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A Hybrid CNN-LSTM Model for Aircraft 4D Trajectory Prediction

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ABSTRACT The 4D trajectory is a multi-dimensional time series with plentiful spatial-temporal features and has a high degree of complexity and uncertainty. Aiming at these features of aircraft flight trajectory and the problem that it is difficult for existing trajectory prediction methods to extract spatial-temporal features from the trajectory data at the same time, we propose a novel 4D trajectory prediction hybrid architecture based on deep learning, which combined Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). An 1D convolution is used to extract the spatial dimension feature of the trajectory, and LSTM is used to mine the temporal dimension feature of the trajectory. Hence the high-precision prediction of the 4D trajectory is realized based on the sufficient fusion of the above features. We use real Automatic Dependent Surveillance -Broadcast (ADS-B) historical trajectory data for experiments and compare the proposed method with a single LSTM model and BP model on the same data set. The experimental results show that the trajectory prediction accuracy of the CNN-LSTM hybrid model is superior to a single model. The prediction error is reduced by an average of 21.62% compared to the LSTM model and by an average of 52.45% compared to the BP model. It provides a certain reference for the trajectory prediction research and Air Traffic Management decision-making.

INDEX TERMS 4D trajectory prediction, deep learning, CNN-LSTM model, spatial-temporal feature.

I. INTRODUCTION

Air Traffic Management (ATM) system is a dynamic, complex, information-driven automation system [1]. It considers the trajectory of the aircraft at all stages of flight and manages these trajectories to avoid conflicts. With the smallest possible deviation from the flight plan, the optimized operation of the entire system is achieved. With the vigorous development of the air transport industry, the scale of the route network has gradually expanded, and airspace resources have become increasingly scarce. In order to meet the challenges brought by the continuous increase in air traffic to the Air Traffic Control (ATC) system, International Civil Aviation Organization (ICAO) regards Trajectory Based Operation (TBO) as the core operating concept of the next generation air navigation system. TBO uses the flight trajectory of the aircraft as the only reference and realizes the sharing of the flight trajectory within the ATM system. All parties concerned make collaborative decisions to accurately manage and control the operation of the aircraft [2], [3].

In addition, the United States has proposed the Next Generation Air Transportation System (NextGen) [4], [5], and the Eurocontrol has launched the Single European Sky ATM Research (SESAR) program [6]. NextGen intends to help controllers make reasonable decisions through trajectory optimization and matching, flight conflict detection and resolution, etc., so as to reduce flight delays, improve flight operational efficiency, and ensure the safety of flights at the same time. SESAR uniformly monitors the airspace of each member state, so that the planning of airspace flow can be free from national boundaries, thereby achieving a reasonable allocation of airspace resources.

4D trajectory prediction is the process of calculating the longitude, latitude, altitude, and time of the aircraft at future moments. Accurate 4D trajectory prediction helps to improve the level of automated decision-making in air traffic, thereby reducing the participation of staff; on the other hand, it helps to avoid potential flight conflicts and enhance air traffic safety.

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In the process of rapid development of artificial intelligence, deep learning has gradually been applied to various fields. At present, great success has been achieved in image classification, machine translation, natural language processing, and human-machine games [7]–[10]. Inspired by this phenomenon, deep learning methods have also been utilized to process time series prediction, for instance, pedestrian trajectory prediction, vehicle trajectory prediction, and traffic flow prediction [11]–[13]. Since the aircraft trajectory can be viewed as multi-dimensional time series, deep learning can be used for processing the trajectory prediction problem. The current flight trajectory prediction mostly uses LSTM networks with memory function. It can better capture the features of the trajectory in the time dimension, but it cannot capture the spatial features of the trajectory well. CNN is more suitable for extracting spatial features, and the combination of CNN and LSTM has also been widely used in classification tasks such as authorship classification of paintings, deep sentiment representation and prediction tasks such as traffic flow prediction, stock market index prediction, etc. [14]–[17]. The above models often use two-dimensional convolution to process image data or embed the convolution into the LSTM modules. The difference is that this paper first extracts the spatial correlation of the trajectory by one-dimensional convolution, and then extracts the time dimension dependence of the trajectory by LSTM network, so as to better integrate the temporal-spatial features of the trajectory.

The main contribution of our research is described below.

a) A novel 4D trajectory prediction method based on combined CNN-LSTM is presented. The 1D convolution of CNN is used for extracting the spatial features of the adjacent area of the trajectory, and the subsequent LSTM module is used to mine the temporal features of the trajectory data, so as to achieve the full fusion of the temporal and spatial features of the prediction point. This method solves the shortcomings of insufficient extraction of trajectory features. To the best of our current knowledge, it is the first time to apply the CNN-LSTM model for achieving the prediction of 4D trajectory.
b) The scheme of single-step and multi-step prediction of 4D trajectory based on the time window are introduced. The future trajectory at one moment or multiple moments is predicted by the historical trajectory information within the time window, which guarantees the real-time prediction of trajectory to a certain extent.
c) We compared the constructed model with a single BP and LSTM model, which greatly improved the prediction accuracy compared to a single model.

The rest of this paper is organized as follows. Section II discusses the related works of trajectory prediction. Section III analyzes the ADS-B trajectory. Section IV introduces the theory of deep learning and presents the model of 4D trajectory prediction. Section V shows the experimental simulation and result analysis. Section VI summarizes the conclusions and gives a future research plan.

II. RELATED WORKS

With the continuous updating of communication, navigation, surveillance and airborne equipment, the requirements for real-time and accuracy of trajectory prediction are constantly increasing. And the prediction methods have been continuously developed into the following categories. (*i*) Aerodynamic-based or aircraft performance model-based methods. (*ii*) Mixed estimation theory-based methods. (*iii*) Machine learning-based methods.

A. AERODYNAMIC-BASED OR AIRCRAFT PERFORMANCE MODEL-BASED METHODS

The prediction method based on aerodynamics or aircraft performance model is to divide the entire flight process of the aircraft into several stages, establish a motion equation for the flight trajectory of each stage, and define the start and end conditions and motion equation parameters of each subphase. Chao *et al*. [18] proposed a four-dimensional trajectory prediction method based on the basic flight model. According to the features in the flight phase, the basic flight model was used to construct the aircraft's horizontal profile, altitude profile, and speed profile. Junfeng *et al*. [19] designed a four-dimensional trajectory prediction model by statistically analyzing the actual radar trajectory data of the aircraft, with a combination of aircraft intent model and aircraft dynamics and kinematics model. Zhou *et al*. [20] combined flight motion model and gray theory to predict the trajectory, which improved the prediction accuracy. Kaneshige *et al*. [21] proposed a trajectory prediction method based on the basic motion model, which can improve the reliability of the trajectory prediction.

