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Terminal Traffic Situation Prediction Model under the Influence of Weather Based on Deep Learning Approaches

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Abstract: In order to quantify the degree of influence of weather on traffic situations in real time, this paper proposes a terminal traffic situation prediction model under the influence of weather (TSPM-W) based on deep learning approaches. First, a feature set for predicting traffic situations is constructed based on data such as weather, traffic demand, delay conditions, and flow control strategies. When constructing weather data, a terminal area weather quantification method (TAWQM) is proposed to quantify various weather feature values. When constructing the traffic situation label, fuzzy C-means clustering (FCM) is used to perform cluster analysis on the traffic situation, and the traffic situation is marked as bad, average, or good. Accordingly, the multi-source data is fused as the input vector, based on the combined prediction model of convolutional neural network (CNN) and gated recurrent unit (GRU), TSPM-W is constructed. Finally, based on the historical operation data of the Guangzhou Baiyun International Airport terminal area, the proposed data set is used to predict the traffic situation time series at intervals of 1 h, 3 h, and 6 h. The comparative experimental results show that the proposed time series prediction model has higher prediction accuracy than other existing prediction methods. The proposed dataset is able to more accurately predict the traffic situation in the terminal area.

Keywords: traffic situation in terminal area; weather impact; traffic situation classification; time series prediction of traffic situation

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1. Introduction

With the rapid development of civil aviation transportation, one of the goals of air traffic management is to reduce the cost of airspace traffic situations estimated manually. Using big data technology to intelligently analyze the massive data of air traffic management can help to achieve this goal. Additionally, it may support the creation of "intelligent air traffic management," as well as a new operating system and management paradigm. In addition, it can provide support for air traffic management decision-making under future weather conditions according to the predicted results. By analyzing the overall traffic situation and strategy release situation through data mining technology, a preliminary quantification of the weather influence on the operation of the terminal area can be achieved. This also helps to effectively improve the efficiency of air traffic management decision-making.

Schultz et al. [1,2] proposed an idea of classification and prediction of the impact of weather on air traffic management, which uses traditional machine learning methods and deep learning networks to predict the impact of weather on airport operations. This traffic situation prediction method quantifies the impact of weather on airport traffic situations. In the scholars' research on traffic situations under the influence of weather, first of all, in the definition of traffic situation, the previous studies took the traffic demand and delay situation as the characteristics of reflecting the traffic situation, and this way of definition is relatively one-sided. This also makes the traffic situation fail to be effectively distinguished. Secondly, in the construction of the training set, the above-mentioned studies generally use few macroscopic features, and do not fully consider the impact of strategy features on the traffic situation. In addition, because the weather features are often relatively complex and diverse, and the overall quantification of the weather's impact is lacking, it is often difficult to capture the degree of weather's impact on the traffic situation. Finally, in terms of research methods, it mainly focuses on clustering and classification to complete the analysis of different scenarios. The time series features of traffic situation data are not considered, and the model selection is mainly based on a single model. However, a single model is often not suitable for multi-feature time series prediction. It has become a trend to consider a combined model to utilize the advantages of multiple models, to make up for the defects of a single model and to improve the prediction accuracy.

This paper attempts to propose a TSPM-W model. First, multiple dimensions of weather, traffic demand, delay status and strategy are selected when constructing a feature set. Then, when constructing weather features, TAWQM is introduced to comprehensively quantify the weather impact index, and when constructing traffic condition labels, FCM is used to classify and mark traffic conditions. Finally, this paper constructs a TSPM-W model that combines CNN and GRU, and the model uses the traffic situation dataset as input. The model realizes the prediction of traffic situations in the terminal area in units of 1 h~6 h.

The work in this paper can be summarized as follows:

(1) A TAWQM algorithm is proposed to quantify the influence of weather on the terminal area.
(2) A new set of traffic situation datasets in the terminal area is created, which takes into account the multi-dimensional features of weather, traffic demand, delay conditions, and traffic flow strategies.
(3) The traffic situation of the terminal area is clustered and divided into three traffic situations.
(4) A TFPM-W is proposed, and it is verified that the proposed model and dataset can better predict the traffic situation of the terminal area on the real operation data of Guangzhou Baiyun International Airport.

2. Related Work

Current research by domestic and international scholars on air traffic situation prediction focuses primarily on large-scale airspace systems or airport weather. The existing research objects can be divided into two main categories.

In the work with the airport as the research object, clustering, statistical quantification, and classification forecasting methods are often used. In air traffic-related clustering research, Reitmann et al. [1,2] used delay time and difference between demand and actual flow as features to describe airport operations. First, the K-Means clustering method is used to classify and mark similar scenarios of airport operating days. Then, using the obtained traffic situation labels as training labels, the Long-term Short-Term Memory network (LSTM) is used to complete the classification of the impact of weather on airport operations. Finally, the research on the airport traffic situation is realized. Grabbe et al. [3] proposed a method to use the features of airport ground delay to measure distance and find the most similar historical day to the reference day. They compared and analyzed the actual operation strategy of the calendar day and the performance of the airport traffic conditions after implementation, and based on the analysis results, they gave a reference day operation strategy suggestion. Mangortey et al. [4] firstly used the characteristics of airport ground delay and departure delay as input, then used a variety of clustering methods to compare the algorithms to determine the appropriate division method, and finally used the classification model to classify the traffic situation. It can be seen that the above traffic situation classification model is mainly characterized by operational traffic features in terms of feature selection. In the study of the condition of air traffic by statistical quantitative methods, Hoffman et al. [5] studied the impact of convective weather on airport ground delays and investigated weather-influenced delays at individual waypoints using the Weather Severity Index (WSI) rasterization of the Weather Avoidance Field (WAF). Smith et al. [6] and others measured the airport traffic situation according to the weather-affected delays, airport ground delays, and other indicators. Williams et al. [1,2,7] used the ATMAP algorithm to quantify the weather data of METAR messages. They studied the change law of key features such as demand and actual flow caused by different weather [8–10]. In terms of air traffic-related classification forecasting, single variable forecasting of air traffic that reflects the traffic situation has solved part of the problem of forecasting the operational features of airports. Smith et al. [11] used a support vector machine to predict the airport capacity under the influence of weather, and then used the prediction results to predict the airport delay [12]. Dhal et al. [13] proposed a multi-level forecasting model that forecasts the arrival and departure capacity of high-congestion airports within a day for the weather.

