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Research on the method of digital twin operation and maintenance platform for intelligent early warning of wind turbine tower

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ABSTRACT

Wind power generators have a complex structure and operate in harsh environments, where working conditions are highly variable. As a result, the operation and maintenance of wind turbines face numerous challenges. In response to the need for the development of wind power operation and maintenance informatization, it is necessary to satisfy the requirements for multi-party collaborative monitoring to ensure the long-term safe and reliable operation of wind turbines.

In this paper,we proposed a method for building an intelligent early-warning digital twin platform focused on the simulation of wind turbines and tower components.

The platform construction method proposed in this article is based on the Web and from the perspective of intelligent operation and maintenance of wind turbines. It establishes a warning model for tower agent simulation and vibration signal time series prediction. The tower mechanism model is established based on the operating data set of a 4MW wind turbine at Shanghai Electric. Different physical responses of the tower under different wind speeds are simulated, and an agent model using LSTM and decision tree models is established for predictive analysis. To account for uncertainty, a Bayesian-LSTM model is established to warn against predictive errors. Finally, a data-driven digital twin wind turbine platform is achieved on the Web.

1. INTRODUCTION

As non-renewable resources such as oil, natural gas, and coal are increasingly depleted, environmental pollution becomes more severe, and the energy crisis becomes more prominent, a new renewable and clean energy source is urgently needed to replace fossil fuels for power generation. Wind power, as the primary application of wind energy, has become the fastest growing power generation technology in the world. From 2012 to 2021, global wind power capacity has increased from 267 GW to 825 GW. The massive deployment of wind power has brought challenges to wind power management, including lagging development of operation and maintenance levels and increasing requirements for multi-party collaborative monitoring.

In solving complex engineering problems, numerical analysis methods based on computer simulations such as Finite Element Model (FEM) are used to analyze the tower structure with the aim of accurately simulating the structural response which requires the assistance of professional simulation software. In creating a finite element simulation model for the tower structure, some simplifications are made to reduce the modeling difficulty while ensuring that the accuracy of the simulation is maintained. When conducting a static analysis on a 600kW wind turbine tower, the simplified model of the tower is studied, including analyzing the impact of flanges, bolts, and doorways on simulation accuracy. The results showed that the reasonably simplified model of the tower had relatively accurate accuracy compared with the accurate model under different working conditions (Xu et al., 2009). Delegation model has been widely used in FEMs to reduce calculation requirements and obtain high-fidelity models without relying on professional simulation software. Similarly, agent models play a crucial role in the mapping of physical entities to relevant virtual entities, and the virtual representation of physical mapping can be applied in real-time monitoring and control.

The decision tree algorithm was first proposed by Morgan J.N and Sonquist J.A in 1963, known as Automatic Interaction Detection (AID), which starts from the root node and recursively splits each node into two child nodes. In 1984, Breiman, Leo, and Ross Ihaka introduced the Classification and Regression Trees (CART) algorithm, which uses a binary split method to establish a binary tree and builds regression trees by minimizing the square error standard division.

In summary, how to apply wind turbine tower mechanism models and prediction uncertainty methods to tower top alerts, establish a multi-alert method for tower-specific situations, and further improve alert efficiency while ensuring prediction accuracy, by establishing a complete tower warning virtual platform is a challenging task. In this study, a 4MW wind turbine from Shanghai Electric was taken as the research object. First, the wind turbine tower mechanism model was established, and the accuracy of different multivariate nonlinear regression models in the mechanism model was explored. At the same time, the performance of LSTM model and other prediction models in wind speed and tower top displacement prediction based on historical operating data of wind turbines was compared. On this basis, Bayesian-LSTM model and evaluate prediction uncertainties. An ahead-of-time proxy model mapping method and a multiple alert method based on Web (Intelligence) and multiple models and sensors were proposed to establish a smart tower top warning virtual platform with multi-monitoring and alert functions for wind turbine towers.

2. Intelligent Early Warning Method For Wind Turbine Tower

2.1. Method Process

The process of the warning method based on wind turbine tower described in this article is shown in Figure 1. The system centers around an intelligent early warning platform and mainly consists of four parts: model processing, data acquisition, server end, and intelligent operation and maintenanceplatform.