The above methods effectively utilize the characteristics of aircraft flight phases to simplify modeling and is suitable for trajectory prediction of complex operating states of aircraft in the terminal area. However, the dynamic parameters of the aircraft constantly change during flight, which is difficult to accurately estimate in advance. As the division of stages is too idealized, the actual flight trajectory may not meet the division of these stages. Therefore, this type of aerodynamic model has certain disadvantages, such as too many parameters, and the prediction accuracy is not high.

B. MIXED ESTIMATION HEORY-BASED METHODS

The trajectory prediction can be regarded as a stochastic linear hybrid system estimation problem. In view of this, Yunxiang *et al*. [22] used the hybrid system theory to construct the parameter evolution model of the aircraft in the flight segment and the state transition model during flight segment switching. By adjusting the corresponding aircraft parameters, a multi-aircraft conflict-free 4D trajectory is planned. Li *et al*. [23] described the aircraft's horizontal motion model based on the hybrid system theory. They proposed an interactive multi-model trajectory prediction algorithm based on the diversity and uncertainty of aircraft motion. Taobo and Baojun [24] proposed a Kalman filter algorithm for real-time trajectory improvement of system noise in prediction models. In view of the multi-modal nature of aircraft motion, the single-model approach is incapable. Although multi-model estimation takes into account the three-dimensional state of aircraft motion, it has the drawback that the algorithm complexity increases exponentially with the number of models. Interactive Multiple Models (IMM) can solve this problem. Interactive multi-model (IMM) algorithm can realize state estimation of hybrid system through state estimation weighted summation, and then realize trajectory prediction [25]. In addition, there are improved interactive multi-model estimation methods. A modal switching update method is proposed in literature [26]. Literature [27] proposed a hybrid estimation method which is related to the state based on wind speed and direction, to realize the trajectory prediction. However, the algorithm complexity of the above methods is too large to meet the real-time requirements.

C. MACHINE LEARNING-BASED METHODS

The continuous rise of artificial intelligence has made machine learning an emerging technology in terms of 4D trajectory prediction. Kun and Wei [28] presented a regression statistical model. This model mainly mines historical flight time, finds out the factors that affect flight time, and predicts the full flight time of the next flight. Then, the position of the aircraft at the beginning of each sampling period is analyzed from the historical position, to achieve a complete 4D trajectory prediction. Song *et al*. [29] processed historical radar trajectory data based on data mining technology to extract a classic trajectory data set. Taobo and Baojun [30] used fuzzy clustering to analyze the flight data of the approaching aircraft's 4D trajectory, thereby providing a basis for the reasonable design of the approach and departure procedures. Aiming at the target trajectory in the hotspot area, Kui *et al*. [31] build a BP neural- network based model for target trajectory prediction.

The above machine learning methods also have corresponding problems. The cluster-based method has limited prediction performance due to the limitation of input information. The regression statistical model must model each flight with massive trajectory data. The BP prediction model only considers the two-dimensional position information of the aircraft's latitude and longitude, so the prediction dimension is insufficient.

Since the LSTM network in deep learning is very expert in processing long sequences, in the year of 2018, Shi *et al*. [32] constructed a 4D trajectory prediction model using LSTM neural network. At the same time, Zhang *et al*. [33] then proposed an LSTM network optimized by the Ant Lion Optimization (ALO) algorithm for trajectory prediction. Han *et al*. [34] also proposed a short-term 4D trajectory prediction model based on LSTM. Zhang and Mahadevan [35] proposed a blended model combining DNN and LSTM for trajectory prediction, in which the uncertainty of model prediction is characterized by Bayesian approach, so as to increase en-route flight safety. In addition, Yin and Tong [36] carried out the influence of GRIB data on the accuracy of 4D trajectory prediction, which is an important research direction. Pang *et al.* [37] proposed a novel network architecture, aiming at solving the problem of aircraft trajectory prediction related to convective weather before takeoff. The convolutional layer is embedded in the repeating modules of the LSTM to extract useful features from weather cube. Unlike the two-dimensional convolution in literature [37], we use one-dimensional convolution to process trajectory data, extracting the spatial correlation between the adjacent areas of the trajectory.

In this paper, we propose a multi-layer CNN-LSTM hybrid model that can fully extract the spatial-temporal features of the trajectory. Since the traditional trajectory prediction methods are not suitable for the situation with a large number of trajectory samples, the model in this paper is compared with the most commonly used BP neural network and the latest LSTM network in the field of 4D trajectory prediction to verify the prediction performance of the proposed model.

III. ANALYSIS OF ADS-B TRAJECTORY

ADS-B connects satellites, aircraft, and ground stations to form a comprehensive system involving three levels of space, air, and ground. It reports the current flight parameters of the aircraft and the specific position information of the aircraft by sending ADS-B messages to the outside.

A. FORMAT OF ADS-B TRAJECTORY

The trajectory data returned by ADS-B is discontinuous, it consists of a series of discrete trajectory points [38].

Let T be the historical trajectory set, which includes N historical trajectory, expressed as

$$T = \{T_1, T_2, \ldots T_k, \ldots, T_N\} \tag{1}$$

where, T_k is the kth trajectory in T.

Suppose each trajectory contains n trajectory points,

$$T_k = \{m_{k1}, m_{k2}, \ldots, m_{ki}, \ldots, m_{kn}\} \tag{2}$$

where, m_{ki} is the i^{th} trajectory point in T_k.

