Vibration monitoring of wind turbine tower based on XGBoost

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Abstract. A tower vibration monitoring method based on XGBoost is proposed to predict the tower vibration trends under different operating conditions. Firstly, the wind turbine operating conditions are classified based on the Kmeans clustering algorithm. Secondly, the impact of state parameters of the wind turbine on the tower vibration is analyzed, and the tower vibration monitoring model is established based on XGBoost algorithm. Finally, the actual SCADA data of the wind farm is used to verify the proposed method. The results show that the vibration monitoring accuracy of tower is effectively improved by considering the operating conditions of the wind turbine.

1. Introduction
With the increase of single-turbine’s capacity, the wind turbine has made higher requirements for the structure and performance of its tower[1]. Because of the random characteristics of wind energy and the turbine controls, the tower is accompanied by vibration during the operation of the wind turbine. However, due to assembly errors or potential defects, the tower will have a large abnormal vibration. If tower vibration exceeds a certain level, it will bring further damage to the tower[2]. Therefore, developing the accurate condition monitoring and identifying early abnormal vibration is important for the operation and maintenance of the wind farm.

The issue of tower vibration has attracted the attention of researchers. Ahmet [3] proposed a dynamic monitoring method of wind turbine blade-tower based on infrared laser scanner. The vibration of the tower was precisely measured by the infrared laser signal reflected by the surface of the turbine. However, installing new sensor equipment required additional maintenance cost. Sun [4] studied the transient response of the tower based on the finite element method. The dynamic response of the tower under fluctuating wind speed was analyzed by establishing a finite element model, and the vibration mode of the tower was analyzed. The finite element method can simulate the local damage of the tower by reducing the local stiffness, but it is difficult to consider the effect of external excitation. Fang [5] studied the dynamic characteristics of tower vibration based on the principal component analysis method, established a vibration model of the tower under normal operating conditions based on SCADA data, and used the model to monitor the operating state of wind turbines. The above research has made great progress in the problem of tower vibration monitoring, but the impact of external excitation caused by wind turbine’s operating conditions on tower vibration has not been considered.

The tower vibration distribution is shown in figure 1. The vibration distribution of the tower is obviously different under different operation conditions. The higher vibration of the tower in the X direction mainly occurs in the constant speed interval or constant power interval where the wind speed and the generator rotation speed are higher, and the higher vibration in the tower Y direction mainly
occurs in the start interval and the shutdown state where the wind speed and the generator rotation speed are lower. The wind speed, pitch angle, and torque controls under different operation conditions all bring a certain degree of external excitation to the tower and affect its vibration. Since the external excitation of the tower is quite different under different operation conditions, it is necessary to comprehensively consider the impact of operation conditions of the wind turbine on the tower vibration, and analyze the correlation between various state parameters and the tower vibration.

![Image](https://example.com/image.png)

a) Tower vibration in the X direction  
b) Tower vibration in the Y direction

Figure 1. The distribution of tower vibration in X and Y directions

The Supervisory Control and Data Acquisition (SCADA) system provides a large amount of data during the operation of wind turbines. This paper proposes a tower vibration monitoring method based on SCADA data. Considering the operating characteristics of wind turbines, this study firstly identifies the operating conditions based on Kmeans clustering. Secondly, selects the condition monitoring features of tower vibration based on the gray correlation analysis method. Finally, based on the XGBoost algorithm, the tower vibration monitoring model is established for different operating conditions.

2. The vibration monitoring method of tower

2.1. Operation condition identification

Due to the complex operating conditions of wind turbines, it is hard to accurately define the boundaries of operating conditions based on engineering experience. Combining the operating characteristics of wind turbines, this paper proposes a wind turbine operating condition identification method based on the Kmeans algorithm.

The state parameters that characterize the operating conditions of the wind turbine are selected to form the state vector which is used cluster analysis. The selected state parameters are shown in table 1. The blade’s encoder value represents the pitch angle of the blade, which directly affects the degree of wind energy capture; The start and shutdown sign refers to the state when the wind turbine executes the start or shutdown command. Due to fluctuations in grid demand, wind power sometimes cannot be completely absorbed. Wind turbines increase the pitch angle to reduce wind energy capture. At this time, the wind turbines are operating in the limited power area, power limit sign is set to 1.

| State parameters of wind turbine |
|---------------------------------|
| Wind speed                      |
| Active power                    |
| Generator rotation speed        |
| Blade’s encoder value           |
| Start and shutdown sign         |
| Power limit sign                |

Table 1. input features of cluster analysis

Due to the different dimensions of the state parameters, the data is normalized; according to engineering experience, the clustering center is set to 6; the clustering center is randomly initialized.
and the Euclidean distance is selected for clustering. The clustering result of the operating conditions are shown in figure 2.

![Figure 2. Scatter diagram of wind speed and active power](image)

**2.2. Feature extraction**

Accurately analyzing the correlation between different state parameters and tower vibration is an important prerequisite for monitoring tower vibration precisely. SCADA data not only has a wealth of state information of the wind turbine, and also contains a lot of noise and irrelevant sensor parameters. In order to analyze the correlation of tower vibration and select features, we introduce the Grey correlation analysis, which is defined as the formula (1).

$$
\zeta_i(k) = \frac{\min_{j} \min_{k} |y_i(k) - x_i(k)| + \rho \cdot \max_{i} \max_{k} |x_i(k) - x_i(k)|}{|y_i(k) - x_i(k)| + \rho \cdot \max_{i} \max_{k} |x_i(k) - x_i(k)|}
$$

(1)

Where $x_i(k)$ is the target variable (the tower vibration), $x_i(k)$ and is the i-th factor variable (the state parameter). $\rho$ is a parameter with a value range of [0, 1], which is used to adjust the gap between the gray correlation degrees of each factor variable.

