Prediction of Wind Speed at Lhasa Gonggar Airport Based on the Support Vector Regression Algorithm

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Abstract Prediction of wind speed at high plateau airports can not only provide certain theoretical basis for the safe and efficient operation of the airports, but also save cost and time for their flight scheduling. In this paper, based on the data of average wind speed and related meteorological factors at the meteorological station of Lhasa Gonggar Airport from 1964 to 2019, a prediction model of wind speed was constructed based on the support vector regression (SVR) algorithm. After the analysis of correlations between various meteorological features, significant features were selected by the random forest algorithm, thereby further improving the prediction performance of the model. The results indicate that both visibility and temperature having high correlations with wind speed are key features determining the final accuracy of the prediction model. Meanwhile, compared with other machine learning algorithms, the SVR algorithm represents more highlighted prediction performance for small sample data.

Key words SVR algorithm; High plateau airport; Prediction of wind speed

DOI 10.19547/j.issn2152 – 3940.2025.06.010

Wind speed is an important factor considered in airport design. The distribution frequency of wind direction and speed directly affects the selection of runway orientation. The takeoff and landing performance, fuel consumption, and selection of flight altitude of aircraft all need to take into account the influence of wind speed[1–2]. The climate environment of high plateau airports is complex and changeable, and the takeoff and landing standards are greatly affected by the weather. Near the ground, due to uneven heating caused by solar radiation and terrain obstruction, there is a strong ground wind with large changes in wind direction and speed, which is prone to cause turbulence, turbulence, wind shear and other phenomena. The Civil Aviation Administration stipulates that high plateau airports refer to airports with an altitude of 2 438 m or above, and China has extremely strict restrictions on the operation of high plateau airports[3]. At the same time, the ground gale at high plateau airports is also one of the main reasons for flight delays. Due to the effect of the flight chain, a single flight delay may lead to large-scale flight delays, affecting the normal operation of flights. Therefore, the prediction of wind speed at high plateau airports can provide certain theoretical basis and suggestion schemes for the prediction of flight delays, facilitate flights to take timely responses and adjustment measures, save time for flight recovery, and ensure the safe and efficient operation of aviation.

At present, many effective methods for the prediction of wind speed have been proposed both domestically and internationally. The methods for the prediction of wind speed can be roughly divided into two categories: one is to establish linear or nonlinear relationships between wind speed and other important meteorological factors; the other is to obtain the probability distribution function of wind speed based on the relationship of time series, thereby constructing the corresponding model for the prediction of wind speed[4]. Li Rongrong *et al.*[5] obtained the prediction residuals of short-term wind speed based on the time series analysis method, and used the residuals as the input of the long- and short-term memory network for prediction. The final prediction result was a linear combination of the calculation results of the two models. Gan *et al.*[6] applied time convolution networks and adaptive interval structure optimization strategies to predict short-term wind speed, and this method utilized deep learning technology, showing outstanding performance in both prediction accuracy and model generalization. Considering the intermittency and fluctuation of wind speed and other issues, Yue Yong *et al.* combined local mean decomposition with time series to establish a prediction model for wind speed, reducing the prediction error[7]. These methods all only aim to study short-term changes in wind speed, but do not analyze the intrinsic relationship between wind speed and meteorological factors as a whole and study the changes of strong winds on the ground at high plateau airports. Based on the data of strong winds at four meteorological stations in the east of the Hexi Corridor, Yang Xiaoling *et al.*[8] analyzed their temporal and spatial distribution, intensity, persistence and other climatic characteristics, and used the optimal subset regression method to establish a forecast equation for strong winds. The accuracy of this forecast equation can reach up to 68.8%, and it can provide effective theoretical guidance for the operational forecast of strong winds, improve aviation operation efficiency, and reduce the rate of aircraft delays. Based on the automatic observation data and daily and hourly observation data of lateral wind at Linzhi Airport in Xizang,

Received: October 19, 2025 Accepted: November 22, 2025

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Ren Yuanji *et al.* [9] used statistical methods to analyze the changing characteristics of strong winds at the plateau airport and explore the impact of strong winds at the plateau airport on aircraft flights on the airport runways. Although the problem of plateau flight is not unique to China, there are basically no plateau airports in North America and Europe, so there are very few studies on strong winds at plateau airports in foreign countries.

