Terminal Traffic Flow Prediction Method Under Convective Weather Using Deep Learning Approaches

PENG Ying[1*], *WANG Hong*[1], *MAO Limin*[2], *WANG Peng*[1]

1. College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, P. R. China;
2. Nanjing LES Information Technology Co.,Ltd, Nanjing 210014, P. R. China

(Received 22 April 2021; revised 30 July 2021; accepted 10 August 2021)

Abstract: In order to improve the accuracy and stability of terminal traffic flow prediction in convective weather, a multi-input deep learning (MICL) model is proposed. On the basis of previous studies, this paper expands the set of weather characteristics affecting the traffic flow in the terminal area, including weather forecast data and Meteorological Report of Aerodrome Conditions (METAR) data. The terminal airspace is divided into smaller areas based on function and the weather severity index (WSI) characteristics extracted from weather forecast data are established to better quantify the impact of weather. MICL model preserves the advantages of the convolution neural network (CNN) and the long short-term memory (LSTM) model, and adopts two channels to input WSI and METAR information, respectively, which can fully reflect the temporal and spatial distribution characteristics of weather in the terminal area. Multi-scene experiments are designed based on the real historical data of Guangzhou Terminal Area operating in typical convective weather. The results show that the MICL model has excellent performance in mean squared error (MSE), root MSE (RMSE), mean absolute error (MAE) and other performance indicators compared with the existing machine learning models or deep learning models, such as K-nearest neighbor (KNN), support vector regression (SVR), CNN and LSTM. In the forecast period ranging from 30 min to 6 h, the MICL model has the best prediction accuracy and stability.

Key words: air traffic management; traffic flow prediction; convective weather; deep learning

CLC number: V355 **Document code:** A **Article ID:** 1005-1120(2021)04-0634-12

0 Introduction

It is well known that convective weather is one of the main causes of flight delays. It accounts for over 50% of the factors that cause flight irregularity (delays, divert, return) in China in recent years, while up to 60% of the flight delays in the United States are caused by convective weather[1]. To improve the efficiency of airspace operations and to reduce flight delays, air traffic flow management initiatives must be made dynamically taking into account airspace condition and weather uncertainty.

Given the weather forecast data, the traffic flow management (TFM) department in collaboration with the air traffic control (ATC) center and the meteorological department, will study the weather and operational condition for the following day[2]. Several traffic management initiatives, for instance, the ground delay program (GDP) and the mile-in-trail (MIT) strategy, will be prepared after dicussions[3]. During the pre-tactical phase, i.e., 2—6 h before the flight taking off, the traffic management strategies are further revised based on the updated weather information. Most likely, this step is manually implemented according to the experience of air traffic controllers (ATCOs). If the MIT strategy was carried out based on the overestimation of weather impact, it would not only waste airspace resources but also cause delay propagation[4]. There-

*Corresponding author, E-mail address: py423@sina.com.

How to cite this article: PENG Ying, WANG Hong, MAO Limin, et al. Terminal traffic flow prediction method under convective weather using deep learning approaches[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2021, 38(4):634-645.

http://dx.doi.org/10.16356/j.1005-1120.2021.04.010

fore, the translation of convective weather forecasts into air traffic flow impact is very important to air traffic flow management, which requires accurate statistics and prediction of the situation of air traffic, as well as its evolution trend.

The study of quantifying convective weather impacts to airspace capacity has been well investigated in the United States for more than a decade[5]. The convective weather information, such as the echo top and the vertically integrated liquid (VIL) level, is collected to build the weather avoidance field (WAF) and route blockage concept[6-7]. And convective weather avoidance models, such as the weather severity index (WSI) and the maximum flow and minimum cut metric, are developed to calculate capacity decreases[8-13]. However, these models are obviously restricted by the airspace geometry and cannot reflect the traffic demand.

And, various techniques have been developed and applied for the air traffic flow prediction (ATFP) task. The 4-D trajectory prediction estimates the fly over time of each waypoint and is further used to predict the air traffic flow[14-16]. Terrab et al.[17] established a stochastic dynamic model that takes into account unfavorable weather conditions to predict traffic flow. Ashley et al.[18] proposed an autoregressive and average moving model to predict traffic flow. Weinreich et al.[19] established a time series forecasting flow model based on historical data. Guo et al.[20] established a grey-Markov forecast model for air traffic flow management. However, these methods cannot capture the random and complex dynamic features of traffic situation under convective weather[21].

With successful applications of deep learning-based model on other fields, it is also introduced to solve the existing problems of aviation research[22]. The support vector machine for regression (OL-SVR) and the linear regression combined with the neural network based algorithms were proposed and improved to predict the air traffic flow[23-24]. A LSTM-XGBoost model was proposed to predict the short-term airport arrival traffic flow using the Meteorological Report of Aerodrome Conditions (METAR) as input[25].

From above discussion, we can see that existing approaches failed to consider the spatial and temporal dependencies of the traffic situation and convective weather comprehensively due to their input organization. To our limited knowledge, there is no relevant research that is proposed for the ATFP under convective weather.

This paper focuses on establishing a set of convective weather geometry features and flight statistical features, then proposes a novel deep learning-based terminal traffic flow prediction model, in which the spatial and temporal features of weather and flight are well captured by the proposed data representation. A multi-input deep learning model (MICL) is introduced to learn the complex weather impact patterns of terminal traffic system. MICL combines one-dimensional CNN (CNN-1D) and long short-term memory (LSTM), which can reduce the variance as much as possible to make the prediction more accurate.

