Research on Evaluation of Tower Vibration State Based on SCADA

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Abstract. Tower is very critical to the safe operation of wind turbines. In this paper, SCADA data is used to evaluate the vibration state of the tower. A tower vibration correlation analysis method based on denoising autoencoder (DAE) is proposed, which evaluates the impact of state parameters on tower vibration based on the reconstruction residual. The tower vibration is predicted based on the Long Short-Term Memory (LSTM) network, and then the tower vibration state is evaluated based on the Wasserstein distance. The actual SCADA data is used to verify the proposed method. The results show that the method accurately predicts the tower vibration trend and quantitatively evaluates the tower vibration state.

1. Introduction
During the operation of the wind turbine, the tower vibrates due to the influence of the lateral force of the wind energy and the control action of the wind turbine[1]. Vibration is an important indicator that reflects the state of the tower, and the evaluation of the vibration state of the tower is of great significance to improve the efficiency of wind farm operation and maintenance[2]. Due to the huge size of the tower and fewer sensors installed, the difficulty of evaluating the tower vibration state is increased. In addition, the external excitation of the tower under different operating conditions is different, and the tower vibration characteristics are affected by the operating conditions of the wind turbine[3].

The Supervisory Control and Data Acquisition (SCADA) system collects nearly a hundred state parameters during the operation of the wind turbine, and these parameters reflect the operating condition of the wind turbine[4]. Considering the impact of wind turbine operating condition on tower vibration, SCADA data is used to establish a tower vibration prediction model under normal conditions. When the tower vibrates abnormally, the model will have a large residual. The distribution of the vibration prediction residuals can be used to evaluate the tower vibration state.

Firstly, based on DAE, the influence of state parameters on tower vibration is analyzed, and state parameters with strong correlation with tower vibration are selected as features. Secondly, considering the impact of wind turbine operating condition on tower vibration, a tower vibration prediction model is established based on LSTM. Finally, according to the distribution of tower vibration prediction residuals, a tower vibration evaluation method based on Wasserstein distance is proposed.

2. The proposed method

2.1. Correlation analysis based on DAE
The Pearson correlation coefficient can only measure the strength of the linear correlation between two variables, and the grey correlation analysis evaluates the consistency of the changing trends of the
two variables. However, there is a nonlinear relationship between different state parameters of wind turbines. In order to explore the impact of wind turbine state parameters on tower vibration, a correlation analysis method based on DAE is proposed. DAE has a powerful information reconstruction ability. The important information in the input data can be reconstructed through two steps of encoding and decoding, and irrelevant noise is ignored. After training, the weight matrix of DAE can learn the correlation between the input variables.

Firstly, the state parameters that need to be analyzed are used as the input of DAE. The six state parameters of wind speed, generator rotation speed, generator torque, active power, blade encoder value and tower vibration acceleration are used as the output of DAE. The first five state parameters characterize the operating conditions of the wind turbine, and the sixth state parameter reflects the tower vibration state. Secondly, the SCADA data is used to train DAE, and the verification set is used to test the generalization ability of the DAE. Finally, the correlation between state parameters and tower vibration is evaluated based on DAE. Replace one state parameter in the input data with its own mean value, and input it into the trained DAE to record the reconstruction error of the tower vibration. If this state parameter has a strong correlation with tower vibration, replacing this state parameter with its own mean value will increase the reconstruction error of tower vibration. If the correlation is weak, the reconstruction error will not change significantly. The above actions are performed for each state parameter in the input data, and the corresponding reconstruction error is recorded. The impact of different state parameters on the tower vibration are evaluated by the increase in reconstruction error.

2.2. LSTM network
Long Short Term Memory network is a special type of Recurrent Neural Network, and its basic cell structure is shown in figure 1. The cell of LSTM contains three specially designed logic gates, namely forget gate, input gate and output gate\(^{(5)}\). The gate structure can effectively avoid gradient explosion and gradient disappearance.

