Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 8
AICT 2024

Flight Trajectory Prediction Based on LSTM

Songang Yang[1, *]

[1]School of Information Science and Technology, Northwest University, Xi'an, China

[*]Corresponding author: ysa0930@163.com

Abstract. Track prediction is a key technology to avoid potential navigation dangers and provide reliable scheduling. Due to the insufficient processing ability of traditional neural networks for long sequence data such as track data, the prediction error of aircraft trajectories is relatively large. In this paper, the Long Short-Term Memory network (LSTM) is used for 4D track prediction, and the excessive dependence between adjacent data is reduced through the sliding window method. The ADS-B track data is standardized, outliers are processed using the 3σ Principle, and the smoothness of the time series is ensured through cubic spline interpolation. Four-dimensional track prediction and two-dimensional prediction of each feature of Height, Speed, Speed, Longitude, and Latitude are carried out for the standard data. Performance is judged by Root Mean Squared Error (RMSE) and the average prediction error of each feature. Through comparison, the track prediction effect of the LSTM neural network is better than the existing BP neural network prediction method.

Keywords: LSTM, Track Prediction, 3σ Principle, Cubic Spline Interpolation.

1. Introduction

In recent years, with the technological development of civil aviation passenger aircraft, the management and control volume of passenger aircraft flight routes has been gradually increasing. According to the data of the "2023 Civil Aviation Industry Development Statistical Bulletin" of the Civil Aviation Administration of China [1], in 2023, the national civil aviation transport airports completed a passenger throughput of 1.26 billion person-times, an increase of 142.2% year-on-year. Fig 1 shows the passenger throughput and increase trend of civil aviation airports from 2019 to 2023. In order to avoid potential risks such as airway congestion and flight collisions, accurate 4D track prediction is required to enhance the monitoring and dispatching of passenger aircraft within the restricted airspace by the ground management center. The International Civil Aviation Organization (ICAO) proposed that the operation based on the four-dimensional track (TBO) is the core operation concept of the next-generation air traffic management system and the core technology to realize the intelligent control.

In recent years, scholars at home and abroad have made a large number of explorations on the track prediction technology. During the process of trajectory prediction, deep neural networks are usually used for research. In practical use, both the BP neural network [2-5] and the TRANSFORMER neural network [6-8] for track prediction have the problem of insufficient processing ability for long sequence data. When dealing with situations such as flight trajectories with a long time dimension and relatively complex data types, the computational effort will increase significantly, and at the same time will lead to an increase in the model's error. If the data is truncated, the change situation of the track within a period of time can be focused on, and compared with the overall prediction, it can adapt to the change of sequence data.