1 Data and Features

1.1 Data preparation

1.1.1 Meteorological data

The radar basic reflectance image used in this paper is generated from the original products of 11 radar stations in Guangdong Province. The image product is drawn based on the basic reflectance of 0—70 dBZ defined by the 14-level color scale from light to dark, which more intuitively reflects the local weather information of the area. As shown in Fig.1, the original image size is 1 188 pixel ×

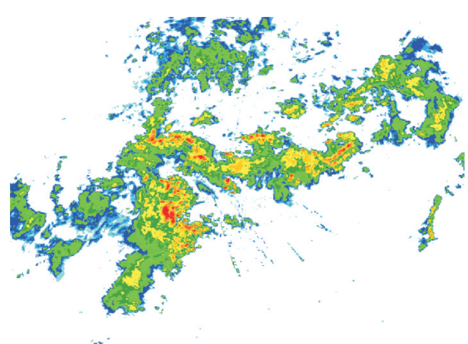

Fig.1 Radar basic reflectance image (color from green to red means the reflectivity gradually increasing)

880 pixel, with the horizontal resolution of 0.01° and the update cycle is 6 min. Another source of the meteorological data is from METAR, which records the weather conditions of the airport every half an hour.

1.1.2 Flight data

The flight data are obtained from the flight data recording (FDR) which contains all the details of every flight in Guangzhou Terminal Area. The following information is used in this study.

(1) Flight ID: The flight identity in the flight management database.

(2) ICAO designator of departure and arrival airport.

(3) Terminal entry time of arrival (UTC+8).

(4) Terminal exit time of departure (UTC+8).

(5) Actual departure time (UTC+8).

(6) Actual landing time (UTC+8).

(7) Estimated departure time (UTC+8).

(8) Estimated landing time (UTC+8).

1.2 Feature analysis

1.2.1 Meteorological features

Although the convolution operation can extract weather features directly from the images, the number of convolution cores will increase sharply due to the huge amount of information in the original images. In order to reduce the computational complexity, we need to extract the key information in the weather pictures and convert it into quantifiable weather features. Among many indicators, WSI indicator represents the proportion of airspace affected by severe weather, which can effectively measure the impact of weather on airspace. Some research results show that when WSI exceeds 70%, it has a non-negligible impact on airspace capacity[10]. WSI is given as

$$\mathrm{WSI}=\frac{S_{wx}}{S} \tag{1}$$

where S_{wx} is the area covered by weather, and S represents the total airspace area. The value of WSI is between 0 and 1.

As severe weather covers different positions in the terminal area, such as runways, arrival routes, departure routes and handover points, it has different influences on the traffic flow[13]. Therefore, the airspace of Guangzhou terminal Area is divided into nine small airspace marked as A—H, as shown in Fig.2. Here A indicates the airspace above the runway, B the airspace near the runway, C the ATAGA/IGONO approach corridor, D the LMN departure corridor, E the IDUMA approach corridor, F the VIBOS departure corridor, G the GYA approach corridor, and H the YIN departure corridor. Based on the direction of the traffic flow, the terminal area is further divided into the northwest arrival and departure direction, the east arrival and departure direction, and the south departure direction, marked as I, J, K. Finally, L is used to represent the whole terminal area. The WSI features are defined as

$$F_{\mathrm{WSI}}=\{\mathrm{WSI}_i \mid i=A,B,\cdots,L\} \tag{2}$$

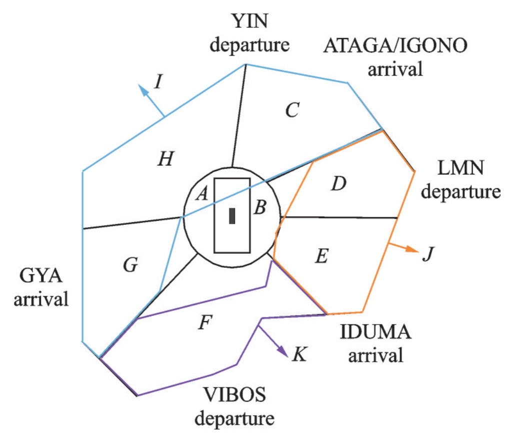

Fig.2 General structure of the Guangzhou Terminal Area

In addition, the METAR feature is given as

$$F_{\mathrm{METAR}}=\{\mathrm{METAR}_j \mid j=\mathrm{DIR},\mathrm{SPD},\mathrm{GUST},\mathrm{VAR_L},\mathrm{VAR_R},\mathrm{VIS},\mathrm{CLOUD},\mathrm{RA},\mathrm{TS},\mathrm{TUC_{CB}}\} \tag{3}$$

where j is the observed variable in METAR, including wind direction, wind speed, gust, wind direction change ranges, visibility, cloud, rain, thunderstorm, and cumulonimbus.

1.2.2 Flight features

Based on the actual arrival or departure time of the flight, the number of aircraft entering the terminal area within a certain time is calculated and arranged in chronological order to obtain the actual flight feature. The actual flight feature is

$$\mathrm{Act}_{\mathrm{flow}}=\{\cdots,\mathrm{flow}_{t-\Delta t}^{\mathrm{act}},\cdots,\mathrm{flow}_{t-1}^{\mathrm{act}},\mathrm{flow}_{t}^{\mathrm{act}},\mathrm{flow}_{t+1}^{\mathrm{act}},\cdots,\mathrm{flow}_{t+\Delta t}^{\mathrm{act}},\cdots\} \tag{4}$$

where $\mathrm{flow}_t^{\mathrm{act}}$ is the actual traffic flow at the current time t, $\mathrm{flow}_{t-\Delta t}^{\mathrm{act}}$ the actual traffic flow at the moment before Δt, and $\mathrm{flow}_{t+\Delta t}^{\mathrm{act}}$ the actual traffic flow at the moment after Δt. This actual flight feature is not only a key feature but also a learning label for traffic flow prediction.