Overall, there are relatively few studies on the prediction of wind speed at plateau airports both domestically and internationally. These studies mainly aim to analyze the short-term changes in wind speed, and no consideration has been given to the actual terrain and various important meteorological factors of high plateau airports. This study aims to explore the correlations between ground wind speed and other meteorological elements at high plateau airports. Based on the data of wind speed at the meteorological station of Lhasa Gonggar Airport from 1964 to 2019, feature analysis and screening were conducted for important meteorological factors according to the environmental characteristics of high plateau airports. After the reasonable selection of features, the SVR regression model was used to predict wind speed. This research method can provide technical reference for the prediction of strong winds at high plateau airports and save time and cost for flight recovery.

1 Analysis of wind speed at Lhasa Gonggar Airport

Lhasa Gonggar Airport is a 4E-class international airport for both military and civilian use. The annual average number of flights reaches 2 500, and the annual number of domestic and international passengers is up to 760 000[10]. Lhasa Gonggar Airport is located in Gongga County (67 km away from Lhasa City) in the Yarlung Zangbo River Basin, with an altitude of 3 670 m. It has a typical plateau temperate semi-arid climate, with long sunshine duration and distinct dry and wet seasons[11]. Gangga Airport is also one of airports with the highest altitude in the world, and it is a typical high plateau airport.

The data of annual average wind speed from the meteorological station of Lhasa Gonggar Airport during 1964 – 2019 were used to predict wind speed. Fig. 1 shows the changes in annual average wind speed at Lhasa Gonggar Airport over the past 60 years. Average wind speed was 3.76 m/s, with a standard deviation of 0.426 m/s. The results indicate that at Lhasa Gonggar Airport, annual average wind speed did not changed much since 1964, and showed a slight decreasing trend overall. From Fig. 1, it can be seen that the changes in annual average wind speed mainly occurred from 1980 to 2016, in which the maximum 4.81 m/s appeared in 1965, while it was the minimum in 2002 (2.92 m/s). In fact, the decrease in annual average wind speed was related to the recent urbanization development and the construction of the airport, and they caused changes in the detection environment near the station[12].

2 Construction of a prediction model of wind speed

2.1 Analysis of correlations The correlations between annual average wind speed and 15 features such as average minimum temperature and average visibility from 1964 to 2019 were analyzed. Fig. 2 presents the Pearson correlation coefficient between average wind speed and these meteorological features. As shown in Fig. 2, most correlations between the 15 features and average wind speed were weak positive correlations. Among them, average wind speed was only positively correlated with the number of days with average temperature ≤0 ℃, the maximum daily precipitation, and the maximum visibility. It had certain negative correlations with average minimum temperature, average maximum temperature, and average temperature (0.5 < correlation coefficient < 0.6). Features such as average dew point temperature, maximum temperature extreme, and precipitation had relatively small correlations with average wind speed, with a correlation coefficient of −0.16, −0.073, and −0.064, respectively. However, the features highly correlated with average wind speed may play a crucial role in the model training process and thus affect the final prediction performance.

Furthermore, since the similarity of the attribute values of these 15 features was relatively high, the Pearson correlation coefficient between the features was also relatively large. During model training, if there are many highly correlated features in training samples, these features will have certain influences on each other, which to some extent causes deviations in the prediction results and reduces the prediction performance of the model[13].

Therefore, these highly correlated features should be deleted as follows: the first step is to calculate the correlation coefficient between each feature and the remaining 14 features; the second step is to record the number of correlation coefficients greater than 0.7, and if the correlation coefficient between the features was greater than 0.7, the feature with the larger number among the two features was deleted; the third step is to repeat the calculation process until the correlation coefficient between any two features among the remaining features was less than or equal to 0.7. Finally, 9 features were obtained, including average minimum temperature, the number of days with average temperature ≥ 18 ℃, average visibility, average dew point temperature, the number of days with minimum temperature ≤ 0 ℃, maximum daily precipitation, minimum visibility, maximum temperature extreme, and the number of precipitation days.