**2.3. The XGBoost algorithm**

The extreme gradient boosting algorithm is an ensemble supervised learning algorithm that ensemble a group of classification and regression trees (CARTs) for learning. By optimizing the CARTs in parallel to improve the learning speed of the model, the XGBoost algorithm is widely used in the field of data mining and has achieved good results. The XGBoost algorithm not only has the powerful learning ability of ensemble learning, but also adjusts the complexity of the model by explicitly adding a regularization item, which is beneficial to prevent overfitting and improve the generalization ability of the model. The XGBoost algorithm is defined as the formula (2).

$$
\hat{y}_i = \Phi(X_i) = \sum_{k=1}^{K} f_k(X_i)
$$

(2)

$K$ is the total number of CARTs, and $f_k$ represents the k-th CART tree. The objective function of the XGBoost algorithm is defined as formula (3).

$$
\text{obj}(\theta) = \sum_{i} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)
$$

(3)

The first part $l$ is the loss function, which reflects the degree of deviation between the predicted value and the actual value. The second part $\Omega$ is a regularization function, which constrains the complexity of the subtree. The XGBoost algorithm uses an additive training method that optimizes the objective function step by step. Firstly, optimize and train the first subtree, and train subsequent subtrees based on the residual between the actual value and the predicted value of the previous subtree.
By minimizing the objective function as shown in formula (4), the t-th CART can be obtained.

\[
\Gamma^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(X_i)) + \Omega(f_t)
\] (4)

Until the K-th subtree is optimized and the prediction result of the entire CARTs reaches the specified requirements, the XGBoost algorithm’s training is completed. The method based on extreme gradient boosting not only requires less computing power, but also has outstanding generalization capability.

3. Case Studies

3.1. Case verification
The real-world SCADA data is used to verify the validity of the tower vibration monitoring model based on XGBoost. Firstly, we collected the SCADA data of a wind turbine from May 1, 2016 to May 15, 2016 as the training set, and the data from May 16, 2016 to May 30, 2016 as the validation set. The input features of the XGBoost model are selected according to the results of the grey correlation analysis. The input features are shown in table 2. Secondly, wind turbine’s operating conditions are identified based on Kmeans clustering, the tower vibration monitoring models under different operating conditions based on XGBoost algorithm are established. Finally, the validation set is used to validate the model, and the result is shown in figure 3.

![Figure 3](a) Validation sample 1  b) Validation sample 2)

**Figure 3.** Tower vibration monitoring based on XGBoost considering clustering conditions

| Input features of the tower vibration monitoring model | Wind speed | Wind speed difference |
|-------------------------------------------------------|------------|----------------------|
| Wind direction                                        | Wind speed difference |
| Active power                                          | Operating condition difference |
| Blade’s encoder value                                 | Generator rotation speed difference |
| Generator torque                                      | Blade’s encoder value difference |
| Blade torque                                          | Generator torque difference |
| Pitch speed                                           |                          |

According to figure 3, The tower vibration monitoring model based on XGBoost, which considers the impact of operating conditions identified by Kmeans clustering, can predict the trend of tower vibration well. The model has learned well the correlation between various state parameters and tower vibration under different operating conditions during the normal operation of wind turbines. Monitoring the tower state based on the residual error distribution of the tower vibration monitoring model, when the residual error exceeds a certain threshold, an abnormal alarm is issued.

3.2. Comparative Experiment
In order to verify the effectiveness of the proposed method, this paper conducts two comparative
experiments. The details and results of the comparative experiments are as follows:

Comparative experiment 1: Regardless of the impact of wind turbine operating conditions on tower vibration, a tower vibration monitoring model is established based on XGBoost, whose input features are shown in table 2 (except for operating condition differences). The result is shown in figure 4. When the vibration change is small, the model can predict the change of the tower vibration trend; however, when the vibration change is large, it cannot predict the tower vibration trend well.

Comparative experiment 2: The tower vibration estimation model is established based on the BP neural network. Model’s output is the tower vibration, and the features in table 2 is used as the model input (except for the operating condition difference). The number of neurons in each layer is [12, 64, 120, 60, 1], the learning rate is set to 0.001, the activation function is Relu, and the loss function is the mean square error. The results are shown in figure 5. When the tower vibration change is small, the BP network can predict the general trend of the vibration, but the residual error is significantly increased; when the vibration change is large, the tower vibration change trend cannot be well predicted and a spike error occurs.

4. Conclusion
A novel tower vibration monitoring method using only SCADA data was proposed in this paper. There are mainly two contributions of our proposed method:

a) Considering the impact of wind turbine operating conditions on tower vibration, an operating condition identification based on the Kmeans algorithm is proposed.

b) Analysing the correlation between state parameters and tower vibration, a tower vibration monitoring model based on XGBoost was established.

The real-world SCADA data was used to evaluate the proposed method and the result show that the propose method improves the accuracy of tower vibration monitoring, and the operating condition identification method based on Kmeans clustering accurately divides the operating conditions of wind
turbines.

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