In the work that takes the terminal area and sector as the research object, classification and deep learning methods are often used for prediction. For the study of classification method prediction, Hoffman et al. [14–18] used relatively macro indicators to measure delay and weather elements, and used classification to study the characteristics of airspace systems in different scenarios. They used the Boosting algorithm to predict which category the daily situation belonged to. Appeal research has carried out an effective prediction on the delay level under the influence of weather by constructing a classification prediction model. For deep learning methods prediction, Klein et al. [19–21] proposed a new prediction model based on the weather-affected traffic index. They first quantified the impact of convective weather on airport operations, and then used delay features and deep learning methods to predict airport delays. Xie et al. [22–24] first proposed an image representation of sector operation scenarios in 2021. Combined with deep learning technology, they proposed a Deep Convolutional Neural Network (DCNN)-based sector computational complexity (SOC) evaluation method. Gianazza et al. [25] used Back Propagation Neural Networks (BPNN) to extract nonlinear features. They transformed air traffic complexity assessment into the problem of classifying air traffic complexity according to complexity factors. This points out a new direction for follow-up research. Migration learning methods [26] and adaptive augmented learning algorithms [27] have been used to assess air traffic complexity with good results. Peng et al. [28–30] made efforts to improve the accuracy and stability of flow prediction in the terminal area under convective weather. They propose a Multi-Input Deep Learning model (MICL)-based method for predicting traffic flow. Building on previous work, they extended the set of weather features affecting traffic flow in terminal areas. Chen et al. [31,32] first proposed a new knowledge migration-based framework for sector traffic situation assessment for small sample environments. Their proposed framework is able to effectively mine the information hidden in the target sector samples. Prandini et al. [33] proposed a new method that measures the probability of airspace occupancy and then uses the measurement results as input to predict and evaluate air traffic conditions in the three-dimensional airspace. The main innovation of the method is that the uncertainty of future aircraft locations is explicitly taken into account when assessing complexity. In order to effectively predict the dynamic capacity of the terminal area, Yang et al. [34,35] proposed a dynamic capacity prediction model under the influence of dangerous weather.

Based on multi-domain terminal area datasets and inspired by these works, we propose a TSPM-W to solve the problem of short-term prediction of the traffic situation in terminal areas.

3. Solution

TSPM-W is proposed to solve the problem of real-time prediction of traffic situations under the influence of weather in the terminal area. The solution framework is shown in Figure 1. Firstly, the terminal area dataset is constructed from multiple dimensions such as weather, traffic demand, delay situation, strategy, etc. In the construction of weather data, the TAWQM algorithm is proposed to quantify the impact of weather on traffic. When constructing the traffic situation label, FCM is used to perform cluster analysis on the traffic situation and label the traffic situation as bad, average, or good. According to this, the multi-source data is fused as the input vector; the single model of CNN and GRU are respectively constructed to carry out prediction. Aiming at the problem that a single model is not suitable for multi-feature prediction, we propose a combined TSPM-W model to make up for the defects of a single model. Based on TSPM-W, traffic situations under the influence of weather can be effectively predicted in units of 1 h, 3 h, and 6 h.

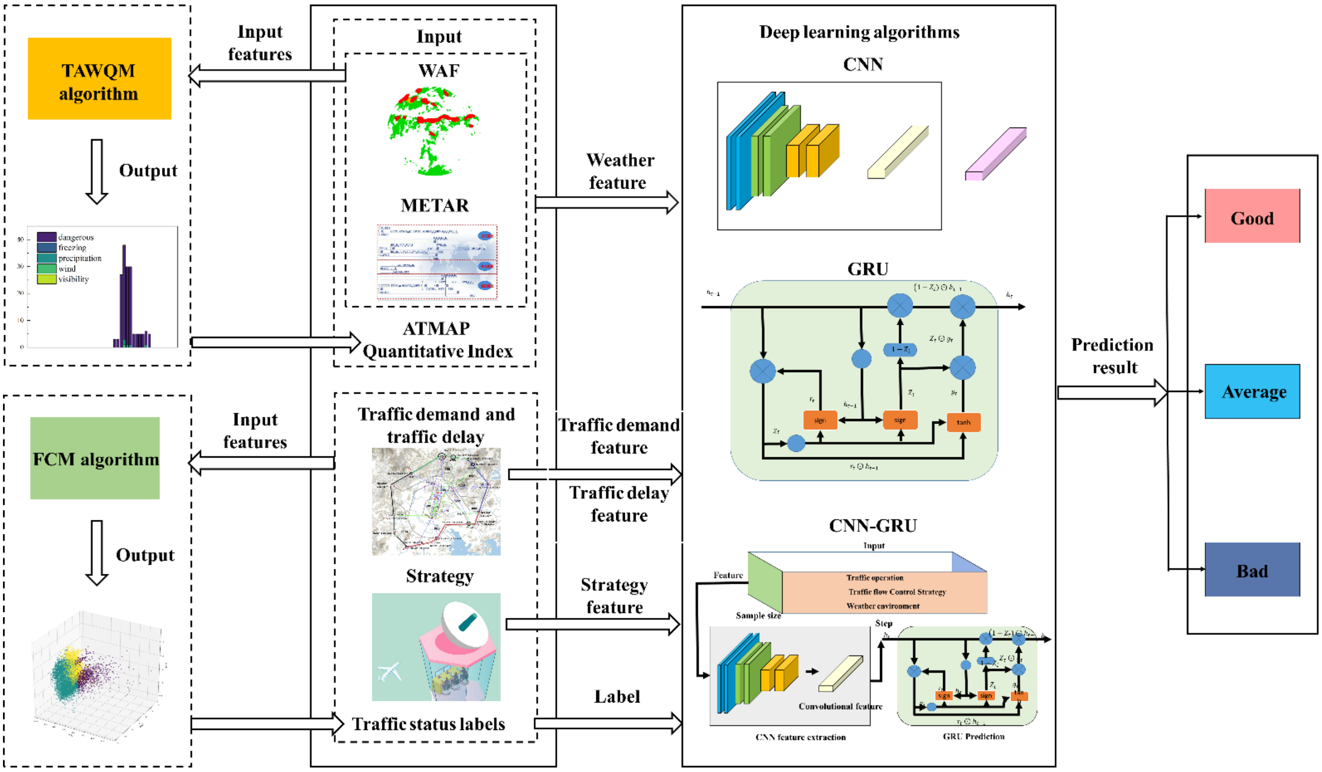


Figure 1. Framework of TSPM-W.

3.1. Construction of Traffic Situation Feature Set

In order to achieve accurate prediction of the traffic situation under the influence of weather, it is first necessary to construct a traffic situation feature set that considers traffic demand, delay conditions, strategy and weather. The Pearson correlation coefficient method is used to determine the specific factors with high correlation of the traffic situation, and the traffic situation feature set is determined as shown in Table 1.

Table 1. Terminal area feature set.

