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Research on Wind Turbine Maintenance Based on Data-Physical Fusion Modeling

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Abstract. With the large-scale application of wind power generation technology, its maintenance and repair have received extensive attention. Since wind turbines are complex equipment coupled with multiple fields, the faults are sudden and diverse, and the fault samples are scattered. At the same time, wind turbine operation data has non-linear and unstable time-series characteristics. Single data-driven and physics-driven methods can no longer well meet the current wind turbine maintenance needs. This paper proposes a wind turbine maintenance method with data-mechanism fusion modeling. A data-driven algorithm considering the time-series characteristics of wind turbine operation data is designed. The fusion strategy for updating the boundary parameters of the machine physical model is proposed. Simulation calculations are completed using a fluid-solid coupling model. Simulation results optimize the wind turbine maintenance strategy to guide wind farm maintenance activities.

Keywords. Data-physical fusion modeling, wind turbine maintenance, LSTM, fluid-solid coupling

1. Introduction

With the increasing global energy demand, wind energy, as one of the most promising clean energy sources, has received widespread attention in the world for its development and utilization [1]. Due to the complex and changing weather conditions of wind farms and the fact that wind turbines are complex electro-mechanical-hydraulic integrated equipment under the action of multi-field coupling. This leads to sudden wind turbine failures and diversification of faults, while current maintenance methods such as regular inspections of wind farms cannot detect potential faults in time. These problems bring great challenges to the maintenance and repair of wind turbines [2].

The core of solving the maintenance problem of wind turbine lies in establishing a model reflecting the change of wind turbine operating state. The current research on the operating state modeling for wind turbine maintenance is mainly divided into data-driven methods [3, 4] and physical-driven methods [5, 6]. However, the data-driven model does not consider the actual physical characteristics of wind power equipment regularity and variability, and does not consider the time-series characteristics of wind power equipment operating data [5]. In practice, wind turbine is a complex working body under the coupling of force, heat, magnetism, electricity and other multi-physical fields. It is

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difficult to establish an accurate operating mechanism model, and the measurement of wind power equipment degradation failure data is limited.

The maintenance approach of data-physical fusion modeling can better address the shortcomings of a single approach. Fusion modeling approaches are also starting to develop in the field of wind turbines. Studies include wind turbine blade icing prediction [7], wind power prediction [8], and wind turbine anomaly monitoring [9], among others. However, few data-mechanism fusion studies have been conducted in wind power equipment maintenance.

Based on this, this paper proposes a data-physical fusion modeling approach for wind turbine maintenance. The time-series characteristics of wind turbine operation data are fully considered. The output of the data-driven model is used to update the boundary conditions of the physical model. Based on the calculation results of the fusion model, the actual maintenance activities are guided so as to optimize the existing wind turbine maintenance activities.

2. Wind Turbine Maintenance Process Based on Data- Physical Fusion Modeling

The wind turbine maintenance process based on data- physical fusion modeling proposed in this paper is divided into two parts. The first part is the data-physical fusion modeling process, and the second part is the maintenance strategy and maintenance process as shown in Figure 1.

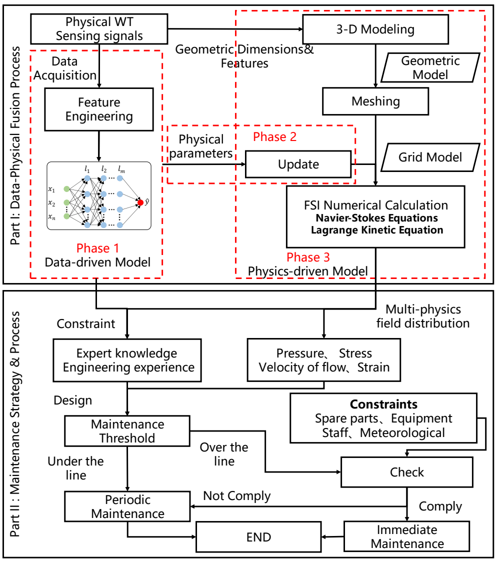


Figure 1. Wind turbine maintenance process based on data-mechanism fusion.

The first part of the data-physical fusion modeling process includes three phases, data-driven modeling, fusion strategy construction and physical-driven modeling.

Phase 1: The wind turbine state variable prediction model based on the LSTM algorithm, the input is the wind turbine time series data.

Phase 2: The fusion method of the data-driven model and the physical-driven model. The fusion method updates the boundary parameters of the physical model for the output of the data-driven model prediction.

Phase 3: The wind turbine aerodynamics-aeroelasticity model. The first step is to construct the geometric model of the wind turbine and complete the meshing. Then the output of the data-driven prediction model is used to update the fluid-solid coupling boundary conditions.

The second part is maintenance strategy and maintenance process. The calculated results are obtained from the first part of the fusion model. Based on expert knowledge and engineering experience, maintenance thresholds are set. Constraints such as staff, spare parts and maintenance equipment are also considered. If the above conditions are met, then the maintenance is carried out immediately. Otherwise maintenance is scheduled to enter the cyclic maintenance for that month. If there is no need to enter the maintenance status, the process will end.