![Figure 1. The structure of LSTM](image)

The forget gate is defined as the formula (1), which determines how much the previous state will be retained. Its inputs are \(h_{t-1}\) and \(x_t\).

\[
f_f = \sigma_f (W_f \cdot [h_{t-1}, x_t] + b_f)
\]  

(1)

The input gate is defined as the formula (2), which determines how much the new information will be stored. The value of \(i_t\) will be updated according to \(h_{t-1}\) and \(x_t\). The tanh layer generates a candidate vector \(\tilde{C}_t\), which is defined as the formula (3). The state \(C_t\) of cell is updated based on the above information.
\[ i_t = \sigma_i(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2) \]

\[ C_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3) \]

\[ C_t = f_i \odot C_{t-1} + i_t \odot C_t \quad (4) \]

The output gate determines the output of the cell state, which is defined as formula (5). The output \( o_t \) of the gate layer of the \( \sigma_o \) is multiplied by the cell state processed by \( \tanh \) to determine the output.

\[ o_t = \sigma_o(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5) \]

\[ h_t = o_t \odot \tanh(C_t) \quad (6) \]

### 2.3. Tower vibration evaluation based on Wasserstein distance

A tower vibration prediction model is established based on LSTM, and it learns the relationship between tower vibration and various state parameters during the normal operation of wind turbines. According to the distribution of vibration prediction residuals, a tower vibration evaluation method based on Wasserstein distance is proposed. The Wasserstein distance is used to measure the difference between two probability distributions[6]. Suppose \( u \) and \( v \) are two different probability distributions, and then the Wasserstein distance between the two distributions can be given by formula (7).

\[
 l(u,v) = \inf_{\pi \in \Gamma(u,v)} \int_{R \times R} |x-y|d\pi(x,y) 
\]

(7)

\( \Gamma(u,v) \) is the set of probability distributions in \( \mathbb{R}^2 \), and its marginal distributions are \( u \) and \( v \) respectively. The Wasserstein distance represents the minimum amount of movement required to transform from probability distribution \( u \) to probability distribution \( v \).

The vibration prediction residual is analyzed based on Wasserstein distance from two aspects:

1. The SCADA data of different stages of one wind turbine are used to establish a tower vibration prediction model based on LSTM and the distribution of vibration residuals are obtained. The Wasserstein distance between the vibration residual distribution of the earliest stage and the vibration residual distribution of the subsequent stages are calculated. The curve of the Wasserstein distance over time reflects the deterioration trend of the tower vibration.

2. Taking into account factors such as similar installation time, the same type, and similar operating environment of wind turbines in the same wind farm, there are similar vibration characteristics of wind turbines in the same farm. Considering the difference of the tower vibration residuals distribution of different turbines, a tower vibration evaluation method based on Wasserstein distance is proposed. The tower vibration prediction model is established for each wind turbine in the same farm, and the distribution of tower vibration prediction residuals is obtained respectively. The wind turbines with the smaller mean and variance of tower vibration are selected as the reference, and the Wasserstein distance of the vibration residual distribution between the reference turbines and other turbines is calculated. By comparing the vibration residuals distribution of each turbine in the entire wind farm, wind turbines with abnormal vibrations can be identified and the further maintenance plan will be formulated.

### 3. Results and discussion

#### 3.1. The prediction of tower vibration

Pearson coefficient, grey correlation analysis and DAE correlation analysis are used to explore the impact of wind turbine state parameters on tower vibration. Some results of the correlation analysis are
shown in table 1. Features are selected based on DAE correlation analysis. Blade encoder value, wind speed, generator torque, active power, wind direction and other 10 variables that have strong correlation with tower vibration are selected to be the input of the LSTM model. Tower vibration acceleration is chosen as the output of the model.

| state parameters          | Pearson coefficient | grey correlation analysis | DAE reconstruction error |
|---------------------------|---------------------|---------------------------|--------------------------|
| Wind speed                | 0.50274             | 0.95055                   | 1649.96                  |
| Active power              | 0.52521             | 0.95741                   | 1645.07                  |
| Generator torque          | 0.52395             | 0.95844                   | 1647.72                  |
| Blade torque              | 0.35536             | 0.93767                   | 1639.09                  |
| Generator rotation speed  | 0.29090             | 0.94381                   | 1627.74                  |
| Impeller speed            | 0.27944             | 0.92378                   | 1628.74                  |
| Absolute wind direction   | 0.04029             | 0.93058                   | 1643.87                  |
| Blade encoder value       | -0.07241            | 0.93252                   | 1703.40                  |
| Wind direction            | 0.01410             | 0.91956                   | 1639.29                  |
| Pitch speed               | 0.01644             | 0.92416                   | 1639.20                  |

In this paper, a two-layer LSTM network and a two-layer fully connected layer network are used to construct the model. The numbers of neurons in the two layers of LSTM are 30 and 35 respectively, and the numbers of neurons in the fully connected layer are individually 40 and 1. The timestep of the input data is set to 2, and Adam is selected as the optimizer of the model. The learning rate is set to 0.001, and the mean square error (MSE) is selected as objective function.