2.2 Support vector regression algorithm Support vector regression (SVR) is essentially an application of the support vector machine (SVM) in function fitting and regression prediction. SVM algorithm, which was first proposed by Corinna, is a data mining method based on statistical learning theory[14]. It performs exceptionally well in solving nonlinear data and small sample problems, so it is thus widely used in various research fields. The core idea of the SVR algorithm is to use a kernel function to map all sample data points to a high-dimensional feature space. In this high-dimensional space, an optimal hyperplane that meets certain conditions needs to be found to minimize the total deviation between the training samples and the regression curve $y = f(x) = \omega\phi(x) + b$ (where ω is weight vector, and b is bias term)[15]. The resulting hyperplane ensures both accuracy and the minimum distance to the nearest sample. Through the kernel function, sample data points in the high-dimensional space exhibit a linearly separable trend, avoiding complex operations in high-dimensional space and then achieving the nonlinearity of linear algorithms. In traditional linear regression, any deviation between the predicted value and the true value is calculated as an error loss. In SVR, the error loss is calculated only when the absolute deviation between the predicted value and the true value exceeds the threshold ε[16–17]. The SVR algorithm follows the principle of minimizing structural risk, and can effectively avoid the overfitting problem, so it is more suitable for regression analysis of small samples.

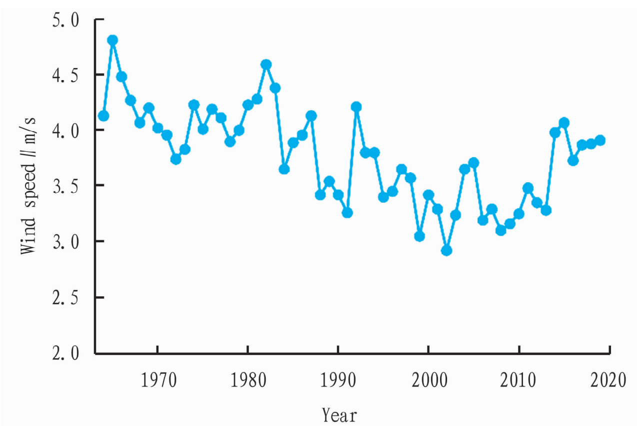

Fig. 1 Variation in annual average wind speed at Lhasa Gonggar Airport from 1964 to 2019

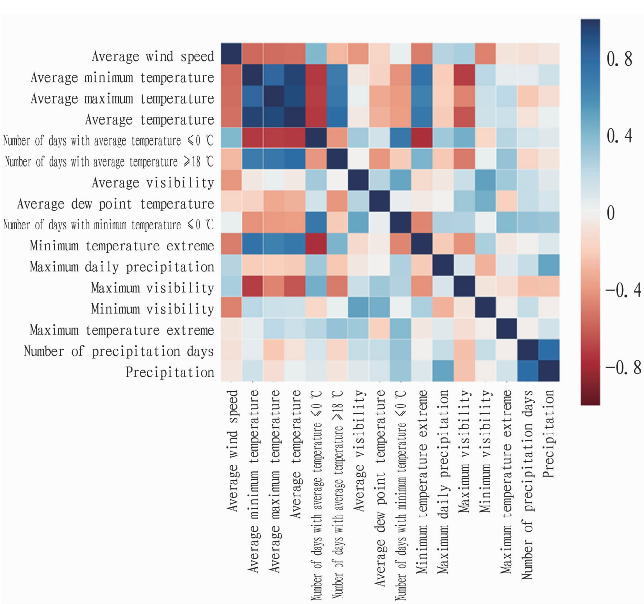

Fig. 2 Heat map of correlation coefficient among various meteorological features

2.3 Model construction The sample data were normalized by using the min-max normalization method to reduce the errors among different feature attributes. The calculation formula is as below:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_{max} is the maximum of sample data, and x_{min} is the minimum of sample data.

After training with the SVR algorithm, the final prediction model of wind speed was obtained. Based on the feature values of training samples, SVR algorithm is applied for training to construct the prediction model of wind speed. The parameters of the model were adjusted to optimize the final prediction results.