3. Data-Physical Fusion Algorithm

3.1. Data-Driven Model of Wind Turbine

3.1.1. Feature Engineering

The feature engineering used in this paper includes data noise reduction, data resampling, and data differential processing.

In this paper, the wavelet transform threshold denoising method is used. Daubechies4 wavelet, VisuShrink threshold and Garrote threshold function are selected for threshold denoising. The denoising process is controlled by:

$$\begin{cases} L = int[\log(N)] \\ DWTx(m,n) = 2^{-\frac{m}{2}} \int x(t)\psi(2^{-m}t - n)dt \\ \phi_{jk}(t) = 2^{-\frac{j}{2}}\phi(2^{-j}t - k) \\ \psi_{jk}(t) = 2^{-\frac{j}{2}}\psi(2^{-j}t - k) \\ \lambda = \sigma\sqrt{2lnN} \\ \omega\lambda = \begin{cases} [sign(\omega)](|\omega| - \lambda), |\omega| > \lambda \\ 0 \qquad\qquad\qquad\quad , |\omega| < \lambda \end{cases} \end{cases} \tag{1}$$

where: L is the number of wavelet decomposition layers, N is the length of the signal sequence, $\phi_{jk}(t)$ is the scale function, $\psi_{jk}(t)$ is the wavelet function, σ is the standard deviation of the noise, λ is the threshold, ω is the original wavelet coefficient, and $\omega\lambda$ is the wavelet coefficient after threshold processing.

The wind turbine time series data set can be transformed by:

$$\begin{cases} \nabla X_t = X_t - X_{t-1} \\ \nabla^d X_t = \nabla(\nabla^{d-1} X_t) \end{cases} \tag{2}$$

where: X_t is the raw data sequence, ∇X_t is the first-order difference result, $\nabla^d X_t$ is the d -order difference result, and d is the difference order. After the above transformation, a trend-smooth sequence $\{\nabla^d X_t\}$ is obtained.

3.1.2. LSTM Algorithm

The long short-term memory (LSTM) network is able to effectively mine the short-term features and long-term features of the data. The long dependency problem can be avoided and the gradient disappearance problem, which often occurs in the training phase of ordinary recurrent neural networks (RNNs), can be alleviated [10].

The LSTM cell can be controlled as:

$$\begin{cases} f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t]\big) + b_f) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \\ o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t = o_t * tanh(C_t) \end{cases} \tag{3}$$

where: W_f, b_f, W_i, b_i, W_c, b_c, W_o, b_o are network weights, f_t, i_t, $\tilde{C}_t$ are internal states of neurons, $\sigma(\cdot)$ is a sigmoid function, and tanh is a hyperbolic cosine function.

To evaluate the predictive performance of the data-driven model, the prediction experiments used two error measures, including MAE (mean absolute error) and R^2.

$$MAE = \frac{(\sum_{t=1}^{N} |X(t) - \hat{X}(t)|)}{N} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{t=1}^{n}[X(t) - \hat{X}(t)]^2}{\sum_{t=1}^{n}\left[X(t) - \frac{1}{n}\sum_{t=1}^{n}\hat{X}(t)\right]^2} \tag{5}$$

where: $X(t)$ is a real data sequence. $\hat{X}(t)$ is a predictive data sequence, and N is the number of data sequences.

3.2. Physical-Driven Model of Wind Turbine

Computational fluid dynamics (CFD) models investigate the flow field by solving the Navier-Stokes (N-S) equations. In this paper, the Shear Stress Transport (SST) $k-\omega$ model is used to simulate the turbulence model [11]. The SST $k-\omega$ equation is:

$$\begin{cases} \frac{\partial(\rho k)}{\partial t} + \frac{\partial}{\partial x_i}(\rho k u_i) = \frac{\partial}{\partial x_i}\left(\Gamma_k \frac{\partial k}{\partial x_j}\right) + G_k - Y_k + S_k \\ \frac{\partial(\rho k)}{\partial t} + \frac{\partial}{\partial x_i}(\rho \omega u_i) = \frac{\partial}{\partial x_i}\left(\Gamma_\omega \frac{\partial \omega}{\partial x_j}\right) + G_\omega - Y_\omega + D_\omega + S_\omega \end{cases} \tag{6}$$

where: Γ_k and Γ_ω are the effective diffusivity terms of k and ω, S_k and S_ω are the user-defined source terms of k and ω, G_k and G_ω are the user-defined source terms of i and j, Y_k and Y_ω are the dissipation terms of k and ω, k and ω are the turbulent kinetic energy and turbulent dissipation rate, respectively; and D_ω is the transverse dissipation term.

In this paper, the structural field part is based on the dynamics equations in Lagrange's description to establish the structural dynamics model of the wind turbine. The equation of motion is:

$$[M]\ddot{x}(t) + [D]\dot{x}(t) + [K]x(t) = \boldsymbol{F}_s + \boldsymbol{F}_F \tag{7}$$

where: $[M]$ is the mass matrix, $[D]$ is the structural damping matrix, $[K]$ is the structural stiffness matrix, x is the structural displacement, $\boldsymbol{F}_s$ is the external load vector function acting on the structure without fluid forces, and $\boldsymbol{F_F}$ is the coupling forces acting on the structure in the fluid domain.

