Probabilistic Airport Traffic Demand Prediction Incorporating the Weather Factors

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Abstract. With the development of air transport industry in China, the congestion problem in the terminal areas of busy airports has become increasingly serious. In order to alleviate the increasingly frequent air traffic congestion, it is necessary to accurately and objectively predict traffic flow. Traditionally, most predicted methods are based on the number of aircrafts flight in the terminal area to obtain deterministic traffic flow data, without considering the impact of uncertain factors on the prediction results. Based on the uncertainty of demand, this paper uses a probability density prediction method based on quantile regression neural network and kernel density estimation, to analyse the variation of traffic flow at different quantiles according to the obtained continuous conditional quantile function. Predicting the probability density of traffic flow on a certain day, and then comparing the point prediction value corresponding to the peak value, which consider the weather factor and the conditional probability density prediction curve without considering the weather factor, it is concluded that considering the weather factor can make the traffic flow prediction more accurate.

1. Introduction
With the sustainable and rapid development of civil aviation transport industry in China, air traffic flow management (ATFM) departments are facing more complex airspace structure, more complex flight activities management and control. This, coupled with the impact of sudden and uncertain disturbance factors, such as bad weather, military activities, major events and facilities failure, has caused increasingly serious air traffic congestion. In order to alleviate the congestion and balance demand-capacity, it is necessary to accurately predict the air traffic flow.

For a certain period of time in the future, traffic demand forecasting cannot be a simple deterministic value, but an expected probability interval corresponding to a certain level. The probability value of traffic demand can be obtained by the result of probability density prediction, as well as the probability density function of future traffic demand [1]. C. Wang et al. [2] established the probability distribution models of aircraft entering sector and proposed a sector congestion prediction probability method. X. Zhao et al.[3] established the density function for relative errors in each region by using kernel density estimation method. D. Cui et al.[4] put forward the idea of using combination forecasting method on the basis of synthesizing the advantages of regression forecasting method and artificial neural network forecasting method. Y. He et al.[5] proposed a probabilistic density prediction method of medium-term load based on neural network quantile regression. C. Wen et al. [6] introduced the method of neural network quantile regression and kernel density estimation to predict
the continuous quantile of future stock price. S. Li et al.[7] established a multi-period airport traffic demand probability distribution model. J. Zhang et al.[8] established an n-stage arrival capacity distribution model. The above results are seldom used in airport terminal area. Based on the actual demand of traffic management in China, this paper establishes a probability density prediction method of airport traffic demand by using the probability density prediction method based on neural network quantile regression and nuclear density estimation. The analysis and verification based on the actual operation data of Baiyun airport terminal area in Guangzhou shows that the proposed prediction method can improve the accuracy of prediction results under the influence of weather factors.

2. Quantile regression neural network (QRNN)

2.1. Neural Network Theory

Artificial neural network (ANN) is a sophisticated calculation network system composed of a large number of highly interrelated simple artificial neuron. ANN is an active frontier interdisciplinary including basic properties such as high nonlinearity, self-learning, robustness, generalization and so on. At the same time, ANN also has the characteristics of non-deterministic calculation. The common forms of artificial neural network are RBF neural network, BP neural network, Hopfield neural network, wavelet neural network and so on. The kernel function of hidden layer of neural network selected in this paper is hyperbolic tangent function. By using this function, the highly complex data can be well non-linearly fitted, and the stable and better non-linear function of prediction ability can be established, so as to provide a better way to improve the accuracy of traffic demand prediction. The form of hyperbolic tangent function is as follows:

\[
\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}
\]  

(1)

in which \(\tanh(x)\) is the expected output value of the hidden layer of the neural network, \(x\) is the matrix composed of input variables. Since the neural network is more suitable for stationary time series, it requires higher data characteristics when using this method to predict. That is to say, the less stationary the data is, the greater the prediction error may be caused by using neural network to predict.

2.2. Quantile Regression Neural Network Model

In this paper, the quantile regression neural network (QRNN) is based on the single hidden-layer neural network model proposed by Taylor[9]. It uses the quantile regression neural network to predict the quantile of airport traffic demand in the future, then uses the hyperbolic tangent function as the hidden layer function of the neural network, and takes the predicted quantile of airport traffic demand as the input variables of density estimation to predict the probability density of airport traffic demand. The expression of neural network quantile regression model is as follows:

\[
Q(\theta|X) = f[x, u(\theta), v(\theta)] = \sum_{j=1}^{I} \frac{2v_j(\theta)}{1 + e^{-2\sum_{i=1}^{N} u_{ij}(\theta)x_i}} - v_j(\theta)
\]

(2)

where \(\theta\) is a quantile point, \(u(\theta)=\{u_{ij}\}_{i=1,2,...,n;j=1,2,...,I}\) is the estimated weight matrix between the input layer and the hidden layer, and \(v(\theta)=\{v_j(\theta)\}_{j=1,2,...,I}\) is the connection weight vector between the hidden layer and the output layer. In order to achieve the final parameter estimation of Eq. (2), the following objective function can be optimized to achieve this optimization process.