Area	Features
Traffic demand and delay conditions (7)	Actual traffic flow; scheduled traffic flow; the difference between traffic capacity and traffic flow; time of flight delay; number of delayed flights; number of cancelled flights; number of normal flights.
Weather (7)	Convective weather intensity coefficient, wind coefficient, wind speed, precipitations, freezing conditions, dangerous phenomena, TAWQM overall coefficient.
Strategy (7)	Release intensity of the flow control strategy, number of flights affected by flow control strategy, whether the strategy is activated, average point interval limit, pass interval limit validity, CTOT conformance rate, CLDT conformance rate.

We use flight plan and flight point data to extract 7 features such as actual traffic flow, number of delayed flights, and number of cancelled flights to represent traffic demand and delay conditions. Meteorological Report of Aerodrome Conditions data and 3-D weather avoidance area data are used to extract 7 features such as the convective weather intensity coefficient, the wind coefficient and so on to represent the weather state. The Mile-In-Trail (MIT) data are used to extract 7 features, such as the release intensity of the flow control strategy, calculated take-off time (CTOT) conformance rate, calculated landing time (CLDT) conformance rate, and the number of flights affected by flow control strategy, to represent the strategy status.

The explanation and calculation formulas for some related features are as follows:

(1) Average point interval limit: The average flight checkpoint limit interval time during the statistical period;
(2) Strategy release intensity: The frequency of traffic flow control strategies caused by weather during the statistical period;
(3) CTOT conformance rate: The ratio of the flight volume with the difference between the actual departure time and the CTOT time between [−5 min, 10 min] to the total flight volume;
(4) CLDT conformance rate: the ratio of the flight volume with the difference between the actual landing time and the CLDT time between [−5 min, 10 min] to the total flight volume;
(5) Whether the strategy is activated: whether the strategy is released due to the weather during the statistical period.

Convective Weather Intensity: During the statistical period, the sum of the values in the specified terminal area WAF.

$$WAF = \sum_{i=1,j=1}^{n=1250} waf_{i,j} \tag{1}$$

Among them, WAF is composed of 1250 × 1250 data points, and $waf_{i,j}$ represents the convective weather intensity of the data points in row i and column j within the range of 200 m × 200 m. The higher the intensity, the higher the impact of weather on traffic volume.

Pass interval limit validity: During the statistical period, the proportion of flight passing point intervals is less than the limit interval. The passing point interval refers to the flight time interval before and after the point, for example, the interval time between one plane going from this point and the next plane entering from this point.

$$V_{Int} = \frac{N_{limit}}{N_{Int}}, (N_{limit} \in N_{Tint} - N_{Int} \leq 0) \tag{2}$$

Among them, N_{Tint} is the flight passing waypoint interval, N_{Int} is the limit waypoint interval, N_{limit} is the number of times the flight passing waypoint interval is less than the limit, and V_{Int} is the validity of the crossing interval restriction.

3.1.1. Quantification of Weather Features Based on TAWQM

Considering that weather features are often complex and diverse and have high dimensions, it is easy to make it difficult to extract important information in the prediction process. In order to realize the quantification of complex weather, this paper proposes a TAWQM algorithm to quantify the weather characteristic values in the terminal area when constructing a dataset in the weather field. TAWQM adds a quantification algorithm for convective weather intensity to the Air Traffic Management Airport Performance (ATMAP) algorithm [1]. The following is the description of the TAWQM algorithm.

(1) Identify and extract the 6 elements of wind speed, visibility, precipitation, freezing conditions, dangerous phenomena, and convective weather intensity from METAR messages and WAF data as in Table 2.
(2) Coefficients are assigned to the different severity levels of the different weather elements. The sum of the coefficients for each weather element is the final weather

score. The factor is 18 when GS (small hail or shale) is present, 24 when FC, DS, SS, VA, SA, GR, PL, TS are present, and 30 when +TS is present.

(3) In the dangerous weather element, the overall convective weather intensity for terminal area is divided into three classes corresponding to a severity factor of 0, 18 and 30.

(4) With this algorithm, each parsed METAR message data can be quantified according to its scoring criteria. For example: METAR ZBTJ 021730Z15008MPS 8000 -TSRA FEW013 BKN033CB 21/14 Q0997NOSIG=; WAF -WSI, the total quantified score for this message is 26.

Table 2. Relevant weather scoring standards in TAWQM algorithm.

Weather Class	Description	Weather Conditions	Coefficient
(1) Ceiling and visibility	Deterioration of visibility	Precision approach runways (CAT I-III) Wind speed	max. 5
(2) Wind	Strong head-/cross-wind	>16 knots (+gusts)	max. 4 (+1)
(3) Precipitation	Runway friction influencing rwy occupancy time	e.g., rain, (+/−) snow, frozen rain	max. 3
(4) Freezing conditions	Reduced runway friction, de-icing	$T \leq 3\ °C$, visible moisture, any precipitation	max. 4
(5) Dangerous phenomena	Unsafe ops, unpredictable impact	TCU/CB, loud cover, (+/−) shower, storm	max. 32
(6) Convective weather intensity	Severe convective weather, unpredictable effects	(+/−) Convective weather	max. 30

3.1.2. Traffic Situation Marking Based on the FCM

In order to get the labels of the traffic situation of the terminal area, the clustering method is used to define and divide the traffic situation of the terminal area [2]. In order to compare the predictive ability of the predictive models in traffic situations constructed with different feature sets, the traffic situation of the terminal area is divided based on three different feature sets, which are called Feature combination 1, Feature combination 2, and Feature combination 3.

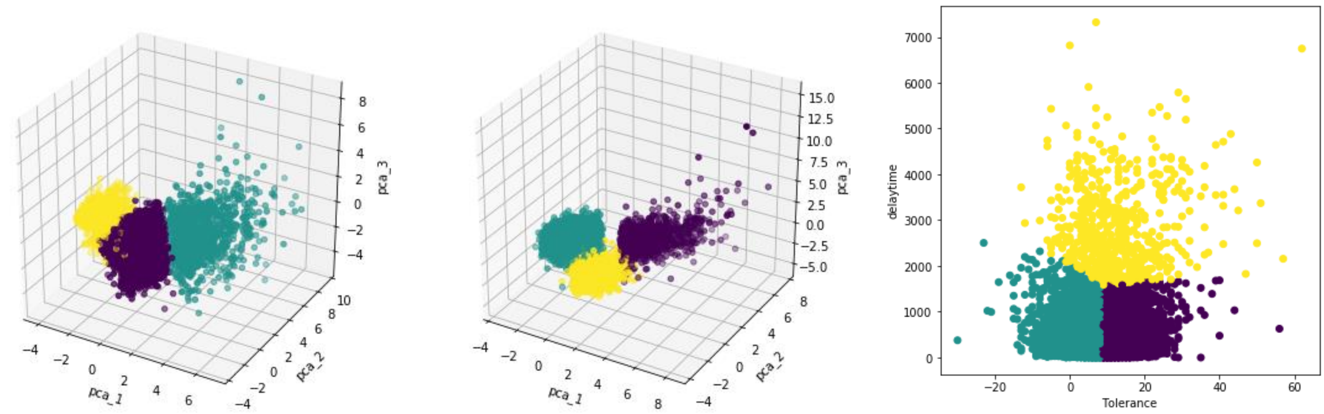
According to the terminal area feature set in Table 1, it includes four categories: weather, traffic demand, traffic delay, and strategy. According to the definition of traffic situation in this paper, weather features are excluded when the traffic situation is clustered. Feature combination 1 considers the clustering of the traffic situation based on the features of traffic demand, traffic delay, and flow control strategy. Feature combination 2 considers throwing away the strategy feature in Feature combination 1. In other words, Feature combination 2 uses traffic demand, traffic delay for clustering. Under Feature combination 3, we refer to the construction method of References [1,2], and select the difference between demand flow and actual flow and flight delay time as indicators to define the traffic situation.