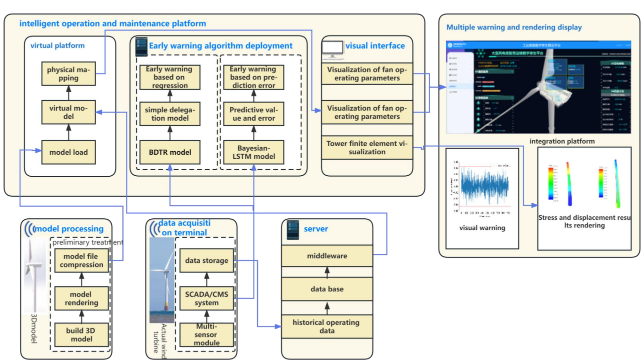

Figure 1. intelligent early warning system

2.1.1 Model processing

The wind turbine unit was modeled in 3D using SolidWorks, and the model was rendered using Blender software. To facilitate dynamic display on the user terminal, the wind turbine model was compressed in GLTF format to improve the loading speed on the web.

2.1.2 Data acquisition terminal

In actual wind turbine units, operating data is collected by multiple sensors and transmitted through communication methods such as TCP/IP and UDP for storage. The data is transmitted from both the Supervisory Control and Data Acquisition (SCADA) system and the Condition Monitoring System (CMS).

2.1.3 Server

Data storage is performed using the MySQL database deployed on a cloud server. Signals collected by wind turbine sensors are transmitted to the cloud-based database via SCADA/CMS systems. The data pool in MySQL can be easily accessed through Axios middleware that is deployed in the cloud, enabling requests and acquisition of wind turbine operating data from the web.

2.1.4 Intelligent operation and maintenance platform

The intelligent operation and maintenance platform is the core of the entire system, which consists of three parts.

（1）Virtual platform.

The virtual platform is deployed on the web end and utilizes http protocol for communication. Based on the Three.js framework, the 3D graphic engine imports and loads wind turbine models after processing. The platform builds virtual wind turbine models to visualize wind turbine operating states, including yawing, pitch variation, and rotor speed, through wind turbine operating data control. These virtual models are based on the real physical status of the wind turbines.

（2）Early warning algorithm deployment

The required algorithms are deployed on the web end using the TensorFlow framework. Abaqus software is utilized to establish a finite element model of the tower, and the finite element post-processing section obtains stress and displacement data for the designated nodes. The tower top vibration signal collected by piezoelectric sensors serves as input to multiple warning methods, such as decision tree algorithms and Bayesian-LSTM models, to monitor and alert the tower movement status.

（3）visual interface

The visualization interface serves as a critical component of human-machine interaction and effectively displaying wind turbine status information facilitates customer wind turbine management. Leveraged by the Three.js framework, we assemble and control the model based on the sensor acquisition signal on the web end. The dynamic display of the model is located at the center of the visualization interface while important wind turbine information, such as pitch, yaw angle, etc., are presented on both sides.

2.2. Analysis of Wind Turbine Parameters and Tower Mechanism

This paper takes the tower of a 4.0MW wind turbine made by Shanghai Electric as the research object. Based on the force characteristics of the tower structure, the tower is simplified as a beam bending problem. To ensure the solution accuracy of the overall model, the flanges, bolts, and door frame structures in the tower structure are ignored to save node and mesh numbers. The bottom of the tower is fixed. The tower adopts a conical tower column structure design, and the material is Q345 steel. The upper end of the tower has a radius of 1478mm and a thickness of 25mm, while the lower end has a radius of 2560mm and a thickness of 60mm. Modeling and static analysis are conducted using Abaqus software. The stress diagram of the tower under the wind turbine generator unit is shown in Figure 2. Due to the impact of wind speed, the tower is subjected to the horizontal thrust of the impeller Ft, the total weight G1 of the wind turbine hub, blades, and nacelle, the weight of the tower itself G2, the bending moment M of the impeller, the torque T generated when the impeller rotates due to wind speed, and the wind load F_w.