If each trajectory point contains p features,

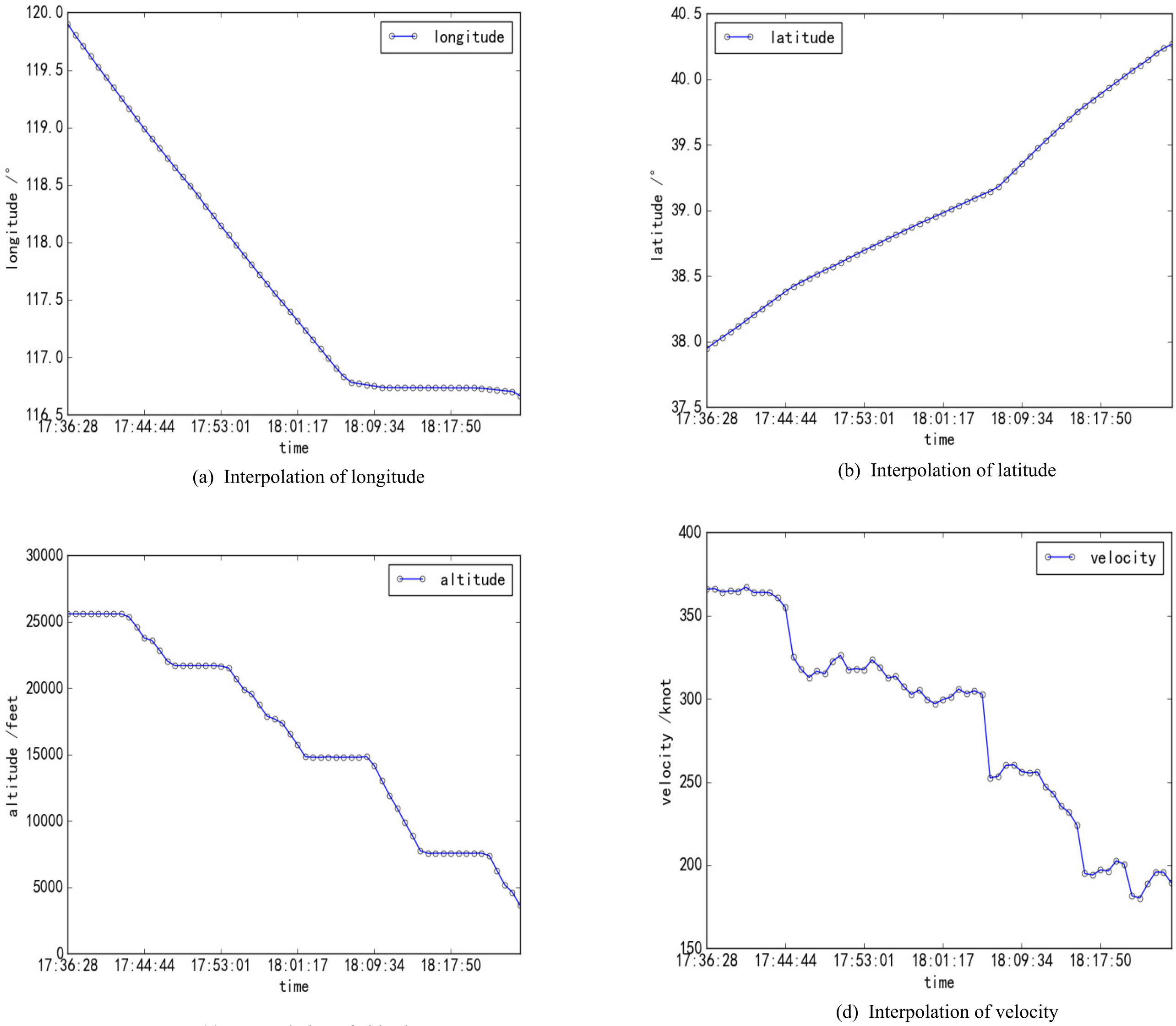
$$m_{ki} = \{r_{ki1}, r_{ki2}, \ldots, r_{kij}, \ldots, r_{kip}\} \tag{3}$$

where, r_{kij} is the j^{th} feature of the point m_{ki}.

The features contained in each collected ADS-B historical trajectory are shown in Table. 1.

B. PREPROCESSING OF ADS-B TRAJECTORY

Due to system errors, signal occlusion, etc., the real ADS-B trajectory data has problems such as repeated trajectory points and missing trajectory points. Repeated trajectory points will affect the availability of data, and we have eliminated duplicate trajectory points. For trajectory with a large number of missing trajectory points, it should be removed. For trajectory with a relatively small number of missing trajectory points, the problem can be solved by interpolation methods.



(a) Interpolation of longitude

(b) Interpolation of latitude

(c) Interpolation of altitude

(d) Interpolation of velocity

FIGURE 1. Example of trajectory interpolation.

TABLE 1. Features of one trajectory point.

Features	Trajectory point
Time	2017-05-06 07:35:10
ICAO address code	780E59
Flight number	XXX
Longitude /°	120.2188
Latitude /°	37.6415
Altitude /feet	25600
Velocity /knot	398.399
Heading /degree	49.071

According to the continuity and smoothness of the flight trajectory, the missing points are supplemented by the cubic spline interpolation algorithm. The specific method is to divide the trajectory into five components related to time t such as longitude, latitude, altitude, velocity, and heading, and obtain their interpolation results respectively.

Fig. 1 shows an example of interpolation of the longitude, latitude, altitude, and velocity of the trajectory. It can be seen from Fig. 1 that the trajectory becomes more complete, and the longitude, latitude, altitude, and velocity features of the trajectory also become more uniform after the processing of cubic spline interpolation. Through cubic spline interpolation, the missing trajectory points are well complemented, and sufficient preparation is made for subsequent splitting of trajectory sample.

IV. METHODOLOGY

In this section, the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are combined to propose a hybrid model for 4D trajectory prediction, called hybrid

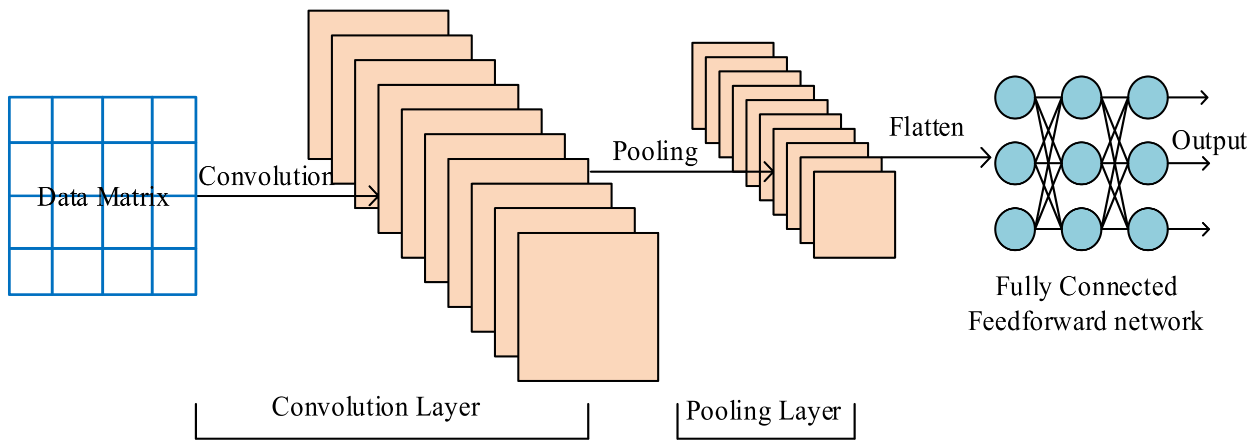


FIGURE 2. Typical structure of CNN network.