The datasets of Feature combination 1, Feature combination 2, and Feature combination 3 are Max-Min normalized and clustered by FCM. We determined the optimal number of clusters based on silhouette score, calinski_harabaz scores and elbow method. The optimal number of clusters is 3. The clustering feature combination results are shown in Table 3, the values in Table 3 represent the mean of the cluster.

The results show that the feature combination classification provides a good differentiation between traffic operations and strategic situations. The main features and numerical distributions of traffic situation in different categories of feature combination are identified, providing a better delineation of the traffic situation in the presentation terminal area. This also obtains the required predictive labels. As shown in Figure 2, the classification results of Feature combination 1, Feature combination 2, and Feature combination 3 are visualized. As shown in Figure 3, Feature combination 1 and Feature combination 2 are displayed in pca_1, pca_2 and pca_3 by using principal components analysis (PCA) to extract the first three main layers for visualization. Feature combination 3 is visualized using the difference between traffic capacity and traffic flow and delay time as coordinate values.

Table 3. Traffic situation based on different feature combination.

Feature Combination	Cluster	Data	Traffic Demand			Traffic Delay		Strategy	Traffic Situation
			Cancellation	Nomal	Capacity Flow Difference	Delay	Delay Time	Strategy Intensity	
Feature combination 1	Cluster0	1827	1.31	45.38	7.80	5.69	246.2	1.28	good
	Cluster1	4513	1.34	19.99	9.65	12.49	461.6	1.79	Average
	Cluster2	1004	3.02	10.54	11.76	34.82	2210.4	5.18	bad
Feature combination 2	Cluster0	1825	1.29	45.43	7.72	5.70	246.7	—	good
	Cluster1	4513	1.34	19.83	9.67	12.51	456.4	—	Average
	Cluster2	1006	3.12	10.5	12.10	34.67	2229.0	—	bad
Feature combination 3	Cluster0	3363	—	—	3.14	—	441.7	—	good
	Cluster1	3372	—	—	13.76	—	467.9	—	Average
	Cluster2	609	—	—	12.78	—	2773.6	—	bad



(**a**) (**b**) (**c**)

Figure 2. The classification results of Feature combination 1, Feature combination 2, and Feature combination 3 are visualized. (**a**) Feature combination 1; (**b**) Feature combination 2; (**c**) Feature combination 3.

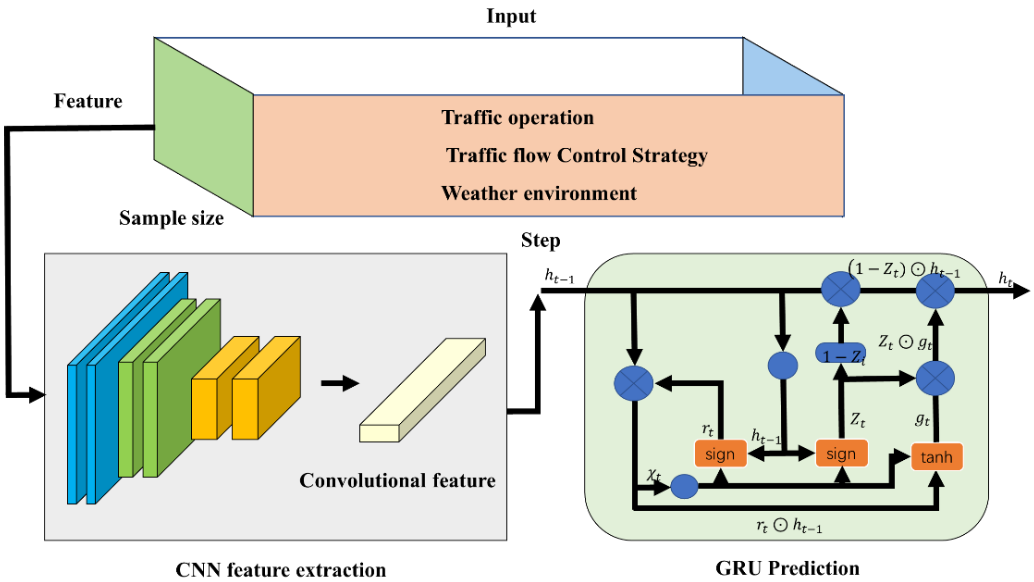


Figure 3. TSPM-W model network structure.

3.2. Predicting Traffic Situation Based on TSPM-W

The CNN model can not only process high-dimensional terminal area data but also automatically extract data features, but the disadvantage of the CNN model is that the accuracy is not enough. The GRU model can simplify the computational complexity and reduce the computational cost while maintaining the prediction accuracy. However, the disadvantage of the GRU model is that it cannot be calculated in parallel, and some features are easily lost during the calculation process. In this paper, a CNN-GRU model is built to predict the traffic situation in the terminal area.

3.2.1. Data Feature Extraction

The Convolutional Neural Network (CNN), including input layer, convolutional layer, pooling layer, fully connected layer, and output layer; the terminal area feature set sequence matrix X' into the input layer, through the convolutional layer and pooling layer to extract the input terminal area features after the pooling layer; the output is

$$O_{c_l}(l) = pool\{\sigma_{c_l}[x_{l,a} \otimes \omega_{c_l}(l) + b_{c_l}(l)]\} \quad (3)$$

where $O_{c_l}(l)$ is the output of the traffic situation after convolution and pooling using the c_l convolutional kernel in layer l; l is the depth of CNN model, $l \in \{1, 2, 3, \cdots\}$, $c_l \in \{1, 2, 3, \cdots, C_l\}$, and C_l is the maximum number of convolutional kernels; $pool(\cdot)$ pooling operation; $x_{l,a}$ is the input vector of the traffic situation in terminal area at the a time interval in layer l; $\otimes$ is the convolution operation; σ_{c_l} is the activation function of the C_l convolutional kernel; $\omega_{c_l}(l)$ and $b_{c_l}(l)$ are the weights and bias vectors of the c_l convolutional kernel in layer l, respectively.

