read from Excel, the input and output of the network are determined, the training set and test set are divided, and the data are normalized. Then the topology of the network and the individual coding length of GA algorithm are determined. The weights, thresholds, population size, maximum number of iterations, crossover probability, mutation probability, and other parameters of the network are randomly initialized. Each individual is selected through the fitness function, and the individuals with high fitness are retained for crossover and mutation operations, so as to obtain a new generation of population. Finally, the position information of the best individual is assigned to the weights and thresholds of BP neural network. The BP neural network optimized by GA is trained and simulated.

### 2.6. Taxi-Out Time Prediction Model Based on SSA-BP

Sparrow search algorithm is a population optimization algorithm based on sparrow foraging behavior and anti-predation behavior. The basic principles of sparrow algorithm are as follows: (1) the discoverer usually has a high energy reserve and is responsible for searching the area with rich food and providing the foraging area and direction for the participants. (2) Once the sparrow finds the predator, it
sends out a call as an alarm signal. When the alarm value is greater than the safety value, the discoverer will take the participants to other safety areas for feeding. (3) The identities of discoverers and accessors change dynamically, but their proportion in the population remains unchanged. (4) The lower the energy, the worse the foraging position. (5) In the process of foraging, participants can always find the discoverer who provides the best food and forage around him. (6) When aware of the danger, the sparrows at the edge of the group will quickly move to the safe area to get a better position, and the sparrows in the middle of the group will walk randomly to get close to other sparrows.

In view of the shortcomings of traditional BP neural network, such as sensitivity to initial weight and threshold,
poor accuracy, and stability, when predicting departure flight taxi-out time, the population fitness and optimal position are continuously updated by using the foraging and antipredation behavior of sparrow search algorithm, so as to obtain the optimal weight and threshold parameters of BP neural network and then carry out training and simulation prediction. The algorithm flowchart is shown in Figure 4 as follows.

Firstly, the overall mean square error of the training set and the test set is selected as the fitness. The smaller the fitness function, the more accurate the training, and the better the prediction accuracy of the model. Reading the sample data from Excel, determine the input and output of the network, divide the training set and test set, and normalize the data. Then determine the topology of the network, randomly initialize the weight and threshold of the network, sparrow population size, maximum iteration times, and the proportion of predators and discoverers, take the minimum mean square error as the optimal fitness, assign the optimized sparrow position information to BP as the weight and threshold, and train and simulate the SSA optimized BP neural network.

3. Results and Discussion

3.1. Data Sources and Data Preparations. The research object of this paper is a hub airport in central and southern China, and its running and taxiing system structure is shown in Figure 5. East runway is 3400 × 45 m, west runway 3800 × 60 m, the distance between the east and west runways is about 1590 m, and the isolated operation mode or relevant parallel approach mode can be selected according to the traffic flow. The data used in this paper comes from the actual operation data of the airport from May 26 to June 8, 2019. There are 12323 records in the data set. Each record is composed of key information such as aircraft call sign, aircraft type, actual departure time, actual gear removal time, actual landing time, runway number, parking space, and so on. Then, we can process the raw data based on the following steps:

1. Delete duplicate records in the data set. All data is divided into departures and arrivals according to the runway number. The departures and arrivals are sorted in ascending order by departure and landing time, respectively. Because either the isolated operation mode or the related approach mode is adopted, it is impossible to have more than two flights taking off or landing at the same time. Therefore, only one record with the same takeoff time or landing time is reserved and the remaining data is deleted as abnormal data.

2. Delete the abnormal data without key information such as actual takeoff time, actual off-block time, actual landing time, or runway number in the data set.

3. Delete the data with abnormal variable taxi-out time in the data set. According to the data analysis, 92.5% of the flights in the data set take off and land on runway 15/16 and only 7.5% of the flights take off and land on runway 33/34 due to the sudden change in wind direction and wind speed. The change of runway often leads to the serious deviation of single departure flight’s taxi-out time from the average value, which should be regarded as abnormal data.

4. The sorted data set includes 5428 departure flights using runway 15 and 6576 arrival flights using runway 15 and runway 16. The information contained in the data set is shown in Table 2.

By sorting out the data, delete the duplicate and abnormal data, and obtain the number of departure flights taxiing at the same time, the number of inbound flights taxiing at the same time, the number of departure flights launched at the same time, half-hour average taxi-out time, taxi distance, number of turns, and actual taxi-out time according to formulas (2)–(6). Finally, 5200 sample data are obtained, as shown in Table 3.

3.2. Taxi-Out Time Prediction Results Based on BP. Programming is based on the neural network toolbox in MATLAB, loading all training sample data and normalizing them. The maximum number of iterations is 1000, the learning rate is 0.01, and the target convergence error is 0.001. Train the sample data and update the weights and thresholds until the network tends to be stable. Randomly select 100 data from the training samples as the test set data, substitute them into the neural network for prediction, inversely normalize the results, and obtain the prediction results and the comparison of error distribution, as shown in Figure 6 and Table 4.