In addition, the flow of a day is not only affected by the weather, but also by demand at different time of the day. For example, there are fewer flights in the early morning. Adding flight plan can improve the traffic features through the number of scheduled flights, specifically, the scheduled flight feature is

$$\mathrm{Yet}_{\mathrm{flow}}=\{\cdots,\mathrm{flow}_{t-\Delta t}^{\mathrm{yet}},\cdots,\mathrm{flow}_{t-1}^{\mathrm{yet}},\mathrm{flow}_{t}^{\mathrm{yet}},\mathrm{flow}_{t+1}^{\mathrm{yet}},\cdots,\mathrm{flow}_{t+\Delta t}^{\mathrm{yet}},\cdots\} \tag{5}$$

where $\mathrm{flow}_t^{\mathrm{yet}}$ is the scheduled traffic flow at the current time t in flight plan, $\mathrm{flow}_{t-\Delta t}^{\mathrm{act}}$ the scheduled traffic flow at the moment before Δt, and $\mathrm{flow}_{t+\Delta t}^{\mathrm{act}}$ the scheduled traffic flow at the moment after Δt.

Then, we have the flight features as

$$F_{\mathrm{flight}}=\{\mathrm{Act}_{\mathrm{flow}},\mathrm{Yet}_{\mathrm{flow}}\} \tag{6}$$

1.3 Data processing

The data set $F_t=\{F_{\mathrm{WSI}},F_{\mathrm{METAR}},F_{\mathrm{flight}}\}$ used in this paper includes not only numeric data but also image data. We used flight data, quantified basic radar reflectance images and METAR, forming a mixed input forecast flow structure of multiple data information, as shown in Fig.3.

For the image data part, since convective weather is generally the product of convective cumulonimbus clouds, it evolves with time. If there is data missing, we can fill in the convective weather picture from the previous time. Next, due to the wide area convered by the original weather picture, to accurately obtain the weather information of the terminal area, it is necessary to perform regional positioning processing and divide the terminal area according to the division rules described in the above meteorological features. Calculation is then made based on the WSI value of processed picture, which converts weather pictures into quantifiable weather metrics for follow-up research. For the numeric data part, the WSI value is originally in the range of 0—1, but features in METAR and the estimated or actual flow values are not, so they need to be normalized. Features mentioned above, including weather and flow, are normalized by

$$x'=\frac{x-\min(x)}{\max(x)-\min(x)} \tag{7}$$

where x' is the normalized result of data x, $\max(x)$ the maximum value of the sample data, and $\min(x)$ the minimum value of the sample data.

There are 24 features in total. This paper takes the hourly flow as the object for prediction, but the update cycle of the basic reflectivity map of the weather radar is 6 min and the update cycle of the airport METAR information is half an hour. Therefore, it is necessary to average the 10 weather snapshots and the two METAR messages within 1 h. In addition, in order to increase the sample size and continuity of the data set, the sliding time window method is used for sampling, such as 12:00—13:00, 12:06—13:06, 12:12—13:12... According to the above sampling principles, the final data set includes 6 880 training data generated by sliding 6 880 h in 30 d and 1 120 test data generated by sliding 1 120 h in 5 d.

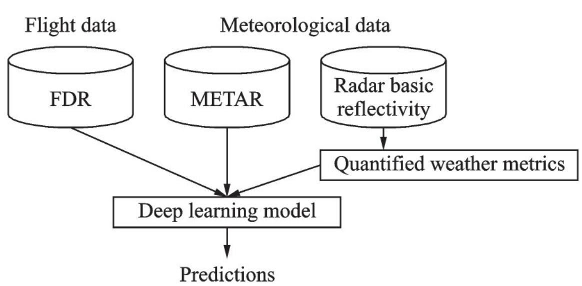

Fig.3 Framework of the deep learning model

2 Methodology

In this section, a deep learning (DL) model combining CNN-1D and LSTM is proposed to predict departure and arrival flow in the terminal area under convective weather.

2.1 Convolutional neural network

A CNN framework generally includes a convolutional layer, a pooling layer, and a fully connected layer[22]. The purpose of convolution is to apply the convolution kernel to all points of a certain tensor and generate a filtered tensor by sliding the convolution kernel on the input tensor, that is, convolution aims to capture the spacial features[26], as shown in Fig.4.

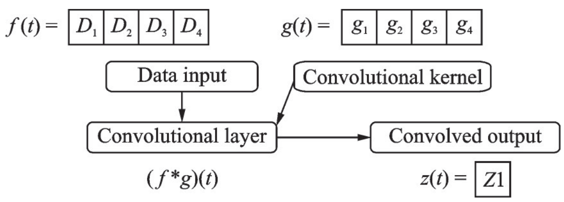

Fig.4 Core process of convolutional layer processing

2.2 LSTM network

The essence of LSTM is a recurrent neural network (RNN), which predicts the outcome of future events based on the features of events in the past period through a key parameter, i.e. forecast period. As Fig.5 shown, LSTM is characterized by the addition of valve nodes in each layer, including the forget gate, the input gate, and the output gate[27].

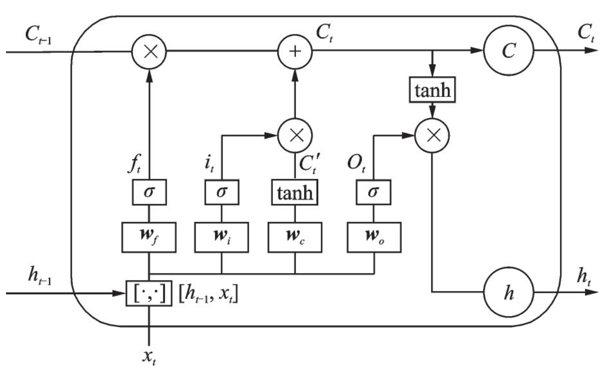

Fig.5 Structure of a basic LSTM cell

The forget gate means that some unimportant information is forgotten in the output result h_{t-1} at the previous moment to obtain C_{t-1}, which is

$$f_t = \text{sigmoid}(\boldsymbol{w}_f \cdot [h_{t-1}, x_t] + \boldsymbol{b}_f) \tag{8}$$