Next, the output data from the convolutional and pooling layers are subjected to a bi-leveling operation, i.e.,

$$O_l = flatten[O_1(l), \cdots, O_{c_l}(l), \cdots, O_{C_l}(l)] \quad (4)$$

where: O_l is terminal area traffic situation output resulting from the deflating operation of the layer $l-1$ output; $flatten(\cdot)$ is the deflating operation.

Finally, the output of the operations of the convolution and pooling layers is put into the GRU model.

3.2.2. Time Series Prediction of Traffic Situation

The Gate Control Recurrent Unit (GRU) neural network and the Long Short-Term Memory (LSTM) neural network are both improvements on the traditional RNN. The important features are preserved through various Gates to ensure that they are not lost even during long-term propagation. Unlike the LSTM, the GRU model has a much simpler cell structure, which saves a lot of time in the case of large training data, while having better prediction results. For data volumes and complex operation of terminal area data, GRU can better reduce efficiency costs in order to achieve real-time prediction of the terminal area traffic situation.

The Gated Recurrent Unit (GRU) neural network consists of an input layer, a hidden layer, and an output layer, where the hidden layer consists of update and reset gates. The memory information H of the hidden layer corresponding to the input matrix X' of terminal area traffic situation is

$$H = (h_1, h_2, \cdots, h_a) \quad (5)$$

where $h_1 \sim h_a$ are the memory information of the end-zone traffic obtained by the GRU neural network in the $1 \sim a$ time interval, respectively.

The outputs of the update gate and reset gate of terminal area traffic obtained by GRU neural network during the a time interval are z_a and r_a, respectively, i.e.,

$$z_a = \sigma_Z[\omega_Z(h_a, x_a) + b_Z] \quad (6)$$

$$r_a = \sigma_R[(\omega_R(h_a, x_a) + b_R] \quad (7)$$

where σ_Z and σ_R are the activation functions selected for the update and reset gates, respectively; ω_Z and ω_R are the weights selected for the update and reset gates, respectively; b_Z and b_R are the bias vectors selected for the update and reset gates, respectively.

Based on z_a and r_a, $\overline{h}_{a+1}$ can be calculated, i.e.,

$$\overline{h}_{a+1} = \tanh[\omega_{\overline{h}_{a+1}}(h_a r_{a+1}, x_{a+1}) + b_{\overline{h}_{a+1}}] \tag{8}$$

where $\overline{h}_{a+1}$ is the information written to the current set of marquees when the gate was reset to control the previous situation; $\omega_{\overline{h}_{a+1}}$ and $b_{\overline{h}_{a+1}}$ are the weights and bias vectors selected when calculating $\overline{h}_{a+1}$, respectively.

Prediction of the actual traffic situation based on data from previous periods: By inputting O_l, h_{a+1} and $\overline{h}_{a+1}$ to the fully connected layer, the predicted traffic situation value $y_{c_l}(a+1)$ of the combined CNN-GRU model is obtained, i.e.,

$$y_{c_l}(a+1) = \sigma_{c_l}\left[\omega_{c_l}\left(O_l, h_{a+1}, \overline{h}_{a+1}\right) + b_{c_l}\right] \tag{9}$$

where σ_{c_l}, ω_{c_l} and b_{c_l} are the activation functions, weights and bias vectors selected for the fully connected layer of the combined CNN-GRU model, respectively.

3.2.3. TSPM-W

The network structure of the combined TSPM-W model is shown in Figure 3.

As can be seen from Figure 3, first, we use CNN to extract the embedded spatial features of the traffic situation data and use it as the input of the GRU model. Then, the hidden information affecting the traffic situation is learned by using the two-layer GRU, and the time series prediction value of the traffic situation in the terminal area under the influence of weather is obtained. The TSPM-W method process is as follows:

Algorithm 1: TSPM-W

Input: training set D_1, test set D_2;
Output: traffic situation predicted value H;

1. Initialize the hyperparameters of CNN model: the feature dimension of the input data, the number of samples, the time step, the number of CNN convolution layers, the size of CNN convolution kernels, and the number of CNN convolution kernels;
2. Put the data sequence matrix X' in the terminal area into the input layer and extract the input features through the convolution layer and the pooling layer; the output after the pooling layer is $O_{c_l}(l)$; perform the flattening operation to obtain O_l;
3. Output the operation O_l of the convolution and pooling layers to GRU model;
4. Initialize the hyperparameters of the GRU model: the feature dimension of the input data, the number of GRU layers, the number of GRU neurons, the dropout probability and the learning rate.
5. Initialize the network weights $\theta = \{\omega_{c_l}, b_{c_l}\} \sim N(0,1)$ of the model;
6. The training dataset D_1 is divided into small batch samples and input to GRU model for training. The O_l input at time t, the information h_{a+1} written to the current candidate set when the current situation is in the current situation, and the information $\overline{h}_{a+1}$ written to the current candidate set when the gate is reset to the previous situation are input to the fully connected layer;
7. Finally, output the traffic situation prediction result $y_{c_l}(a+1)$ of the model;
8. Calculate the mean square loss $Loss\{O_l, y_{c_l}(a+1)\} = \{O_l - y_{c_l}(a+1)\}^2$; and use the *Adam* optimizer to update the network weight θ according to the loss value *Loss*;
9. Repeat steps 6–8 until the loss converges or the maximum number of iterations is reached;
10. Input the test set D_2 into the best model trained in the previous steps to get the prediction result H.

After comparing models with different structures, a model consisting of one layer of two-dimensional convolutional neural networks and two layers of gate control loop units was chosen to predict the short-term traffic situation in the terminal area.

4. Experimental Results

4.1. Experimental Setup

In order to verify the effect of weather feature quantization using TAWQM on prediction accuracy, we conduct comparative experiments on datasets with and without feature quantization.

In order to verify the influence of strategy features on the prediction accuracy, we conducted comparative experiments on the datasets with and without strategy features.

In order to verify the effect of feature selection using Pearson coefficients on prediction accuracy, we conducted comparative experiments on datasets without feature selection and feature selection.

In order to verify the effectiveness of the proposed TSPM-W, we compared its prediction accuracy with four other single deep learning models, CNN, RNN, LSTM, and GRU.

In order to verify the stability of the proposed TSPM-W model, we compared the prediction accuracy for 1 h, 3 h, and 6 h.