It can be seen that the 3-element prediction models can effectively predict the departure flight taxi-out time, and the effect of the 4-element combination prediction model is the best. Among them, the curve goodness of fit \( R^2 \) of the 3-element combination prediction model is 0.8772. Only the strongly related surface traffic flow is considered in the model, and the influence of the average taxi-out time on the taxi-out time is not considered. Therefore, the deviation between the prediction result and the real value is slightly large. The curve goodness of fit of the 4-element combined prediction model is as high as \( R^2 = 0.9298 \). The model comprehensively considers many main factors such as ground instantaneous traffic flow, time-varying characteristics of traffic flow, average taxi-out time, and so on. Therefore, the deviation between the prediction result and the real result is the smallest. The curve fitting degree of the 6-element combination prediction model is \( R^2 = 0.8954 \), which is lower than that of the 4-element combination prediction model, indicating that the introduction of the weak correlation taxi distance and number of turns is unfavorable to the prediction result of the taxi-out time.

The model was evaluated based on the error distribution range, average absolute error percentage (MAPE), average absolute error (MAE), and root mean square error (RMSE)
of the prediction results. The prediction result error of the 4-element combined prediction model considering strong correlation and medium correlation factors is the smallest, accounting for 92% within ±300 s, MAPE is 10.61%, MAE is 90.24 s, and RMSE is 114.02 s. The accuracy of 6-element combination prediction results considering strong correlation, medium correlation, and weak correlation factors is higher than that of 3-element combination prediction model and lower than that of 4-element combination prediction model, which further shows that the introduction of weak correlation factors will affect the accuracy of model prediction.

Through the analysis of the existing research results, the accuracy of the taxi-out time prediction model based on queuing theory is about 78%, while the taxi-out time prediction model based on machine learning can reach about 82%. The prediction accuracy of the taxi-out time prediction model considering quantifiable factors proposed in this paper can reach 85%, indicating that the prediction results are basically reliable. However, the prediction results are
sensitive to the initial weight and threshold of BP neural network, and the accuracy and stability of the model output are not ideal, which will be improved in this paper.

3.3. Taxi-Out Time Prediction Results Based on GA-BP and SSA-BP. Based on the neural network toolbox in MATLAB, the maximum number of iterations of BP neural network is set to 10000, the learning rate is 0.001, and the target convergence error is 0.001. The initial population size of genetic algorithm is 30, the maximum number of iterations is 50, the crossover probability is 0.8, and the mutation probability is 0.2. The initial population size of sparrows is 50, the maximum number of iterations is 60, the proportion of discoverers and accessors in the population is 0.5, and the proportion of sparrows who can be aware of danger in the population is 0.2. 5000 data are randomly selected from the sample data set for training, and the remaining 200 data are used as the test set. The comparison between the predicted value and the real value of BP neural network before and after GA and SSA optimization is shown in Figures 7(a) and 7(b), respectively.

From Table 5, it can be seen that BP, GA-BP, and SSA-BP can effectively predict the taxi-out time of departure flights. However, the prediction results of taxi-out time based on BP neural network are sensitive to the initial weight and threshold, and the accuracy and stability are not good, which needs to be further improved. Therefore, this paper uses GA and SSA intelligent optimization algorithms to obtain the optimal weight.

| Call sign | Aircraft type | Actual takeoff time | Actual off-block time | Actual landing time | Runway | Parking base |
|-----------|---------------|---------------------|-----------------------|--------------------|--------|--------------|
| CCA1306   | B738          | 2019/05/27 02:56:00 | 2019/05/27 02:19:42  | 2019/05/27 05:40:00 | 15     | 320          |
| CSN6333   | A320          | 2019/05/27 02:58:00 | 2019/05/27 02:23:00  | 2019/05/27 05:57:00 | 15     | 332          |
| CSN6205   | A320          | 2019/05/27 03:00:00 | 2019/05/27 02:30:00  | 2019/05/27 03:59:00 | 15     | 352          |
| CSN3663   | A321          | 2019/05/27 03:02:00 | 2019/05/27 02:45:42  | 2019/05/27 04:26:00 | 15     | 62           |
| CXA8077   | B738          | 2019/05/27 03:04:00 | 2019/05/27 02:36:58  | 2019/05/27 04:17:00 | 15     | 509          |
| CSC8702   | A320          | 2019/05/27 03:07:00 | 2019/05/27 02:43:07  | 2019/05/27 05:18:00 | 15     | 331          |

| Aircraft call sign | x1 | x2 | x3 | x4  | x5  | x6  | Taxi-out time |
|---------------------|----|----|----|-----|-----|-----|---------------|
| CCA1364             | 21 | 15 | 12 | 1317| 3557| 5   | 2178          |
| CSN6393             | 20 | 11 | 12 | 1317| 2262| 3   | 2100          |
| CES5325             | 17 | 8  | 11 | 1317| 3465| 6   | 1800          |
| CSN3113             | 10 | 6  | 5  | 1004| 1909| 4   | 978           |
| CXA8207             | 16 | 8  | 9  | 1004| 1896| 3   | 1622          |
| CSC8662             | 14 | 8  | 8  | 1004| 2615| 3   | 1433          |
| CSZ9721             | 12 | 6  | 5  | 1004| 2550| 4   | 1210          |
| CSC8886             | 12 | 6  | 6  | 1004| 2615| 3   | 1288          |
| CES5321             | 9  | 4  | 6  | 957 | 886 | 2   | 786           |