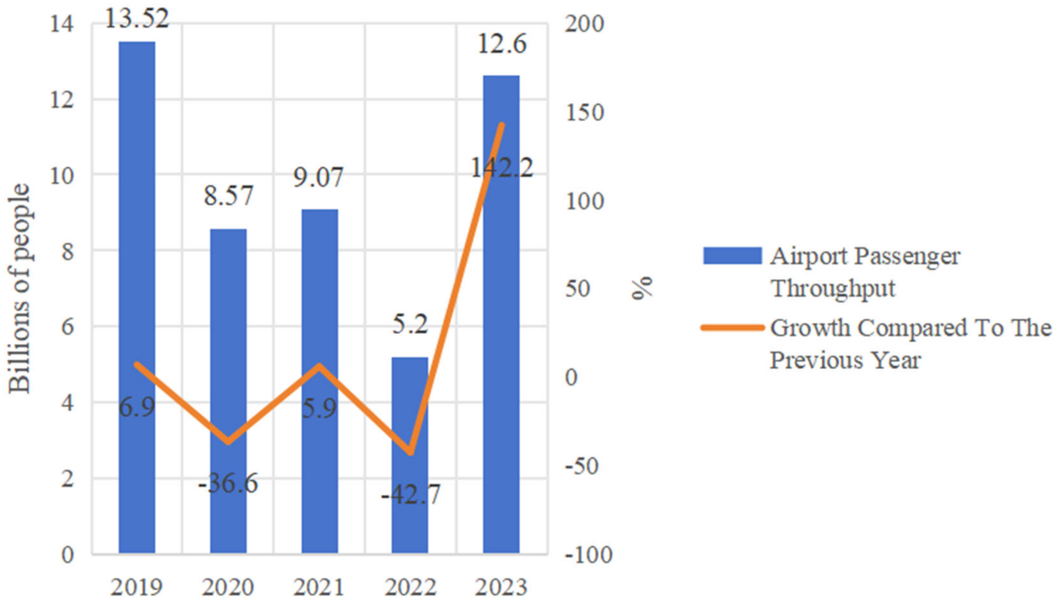

Figure 1. Passenger throughput of civil aviation airports from 2019 to 2023

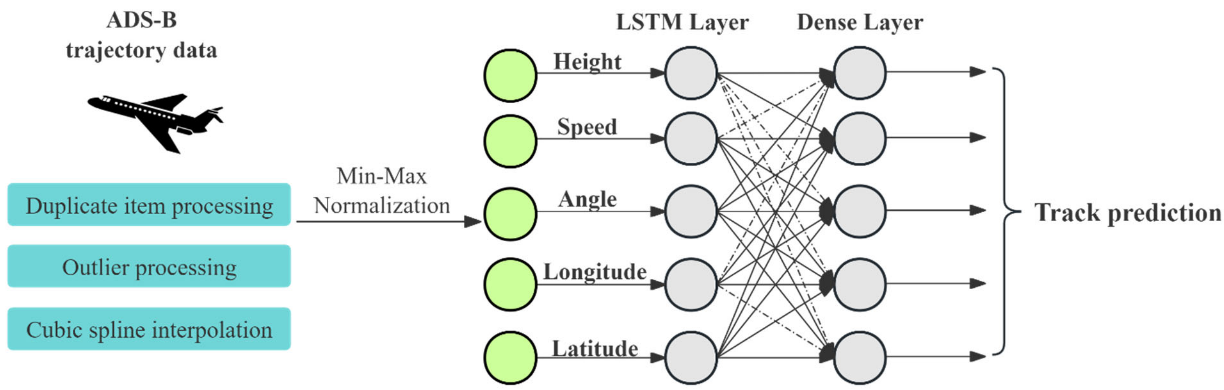

Figure 2. Flight trajectory prediction based on LSTM

The Long Short-Term Memory network (LSTM) used in this paper for 4D track prediction solves the problem of prediction error caused by long-term dependence. There are mainly the following three steps: collection and processing of the flight trajectory data set, construction of the neural network, and judgment of the accuracy of track prediction.

2. Methodology

In this section, we will focus on the key steps and main methods of 4D track prediction based on LSTM.

2.1. The Collection of ADS-B Track Data

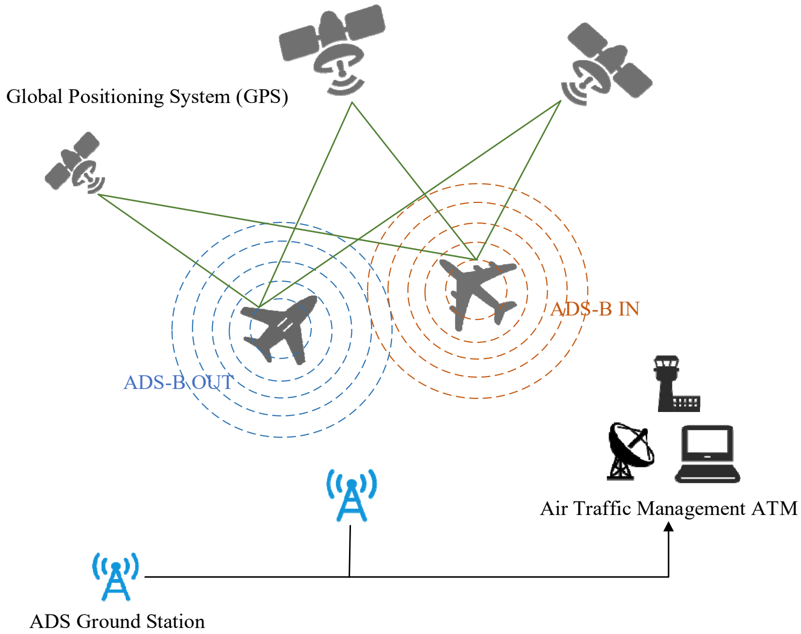

Figure 3. ADS-B surveillance system

Automatic Dependent Surveillance-Broadcast (ADS-B) is an integrated information system that combines communication and surveillance functions. The equipment of the entire system is composed of airborne equipment and ground equipment[9], and its structure is shown in Figure 3. The fixed-point automatic monitoring of the track is realized through the adoption, transmission and processing of information.

The trajectory data of ADS-B reflects the discrete trajectory point information of the aircraft throughout a certain historical flight.

Assuming that the trajectory set of a certain aircraft is H, which contains N trajectory records, It can be calculated as:

$$H = \{H_1, H_2, \ldots, H_x, \ldots, H_N\} \tag{1}$$

H_x represents the x-th track record in H.

There are n trajectory points recorded each time, is calculated as:

$$H_x = \{m_1, m_2, \ldots, m_i, \ldots, m_n\} \tag{2}$$

m_i is the ith trajectory point in H_x.

There are k features in each trajectory point, is calculated as:

$$m_i = \{m_{i1}, m_{i2}, \ldots, m_{ij}, \ldots, m_{ik}\} \tag{3}$$

m_{ij} is the jth feature of m_i.

2.2. The processing of ADS-B track data

After the ADS-B track data needs to be processed, the integrity and accuracy of the data can be ensured to improve the accuracy of subsequent predictions.