The input gate is based on the last time and C_t' obtained by the current input value x_t, so as to update the memory state C_t, which are

$$i_t = \text{sigmoid}(\boldsymbol{w}_i \cdot [h_t, x_t] + \boldsymbol{b}_i) \tag{9}$$

$$C_t' = \tanh(\boldsymbol{w}_c \cdot [h_{t-1}, x_t] + \boldsymbol{b}_c) \tag{10}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C_t' \tag{11}$$

The output gate determines the output h_t, which is

$$O_t = \text{sigmoid}(\boldsymbol{w}_o \cdot [h_{t-1}, x_t] + \boldsymbol{b}_o) \tag{12}$$

where $\boldsymbol{w}_f$, $\boldsymbol{w}_i$, $\boldsymbol{w}_o$ are the weight matrices that control the behavior of these gates, and $\boldsymbol{b}_f$, $\boldsymbol{b}_i$, $\boldsymbol{b}_o$ are the bias matrices.

2.3 Multi-input deep learning model

CNN-1D has advantages in extracting internal spatial features. LSTM can play a very good role in dealing with data with sequence attributes. However, using CNN or LSTM methods alone cannot predict the traffic flow in convective weather conditions well. Therefore, we propose a mixed DL model with multiple input data sources, integrating the advantages of these two methods. The model can accurately use the weather and flow characteristics to predict traffic flow that there will be a certain period time in the future when convective weather occurs.

The first part of the model is a CNN-1D network designed to process quantitative weather data from weather images. WSI features are input through dense layer. The convolution kernel is used to extract the weather features that affect the traffic in the terminal area. The size of the convolution kernel is 1×3, and the number is 32. After being activated by the activation function Relu, the information is passed to the maxpooling layer with the windows of 2 for dimensionality reduction. The processes of convolution, activation and pooling are repeated twice to be able to extract features in depth. To prevent convolution from overfitting, we use a dropout layer with a size of 0.2 and then use a fully connected layer to connect the feature information. Finally, the dense layer outputs the feature results of the part.

The second part is LSTM, which is used to predict traffic flow of the terminal area within a period time in the form of time series. This part inputs

METAR features, actual flow data and scheduled flow data through dense layer. Then the two-layer LSTM with an output dimension of 50 is used to learn to mine the hidden information. The activation function is the same as that in the CNN part. Finally, the result is output by the Dense layer.

The two parts are connected with a simple perceptron combination, which consists of an input dense layer and an output dense layer. The Adam is selected as optimizer and the activation function is Relu. However, to ensure that the two outputs can be connected, the final output dimensions of the two parts need to remain the same.

Finally, as shown in Fig.6, MICL model with 1-hour forecast period is formed. The left side of each box represents the layer of the model, and the right side is the three-dimensional tensor of the input and output of the layer. The first dimension "None" refers to the size of the batch sample, where None indicates that samples can be of any size, the second dimension is the time steps of the model, and the third dimension is the features of the sample.