CNN-LSTM. Before that, we introduced the basic theories of deep learning that are indispensable for data modeling, including CNN and LSTM.

A. CNN NETWORK

CNN is a feedforward neural network with a deep structure, which is expert in processing image-related problems [39], [40]. The general structure of CNN is shown in Fig. 2.

Fig. 2 indicates that CNN consists of four layers, which is data matrix input, pooling, convolution, and fully connected layer.

The core of the CNN is the convolution operation. The biggest difference from the fully connected structure is that the convolution operation takes full advantage of the information in the adjacent areas of the data matrix. The size of the parameter matrix is greatly reduced by sparse connections and sharing weights. The pooling layer creates its own feature map by getting the average value or the maximum value, which achieves the compression of features and can avoid overfitting to a certain extent. We can construct multi-layer convolution and pooling operations in CNN. The deeper the layer of the network structure, the more abstract the features it extracts. The extracted abstract features are merged through a fully connected layer, and finally the classification problems and the regression problems can be solved through softmax or sigmoid activation function [41]. We just use the one-dimensional convolution in CNN to effectively extract the spatial feature of the trajectory dat.

B. LSTM NETWORK

Recurrent Neural Network (RNN) is a neural-network with short-term memory, which is suitable for processing time-series related problems. In recent years, RNN has made great success in the prediction of time series, but it has a Long-Term Dependencies problem in the training process of long series [42]. LSTM is improved to solve the Long-Term Dependencies problem. Trajectory can be considered as multiple time series, so we can take advantage of LSTM to process time series data and learn the Long-Term Dependencies of 4D trajectory data.

Compared with standard RNN, the main improvement of LSTM is the introduction of gating mechanism, namely input gate, forget gate and output gate, so as to control the information transmission in neural networks. The key to LSTM is the cell state. The first is to determine what and how much information we will discard from the cell state. This discard action is done through the forget gate. The next step is to determine what new information will be sent into the cell state. This operation is done through the input gate. Finally, the output gate determines what information is output. The architecture of the LSTM unit is illustrated in Fig. 3.

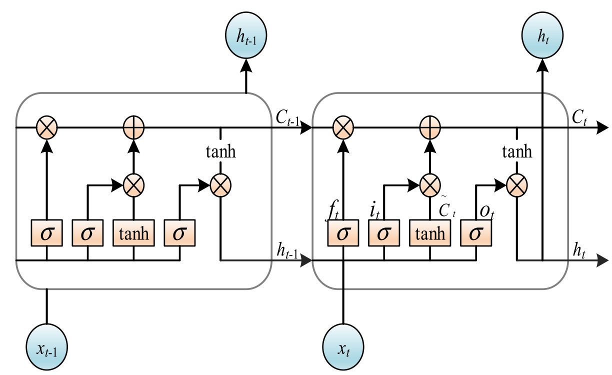


FIGURE 3. Standard structure of LSTM unit.

On the basis of the original short-term memory unit h_t, the LSTM model adds a memory unit C_t to maintain long-term memory, that is, the state of the cell. As can be seen from Fig. 3, an LSTM unit receives three inputs at each time step, the input x_t at the current moment, the state C_{t-1} and the output h_{t-1} from the last moment. Among them, x_t and h_{t-1} are used as inputs of three gates at the same time. The update process of the LSTM network is as follows.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$

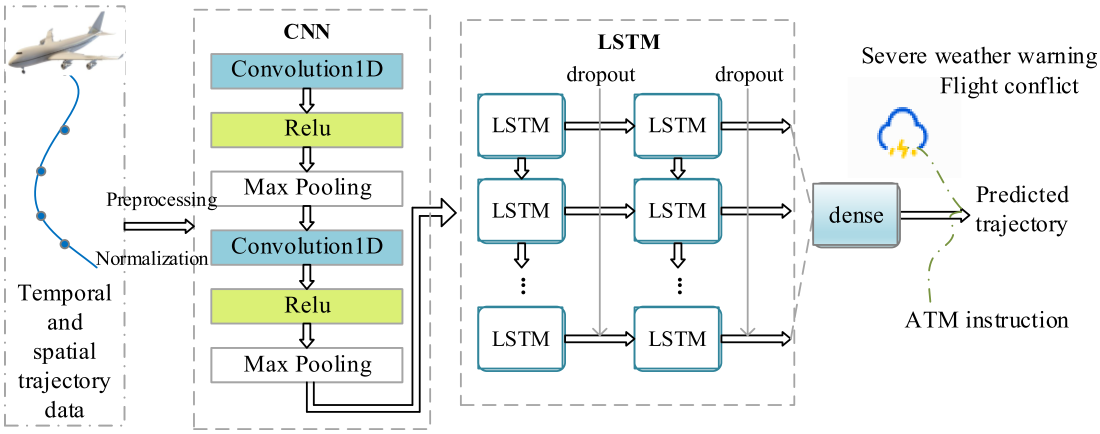


FIGURE 4. The proposed CNN-LSTM hybrid model architecture.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{6}$$

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{7}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{8}$$

$$h_t = o_t \times \tanh(C_t) \tag{9}$$

where, W_f, W_i, W_c, W_o are the coefficient matrix, b_f, b_i, b_c, b_o are the bias matrix, σ represents a sigmoid activation function. f_t represents forget gate and i_t represents input gate. At each moment, the forget gate controls how much memory is forgotten at the last moment, and the input gate controls how much new memory $\tilde{C}_t$ is written to the long-term memory. o_t represents the output gate, which controls how short-term memory is influenced by the long-term memory.

C. 4D TRAJECTORY PREDICTION MODEL BASED ON CNN-LSTM

CNN is more suitable for spatial expansion and can extract local spatial features very effectively [41], while LSTM has a certain memory capacity and is mostly used for processing time series data. Combining the advantages of CNN and LSTM, we propose a 4D trajectory prediction model that can effectively express the spatial-temporal features of the trajectory. The overall architecture of the model is shown in Fig. 4.

The model reflects the entire process of trajectory prediction: input of trajectory data, training of trajectory data by the model, and output of predicted trajectory. We will describe the three parts in the following section.