Due to the small number of sample data, the leave-one-out method was used to evaluate the final prediction model. The leave-one-out method is a special case of the cross-validation method in machine learning, and is more suitable for small sample datasets. The results obtained by using the leave-one-out method are closest to the expected value of training the entire test set, and the evaluation results are generally considered to be relatively accurate[18]. The basic principle of the leave-one-out method is to select the first sample from the original sample data (n samples) as the test set, and the remaining $n-1$ samples as the training set for the first model training and calculation. Then the second sample is selected as the test set, and all the original samples except for the second sample are as the training set. The above process is repeated until all samples are selected as the test set, and the final result is the average of n test results.

2.4 Model evaluation In this paper, three error evaluation indicators, namely mean absolute error (*MAE*), root mean square error (*RMSE*), and mean absolute percentage error (*MAPE*), were used to assess the prediction performance of the model. The formulas of various indicators are as below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \tag{4}$$

where y_i means the actual value of wind speed; $\hat{y}_i$ is the prediction value of wind speed; n denotes the number of samples.

3 Experimental results

3.1 Impact of highly correlated features on prediction performance To study the impact of highly correlated features on the model, the prediction models of wind speed were constructed by using all features of the sample data and the 9 features with lower correlation. The comparison results of the prediction performance of the models based on SVR algorithm are shown in Table 1. The MAE, RMSE and MAPE of the prediction model constructed by using all features are 0.251, 0.200, and 5.452%, respectively. The three errors of the prediction model constructed by using the 9 features increase by 0.017, 0.011, and 0.318%, respectively. After highly correlated features were removed, the prediction performance of the model slightly decreases, indicating that highly correlated features still has a certain impact on the accuracy of the prediction model. This may be because the sample data involved a relatively small number of feature types, and similar features had subtle differences, thereby affecting the prediction performance of the model. Therefore, removing highly correlated features to screen the features of the sample data cannot improve the prediction performance of the model.

Table 1 Comparison results of features with lower correlation coefficient and all features for the prediction model

Features	MAE m/s	RMSE m/s	MAPE %
All features	0.251	0.200	5.452
Features with lower correlation coefficient	0.268	0.211	5.770

3.2 Score of the importance of features In this paper, the random forest (RF) method was used to score the importance of features in the training samples, thereby selecting the features that play a crucial role in the prediction performance of the model. Currently, using the RF algorithm to score the importance of features has been widely applied in fields such as genomics and proteomics in bioinformatics. The RF algorithm first calculates the variance of internal nodes in its decision trees, and the feature within internal nodes is regarded as the important feature if it has the largest reduction in regression variance. The importance of the final feature is determined by the average of all decision trees. The score of the importance of 15 features obtained by the RF algorithm is shown in Fig. 3. From the figure, it is seen that average visibility plays the most crucial role among all the features, and the score of its importance is 0.254. According to the results of the correlations in Fig. 2, the correlation coefficient between average visibility and average wind speed was −0.41. This also verifies that average visibility is an important feature determining the accuracy of the model. Average temperature and average maximum temperature have similar impact on the prediction model. The importance of precipitation and temperature extremes is relatively small.

According to the score of the importance of all features, the top-ranked features were selected from the sample data and used to construct the prediction model of wind speed. When the top 10 features were selected for model training, the obtained prediction results are the best. The prediction errors MAE, RMSE and MAPE are 0.238, 0.186, and 5.063%, respectively. Compared with the prediction model constructed by using all features, the prediction performance of the model obtained by the features selected by the RF algorithm is better, and the errors MAE, RMSE, and MAPE decrease by 0.013, 0.014, and 0.389%, respectively.

Fig. 4 shows the fitting results of the prediction model constructed by the features selected by the RF algorithm. It can be seen that the prediction values of wind speed has a slight delay over time. As wind speed fluctuates significantly, the prediction accuracy decreases. From 1983 to 1991, there was a large error between the prediction and actual values of annual average wind speed. The main reason for the large error is that the feature values of the sample data are relatively few, and wind speed is a comprehensive manifestation of various factors. Wind speed is not only related to meteorological factors such as temperature and visibility, but also related to other factors. The limited data collected by the meteorological station, a small number of sample data, and relatively simple feature types will affect the final prediction performance.