Due to reasons such as constant-speed flight of the aircraft, the change in the characteristic value is not significant, resulting in an increase in duplicate items and an increase in useless data. Deleting duplicate items during data processing can improve the computational efficiency and at the same time reduce the prediction error caused by duplicate data.

Due to the influence of factors such as special weather, sensor failures, and signal interference, abnormal data will be recorded during the collection process of the track data, resulting in data deviations and affecting the accuracy of the track prediction. 3σ principle can be used to effectively eliminate outliers. 3σ principle is a common method for data screening and outlier elimination through normal distribution, which can be calculated as:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n} \tag{4}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}} \tag{5}$$

Where μ represents the mathematical expectation of the characteristic values of all track points, n represents the number of track points, x_i represents the characteristic value corresponding to each track point, and σ represents the standard deviation of the characteristic values of all track points.

When the characteristic value x_i of the track point satisfies $|x_i - \mu| > 3\sigma$, then x_i is determined to be an outlier, the outlier should be eliminated.

After the outliers are removed, the missing data are filled in by cubic spline interpolation[10-11], and the data are smoothed to obtain a smoother and more continuous flight trajectory curve.

The cubic spline interpolation function is:

$$s(t) = \theta(t) \qquad t \in [t_0, t_n] \tag{6}$$

Its second order derivative:

$$s''(t_i) = M_{i+1} \tag{7}$$

$s(t)$ on the subinterval $[t_i, t_{i+1}](i = 1,2,\ldots,n)$ is a polynomial with no more than three terms on $[t_i, t_{i+1}]$ for $s''(t_i) = M_i$ interpolated over$[t_i, t_{i+1}]$:

$$S''(t_i) = \frac{(t_{i+1} - i)}{h_i} M_i + \frac{(t - l_i)}{h_i} M_{i+1} \tag{8}$$

where $h_i = t_{i+1} - t_i$. obtained by quadratic integration of $s''(t_i)$ according to $s(t_{i+1}) = \theta(t_{i+1})$ and $s(t_{i+1}) = \theta(t_{i+1})$:

$$s(t) = \frac{(t_{i+1} - t)^3}{6h_i} M_i + \frac{(t - t_i)^3}{6h_i} M_{i+1} + \frac{t_{i+1} - t}{h_i}\left(\theta(t_i) - \frac{h_i^2}{6} M_i\right) + \frac{t - t_i}{h_i}\left(\theta(t_{i+1}) - \frac{h_i^2}{6} M_{i+1}\right) \quad (9)$$

First order derivation of $s(t)$:

$$s'(t) = \frac{(t_{i+1} - t)^2}{2h_i} M_i + \frac{(t - t_i)^2}{2h_i} M_{i+1} + \frac{\theta(t_{i+1}) - \theta(t_i)}{h_i} - \frac{h_i}{6}(M_{i+1} - M_i) \quad (10)$$

The collation yields:

$$s'(t_i + 0) = \frac{x_{i+1} - x_i}{h_i} - \frac{h_i}{3} M_i - \frac{h_i}{6} M_{i+1} \quad (11)$$

Similarly we get $s(t)$ on the sub-interval $[t_{i-1}, t_i](i = 1,2,\ldots,n)$ The first-order derivative on $[t_{i-1}, t_i](i = 1,2,\ldots,n)$ is expressed as:

$$s'(t_i - 0) = -\frac{h_{i-1}}{6} M_{i-1} + \frac{h_{i-1}}{3} M_i + \frac{x_i - x_{i-1}}{h_{i-1}} \quad (12)$$

According to Eq. (11) and Eq. (12) get:

$$\mu_i M_{i-1} + 2M_i + \lambda_i M_{i+1} = d_i \quad (13)$$

Where:

$$\begin{cases} \mu_i = \dfrac{h_{i-1}}{h_{i-1} + h_i} \\ \lambda_i = \dfrac{h_i}{h_{i-1} + h_i} \\ d_i = \dfrac{6}{h_{i-1} + h_i}\left(\dfrac{x_{i+1} - x_i}{h_i} - \dfrac{x_i - x_{i-1}}{h_{i-1}}\right) = 6f[t_{i-1}, t_i, t_{i+1}] \end{cases} \quad (15)$$

If you need to calculate M_0、$M_1 \cdots M_n$ from Eq. (13), you need to get the end-point equations, so that $\lambda_0 = 1$, $\mu_n = 1$:

$$\begin{cases} 2M_0 + M_1 = \dfrac{6}{h_0}(f[t_0, t_1] - x'_0) = d_0 \\ M_{n-1} + 2M_n = \dfrac{6}{h_{n-1}}(x'_n - f[t_{n-1}, t_n]) = d'_n \end{cases} \tag{16}$$

The matrix form of the system of linear equations of order $n + 1$ for M_i is obtained from Eq. (10) and Eq. (11) as:

$$\begin{bmatrix} 2 & \lambda_0 & & & \\ \mu_1 & 2 & \lambda_0 & & \\ & \ddots & \ddots & \ddots & \\ & & \mu_{n-1} & 2 & \lambda_{n-1} \\ & & & \mu_n & 2 \end{bmatrix} \begin{bmatrix} M_0 \\ M_1 \\ \vdots \\ M_{n-1} \\ M_n \end{bmatrix} = \begin{bmatrix} d_0 \\ d_1 \\ \vdots \\ d_{n-1} \\ d_n \end{bmatrix} \tag{17}$$

This yields M_0, M_1,…, M_n, and hence the cubic spline interpolation results of the eigenvalue data over time.