The input to the model is ADS-B trajectory data. ADS-B trajectory data is composed of a series of trajectory points that change with time, which has rich spatial-temporal information. Features of each trajectory at the time of t are defined as

$$X(t) \overset{\text{def}}{=} \{t, lon, lat, alt, vel, h\} \tag{10}$$

where t, lon, lat, alt, vel, h respectively refer to the time, longitude, latitude, altitude, velocity, heading of the aircraft at time t. We need to perform preprocessing such as supplementing the missing trajectory point on the input data, and we need to normalize it before sending it to the model. The input data of a traditional neural network is a vector, while the input data of CNN and LSTM is a tensor containing time series, that is, the time_step dimension is added. In order to facilitate CNN's convolution operation, time_step is set to 6, that is, the trajectory characteristic data of 6 consecutive time is used to predict the trajectory data at the next time. So, each of our samples is a 6×6 square matrix.

The core part of the model includes 1D CNN, LSTM and a fully connected layer. We use one-dimensional convolution to extract the spatial feature of the trajectory. The process is as follows. The trajectory data first pass through a convolution layer (convolution1D), the number of 1×3 convolution kernel is 32, the activation function is Relu, and then through a max pooling layer with a window size of 2. Then, the processed data is sent to the LSTM module after repeating the same convolution, activation, and pooling operations. We design two layers of LSTMs to mine the temporal features, and the output dimension of each layer of LSTM is 50, and each layer of LSTM uses dropout to avoid overfitting. Dropout randomly resets part of the weight or output of the hidden layer to zero to reduce the interdependence between the nodes of the neural network, so as to achieving the purpose of avoiding overfitting. The first LSTM layer takes the output at all moments, and the second LSTM layer takes the output at the last moment of the hidden layer. Finally, the trajectory data processed by CNN and LSTM will be sent to a fully connected layer.

The output of the prediction model is the time, longitude, latitude, and altitude information of the aircraft at future moments.

V. EXPERIMENTS

In this section, we use real ADS-B historical trajectory data from Qingdao to Beijing route for experiments. These trajectories are time series of varying lengths. The model is implemented on the Keras deep learning platform based on TensorFlow. The whole process of the experiment is shown in Fig. 5.

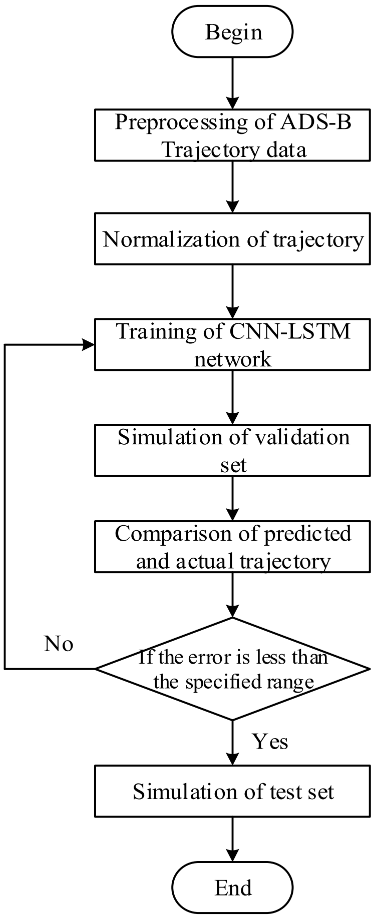


FIGURE 5. **The Flow chart of experimental steps.**

We first preprocess the ADS-B trajectory data, normalize it and send it to the network for training. Then the validation set is simulated, and the predicted and actual trajectories are compared. If the error is within the specified range, the model is tested through the test set, otherwise the model continues to be trained until the requirements are met.

In order to be able to fully test the performance of our proposed model, the prediction results of CNN-LSTM are compared with a single LSTM network and BP network respectively. In addition, we performed single-step and multi-step prediction on trajectory respectively, in which 3 and 5 are selected as the step length in the multi-step prediction. Therefore, we construct three data sets D_1, D_2 and D_3.The sample division of the three data sets is shown in Table 2. As can be seen from Table 2, each data set is divided into a training set and a test set, and 10% of the training set for each data set is selected as the validation set to verify and adjust of the model. Finally, the test set is used to evaluate the performance of our model.

TABLE 2. **Sample division.**

Data set	Training set	Test set
D_1	340132	47647
D_2	339852	47607
D_3	339572	47567

A. DATA PREPARATION

We use the trajectory data collected and decoded by ADS-B from February to May 2017. For reasons of privacy protection, flight numbers have been omitted.

1) CONSTRUCTION METHOD OF TRAJECTORY SAMPLES

4D trajectory prediction is a supervised learning problem, and the trajectory data needs to be split into training samples and labels. We take a single-step prediction as an example to give the sample construction method, as shown in Fig. 6.

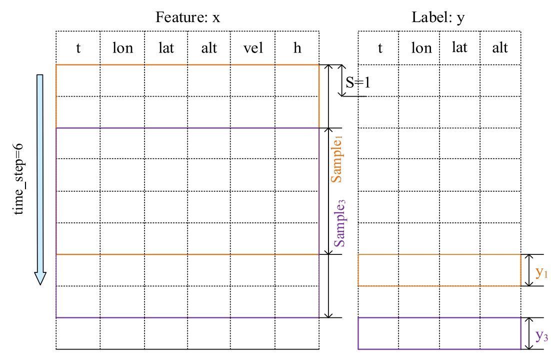


FIGURE 6. **Illustration of sample splitting.**

In Fig. 6, the rows represent time steps and columns represent training features. We start from the first trajectory point and go down in time sequence, selecting the time, longitude, latitude, altitude, velocity and heading of the first 6 trajectory points to predict the time, longitude, latitude and altitude of the next trajectory point (y_1 in the figure). Then, starting from the second trajectory point (to ensure the continuity of the samples in time, the separation interval S is selected as 1), the same method is used to select the training samples. The constructed sample ($Sample_1$ in Fig. 6), as described in Part C of Section IV, is a 6×6 square matrix.

2) SAMPLE NORMALIZATION

The trajectory data needs to be normalized before entering it into the model. We refer to the method of Dispersion Normalization in literature [43], which is defined as

$$N = \frac{X - min}{max - min} \tag{11}$$

where, X is the original sample data, max represents the maximum value of the sample, min represents the minimum value of the sample, and N is the normalized sample.

B. EVALUATION METRICS

Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) are the most commonly used evaluation indicators for regression problems. RMSE is the expected value of the square of the difference between the predicted result and the actual target, and then takes the square root operation. MAE is the average of the absolute errors between predicted and observed values. MAPE is a process of comparing with the original data, considering the ratio between the error and the actual value. We use the above three indicators to evaluate the effectiveness of CNN-LSTM model. The calculation formulas of the three indicators are shown in equations (12) to (14).