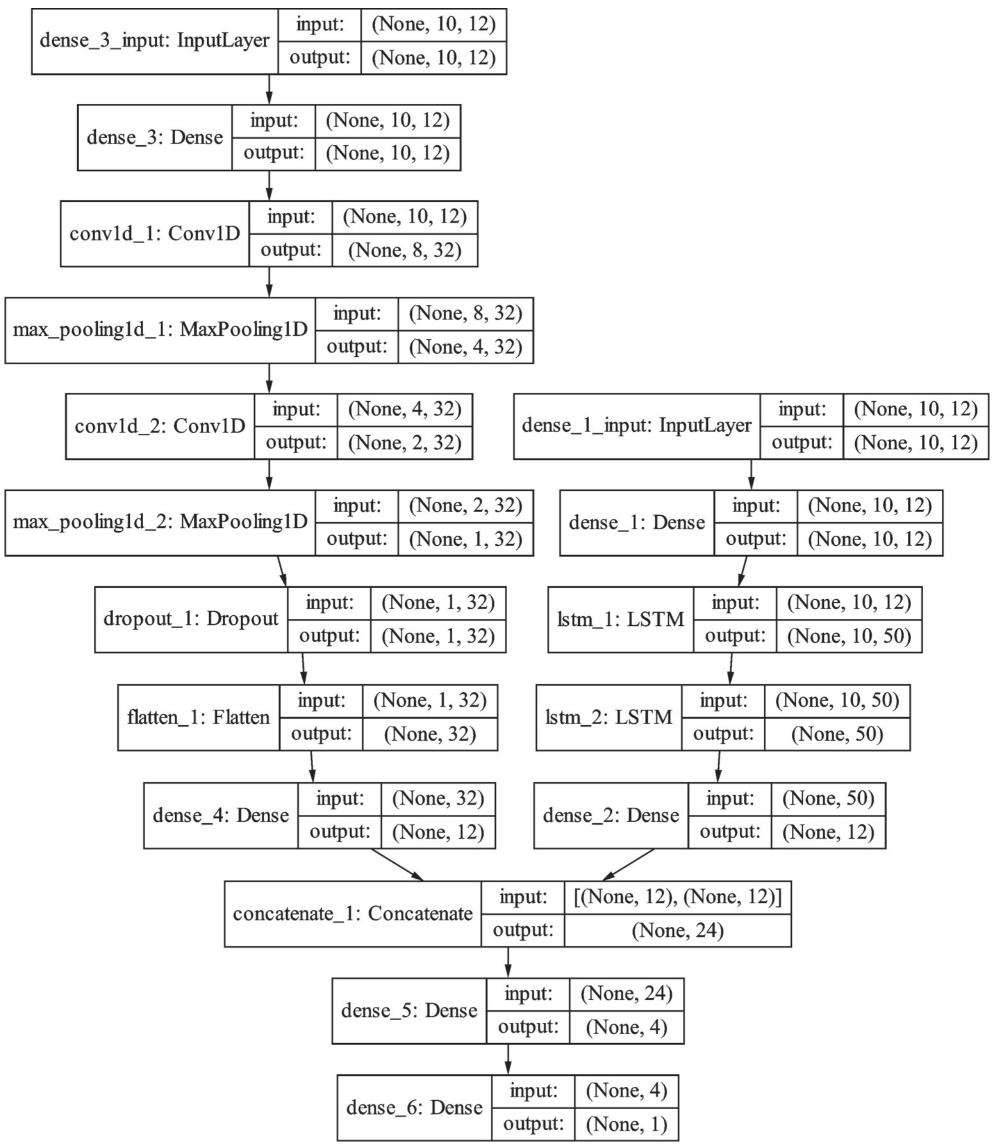

Fig.6 Structure and parameters of MICL model with 1-hour forecast period

2.4 Model performance evaluation

To evaluate the performance of the traffic prediction model, we select the following three commonly-used regression evaluation metrics: Mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE), which are calculated as

$$\mathrm{MSE}=\frac{1}{N_{\mathrm{T}}}\sum_{i=1}^{N_{\mathrm{T}}}\left[y_i-f(\boldsymbol{x}_i)\right]^2 \tag{13}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{N_{\mathrm{T}}}\sum_{i=1}^{N_{\mathrm{T}}}\left[y_i-f(\boldsymbol{x}_i)\right]^2} \tag{14}$$

$$\mathrm{MAE}=\frac{1}{N_{\mathrm{T}}}\sum_{i=1}^{N_{\mathrm{T}}}\left|y_i-f(\boldsymbol{x}_i)\right| \tag{15}$$

where N_{T} is the total number of samples in the test dataset, y_i the true value of the test sample i, f the mapping learned from the training data, and $\boldsymbol{x}_i$ the input feature vector of the test sample i.

3 Case Study in Guangzhou Terminal Airspace

3.1 Feature correlation analysis

To validate whether the model can accurately estimate the traffic flow and to gain a better understanding of the dataset, the correlation analysis of the features and the target flow is carried out. The first correlation analysis is shown in Fig.7, in which the color indicates the correlation of any two features. The number in the box is the correlation coefficient. Color represents the coefficients as well. It can be seen that the most relevant to the actual flow is the flight plan flow, and the remaining meteorological features account for 10%. If two airspace zones or routes are close in space, two metrics are highly correlated, such as A and B for runway zones, and then a strong correlation will occur. This is to be expected because the weather is mainly systemic and usually wide in scope to affect many airspace units simultaneously. The reason why there is high correlation among RA, TS and $\mathrm{TCU_{CB}}$ is that the occurrence of convective weather is often accompanied by thunderstorms and cumulonimbus clouds. The SPD and CLOUD in the METAR have nothing to do with $\mathrm{Act_{flow}}$. Therefore, these two features are removed and not used as input features.

3.2 Model accuracy

To evaluate the performance of our model, we compare our MICL model with three deep learning

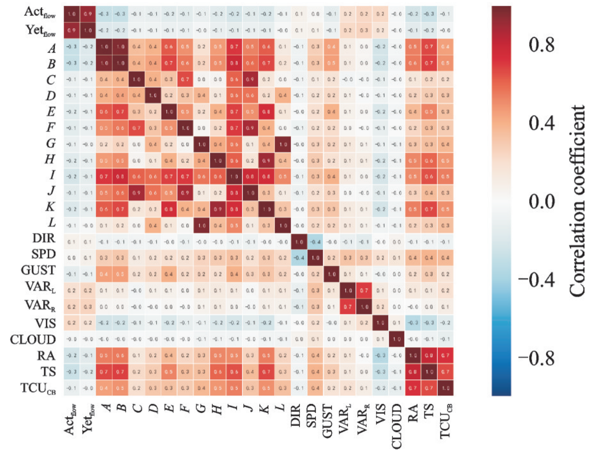

Fig.7 Correlation coefficient heat map of features

models including CNN-1D, LSTM and MICL model without WSI features, and two machine learning models including K-nearest neighbors (KNN) and support vector regression (SVR). Various forecast periods were tested, including 6 min, 30 min, 1 h, 2 h, and 6 h. The evaluation results are presented in Table 1. Note that the target values are standardized, thus, the predictions are not integers to be inconsistent with the actual operation. Therefore, we have to convert the predicted results into integer to evaluate performance.

Compared with machine learning models (KNN and SVR), deep learning models are far superior when we focus on regression evaluation metrics. Especially with the increase of the forecast period, the difference between the metrics of the two types of methods also gradually increases, which also verifies the superiority of the neural network in time series forecasting.

The values of MICL in MSE, RMSE and MAE are smaller than that of CNN-1D or LSTM in all forecast periods, which indicates that MICL model has the advantages of CNN model to capture spatial features and LSTM model to capture temporal features. We also conduct experiments using the MICL model without the WSI features, the prediction results are worse than results of CNN-1D, LSTM and MICL model with WSI features. That means WSI features improve the model performance obviously.