Finally, the degree of agreement between the predicted results of typical operating days and the real traffic situations was analyzed.

The experimental setup used an adaptive moment estimation (Adam) method for stochastic optimization of TSPM-W neural networks for debugging. The tensorflow 2.0 from the Google AI team in the USA is used as the setup environment. A grid search method was used to select optimal model parameters [36]. The TSPM-W model used a number of convolutional layers of 1, a number of convolutional kernels of 64, and a convolutional kernel size of 3 for CNN in the experimental parameter settings. The number of GRU layers was 4 and the number of neurons was 128. The number of iterations was 30, the gradient threshold was 1, the length of the time series was set to 10, the initial learning rate was 0.01, and the Dropout probability was 0.4.

The data set is constructed from the operation data of Guangzhou Baiyun International Airport terminal area in 2018. The sample size is 8760, of which 80% of the samples are used as training samples, and the remaining 20% are used as test samples. This article uses data from the first 10 months of 2018 to forecast traffic situations in November and December. In this paper, Accuracy, R-square, precision and F1-score are used to evaluate the performance of CNN-GRU models for traffic situation prediction in terminal areas. The formulas for accuracy, precision, R-squared coefficient of determination and F1-score are shown below.

$$accuracy = \frac{(True\ Positive + True\ Negative)}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \tag{10}$$

$$precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{11}$$

$$R - square = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n} w_i(\hat{y}_i - \overline{y}_i)^2}{\sum_{i=1}^{n} w_i(y_i - \overline{y}_i)^2} \tag{12}$$

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{13}$$

In Equation (10), True Positive is making a Positive decision and the decision is correct, False Positive is making a Positive decision and the decision is incorrect, True Negative is a correct Negative decision and False Negative is an incorrect Negative decision. In Equation (12), the denominator is understood as the degree of dispersion of the original data and the numerator as the error between the predicted and true data. Dividing the two removes the effect of the degree of dispersion of the original data. The closer to 1, the better the variables of the equation explain y, and the better this model fits the data. In

Equation (13), it is the summed average of the precision and recall rates, with a maximum of 1 and a minimum of 0.

4.2. Comparison Experiments

4.2.1. Experiment on the Quantification of Weather Features

In order to verify the influence of weather feature quantification using TAWQM on the prediction accuracy, we trained the TSPM-W prediction model with and without weather feature quantification, respectively. The comparative experimental results are shown in Table 4.

Table 4. Comparison of experimental results of weather feature quantification effect.

Feature Combination	Model	Accuracy	R-Square	Precision	F1 Score
Feature combination 1	TSPM-W	97.4%	87.9%	97.3%	97.2%
	TSPM-W (without weather quantification)	95.7%	84.9%	96.3%	95.6%
Feature combination 2	TSPM-W	97.4%	80.0%	96.9%	97.1%
	TSPM-W (without weather quantification)	96.2%	76.1%	95.9%	95.0%
Feature combination 3	TSPM-W	65.5%	66.3%	66.1%	65.5%
	TSPM-W (without weather quantification)	63.6%	62.4%	64.4%	64.0%

It can be seen from Table 4 that the prediction results after weather feature quantification have higher accuracy no matter in Feature combination 1, Feature combination 2, or Feature combination 3. On the entire Feature combination 1 dataset, the Accuracy, R-square, Precision, and F1 scores of predictions with weather feature quantification are improved by 1.7%, 3%, 1%, and 1.6%, respectively, compared to predictions without weather feature quantification. On the entire Feature combination 2 dataset, the four values are 1.2%, 3.9%, 1% and 2.1%. On the entire Feature combination 3 dataset, these four values are 1.9%, 3.9%, 1.7% and 1.5%. The traffic situation prediction effect defined by the traditional Feature combination 3 is poor, and the Feature combinations 1 and 2 proposed by us is better. It can be seen that the addition of weather feature quantification can effectively improve the accuracy of traffic situation prediction.

4.2.2. Strategy Feature Influence Experiment

In order to verify the influence of strategy features on prediction accuracy, we train the TSPM-W prediction model with and without strategy influence, respectively. The comparative experimental results are shown in Table 5.

Table 5. Strategy features affect the results of comparative experiments.

Feature Combination	Model	Accuracy	R-Square	Precision	F1 Score
Feature combination 1	TSPM-W	97.4%	87.9%	97.3%	97.2%
	TSPM-W (without strategy)	96.0%	84.9%	95.6%	96.1%
Feature combination 2	TSPM-W	97.2%	77.1%	96.9%	97.0%
	TSPM-W (without strategy)	95.7%	66.8%	94.2%	95.5%
Feature combination 3	TSPM-W	65.5%	66.3%	66.1%	65.5%
	TSPM-W (without strategy)	62.6%	39.7%	63.0%	62.9%

As can be seen from Table 5, whether in Feature combination 1, Feature combination 2, or Feature combination 3, the prediction results after adding the strategy feature have higher accuracy. On the entire Feature combination 1 dataset, the Accuracy, R-square, Precision, and F1 scores of predictions with strategy features are improved by 1.4%, 3%, 1.7%, and 1.1%, respectively, compared to predictions without strategy features. On the entire Feature combination 2 dataset, the four values are 1.5%, 10.3%, 2.7% and 1.5%. On the entire Feature combination 3 dataset, these four values are 2.9%, 26.6%, 3.1%, and 2.6%. The traffic situation prediction effect defined by the traditional Feature combination 3 is poor, and the feature combinations 1 and 2 proposed by us is better. It can be seen that the addition of strategy features can effectively improve the accuracy of traffic situation prediction.

4.2.3. Feature Selection Influence Experiments

To verify the effect of feature selection using Pearson's correlation coefficient on prediction accuracy, we trained TSPM-W prediction models with and without feature selection, respectively. The comparative experimental results are shown in Table 6.

Table 6. Feature selection comparison experiment results.

Feature Combination	Model	Accuracy	R-Square	Precision	F1 Score
Feature combination 1	TSPM-W	97.4%	87.9%	97.3%	97.2%
	TSPM-W (without feature selection)	95.0%	80.8%	95.0%	95.4%
Feature combination 2	TSPM-W	97.2%	77.1%	96.9%	97.0%
	TSPM-W (without feature selection)	96.3%	72.5%	95.9%	96.0%
Feature combination 3	TSPM-W	65.5%	66.3%	66.1%	65.5%
	TSPM-W (without feature selection)	60.3%	56.6%	61.7%	50.2%

It can be seen from Table 6 that the prediction results after feature selection have higher accuracy no matter in Feature combination 1, Feature combination 2, or Feature combination 3. On the entire Feature combination 1 dataset, the Accuracy, R-square, Precision, and F1 scores of predictions with feature selection improved by 2.4%, 7.1%, 2.3%, and 1.8%, respectively, compared to predictions without feature selection. On the entire Feature combination 2 dataset, the four values are 3.9%, 14.6%, 3% and 3%. On the entire Feature combination 3 dataset, these four values are 5.2%, 9.7%, 4.4%, and 15.3%. The traffic situation prediction effect defined by the traditional Feature combination 3 is poor, and the feature combinations 1 and 2 proposed by us is better. It can be seen that using Pearson for feature selection can effectively improve the accuracy of traffic situation prediction.