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(P_i - R_i)^2\right]^{\frac{1}{2}} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - R_i| \tag{13}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - R_i}{P_i}\right| \times 100\% \tag{14}$$

where, P_i represents the predicted trajectory at time i, and R_i represents the actual flight trajectory at time i . The smaller the values of the three-error metrics, the closer the predicted trajectory is to the actual trajectory, which also indicates that the model's prediction accuracy is higher.

C. COMPARATIVE ANALYSIS OF EXPERIMENTAL RESULTS

BP model, LSTM model and the proposed CNN-LSTM hybrid model are used to carry out experimental simulation on the same data set. Therefore, we compare and analyze the models from the following three aspects: model structure and parameters, 4D trajectory prediction curve, and the error values of the predictive measures of different models.

1) COMPARISON OF MODEL SRTUCTURE AND PARAMETER

Fig. 7 shows the structure and parameters of the three models. The BP model designed in this paper includes an input layer, two hidden layers and a fully connected output layer. Since time_step is set to 6, and the number of training features is 6, the input is a vector of length 36, which corresponds to the first six trajectory point. The number of nodes in each hidden layer is 50, and a dropout layer is added behind it to prevent overfitting. The number of output nodes is 4, corresponding to the trajectory feature at the next moment. The LSTM network model includes an input layer, two LSTM hidden layers, and a fully connected layer. The time_step in the input layer is selected as 6, which indicates that the scale of input data for training and testing is a 6 × 6 matrix, which also corresponds to the first six trajectory point. The number of nodes in each hidden layer of the LSTM is also set to 50. Similarly, a dropout is added after each hidden layer. The number of LSTM output nodes is 4, which corresponds to the trajectory feature at the next moment.

The structure of the second half of the CNN-LSTM network model is the same as the LSTM model. Before the data enters the LSTM unit, the data is subjected to one-dimensional convolution and pooling processing. Taking the CNN-LSTM model as an example, the dimensional changes of the input and output data of each layer of the model are described in detail. The input data is a three-dimensional tensor (None, 6, 6), and None represents the number of batch samples during model training. The data first passes through a one-dimensional convolution layer (conv1D) containing 1×3 convolution kernels, the number of which is 32. Currently, the dimension of the tensor becomes (None, 6, 32). Then after activated by Relu, passing a max pooling layer (maxpooling1D) with a window size of 2, the tensor dimension becomes (None, 3, 32). Then after the same round of processing as above, the tensor shape becomes (None, 1, 32). After processing by CNN, the tensor passes through the first LSTM layer with output dimension of 50 (take the output at all times), the shape becomes (None, 1, 50). After the first layer of dropout, the shape remains the same. After passing the second layer of LSTM (take the output of the last moment) and dropout, the tensor dimension becomes (None, 50). Finally, the tensor passes through a fully connected layer with 4 nodes, and the output dimension becomes (None, 4).

2) COMPARISON OF PREDICTED AND ACTUAL TRAJECTORY

Taking into account two actual flights (the flight number is replaced by A and B here) as examples to give the model's single-step prediction result, as illustrated in Fig. 8-Fig. 9.

Fig. 8 is the prediction result of flight A, and Fig. 9 is the prediction result of flight B. Fig. 8 (a) is a two-dimensional graph of the predicted and the actual trajectory in latitude and longitude coordinates. Fig. 8 (b) is a three-dimensional display of the predicted and the actual trajectory. As can be seen from Fig. 8 (a) that the longitude and latitude prediction of the three models can keep the same trend with the actual trajectory, but the prediction curve of the BP model deviates significantly from the actual trajectory compared with the other two models. LSTM and CNN-LSTM models have smaller errors for the prediction of latitude and longitude. We can also see from the three-dimensional figure that the altitude prediction error of the models is slightly larger than the latitude and longitude. Compared with the actual altitude, the predicted trajectory points of the BP model have large fluctuations at each position. Although the altitude prediction error of the LSTM model is within an acceptable range, it can still be seen directly from Fig. 8 (b) that it has larger prediction error than the CNN-LSTM model. It can also be seen from Fig. 9 that the trajectory predicted by the proposed CNN-LSTM model is closest to the actual trajectory, with the smallest error, followed by LSTM and BP. The prediction error of BP model