3.3 Impact of kernel functions on the prediction model In the nonlinear SVR algorithm, kernel functions realize the transformation of sample data from a high-dimensional space to a low-dimensional space, which plays a significant role in the prediction results of the model. Four different kernel functions (Gaussian radial basis kernel function, polynomial kernel function, linear kernel function, and Sigmoid kernel function) in the SVR algorithm were used to train the sample data, and different prediction models of wind speed were obtained. The parameter values of the model were adjusted to optimize the prediction results. The prediction results obtained by different kernel functions are shown in Table 2. The calculation results of the Gaussian radial basis kernel function have the smallest errors, while the prediction results of the Sigmoid kernel function model have the largest errors (MAE > 0.25, RMSE > 0.20). The prediction results of the polynomial kernel function and linear kernel functions are between the two, and their errors are the closest. Generally speaking, the Gaussian radial basis kernel function has a smaller deviation, and requires fewer parameters compared to the polynomial kernel function, thereby improving the computational efficiency while reducing the complexity of the model. At the same time, the Gaussian radial basis kernel function can achieve the mapping of nonlinear data, and maintains good generalization performance even without parameter adjustment[19]. The linear kernel function is a special case of the Gaussian radial basis function. Its advantages can be demonstrated only when the number of features of the data is large, while the performance of the Sigmoid kernel function is similar to that of certain parameterized Gaussian radial kernel function[20]. Hence, based on the prediction results of the models, the Gaussian radial basis kernel function should be selected as the kernel function of the prediction model of wind speed.

3.4 Comparison of prediction results of wind speed by different machine learning methods To further verify the effectiveness of the prediction model of wind speed, three machine learning algorithms, namely *k*-Nearest Neighbor (*k*NN), gradient boosting decision tree (GBDT), and ridge regression (RR), were used to construct different prediction models of wind speed based on the same sample data. The parameters of the machine learning algorithms used for comparison were all optimized during testing. The comparison results of these methods are shown in Table 3. It can be seen that all classification algorithms exhibit good predic-

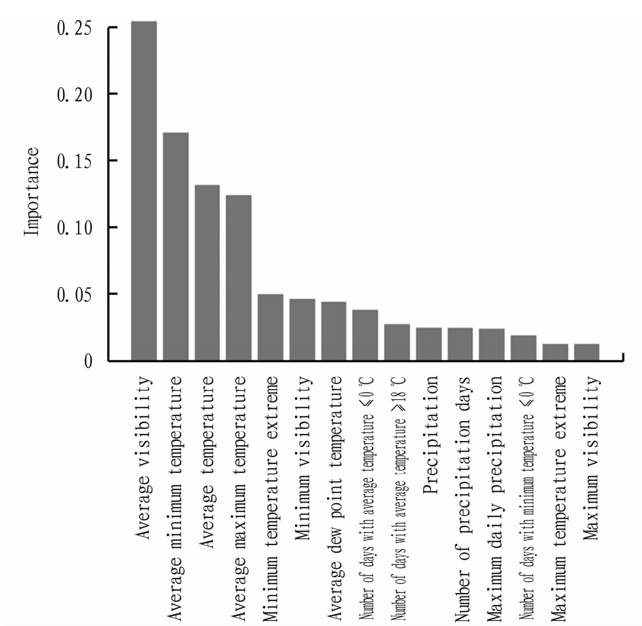

Fig. 3 Score of the importance of all features

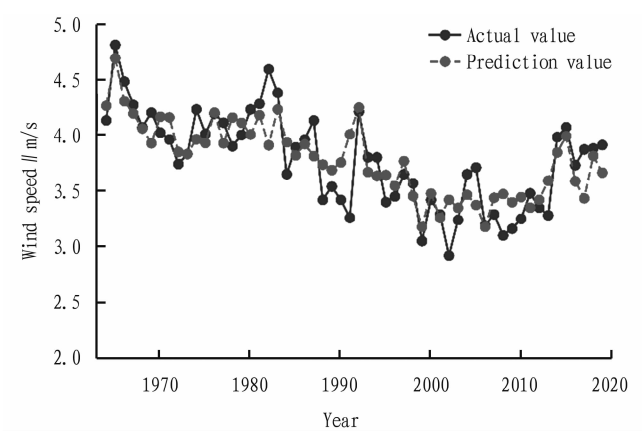

Fig. 4 Fitting results of the prediction model based on the SVR algorithm

Table 2 Comparison results of different kernel functions of SVR algorithm for the prediction model