4.2.4. TSPM-W Validity Verification

To verify the effectiveness of the proposed TSPM-W model, we compared the prediction results of the TSPM-W model with four traditional single deep learning models, CNN, RNN, LSTM, and GRU. The results of the comparative experiments are shown in Table 7.

It can be seen from Table 7 that the prediction accuracy based on TSPM-W is higher than the other four models in Feature combination 1, Feature combination 2 and Feature combination 3. The accuracy is improved by 11.6%, 2%, 4.6%, and 2%, respectively. The traffic situation prediction effect defined by the traditional Feature combination 3 is poor, and the traffic situation prediction effect of the feature combinations 1 and 2 proposed by us is better. It shows that the proposed TSPM-W model can effectively improve the time series prediction performance for the traffic situation in the terminal area.

4.2.5. TSPM-W Stability Verification

In order to verify the stability of the proposed TSPM-W, we used TSPM-W to test the results with 1 h, 3 h, and 6 h as prediction periods on real datasets, respectively. The results are shown in Table 8.

As can be seen from Table 8, no matter in Feature combination 1, Feature combination 2 or Feature combination 3, the prediction accuracy based on TSPM-W can maintain stable prediction accuracy at 1 h, 3 h and 6 h. The traffic situation prediction effect defined by the traditional Feature combination 3 is poor, and the traffic situation prediction effect of the feature combinations 1 and 2 proposed by us is better. It shows that the proposed TSPM-W can stably improve the time series prediction performance for the traffic situation in the terminal area.

Table 7. Performances of five prediction models.

Feature Combination	Model	Accuracy	R-Square	Precision	F1 Score
Feature combination 1	TSPM-W	97.4%	87.9%	97.3%	97.2%
	GRU	95.4%	85.6%	95.8%	95.2%
	CNN	85.8%	80.8%	86.0%	85.6%
	LSTM	95.4%	83.3%	95.3%	95.7%
	RNN	92.8%	83.3%	93.2%	93.3%
Feature combination 2	TSPM-W	97.2%	77.1%	96.9%	97.0%
	GRU	95.9%	74.8%	95.8%	95.8%
	CNN	86.3%	65.7%	85.9%	86.1%
	LSTM	95.7%	74.4%	95.3%	95.2%
	RNN	93.5%	74.5%	92.0%	93.4%
Feature combination 3	TSPM-W	65.5%	66.3%	66.1%	65.5%
	GRU	60.7%	61.0%	62.9%	62.9%
	CNN	60.0%	50.0%	61.4%	60.3%
	LSTM	61.9%	55.2%	62.6%	62.2%
	RNN	61.2%	47.0%	62.0%	62.2%

Table 8. Performance evaluation results of different prediction periods.

Feature Combination	Prediction Period	Accuracy	R-Square	Precision	F1 Score
Feature combination 1	1 h	97.4%	87.9%	97.3%	97.2%
	3 h	94.2%	76.7%	95.4%	94.5%
	6 h	94.2%	78.6%	95.7%	94.7%
Feature combination 2	1 h	97.2%	77.1%	96.9%	97.0%
	3 h	95.2%	76.1%	96.0%	95.4%
	6 h	87.7%	89.7%	90.4%	75.7%
Feature combination 3	1 h	65.5%	66.3%	66.1%	65.5%
	3 h	62.9%	63.5%	73.0%	70.2%
	6 h	57.9%	60.4%	68.1%	68.3%

4.3. Predictive Results Analysis

We trained the respective TSPMs on the samples in Feature combination 1, Feature combination 2 and Feature combination 3, and give the traffic situation prediction results in the test set. Tables 9–11 shows the prediction results under typical operating days of the three Feature combination, respectively. The figure shows that the prediction quality of the TSPM-W method is close to 100%. The model can better predict the trend of the future traffic situation.

Table 9. Traffic situations' prediction (Feature combination 1) for 5th November 2018 13:00 to 19:00.

	Timelot					
t = 13:00	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
	Label					
True	2	2	3	3	3	3
TSPM-W	2	2	3	3	3	3
GRU	2	2	3	3	3	3
LSTM	2	2	3	3	3	3
RNN	2	2	*2*	3	3	3
CNN	*1*	2	*2*	3	3	3

Table 10. Traffic situations' prediction (Feature combination 2) for 29th November 2018 13:00 to 19:00.

			Timelot			
***t* = 13:00**	***t* + 1**	***t* + 2**	***t* + 3**	***t* + 4**	***t* + 5**	***t* + 6**
			Label			
True	1	1	3	3	3	3
TSPM-W	1	1	3	3	3	3
GRU	1	1	*2*	3	3	3
LSTM	1	1	*2*	3	3	3
RNN	1	1	*1*	3	3	3
CNN	1	1	*1*	3	3	3

Table 11. Traffic situations' prediction (Feature combination 3) for 7th December 2018 13:00 to 19:00.

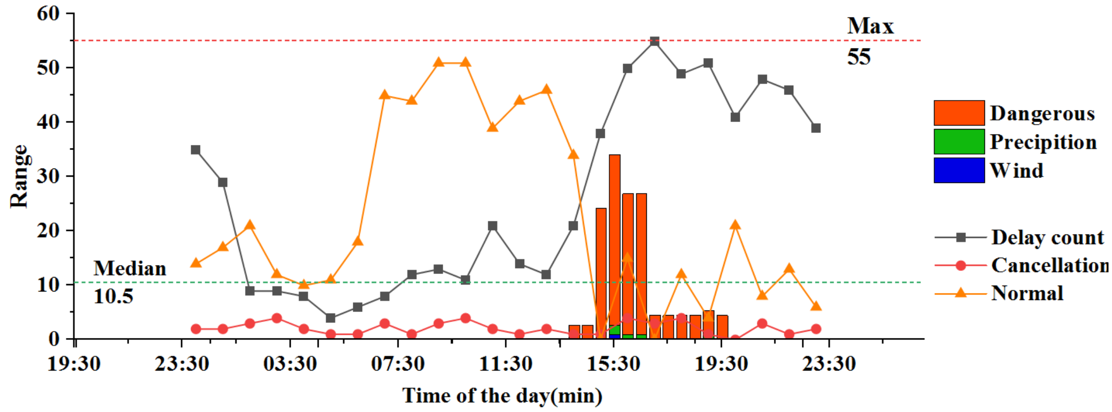
			Timelot			
***t* = 13:00**	***t* + 1**	***t* + 2**	***t* + 3**	***t* + 4**	***t* + 5**	***t* + 6**
			Label			
True	1	2	2	3	3	3
TSPM-W	1	2	2	3	3	3
GRU	1	2	2	*2*	3	3
LSTM	1	2	2	*2*	3	3
RNN	1	2	2	*2*	3	3
CNN	1	2	2	*2*	*2*	3

In order to analyze the correlation between the features and the prediction results of traffic conditions, we used the data before 7 August 2018 to train to predict the traffic conditions from 00:00–24:00 on 7 August 2018. We analyzed traffic demand, delays, strategies, weather, and correlation of forecast results.