2.3. Construction of LSTM Neural Network

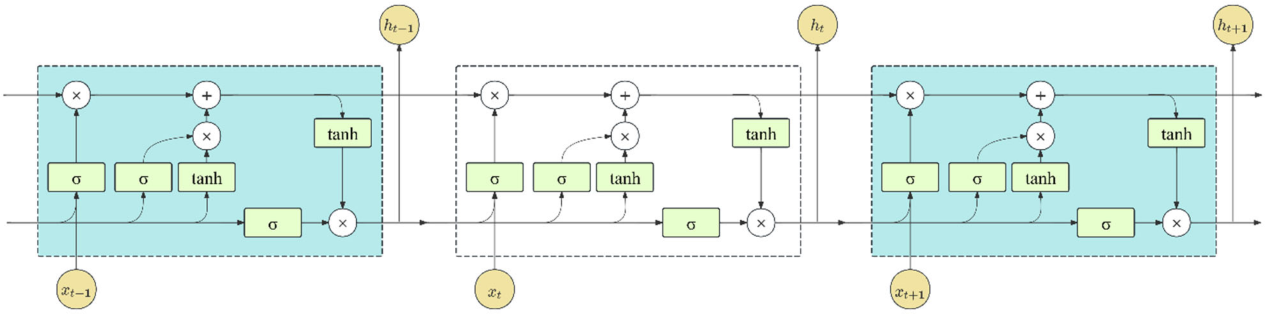

Figure 4. LSTM neural network structure

The LSTM neural network solves the problem of gradient vanishing and exploding in Recurrent Neural Networks (RNN) due to the existence of long time series data. It usually includes a sequential memory unit h_t, a long-term memory unit C_t, a data input gate, a forget gate, and an output gate. Its structure is shown in Figure 4, where the forget gate determines that the input data will be discarded, and the output gate outputs it as the next input data. The mathematical representation is:

$$\begin{cases} f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t = tan\,h(W_c \cdot [h_{t-1}, x_t] + b_c) \\ C_t = f_t \times C_{t-1} + i_t \times \vec{C}_t \\ o_t = \sigma(W_0 \cdot [h_{t-1}, x_t] + b_0) \\ h_t = o_t \times tan\,h(C_t) \end{cases} \tag{18}$$

W_f, W_i, W_c, W_o are coefficient matrices, b_f, b_i, b_c, b_o are paranoid matrices, σ represents the activation function selected as Rectified Linear Unit (ReLU), f_t represents the forget gate, and i_t

represents the input gate, which includes updates to long-term memory units and forward memory units.

The ADS-B trajectory data is processed to be smooth and have equal time intervals, and the input data is segmented using the sliding time window method:

$$X = \{X_1, X_2, \ldots, X_i, \ldots, X_N\} \tag{19}$$

where i is the ith segmentation data of X.

$$X_i = \left[X_i^{t-m+i}, X_i^{t-m+i+1}, \cdots, X_i^{t+i}\right] \tag{20}$$

where m is the sliding time window size, and the $t + i + 1th$ data is predicted by the $t - m + ith$ to $t + ith$ data to predict the whole navigation trajectory of the vehicle.

3. Experience

In this section, the specific process and processing content of the experiment of track prediction using LSTM will be mainly introduced.

Our data is collected by the ADS-B ground station from the flight from Xi'an Xianyang Airport to Tianjin Binhai Airport, with the model number CA2900. The data collection interval is all the flight track data of this flight from June 1, 2024 to July 3, 2024. The features of each track point are the same as one track point shown in Table. 1.

Table 1. Single track point feature

Feature	Track point data
Time	1717209444
Fnum	CA2900
Height	525.78
Speed	300.024
Angle	50
Longitude	108.772049
Latitude	34.43614197

3.1. Data analysis

Taking the data shown in Table 2 as an example, items with the same Height, Speed, Speed, Longitude, and Latitude are defined as duplicate items. If there are certain duplicate items in the original data, the duplicate items will be removed, and the result after removal is shown in Table 3.