Table 1 Performance evaluation results of various models

Forecast period	Model	MSE	RMSE	MAE
6 min	CNN-1D	20.41	4.52	3.78
	LSTM	16.27	4.03	3.10
	LSTM-XGBoost	5.87	2.42	1.90
	MICL without WSI	20.88	4.57	3.58
	SVR	18.67	4.32	3.06
	KNN	45.94	6.78	4.89
	MICL	9.38	3.06	2.37
30 min	CNN-1D	19.05	4.36	3.55
	LSTM	17.63	4.20	3.30
	LSTM-XGBoost	22.01	4.69	3.55
	MICL without WSI	32.00	5.66	4.09
	SVR	24.40	4.94	3.56
	KNN	53.83	7.34	5.34
	MICL	7.11	2.67	2.07
1 h	CNN-1D	10.64	3.26	2.41
	LSTM	13.64	3.69	2.95
	LSTM-XGBoost	44.98	6.71	5.13
	MICL without WSI	52.19	7.22	5.46
	SVR	25.78	5.08	3.67
	KNN	63.78	7.99	5.83
	MICL	6.49	2.55	1.97
2 h	CNN-1D	13.22	3.64	2.71
	LSTM	14.21	3.77	3.06
	LSTM-XGBoost	78.70	8.87	7.06
	MICL without WSI	54.29	7.37	5.52
	SVR	32.18	5.67	4.22
	KNN	76.28	8.73	6.61
	MICL	7.30	2.70	2.06
6 h	CNN-1D	18.57	4.31	3.23
	LSTM	17.52	4.19	3.24
	LSTM-XGBoost	162.62	12.75	9.26
	MICL without WSI	42.93	6.55	4.78
	SVR	48.52	6.97	5.25
	KNN	176.97	13.30	9.29
	MICL	13.87	3.72	2.95

When the forecast period is 6 min, the LSTM-XGBoost model has the best prediction performance, and the MICL model is the second. But when the forecast period gets longer, the prediction performance of LSTM-XGBoost is getting worse and worse. This indicates that although LSTM-XGBoost has superiority in the prediction of airport arrival flow[25], it is relatively insensitive to the spatial domain meteorological features used in this paper, and its predictive performance is correspondingly reduced. On the contrary, the performance of the MICL model is better in all forecast periods. When the forecast period is 1 h, the MICL model gets the lowest MSE (6.49), RMSE (2.55) and MAE (1.97) of all. CNN-1D and LSTM also get their own minimum performance indicator values, but higher than those of MICL. While MICL model without WSI and LSTM-XGBoost model get their minimum performance indicator value when the forecast period is 6 min.

In order to further test the performance of the above algorithms, we select three typical weather impact scenarios, each with a duration of 1 h and covering different locations in the terminal area, as shown in Fig.8. KNN and SVR algorithms are not used in the following experiments because of their poor prediction performance.

Scenario 1 started from 21: 12 on June 1, 2019. Convective weather covered most of GYA arrival and a small part of YIN departure and ATAGA /IGONO arrival airspace. GYA is the arrival fix with the largest arrival flow, followed by ATAGA and IGONO. YIN is also the most important departure point. Therefore, this weather condition greatly increased the difficulty of dispatching arrival and departure flights, and the airport traffic volume was significantly reduced.

Scenario 2 started from 9:00 on June 3, 2019. The convective weather mainly covered the arrival airspace of ATAGA /IGONO. However, because the weather distribution was relatively scattered, there were more airspace for aircraft to avoid bad weather, so the airspace flow in this scenario did not decrease much.

Scenario 3 started from 14: 24 on June 4, 2019. The weather coverage extends from near the runway to the south arrival and departure direction, including GYA, VIBOS and IDUMA. This situation not only affects the traffic flow of the terminal area but also affects the take-off and landing of the airport runway. Aircraft can only hold in the air-

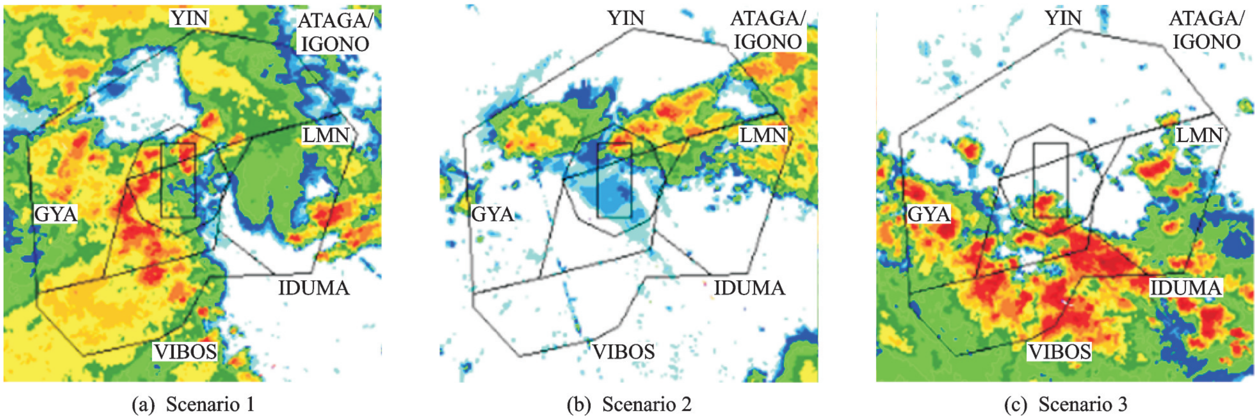

Fig.8 Convective weather scenarios at the beginning of each period (the avoided area marked in red)

space or return, resulting in a sharp drop in traffic flow.

By comparing the predicted flow curve with the actual flow curve, it can be found that the MICL model without WSI features model has the largest prediction deviation in all scenarios, which indicates that the WSI features play a key role in improving the prediction accuracy. The prediction accuracy of LSTM-XGBoost model in Scenario 2 is higher than that of the other two scenarios, because the convective weather in Scenario 2 has little impact on flow, indicating that the model is not suitable for the airspace environment with high uncertainty. The prediction results of CNN model and LSTM model are consistent with the actual flow trend, but the prediction accuracy is lower than MICL model.