Kernel functions	MAE m/s	RMSE m/s	MAPE %
Gaussian radial basis kernel function	0.238	0.186	5.063
Polynomial kernel function	0.247	0.195	5.285
Sigmoid kernel function	0.251	0.203	5.506
Linear kernel function	0.249	0.195	5.289

tion performance, among which the prediction performance of the SVR algorithm is the best. Although the RR algorithm further reduces model overfitting by adding a regularization term based on the squared error, the final fitting result is significantly better than that of the GBDT and *k*NN algorithms. However, the MAE, RMSE, and MAPE of the model obtained by using the SVR algorithm are 0.016%, 0.017%, and 0.042 7% lower than those of the RR algorithm, respectively. Therefore, compared with other machine learning methods, SVR has more advantages in the prediction of small sample datasets, and can predict the annual average wind speed at Lhasa Gonggar Airport more accurately, so the prediction model of wind speed is effective.

Table 3 Comparison of prediction results of wind speed by different machine learning methods

Machine learning methods	MAE // m/s	RMSE // m/s	MAPE // %
SVR	0.238	0.186	5.063
GBDT	0.287	0.229	6.295
kNN	0.333	0.253	6.732
RR	0.254	0.203	5.490

4 Conclusions

Based on the data of wind speed at Lhasa Gonggar Airport from 1964 to 2019, the SVR algorithm was applied to construct the prediction model of wind speed after the features were selected by using the random forest method. Compared with the screening method of removing highly correlated features, this method can further improve the prediction performance. The conclusions obtained are as follows:

(1) From 1964 to 2019, annual average wind speed was negatively correlated with average minimum temperature, average maximum temperature, and average temperature. However, the high correlation among different features have little impact on the prediction model.

(2) Compared with other machine learning methods, the SVR algorithm has obvious advantages in handling small sample data sets, and the prediction performance obtained by using the Gaussian radial basis kernel function is better.

(3) Average visibility and average minimum temperature are two important features affecting the prediction performance of the model.

The constructed prediction model of wind speed based on the SVR algorithm can provide reasonable reference and effective theoretical basis for the prediction of wind speed at high plateau airports, thereby ensuring the safe and efficient operation of high plateau airports. However, this study still has problems such as limited research data and few feature attributes used for training. Wind speed not only has periodicity in time but also has a close relationship with the surrounding environment and meteorological conditions of the airport. Hence, how to comprehensively analyze and predict the wind speed of high plateau airports is a topic that needs to be studied further in the future.

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In addition, there are still the following problems in the practical process:

The complexity of AI tools: the generation quality of free AI tools depends on the design of prompt words, and some complex tasks (such as thematic maps) still require manual intervention. Moreover, multimodal output lacks professionalism and is difficult to completely replace teacher creativity.

Limitations of teacher technology: some teachers' understanding of AI technology still remains at the surface level of application, and their awareness of technology application is weak. It is necessary to strengthen the integration ability of "technology – literacy – application" through school-based training.

Data security: the development of intelligent agents involves the collection of student behavior data, and it is necessary to improve the confidentiality mechanism of campus data to avoid privacy leakage risks.

In future research, it will further explore multi-agent collaboration models (such as "lesson preparation – teaching – evaluation" chain agents) and develop lightweight AI – GIS tools to enhance the characteristics of geography. In addition, attention should be paid to the dynamic balance of teacher – student relationships under technological empowerment, in order to avoid the weakening of humanistic nature of education by excessive reliance on AI. The digital transformation of education is not only about tool innovation, but also requires the construction of a sustainable practical paradigm between "technological rationality" and "educational essence".

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