Table 2. Track data with duplicate items included

Time	Fnum	Height	Speed	Angle	Longitude	Latitude
1717215473	CA2900	0	14.816	348	117.3550034	39.1273613
1717215519	CA2900	0	5.5559998	33	117.3557129	39.12844849
1717215549	CA2900	0	5.5559998	33	117.3557129	39.12844849
1717215549	CA2900	0	0	33	117.3557892	39.12854004
1717215549	CA2900	0	0	33	117.3557892	39.12854004

Table 3. Track data after removing duplicate items

Time	Fnum	Height	Speed	Angle	Longitude	Latitude
1717215473	CA2900	0	14.816	348	117.3550034	39.1273613
1717215549	CA2900	0	5.5559998	33	117.3557129	39.12844849
1717215549	CA2900	0	0	33	117.3557892	39.12854004

After eliminating the duplicate items, as shown in Figure 5, the red dotted line indicates the outlier data outside the 3σ range. The outliers are cleaned, and a data set with irregular time intervals and partial missing track data is obtained. As shown in Figure 6, the results of cubic spline interpolation for Height, Speed, Speed, Longitude, and Latitude respectively, the track curves are relatively smooth, and the missing track point data is also completed.

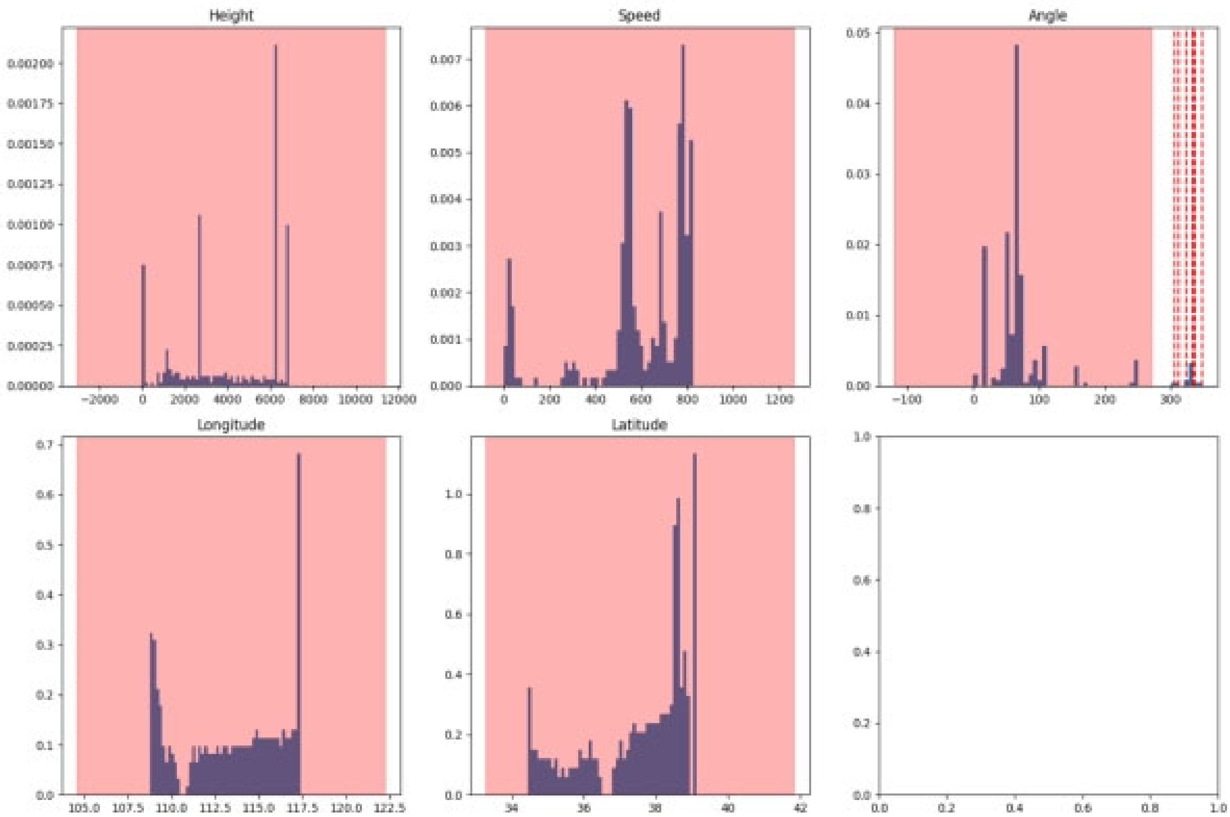

Figure 5. Outlier detection situation by the 3 σ principle

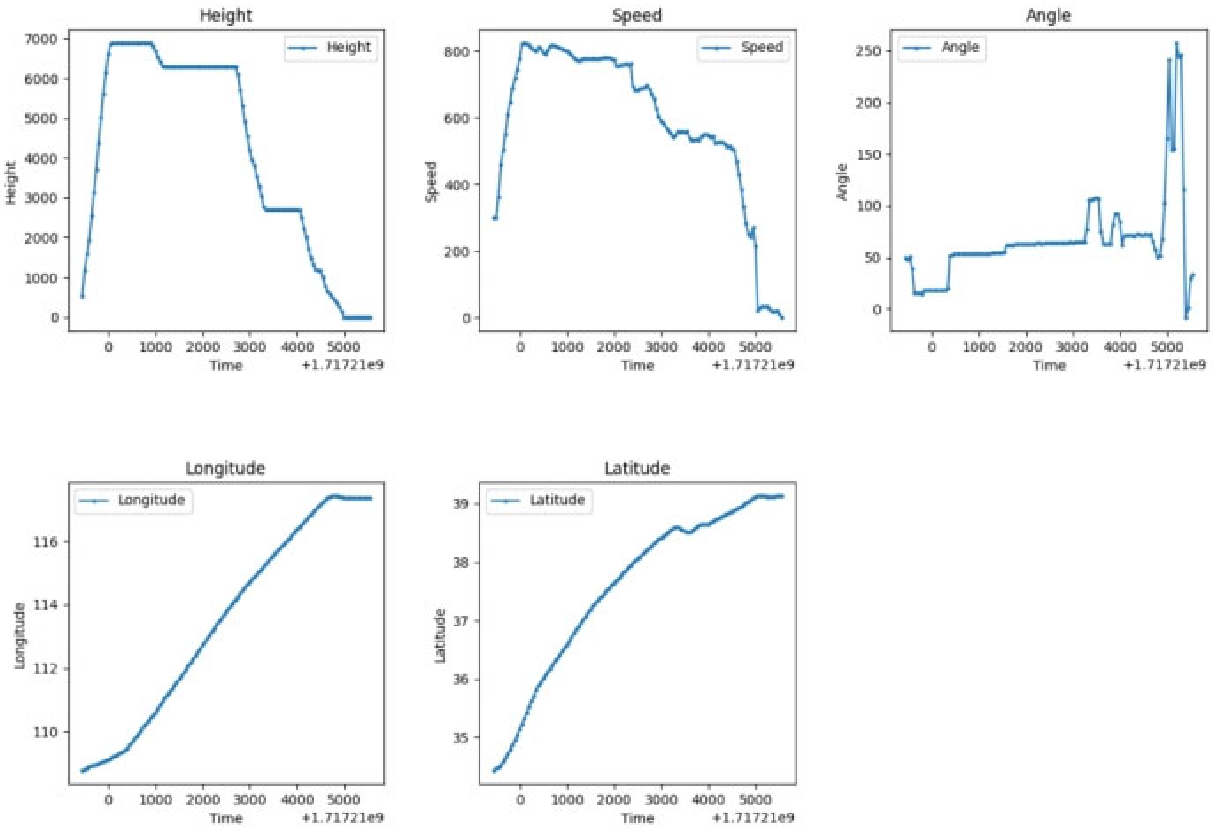

Figure 6. The result of cubic spline interpolation

3.2. Model training

We have established an LSTM neural network for the training and prediction of track data.

The activation function selected for the LSTM neural network is ReLU, which can effectively solve the problem of vanishing gradients. Its expression is:

$$f(x) = max(0, x) \tag{21}$$

en x is positive, the independent variable itself is output, and when the input is negative, the output is 0.