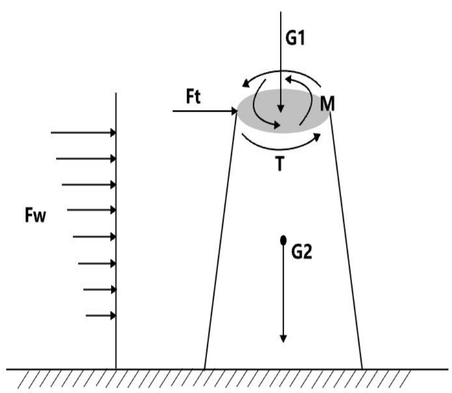

Figure 2. Tower force diagram

（1）Mechanical Losses in the Transmission Chain:

$$\eta = \eta_l \cdot \eta_c \tag{1}$$

The wind turbine generator structure is doubly-fed induction type,η_l is conversion efficiency for power generation, 95%; η_c is transmission chain conversion, 97%.

（2）Torque of wind rotor and hub, M:

$$M = \frac{9549P}{n \cdot \eta} \tag{2}$$

In the formula, P denotes generator output power, kW; n denotes wind rotor speed, r/min. According to SCADA system data, the reactive power is relatively small, so the effect of reactive power on the generator output power is not considered.

（3）The horizontal thrust of the impeller, F_t:

$$F_t = \frac{1}{2} K \rho V^2 S \tag{3}$$

Kis the thrust coefficient, which is generally taken as 1.0 at the cut-in wind speed and 0.5 at the cut-out wind speed. According to the Betz formula,$K = 8/9$; ρrepresents the air density， which is taken as 1.293 kg/m3; Vrepresents the wind speed, m/s; Srepresents the swept area, which is taken as 5938.13 m^2.

（4）Gravity in impeller and engine room, G1:

$$G_1 = m_1 g \tag{4}$$

In the formula: m_1 represents the total mass of hub, nacelle and blades, which is taken as 350000 kg; g represents the gravitational acceleration, which is taken as 9.8 m/s2.

（5）The gravity of the tower, G2:

$$G_2 = m_2 g \tag{5}$$

m_2 is the tower mass, 347460kg.

（6）Impeller bending moment, M:

$$M = F \cdot x \tag{6}$$

F is the gravity of the rotor and nacelle, and x is the distance between the center of the rotor and nacelle and the tower axis.

（7）Wind load, q_w:

$$q_w = \frac{C_D \rho V^2 A}{2H} \tag{7}$$

C_D is the resistance coefficient of flow around the tower barrel, 0.7; HIs the height of the tower, m;A is the windward area of tower barrel structure, m^2.

3. Construction of Numerical Wind Turbine Virtual Entity And Result

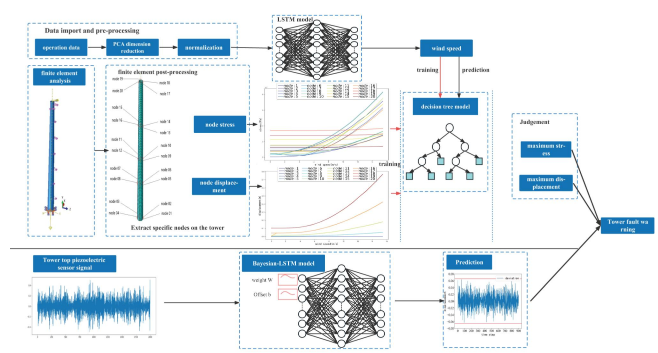

Figure 3. Logical process of early warning algorithm

The overall process of the tower-based early warning algorithm constructed in this article is shown in Figure 3.

3.1. Wind speed prediction and node regression

The tower-based early warning algorithm constructed in this article is divided into two parts as shown in the upper half of Figure 3. The finite element model of the tower is first built, and then the stress and displacement values of 20 nodes under different wind speeds are obtained through post-processing. The relationship between the displacement and stress values of the 20 nodes at different wind speeds is shown in the figure. It can be analyzed that the displacement values at the bottom of the tower remain zero due to fixed constraints, and in the case where wind direction does not change, the stress and strain of the nodes at the windward and leeward boundaries of the tower remain relatively constant at lower wind speeds, whereas the stress and strain increase as the wind speed approaches the rated value. The wind speed data and the stress and displacement values of the nodes are respectively used as inputs and outputs for training the decision tree algorithm. The wind speed data is obtained by selecting the operational data of a wind turbine unit from January to December 2019 with a data sampling interval of 10 minutes. After applying PCA dimensionality reduction and normalization techniques, this data is input into an LSTM single-step prediction model, and the resulting data for the next 10 minutes is used as input for a Bagging regression decision tree algorithm to obtain the values of specific nodes.