\[
E_\theta = \frac{1}{N} \sum_{i=1}^{N} \rho_\theta \{y_i - f[x, u(\theta), v(\theta)]\}
\]

(3)
However, in order to keep the trained neural network from over-fitting, a penalty parameter is added to the objective function and a new objective function is obtained and shown below:

$$E_\theta(u(\theta), v(\theta)) = \tilde{E}_\theta + \lambda_1 \sum_{i,j} u_{ij}(\theta) + \lambda_2 \sum_{i,j} v_{ij}(\theta)$$  \hspace{1cm} (4)

where $\lambda_1$, $\lambda_2$ are penalty parameters. By determining the optimal penalty parameters, we can effectively prevent the model from falling into excessive fitting of empirical data, reduce prediction errors and improve prediction accuracy. The optimal estimate of $u(\theta)$ and $v(\theta)$, $\tilde{u}(\theta)$ and $\tilde{v}(\theta)$, can be obtained by optimizing Eq. (3). Then, $\tilde{u}(\theta)$ and $\tilde{v}(\theta)$ are substituted into Eq. (4) to obtain the conditional quantile estimation function of the response variable.

3. Kernel density estimation

In the process of probability density estimation, if the distribution of random variables is known, it can be estimated directly by using parameter estimation methods, such as maximum likelihood estimation. However, in practice, the parameters of random variables are unknown, so non-parametric estimation is needed. Kernel density estimation is a method of non-parametric estimation. Kernel density estimation is a method to study the characteristics of data distribution from the data sample itself. It does not need to make any assumptions about the prior distribution of random variables. It only needs to determine the input variables and the kernels, and then continuous probability density curve [10-12] of traffic flow can be obtained by using the method according to the forecasted continuous traffic flow of one day in the future. The essential idea of kernel density estimation is to estimate a reasonable density function by using the kernel density estimator. For independent and identically distributed random variables $x_1, x_2, \ldots, x_n$, the kernel density estimator of the probability density function $f(x)$ is as follows:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} \frac{k\left(\frac{x_i - x_0}{h}\right)}{k\left(\frac{x_i - x_0}{h}\right)} = \frac{1}{n} \sum_{i=1}^{n} k_h(x_i - x_0)$$  \hspace{1cm} (5)

where $k(\bullet)$ is the kernel, density estimation, $h$ is a given positive number, commonly referred to as bandwidth, the kernel density estimator $\hat{f}(x)$ is not only related to the given sample set, but also to the choice of the kernel function and the bandwidth parameter.

4. Numerical results

4.1. Data source and case description

In this paper, the data of departure, landing and meteorological data of Baiyun Airport in Guangzhou from June 1 to 30, 2016 are taken as sample. The traffic flow of every 15 minutes from June 1 to 21 in Baiyun Airport is selected as input variable, and the traffic flow of every 15 minutes on June 22 is taken as output variable. Through rolling prediction method, 2016 samples are obtained. Firstly, it is found that the sample data do not conform to the assumption of normal distribution. Therefore, the probability density prediction method proposed in this paper can be used. Secondly, the sample data are input into the quantile regression model of the neural network for training to determine the parameters and structure of the neural network. The model built in this paper is based on the single hidden-layer neural network quantile regression. When weather factors are not considered in this paper, the number of variables in the input layer is 21, the number of variables in the hidden layer is 1, the number of variables in the output layer is 1, and the structure of the neural network is 21-1-1. When weather factors are considered, the number of variables is 24, the number of variables in the hidden layer is 1, the number of variables in the output layer is 1, and the structure of the neural network is 24-1-1. The number of iterations of the neural network is 5000. In order to prevent the quantile regression network of the neural network from falling into over-fitting, the penalty parameters of the model are set to 0.1. The quantile points in the model start from 0.0001 to 0.9999 with an interval of
0.01. A total of 100 quantile points are generated. Thus, the parameters of the quantile regression neural network are determined, and then the continuous conditional quantiles are predicted every 15 minutes for the period from 22 to 30 June. Then, substituting the continuous conditional quantiles into the nuclear density estimation model, the continuous probability density curve is obtained.

4.2. Analysis of Weather Factors
Bad weather is one of the main reasons that restrict the traffic flow of the airport. In actual operation, the change of flight speed, altitude and flight direction caused by dangerous weather such as thunderstorms and severe convective weather, low visibility, low-altitude wind shear, turbulence and ice accumulation will result in flight cancellations, delays of departure flights and the deviation between actual flight path and the flight routes of aircraft under traditional track prediction methods, which leads to a decrease in the accuracy of the determination results[1]. In this paper, the main weather factors considered affecting traffic flow are thunderstorms, strong convective weather, low visibility and cloud cover.