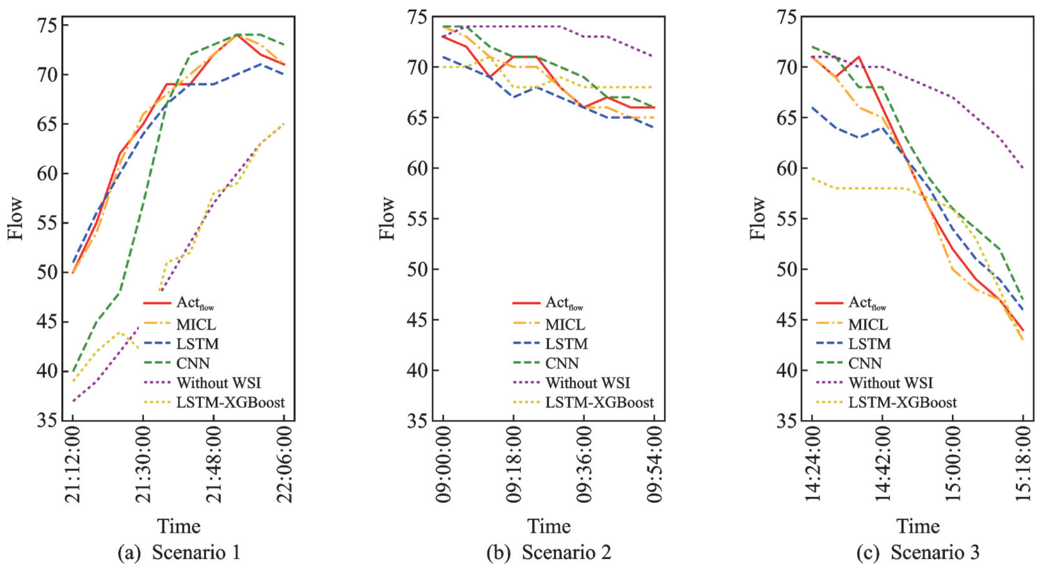

Fig.9 Actual and predicted flow value compared in three scenarios

According to the different weather coverage in scenarios 1—3 and the comparison between the predicted flow and the actual flow in Fig.9, we can find that if the airspace near the runway is covered by the weather, the flight will be unable to take off and land on the runway, which will have the greatest impact on the airport flow. If the severe weather covers the main arrival and departure routes, the greater the coverage, the more obvious the flow reduction. At the same time, the distribution of weather also affects the airspace flow. If the weather cells are loosely distributed, there is still a certain space for flight regulation and allocation, and the impact on the flow will be reduced.

Based on the above analysis, the MICL model has good prediction accuracy and stability under different weather scenarios.

4 Conclusions

For the research of terminal traffic flow prediction under convective weather, we apply a deep learning model called MICL in this paper. The proposed model is a deep neural network model, combined with CNN-1D and LSTM, which were proved to be effective for modeling spatial and temporal dependencies of air traffic. The MICL module not only preserves the advantages of the LSTM block on sequence modeling but is also very suitable for processing spatiotemporal data due to its inherent convolutional structure. By analyzing spatial characteristics of convective weather in terminal area, we establish a set of meteorological features such as WSIs, which represent the severe weather coverage ratio of runway adjacent airspace, arrival and departure routes, etc. By removing these meteorological features from MICL model, we have shown that these features are very effective in improving model performance because they contain rich information about meteorological location and intensity. Our experiments show that deep learning models are generally superior to machine learning models in terminal traffic flow prediction, and MICL model is proved to have the best accuracy and robustness by our designed experiments on real weather forecast data and flight data.

This paper provides an effective method for traffic controllers to predict the future traffic situation in convective weather. However, due to the uncertainty of the weather, all weather scenarios could not be enumerated. Therefore, how to cluster convective weather, extract important features, and provide auxiliary decision support for traffic management department under severe weather is one of the future research directions.

References

[1] MATTHEWS M P, VEILLETTE M S, VENUTI J C, et al. Heterogeneous convective weather forecast translation into airspace permeability with prediction intervals[J]. Journal of Air Transportation, 2016, 24 (2): 41-54.

[2] GORRIPATY S, LIU Y, HANSEN M, et al. Identifying similar days for air traffic management[J]. Journal of Air Transport Management, 2017, 65: 144-155.

[3] LIU Y, SEELHORST M, POZDNUKHOV A, et al. Assessing terminal weather forecast similarity for strategic air traffic management[C]//Proceedings of International Conference on Research in Air Transportation. [S.l.]: [s.n.], 2014.

[4] CHEN J T, KICINGER R, SCHELLING S, et al. Using weather translation and machine learning to identify similar weather impact day[C]//Proceedings of AIAA Guidance, Navigation, and Control Conference. USA: AIAA, 2017.

[5] KROZEL J. Survey of weather impact models used in air traffic management[C]//Proceedings of the 10th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference. USA: AIAA, 2010.

[6] CALLAHAM M B. Assessing NAS performance: Normalizing for the effects of weather[C]//Proceedings of the 4th USA/Europe Air Traffic Management R&D Symposium. California, USA: [s. n.], 2001: 3-14.

[7] KLEIN D A, JEHLEN R, LIANG D. Weather index with queuing component for national airspace system performance assessment[C]//Proceedings of the 7th USA/Europe ATM R&D Seminar (ATM 2007)). Barcelona: [s.n.], 2007: 1-10.

[8] HOFFMAN B, KROZEL J, JAKOBOVITS R, et al. Weather forecast requirements to facilitate fix-based airport ground delay programs[C]//Proceedings of the 86th AMS Annual Meeting. Atlanta, GA, USA: [s.n.], 2006: 1-6.

[9] PRETE J, KROZEL J. Benefit of a raycast weather severity metric for estimating transition airspace capacity[C]//Proceedings of the 10th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference. USA: AIAA, 2010.

[10] KROZEL J, POLISHCHUK V. Capacity estimation for airspaces with convective weather constraints[C]//Proceedings of AIAA Guidance, Navigation & Control Conference & Exhibit. USA: AIAA, 2008: 1-15.

[11] MITCHELL J, POLISHCHUK V, KROZEL J. Airspace throughput analysis considering stochastic weather[C]//Proceedings of AIAA Guidance, Navigation & Control Conference & Exhibit. USA: AIAA, 2004: 1-19.