Figure 6: Comparison of taxi-out time prediction results based on BP neural network. (a) 3-element combination model. (b) 4-element combination model. (c) 6-element combination model.
and threshold parameters of BP neural network, respectively. The final prediction results are closer to the real value, and the error distribution is more concentrated and uniform. At the same time, it can be seen from Table 4 that the accuracy of BP neural network prediction results based on GA optimization error within ±60 s is improved by 14%, the accuracy within ±180 s is improved by 10%, and the accuracy within ±300 s is improved by 4%. Based on the BP neural network prediction results optimized by SSA, the accuracy of error within ±60 s is improved by 20%, the accuracy within ±180 s is improved by 12%, and the accuracy within ±300 s is improved by 6%. The above indicators fully show that SSA algorithm is more powerful than GA algorithm in optimizing the model.

In order to further scientifically evaluate the prediction results of BP neural network optimized based on GA and SSA, the average absolute error percentage (MAPE), average absolute error (MAE), and root mean square error (RMSE) are verified in this paper. The results are shown in Table 6.

It can be seen that the prediction result of BP neural network optimized based on GA is 1.79% higher than that of MAPE before optimization, MAE is reduced by 7.4 s, and RMSE is reduced by 6.93 s. The prediction result of BP neural network optimized based on SSA is 3.05% higher than that of MAPE before optimization, MAE is reduced by 16.55 s, and RMSE is reduced by 14.31 s. The above data fully shows that the intelligent optimization algorithm can effectively obtain

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**Table 4: Comparison of error distribution of taxi-out time prediction results.**

| Models                     | Prediction accuracy with error of ±60 s (%) | Prediction accuracy with error of ±180 s (%) | Prediction accuracy with error of ±300 s (%) | MAPE (%) | MAE (s)  | RMSE (s) |
|----------------------------|--------------------------------------------|----------------------------------------------|----------------------------------------------|----------|----------|----------|
| 3-element combination forecast | 31                                         | 73                                           | 85                                           | 14.14    | 120.75   | 154.24   |
| 4-element combination forecast | 34                                         | 79                                           | 92                                           | 10.61    | 90.24    | 114.02   |
| 6-element combination forecast | 33                                         | 77                                           | 89                                           | 11.23    | 94.69    | 120.29   |

**Table 5: Comparison of error distribution of taxi-out time prediction results.**

| Models                     | Prediction accuracy with error of ±60 s (%) | Prediction accuracy with error of ±180 s (%) | Prediction accuracy with error of ±300 s (%) |
|----------------------------|--------------------------------------------|----------------------------------------------|----------------------------------------------|
| BP prediction              | 37                                         | 79                                           | 92                                           |
| GA-BP prediction           | 51                                         | 89                                           | 96                                           |
| SSA-BP prediction          | 57                                         | 91                                           | 98                                           |
the local optimal weight and threshold of neural network and effectively improve the accuracy of departure flight taxi-out time prediction results, and the sparrow search algorithm has better optimization effect on the model than genetic algorithm. After BP is optimized by the intelligent optimization algorithm, the accuracy of the taxi-out time prediction results can be improved by about 5%, the accuracy within ±300 s can be improved to 98%, and the error distribution is becoming more and more uniform, which verifies the effectiveness of the intelligent optimization algorithm.

4. Conclusion

(1) The departure flights’ taxi-out time has a strong correlation with the airport surface traffic flow, a moderate correlation with the average taxi-out time, and a weak correlation with the taxi distance and the number of turns.

(2) The prediction accuracy of the taxi-out time of the 4-element combined prediction model considering the quantifiable factors of strong correlation and medium correlation is the highest. The prediction accuracy of the model is reduced after introducing the weak correlation taxi distance and the number of turns.

(3) By obtaining the local optimal weight and threshold of neural network, intelligent optimization algorithm can effectively improve the accuracy of departure flight taxi-out time prediction results, and sparrow search algorithm has better optimization effect on the model than genetic algorithm.

(4) The next work will focus on the launch of departure flights and taxi control strategy based on taxi-out time prediction.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by key project of Civil Aviation Flight University of China (ZJ2021-05) and Sichuan Science and Technology project (22ZDYF2832).

Supplementary Materials

The compressed package in the attachment material is the editable version of all figures of the article, and the data used in the article is an Excel file. (Supplementary Materials)

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