The selected loss function is Mean Squared Error (MSE), which can reflect the arithmetic square difference between the predicted data and the real data. Its expression is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 c \tag{22}$$

Where n is the total sample size, y_iy_i is the real value of the track, and $\hat{y}_i$ is the predicted value of the track.

The optimizer selected is Adaptive Moment Estimation (Adam), and the learning rate is set to 0.001.

The LSTM model constructed in this paper is divided into two layers: the LSTM layer and the Dense layer. The LSTM layer is set with 128 LSTM units, the time step value of the sliding time window time_step is set to 26, and the input is the Height, Speed, Speed, Longitude, and Latitude characteristic values after maximum and minimum normalization. The input shape is (26, 5). The output of the Dense layer is 5. Through the Dense layer, the output data of the LSTM layer is transformed into the same dimensional space as the target variable, that is, the predicted values of the five characteristics in the track prediction.

When training the model, the batch size value is set to 32, and the number of training epochs value is set to 100.

3.3. Experimental results

We measure the performance strength of the model through Root Mean Squared Error (RMSE) and the average prediction error of each characteristic. At the same time, the learning situation of the model during the training process is reflected through training loss and validation loss.

Meanwhile, comparing the prediction effect of the LSTM neural network with that of the BP neural network, it can be clearly observed that the effect of LSTM is better than that of the BP neural network.