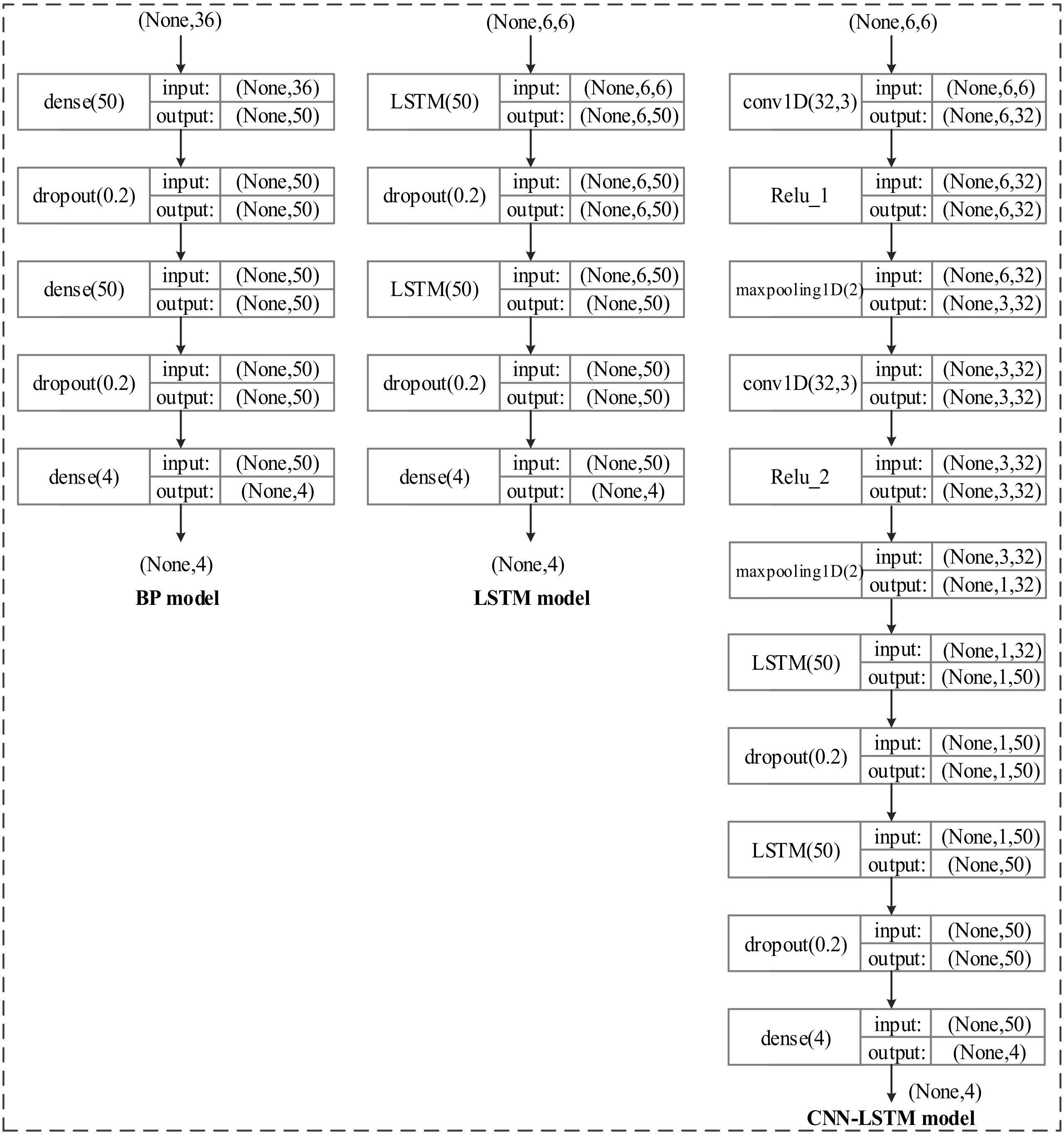


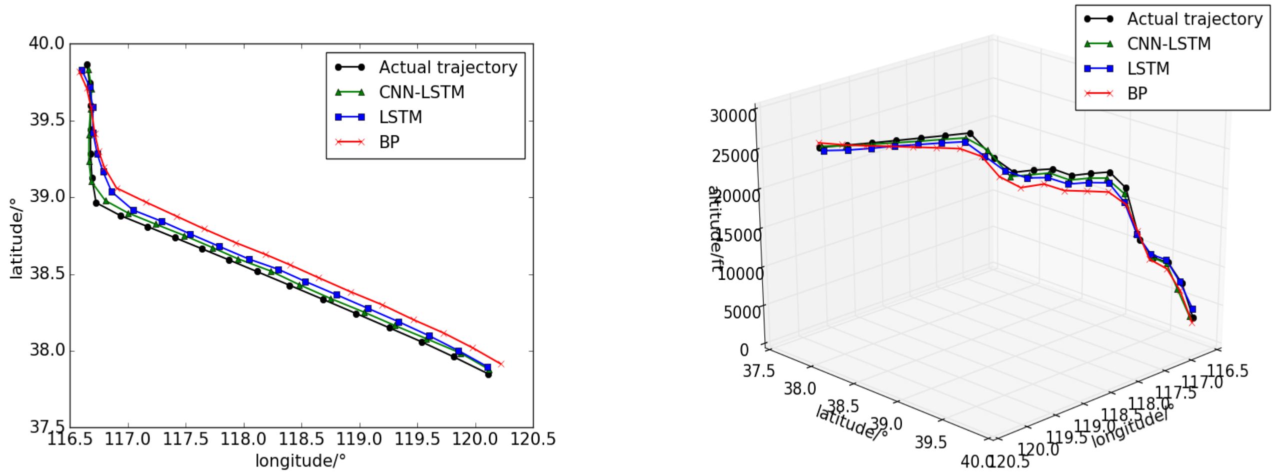
FIGURE 7. Structure and parameters of each model.

is greatest. So, in general, the prediction accuracy of the models is ranked as CNN-LSTM> LSTM> BP.

3) COMPARISON OF METRICS ERROR VALUES

Based on the predicted and actual trajectory, the values of the three-evaluation metrics of RMSE, MAE and MAPE can be obtained. We conduct statistical analysis on the single feature (time, longitude, latitude, and altitude) errors in the single-step prediction, and the results are illustrated in Fig. 10-Fig. 12. We can see from Fig. 10-Fig. 12 that the three-evaluation metrics of CNN-LSTM on a single feature prediction of the trajectory is better both than LSTM and BP. In addition, the three-evaluation metrics of the LSTM model on a single feature are better than the BP model, indicating that LSTM is more suitable for processing time series data than BP.

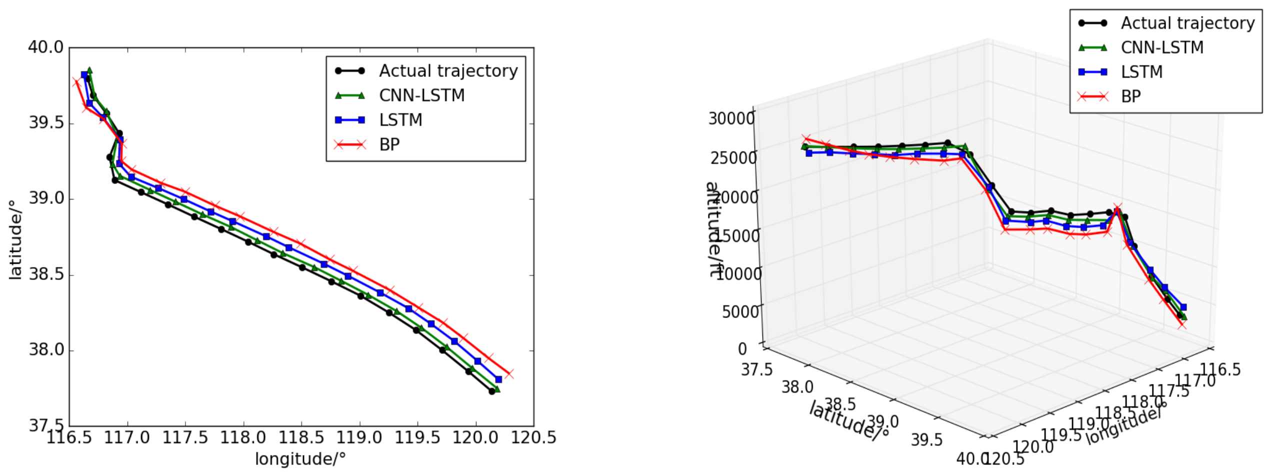
We have also separately calculated the average error of the predicted time, predicted longitude, predicted latitude, and predicted altitude features of models in the case of single-step and multi-step prediction, which are shown