In order to verify the superiority of Bagging regression decision tree algorithm in multi-dimensional nonlinear regression for wind turbine towers and check the model performance, this article uses K-Nearest Neighbor (KNN), Random Forest Regressor (RFR), Bagging-KNN and decision tree regression (DTR) as comparative methods. The results are shown in Figure 4.

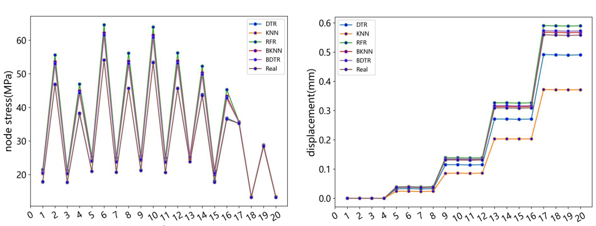

Figure 4. (left)The stress magnitude of different nodes;(right) the displacement magnitude of different nodes

In this article, we use the root mean square error (RMSE) is used as an evaluation criterion to measure the quality of the multi-dimensional nonlinear regression model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2}{n}} \tag{8}$$

n represents the sample size, $\widehat{y}_i$ represents the predicted value of the th sample, and y_i represents the true value of the th sample.

Table 1. Error comparison of different regression algorithms.

algorithm	node stress(RMSE)	displacement(RMSE)
BDTR	0.611	0.007
DTR	4.462	0.035
RFR	2.083	0.017
KNN	0.937	0.983
BKNN	0.630	0.005

According to Table 1, it can be seen that by comparing the performance of different algorithms in terms of node stress and displacement error, Bagging's KNN and DTR have relatively small errors compared to other algorithms, and their accuracy is much higher than that of other algorithms in the table. Therefore, Bagging's DTR is selected to solve the regression prediction problem.

After implementing tower monitoring, in order to enable the monitoring system to achieve the effect of early warning, a critical value needs to be determined as the threshold for controlling the monitoring system alarm. When the predicted data exceeds this threshold, the system will automatically sound an alarm and take a series of follow-up measures such as shutting down maintenance.

Based on the displacement restriction using the piezoelectric signal at the tower top, this paper introduces the monitoring of the tower top displacement signal. During operation, according to the standard JB/T4710-2005 "Steel Tower-Shaped Vessels", for steel tower-shaped containers with a nominal diameter greater than 2000mm, the deflection of the tower top should be less than the tower top height in meters.

3.2. Prediction of Uncertainty Based on Tower Top Displacement Signal.

Regarding the mechanism analysis of the tower body, the displacement at the top of the tower is the largest. The displacement signal is collected through a piezoelectric sensor installed on the fan tower top. However, this sensor is affected by noise interference from components such as the nacelle and blades, as well as its own sensor noise. Therefore, using an LSTM for prediction cannot eliminate the influence of these errors, as shown in the lower half of Figure 3. Therefore, this paper introduces uncertainty analysis and uses a Bayesian-LSTM model to predict uncertainty.

As shown in Figure 5, the predicted data and actual data are compared using a Bayesian-LSTM model for single-step prediction and ten-step prediction. The impact of changing the prediction step length on the prediction results is analyzed.

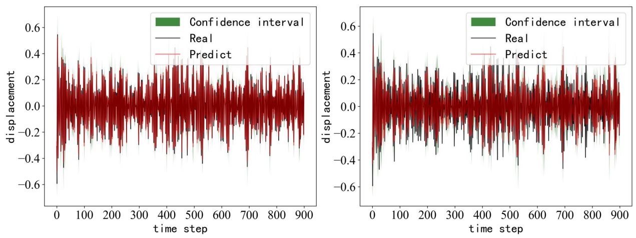

Figure 5. Single-step displacement prediction (left) and ten-step displacement prediction (right).

The model prediction performance was evaluated using RMSE, with values of 0.022 and 0.073 for single-step and ten-step prediction step lengths, respectively. To achieve the purpose of early warning, a prediction method with a shorter step length should be used in practical applications to obtain higher accuracy prediction results.