Table 4. The average error of the predicted characteristic values by LSTM

Feature	Everage Error
Height	7.5963
Speed	0.8645
Angle	0.4027
Longitude	0.0199
Latitude	0.0143

Table 5. The comparison of RMSE between LSTM and BP neural networks

Neural Network	RMSE Train Score	RMSE Test Score
LSTM	12.98	7.99
BP	36.00	46.96

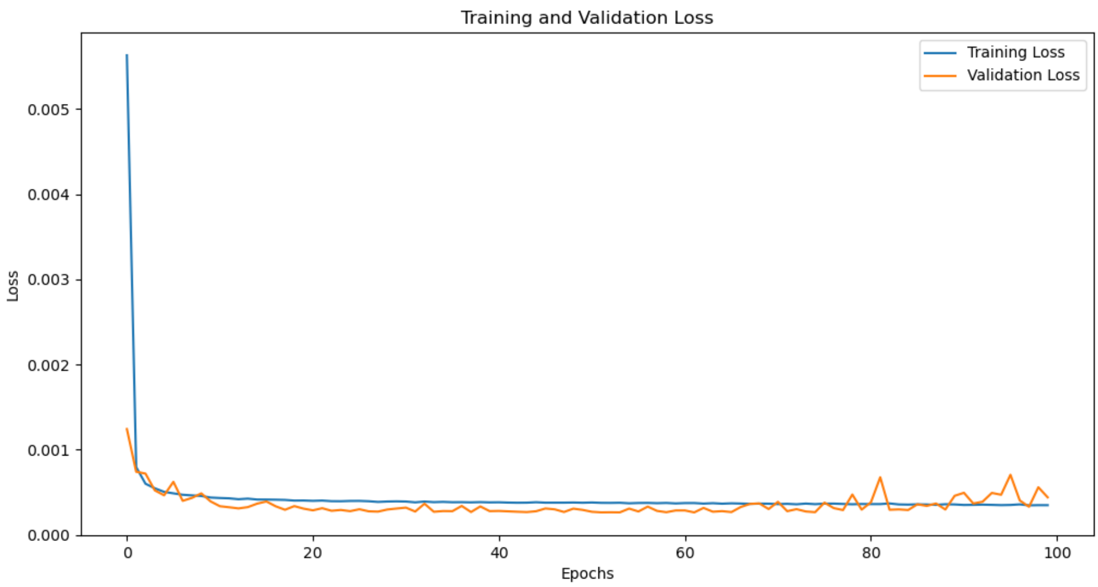

Figure 7. Training and validation loss of LSTM

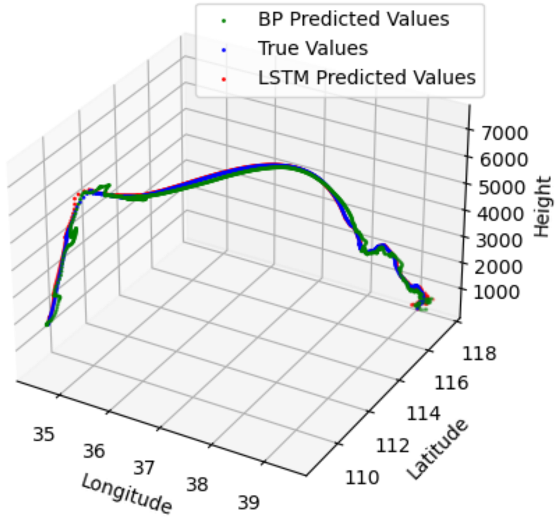

Figure 8. The 4-dimensional track prediction of LSTM and BP neural networks

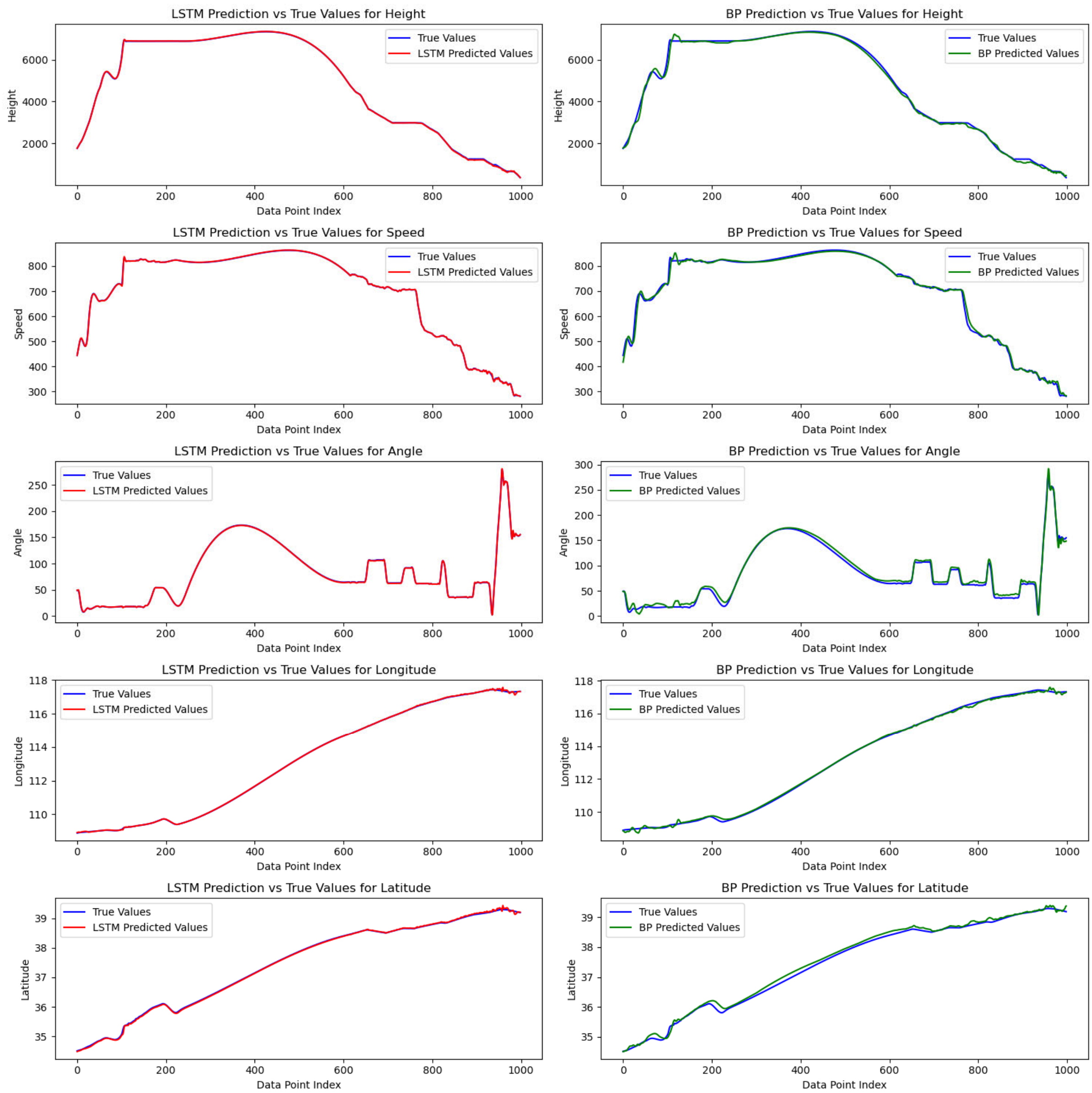

Figure 9. The track prediction characteristic values of LSTM and BP neural networks

4. Conclusions

We established an aircraft track prediction model based on the LSTM neural network. Through training with the track data collected by the ADS-B ground station, the LSTM network solved the problem caused by the insufficient learning ability of traditional neural networks for long sequence data and accurately predicted the movement track of flight CA2900. The experimental results show that the ability of this model is better than methods such as the BP neural network.

References

[1] Civil Aviation Administration of China. Development Planning Department. "Statistical Bulletin on the Development of the Civil Aviation Industry in 2023" [EB/OL]. (2024-05-31) [2024-08-23]

[2] Bai Xiang'en, Chen Nuo, Xu Xiaofeng. Research on Ship Track Prediction Based on IPSO-BP [J]. Packaging Engineering, 2024, 45(09): 201-209.