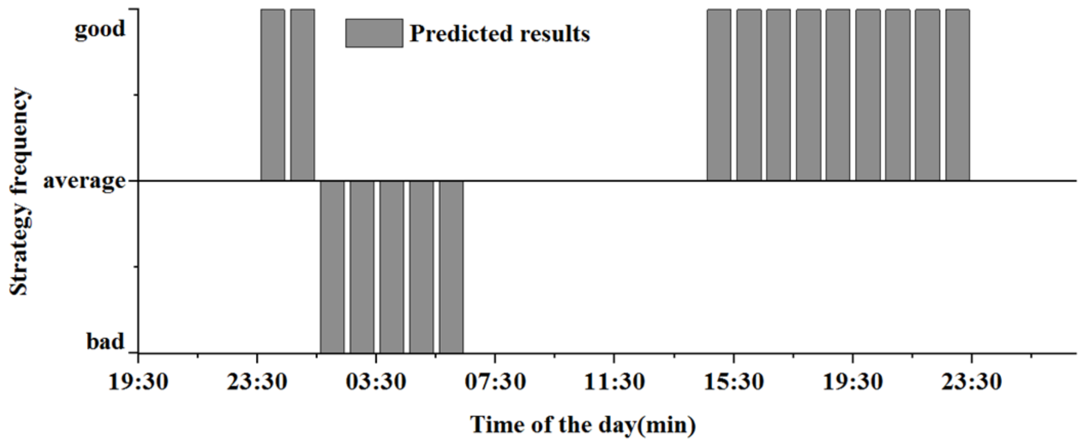
As shown in Figure 4, between 0:00 and 4:30 on that day, there was a transition process from high to low in the number of delayed flights, and the traffic situation was poor, which was considered to be caused by the low visibility during this period. Traffic conditions returned to normal since 4:30. From 9:30 to 13:00, there were cumulus clouds and the cloudiness was cloudy. From 13:30 to 14:30, the weather changed to heavy rainfall accompanied by thunderstorms and low visibility. The increasing intensity of precipitation gradually increased the number of delayed flights. The highest number of delayed flights reached 57. The rain stopped at 19:00, and the delay gradually decreased, but the degree of delay was relatively high. This is due to the accumulation of delays due to weather, with high delay conditions continuing to dissipate for a period of time even in the absence of severe weather. The model has a good prediction effect on the overall traffic situation of the terminal area.

In summary, the following conclusions can be drawn from the results of the experiments in Tables 9–11 and Figure 4:

The proposed TSPM-W has a good prediction effect on traffic situations constructed in different Feature combinations. In the process of air traffic management, the traffic situation of the terminal area in the short term can be predicted according to the model, and corresponding control strategies can be adopted for the traffic situation in advance. This also provides help to support the establishment of Feature combination-based terminal area pre-tactical assistance decision-making.



(**a**)



(**b**)

Figure 4. Feature combination 1 traffic situation changes throughout the day. (**a**) Feature Combination 1 Changes in weather and traffic features, 00:00–24:00 on 7 August 2018. (**b**) Traffic situation change for feature combination 1, 00:00–24:00 on 7 August 2018.

5. Conclusions

In this paper, a traffic situation time-series prediction model in the terminal area under convective weather is built using deep learning approaches. Different from previous studies, this model first considers the influence of strategy features on the traffic situation and constructs a feature set for predicting traffic situation based on data such as terminal area weather, traffic demand, delay conditions, and flow control strategies. When constructing weather features, considering the complexity of weather features, the quantification of weather features is realized based on the proposed TAWQM method. Then, when constructing the traffic situation label, the FCM clustering algorithm is used to realize the classification of traffic situations in different Feature combinations, and the classification results of traffic situations are determined to be good, average, or bad. Further, a time series prediction model is carried out for the traffic situation in different Feature combinations. We carried out a series of comparative experiments on the actual operation data of Guangzhou Baiyun International Airport. The specific conclusions are as follows:

(1) Considering the complexity of weather data, a weather feature quantification algorithm named TAWQM is proposed. Experiments show that weather feature quantification can effectively improve the prediction accuracy when training the model. The Accuracy, R-square, Precision, and F1 scores of predictions with weather feature quantification are improved by an average of 1.6%, 3.6%, 1.3%, and 1.7%, respectively.

(2) Considering the influence of the flow control strategy on the traffic situation, using the flow control strategy data for training, the model can effectively improve the prediction accuracy. The Accuracy, R-square, Precision, and F1 scores of predictions

with weather feature quantification are improved by an average of 2.0%, 13.3%, 2.5%, and 1.7%, respectively.

(3) Considering the influence of feature selection on the prediction results, using the Pearson correlation coefficient for training the model can effectively improve the prediction accuracy. The Accuracy, R-square, Precision, and F1 scores of predictions with weather feature quantification are improved by an average of 3.8%, 10.5%, 3.23%, and 6.7%, respectively.

(4) Considering that a single model is not suitable for multi-feature prediction, the TSPM-W model is constructed and compared with the traditional CNN model, GRU model, RNN and LSTM model. The proposed TSPM-W model can effectively improve the time series prediction performance for the traffic situation in the terminal area. The accuracy is improved by 11.6%, 2%, 4.6%, and 2%, respectively.

(5) The proposed TSPM-W can better quantify the influence of weather on the traffic situation in real time and predict the traffic situation of the terminal area in the future. The predicted traffic situation can be consistent with the multi-feature distribution of traffic demand, delay, strategy, and weather. The controller can adopt corresponding control strategies based on the predicted traffic situation in advance to provide support for auxiliary control decision-making.

The work of this paper provides support for controllers to formulate appropriate control strategies for traffic situations under the influence of weather. Due to the uncertainty of the weather, how to accurately divide the traffic situation and achieve a more accurate prediction deserves further study.

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