The SCADA data of the 12\textsuperscript{th} wind turbine was collected to carry out the experiment. The data from February 15, 2016 to April 30, 2016 are used as the training set, and the data from May 12 to May 16 and May 28 to May 31 are used as the test set. Through the preprocessing of the data, the data of the training set are 79560 groups, and the data of the test set are 4170 groups and 4980 groups respectively. After using the training set to establish tower vibration prediction model based on LSTM, the prediction result of the test sets are shown in figure 2.

![Figure 2. Tower vibration prediction results](image)

It can be seen from figure 2 that the LSTM model can predict the vibration trend of the tower well. When the tower vibration amplitude is low, the predicted residual remains within 0.1. When the tower vibrates frequently and the vibration amplitude is high, the predicted residual is greater than 0.1, which may be due to the abnormal vibration of the tower caused by the start and shutdown of the wind turbine, yaw, pitch, and other external excitations.
3.2. The evaluation of Tower vibration

The vibration trend of the tower is predicted based on LSTM, and then the state of the tower is evaluated according to the distribution of the predicted residuals. The trend of the tower vibration prediction residual error over time is analyzed based on Wasserstein distance. The 6-month SCADA data of the 11th and 16th wind turbines were selected for analysis. Using 10 days as a period, the six-month data is divided into 18 stages. The vibration residual distribution of the first period from January 1 to January 10 is used as a reference standard, and the Wasserstein distance between the vibration residual distribution of the subsequent stages and the vibration residual distribution of the first period is calculated, and the results are shown in figure 3. According to the change trend of the Wasserstein distance, it can be seen that the tower vibration prediction residual has a slight increase with the increase of the operating time of the wind turbine. According to the change of the Wasserstein distance of tower vibration residual distribution, the deterioration trend of the abnormal tower vibration can be seen, and the further maintenance plan is formulated for the tower with the rapid increase of the Wasserstein distance.

![Figure 3. The Wasserstein distance of vibration residual distribution of each stage](image)

According to the difference of the vibration prediction residuals of different wind turbines in the wind farm, the tower state is evaluated based on the Wasserstein distance. Firstly, count the mean value and variance of the tower vibration of each turbine in the wind farm, and select the wind turbine with the smaller mean and variance of the tower vibration as the reference turbine. Secondly, build the tower vibration prediction models of each wind turbine based on LSTM and get vibration prediction residuals. Finally, calculate the Wasserstein distance between the vibration residual distribution of each turbine and the vibration residual distribution of reference turbine. If the vibration residual distribution of a turbine is quite different from that of the reference turbine, it indicates the tower state of this wind turbine is abnormal. Based on the analysis of the SCADA data of 30 wind turbines in a wind farm, the 12th and 30th turbine with small mean and variance of tower vibration were selected as the reference turbine. The results are shown in figure 4.

![Figure 4. The Wasserstein distance of vibration residual distribution of different turbines](image)
According to the Wasserstein distance of the vibration residual distribution of each turbine in figure 4, it can be seen that the Wasserstein distance of vibration residual distributions of the 27th, 29th turbine are significantly higher than that of other turbines, which indicates that the abnormal vibration frequency of the above two turbines is higher than other turbines. In the wind farm operation records, the 27th and 29th wind turbines have repeatedly issued abnormal alarms of tower vibration, which proves the validity of the tower vibration evaluation method proposed in this paper. It is only necessary to formulate further tower maintenance plans for turbines with large differences in the distribution of vibration residuals to ensure the health of all towers in the entire wind farm. This method improves the efficiency of wind farm operation and maintenance.

4. Conclusion
Based on the DAE reconstruction error, the impact of different state parameters on the tower vibration is evaluated, and the state parameters with strong correlation are selected as the features. The LSTM network is used to establish a tower vibration prediction model, which can well predict the change trend of tower vibration under normal operating conditions. The tower vibration residual is analyzed using the Wasserstein distance. By comparing the residual distribution of the vibration prediction at different stages of the same wind turbine, the deteriorating trend of the tower vibration state can be obtained. According to the difference in the vibration residual distributions between different wind turbines in the same farm, wind turbines with abnormal vibrations can be quickly identified.

Acknowledgments
The research was supported by National Defense Basic Research Program (JCKY2019407C002).

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