[3] Liu Shuang, Wu Huzi, Geng Jianzhong. An Optimized BP Neural Network Flight Trajectory Real-time Tracking Algorithm [J]. System Simulation Technology, 2014, 10(03): 229-233.

[4] Liu Kai. Trajectory Tracking Control of Quadrotor Double Closed-loop PID Based on BP Neural Network [J]. Industrial Control Computer, 2018, 31(11): 62-63.

[5] Jia Ying. Anomaly Trajectory Detection Method Based on BP Neural Network [J]. Microcomputer Applications, 2020, 36(10): 79-81.

[6] Zhang Qi. Research on Track Prediction Method in Terminal Area Based on Deep Learning [D]. Civil Aviation University of China, 2023.

[7] Yuan Yubin, Wu Yiquan. Research on Multi-target Tracking Algorithm of Unmanned Aerial Vehicles Based on Transformer [J]. Journal of Ordnance Equipment Engineering, 2024, 45(07): 11-18.

[8] Di Ziqi, Wang Xiangyu, Wu Shuang, et al. Hypersonic Vehicle Trajectory Generation and Prediction Algorithm Based on Transformer Architecture [J]. Air and Space Defense, 2023, 6(04): 35-41.

[9] Guo Junpeng. The Application and Influence of ADS-B in General Aviation Airports [J]. Modern Business Trade Industry, 2018, 39(09): 183-184.

[10] Han Yanxiao, Peng Shuhua. Trajectory Planning of Snake-like Robot Based on Cubic Spline Interpolation Function [J]. Journal of Beijing Information Science and Technology University (Natural Science Edition), 2015, 30(03): 75-79.

[11] Zhang Xiaojiang, Gao Xiuhua. Improved Research on the Application of Cubic Spline Interpolation in Robot Trajectory Planning [J]. Machinery Design & Manufacture, 2008, (09): 170-171.