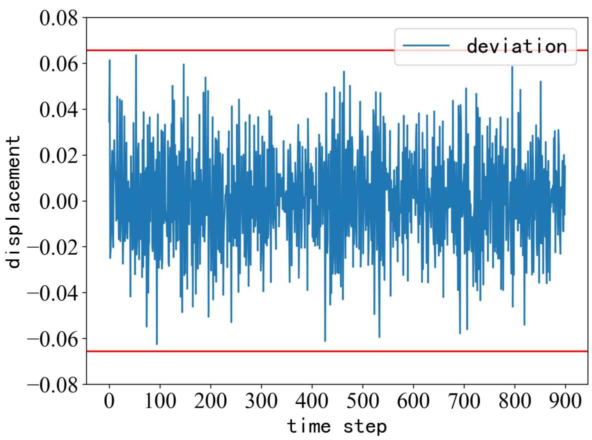

Figure 6. Mean-Standard deviation constraint chart for tower top displacement error.

In Figure 6, we interval prediction and error analysis of tower top displacement signal were realized by setting a limit on the error between the predicted results and monitoring data. According to the central limit theorem, as the sample size increases, the sample will tend to a normal distribution. Therefore, the early warning method is adopted based on the principle that 99.73% of normal data is within the range, and abnormal values are defined as values in the sample that deviate from the mean by more than three times the standard deviation. When the number of accumulated signals that exceed the normal deviation in a monitoring signal exceeds 1% of the normal signals, the system will issue an alarm.

4. Conclusion

This study established a basic digital twin-oriented virtual platform for wind turbines and focused on tower top displacement from the perspective of early warning through finite element analysis and prediction using neural network models, taking into account sensor acquisition and the working environment of the wind turbine, with reference to uncertainties. A Bayesian-LSTM model was established for tower top displacement to monitor and warn the tower's operating status from multiple perspectives. This paper has made some progress in promoting the digital twin of wind turbines in both application and algorithm ends. In terms of the overall construction of the wind turbine virtual platform, from Web display to database and algorithm deployment, it has established a relatively complete wind turbine virtual platform with monitoring and warning functions for wind turbine towers.

References

IRENA, "Renewable capacity statistics 2022," *International Renewable Energy Agency (IRENA)*, Abu Dhabi, 2022.

Xu, Y., Sun, W. L., & Zhou, J. P. (2008). Static and dynamic analysis of wind turbine tower structure. *Advanced Materials Research* (Vol. 33, pp. 1169-1174). Trans Tech Publications Ltd. doi:10.4028/www.scientific.net/amr.33-37.1169

Kudela, J., & Matousek, R. (2022). Recent advances and applications of surrogate models for finite element method computations: a review. *Soft Computing,* 26(24), 13709-13733. doi:10.1007/s00500-022-07362-8

Morgan, J. N., & Sonquist, J. A. (1963). Problems in the analysis of survey data, and a proposal. *Publications of the American Statistical Association*, 58(302), 415-434. doi:10.1080/01621459.1963.10500855

Breiman, L., & Ihaka, R. (1984). Nonlinear discriminant analysis via scaling and ACE. *Davis One Shields Avenue Davis*, CA, USA: Department of Statistics, University of California.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780. doi:10.1162/neco.1997.9.8.1735

Yu, Y., Si, X., Hu, C., & Zhang, J. (2019). A review of recurrent neural networks: LSTM cells and network architectures. *Neural computation*, 31(7), 1235-1270. doi:10.1162/neco_a_01199

Elsaraiti, M., & Merabet, A. (2021). A comparative analysis of the arima and lstm predictive models and their effectiveness for predicting wind speed. *Energies*, 14(20), 6782.doi:10.3390/en14206782

Liu, Y., Guan, L., Hou, C., Han, H., Liu, Z., Sun, Y., & Zheng, M. (2019). Wind power short-term prediction based on LSTM and discrete wavelet transform. *Applied Sciences*, *9*(6), 1108.doi:10.3390/app9061108

Choe, D. E., Kim, H. C., & Kim, M. H. (2021). Sequence-based modeling of deep learning with LSTM and GRU networks for structural damage detection of floating offshore wind turbine blades. *Renewable Energy*, *174*, 218-235.doi:10.1016/j.renene.2021.04.025

Lei, J., Liu, C., & Jiang, D. (2019). Fault diagnosis of wind turbine based on Long Short-term memory networks. *Renewable energy*, *133*, 422-432.doi:10.1016/j.renene.2018.10.031

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