(a) Prediction of latitude and longitude

(b) Three-dimensional prediction of trajectory

FIGURE 8. **Prediction result of flight A.**



(a) Prediction of latitude and longitude

(b) Three dimensional prediction of trajectory

FIGURE 9. **Prediction result of flight B.**

in Table 3. By analyzing the contents of Table 3, we can draw the following conclusions. The prediction error of the CNN-LSTM model is much smaller than that of LSTM and BP in the single-step prediction. While in the multi-step prediction, as the number of selected prediction steps increases, the prediction error of the LSTM model gradually approaches the CNN-LSTM model. On the D_3 dataset, although the CNN-LSTM model is better than the LSTM on the RMSE and MAE indicators, there is not much difference between both of them. In addition, whether it is a single-step prediction or a multi-step prediction, the prediction error of the BP model is much larger than the CNN-LSTM model and LSTM model. Based on the MAPE indicator, we can also see that the accuracy (1-MAPE) of the CNN-LSTM model in the three prediction tasks can reach as low as 91% and as high as 95%, indicating that the prediction performance is relatively stable. While the prediction accuracy of the LSTM and BP models decrease greatly with the increase of selected prediction steps. The prediction accuracy of the BP model on the D_3 dataset has even dropped below 80%. Therefore, the prediction performance of the CNN-LSTM model is superior to the LSTM and BP models.

For further comparison, in the single-step prediction, the prediction error of the CNN-LSTM model is 29.06% lower than the LSTM model on average, and 59.72% lower than the BP model on average. In the three-step prediction, the prediction error of the CNN-LSTM model is reduced by an average of 24.31% compared to the LSTM model and is reduced by an average of 50.42% compared to the BP model. In the five-step prediction, the prediction error of the CNN-LSTM model is reduced by an average of 11.50% compared to the LSTM model, and 47.20% compared to the

TABLE 3. Comparison of the Three Metrics for different models.

Data	CNN-LSTM			LSTM			BP		
	RMSE	MAE	MAPE/%	RMSE	MAE	MAPE/%	RMSE	MAE	MAPE/%
D1	10.192	8.595	4.56	15.918	11.297	6.69	24.521	19.645	12.85
D2	18.043	15.270	6.31	23.318	18.918	9.15	31.960	28.078	16.65
D3	36.024	28.011	9.23	38.655	29.041	12.17	65.032	47.304	21.08

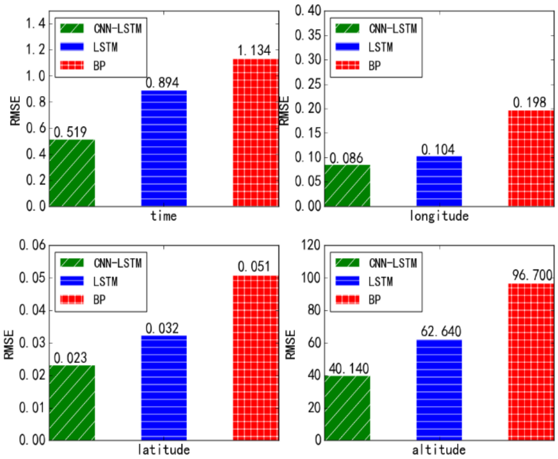


FIGURE 10. RMSE metrics for single feature.

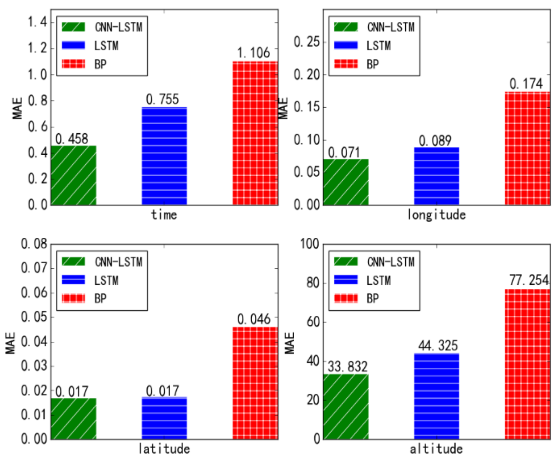


FIGURE 11. MAE metrics for single features.

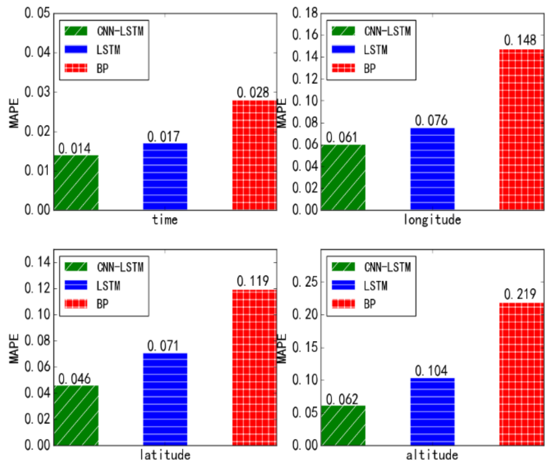


FIGURE 12. MAPE metrics for single features.

BP model. Based on the combined single-step prediction and multi-step prediction, the prediction error of the CNN-LSTM model is reduced by an average of 21.62% compared to the single LSTM model, and is reduced by an average of 52.45% compared to the single BP model. It can be seen from the above analysis that compared with the single BP and LSTM model, the prediction result of the CNN-LSTM hybrid model is more accurate and can better meet the requirements of aircraft 4D trajectory tracking.

VI. CONCLUSION

This paper proposes a hybrid model for 4D trajectory prediction of aircraft. We combined CNN and LSTM in deep learning to effectively extract the spatial-temporal features of the trajectory. The proposed method solves the problems of low prediction accuracy, insufficient prediction dimensions, and insufficient extraction of trajectory features in the existing trajectory prediction methods. We used RMSE, MAE, and MAPE indicators to measure the model. Based on this, we compared the proposed model with a single LSTM model and BP model. Experimental results demonstrate that the proposed CNN-LSTM model can more precisely predict the 4D trajectory of the aircraft, and the prediction accuracy is much higher than that of a single model.

However, the method proposed in this paper also has the following disadvantages: (*i*) The model's prediction of the 4D trajectory is short-term, not long-term. (*ii*) The ADS-B historical trajectory data used in our model is only on a single route, which has a limited scope of application. (iii) The trajectory of the aircraft is also affected by many other factors, such as meteorological conditions and control orders. Due to the limited trajectory information received by ADS-B, the model does not consider the influence of such factors. 4D trajectory prediction in the airspace has a variety of situations, and the influencing factors are also random. Corresponding prediction models need to be established for different scenarios. In the future, further research on 4D trajectory prediction can be made from the above aspects.

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