[12] KROZEL J, PRETE J, MITCHELL J, et al. Capacity estimation for super-dense operations[C]//Proceedings of AIAA Guidance, Navigation & Control Conference & Exhibit. USA: AIAA, 2008.

[13] SONG L, WANKE C, GREENBAUM D, et al. Predicting sector capacity under severe weather impact for traffic flow management[C]//Proceedings of the 7th AIAA ATIO Conference. USA: AIAA, 2015.

[14] LIN Y, ZHANG J W, LIU H. An algorithm for trajectory prediction of flight plan based on relative motion between positions[J]. Frontiers of Information Technology & Electronic Engineering, 2018, 19(7): 95-106.

[15] CHEN Shaofei. Short-term air traffic flow prediction based on run-time data of Eurocat-X system[J]. Information & Communications, 2013(5): 42-44. (in Chinese)

[16] HU Minghua. Theory and method of air traffic flow management [M]. China: Science Press, 2010. (in Chinese)

[17] TERRAB M, PAULOSE S. Dynamic strategic and tactical air traffic flow control[C]//Proceedings of IEEE International Conference on Systems. USA: IEEE, 1992.

[18] ASHLEY D J, HANSON P, VELDHUIS J. A policy-sensitive traffic forecasting model for Schiphol Airport[J]. Journal of Air Transport Management, 1995, 2(2): 89-97.

[19] WEINREICH I, RICKERT H, LUKASCHEWITSCH M. Wavelet-based time series prediction for air traffic data[C]//Proceedings of SPIE. [S. l.]: The International Society for Optical Engineering, 2004: 52-66.

[20] GUO S, ZHANG Z, WANG L, et al. The gray-Markov model for forecasting air traffic flow based on residual correction[J]. Proceedings of the Eastern Asia Society for Transportation Studies, 2008, 2007: 87.

[21] LI N, JIAO Q, ZHU X, et al. Prediction of departure aircraft taxi time based on deep learning[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2020, 37(2): 232-241.

[22] MAHESHWARI A, DAVENDRALINGAM N, DELAURENTIS D A. A comparative study of machine learning techniques for aviation applications[C]//Proceedings of Aviation Technology, Integration, & Operations Conference. [S. l.]: [s. n.], 2018.

[23] CASTRO-NETO M, JEONG Y S, JEONG M K, et al. Online-SVR for short-term traffic flow prediction under typical and atypical traffic conditions[J]. Expert Systems with Applications, 2009, 36(3): 6164-6173.

[24] ZHANG Ming, HAN Songchen, HUANG Linyuan. Air traffic flow combinational forecast based on double gravity model and artificial neural network[J]. Journal of Southwest Jiaotong University, 2009, 44(5): 764-770. (in Chinese)

[25] YANG Z, WANG Y, LI J, et al. Airport arrival flow prediction considering meteorological factors based on deep-learning methods[J]. Complexity, 2020. DOI: 10.1155/2020/63092721.

[26] ZHAO J, MAO X, CHEN L. Speech emotion recognition using deep 1D & 2D CNN LSTM networks[J]. Biomedical Signal Processing and Control, 2019, 47: 312-323.

[27] HOCHREITER S, SCHMIDHUBER J. Long short-term memory[J]. Neural Computation, 1997, 9(8): 1735-1780.

Acknowledgement This work was supported by the Civil Aviation Safety Capacity Building Project.

Author Dr. **PENG Ying** received the B. S. degree in air traffic management and dispatch from Nanjing University of Aeronautics and Astronautics (NUAA) in 2003 and the Ph. D. degree in air traffic management and dispatch from NUAA in 2014. She joined the College of Civil Aviation, NUAA in 2003. She is currently the director of the Airspace and Flow Collaborative Research Office of the National Air Traffic Control Flight Flow Management Technology Key Laboratory. Her research is focused on airspace capacity assessment and relevant fields.

Author contributions Dr. **PENG Ying** designed the study, complied the models, conducted the analysis, interpreted the results and wrote the manuscript. Miss **WANG Hong** contributed to data processing and feature extraction of the model. Mr. **MAO Limin** concluded the research background. Miss **WANG Peng** contributed to figures and tables. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

(Production Editor: ZHANG Huangqun)

基于深度学习的对流天气下终端区流量预测方法

彭 瑛[1], 王 洪[1], 毛利民[2], 王 鹏[1]

(1.南京航空航天大学民航学院,南京 211106, 中国; 2.南京莱斯信息技术股份有限公司,南京 210014,中国)

摘要: 为提高对流天气下终端区流量预测的准确性和稳定性,提出了一种多输入深度学习模型(Multi-input deep learning, MICL)。在前人研究的基础上,扩展了影响终端区交通流的天气特征集,涵盖天气预报数据和机场气象报告(Meteorological Report of Aerodrome Conditions, METAR)数据。将终端空域根据功能划分为较小的空域,并通过天气预报数据建立天气危险指数(Weather severity index, WSI)特征,以更好地量化天气的影响。MICL模型结合了卷积神经网络(Convolution neural network, CNN)和长短期记忆网络(Long short-term memory, LSTM)模型的优点,采用双通道分别输入WSI数据和METAR报告数据,可以充分反映终端区天气的时间与空间分布特征。以广州终端区在典型对流天气下运行的真实历史数据设计多场景实验,结果表明MICL模型与K近邻算法(K-nearest neighbor, KNN)、支持向量回归(Support vector regression, SVR)、CNN、LSTM等既有机器学习或深度学习模型相比,在均方误差(Mean squared error, MSE)、均方根误差(Root MSE, RMSE)和平均绝对误差(Mean absolute error, MAE)等性能指标上表现优秀,在30 min至6 h不等的预测时间范围内均具有最佳的预测精度和稳定性。

关键词: 空中交通管理;交通流量预测;对流天气;深度学习