4.3. Empirical results and analysis
According to the above content, this paper takes 9:00-9:15 on June 22, 2016 as an example. Without considering the influence of weather factors, the samples are substituted into the quantile regression neural network model for training, and 100 consecutive conditional quantiles are obtained. Then the conditional quantiles are substituted into the nuclear density estimation method, and the probability density curve of traffic demand in the 15-minute period of a day is obtained. Six of the 100 prediction results selected randomly are shown in Fig. 1.

![Figure 1. Probability density curve without considering weather factors](image)

Because of the randomness of the neural network method, the traffic demand values of each prediction are different. In addition, it is found that the probability density distribution does not conform to a certain distribution law, because the prediction probability of some traffic demand values corresponds to zero, so jumps will occur, which further confirms the correctness of the nuclear density estimation method. Taking the 9:00-9:15 period of June 22, 2016 as an example, considering the influence of weather factors, the airport meteorological data trained as input variables and traffic flow data are substituted into the neural network quantile regression model. The probability density curve of the same 15-minute period of the forecast day is obtained. Six of the 100 results selected randomly are shown in Fig. 2.
By comparing the continuous probability density prediction curves in Fig. 1 and Fig. 2, we can see that considering weather factors, the true value (red marking) does not appear near the highest point of the probability density curve, but the predicted value (black marking) corresponding to the probability value obtained after integrating the probability density curve is very close to the real value. In the case of not considering weather factors, although the real value is very close to the predicted value after integration, there is still a certain distance in comparison, which further shows that considering weather factors can make the predicted results more accurate and less error. In order to better illustrate that the probability density prediction method used in this paper can more accurately predict traffic demand, the traditional BP neural network prediction method is also used to predict the traffic flow in the 9:00-9:15 period of June 22, 2016, considering weather factors and not considering the influence of weather factors. The results are shown in Table 1:

| Number | Actual value | Probability density prediction method | BP neural network prediction method |
|--------|--------------|---------------------------------------|-----------------------------------|
|        |              | Consider weather factors | Without considering weather factors | Consider weather factors | Without considering weather factors |
|        |              | Prediction value | Relative error | Prediction value | Relative error | Prediction value | Relative error | Prediction value | Relative error |
| 1      | 11           | 10.7749       | 2.04%          | 11.4971       | 4.51%          | 12.0921       | 9.93%          | 14.1704       | 28.82%         |
| 2      | 11           | 10.9164       | 0.76%          | 10.5286       | 4.28%          | 11.9570       | 8.7%           | 16.0547       | 45.95%         |
| 3      | 11           | 11.2461       | 2.24%          | 11.6242       | 5.67%          | 12.3001       | 11.82%         | 12.3904       | 12.64%         |
| 4      | 11           | 11.3008       | 2.73%          | 11.5175       | 4.7%           | 10.6918       | 2.8%           | 19.8451       | 80.41%         |
| 5      | 11           | 10.9515       | 0.44%          | 11.2331       | 2.11%          | 11.0341       | 0.31%          | 25.0182       | 127.44%        |
| 6      | 11           | 11.3160       | 2.87%          | 11.6712       | 6.1%           | 11.2111       | 1.92%          | 12.2799       | 11.64%         |
| 7      | 11           | 10.6800       | 2.91%          | 11.6451       | 5.86%          | 12.1904       | 10.82%         | 12.1712       | 10.65%         |
| 8      | 11           | 10.6890       | 2.83%          | 11.5359       | 4.87%          | 11.5513       | 5.01%          | 10.7912       | 0.19%          |
| 9      | 11           | 10.7475       | 2.29%          | 10.4618       | 4.89%          | 11.7064       | 6.42%          | 11.5136       | 4.67%          |
| 10     | 11           | 11.3929       | 3.57%          | 11.5120       | 4.65%          | 13.2706       | 20.64%         | 21.3178       | 93.8%          |
The results show that when the uncertainty of weather factors is taken into account, the prediction results of probability density prediction method are generally better than those without considering weather factors, and their relative errors are basically controlled within 4%.

5. Conclusion
Guangzhou Baiyun Airport is a typical busy airport. Because of its geographical location, the weather is changeable. It is often affected by bad weather. Therefore, it is very important to predict its traffic flow accurately and effectively. This paper separately analyzed the prediction results considering weather factors and not considering weather factors. The comparison results showed that although the true value did not appear near the highest probability point, it was close to the predicted value corresponding to the probability value obtained after integrating the probability density curve using weather factors as characteristic variables. The probability value obtained by degree integral was very close to the real value. Then, the traditional BP neural network prediction method was used to predict the results which were very volatile. Even with the addition of weather factors, the accuracy of the prediction was still not high, which further illustrated the applicability of the method used in this paper.

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7. References
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