4. Case Study

This paper uses the above-mentioned data-physical fusion method for the maintenance study of wind turbine blades.

4.1. Data and Case Wind Turbine

The case data in this paper is sourced from a wind farm in China, including the SCADA monitoring data, SCADA fault alarm data and unit maintenance records.

The blade used in this paper's wind turbine is 2MW horizontal axis wind turbine blade. Blade design parameters as shown in Table 1.

Table 1. 2MW horizontal axis wind turbine blade design parameters.

Property	**Value**
Material	GFRP
Length (m)	42.2
Leaf tip pre-curve (m)	1.519
Rated power (KW)	2000
Rated speed (rpm)	17.0
Rotational speed range (rpm)	9.35-19.1
Cutting in wind speed (m/s)	3
Cutting out wind speed (m/s)	25
Taper angle (°)	3.0°
Blade deformation (m)	3

4.2. Wind Turbine Blade Rotational Speed Prediction

The selected characteristic variables are: wind turbine height wind speed W, pitch angle A_1, and yaw azimuth A_2, which are all data collected by the SCADA system. The inputs to the model are:

$$X = [W, A_1, A_2] \tag{8}$$

Noise reduction is applied to the raw data using equation (1). The noise effect index uses signal-to-noise ratio (SRN) and mean squared error MSE. It can be seen from Figure 2b that the signal data after noise reduction keeps the waveform better. As shown in Table 2, the signal-to-noise ratio is 60dB, and the mean squared error is 0.8, which is a good noise reduction effect.

Table 2. Wavelet noise reduction parameters and performance indicators.

WaveName	**Layer**	**Threshold function**	**Threshold value**	**SRN**	**MSE**
db5	4	Garrote	Sqtwolog	60	0.8

In this paper, the original data with a sampling time interval of 1 min are resampled by taking the average value in a 10-minute averaging period. And the first-order difference series of the dataset is used for time series dataset transformation. The constructed wind speed difference series is shown in Figure 2c, which converges between -0.20 and 0.15.

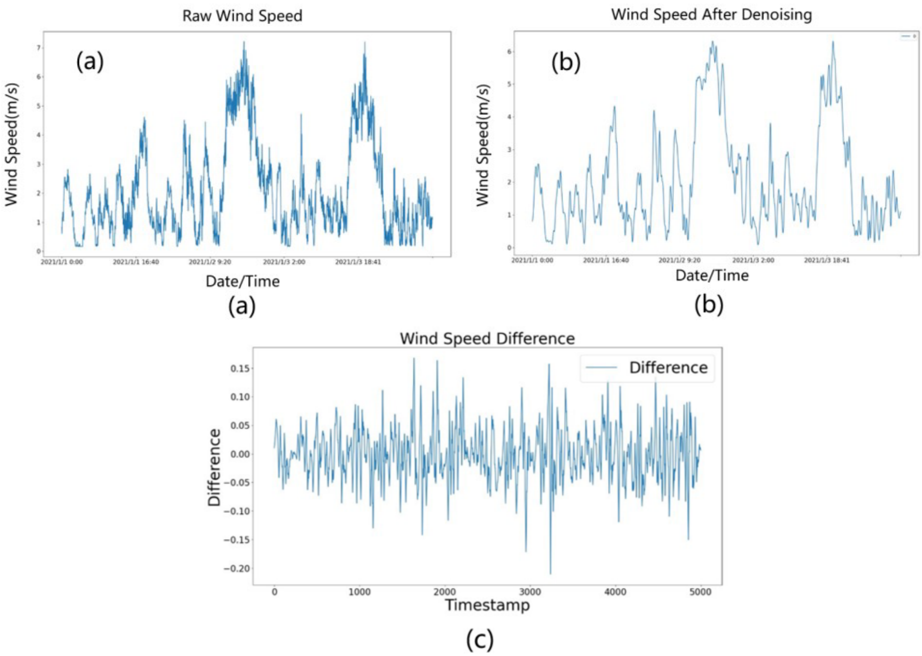


Figure 2. Wind turbine time series data feature engineering results.

The historical time-series data of 24h, 48h, and 72h were used to predict the future time-series data of wind turbine speed for 30 min, 2h, and 3h. As shown in Table 3, the prediction model has good results in short-term prediction and poor performance in long-term prediction.

Table 3. Data-driven model prediction performance.

	History	**Future**	**History**	**Future**	**History**	**Future**
	24h	**30 min**	**48h**	**2h**	**72h**	**3h**
$\boldsymbol{MAE}$	1.1080		2.5124		2.7647	
$\boldsymbol{R^2}$	0.8622		0.6976		0.4653	

4.3. Calculation of Fluid-Solid Coupling

In this paper, ANSYS WorkBench platform is used for computational analysis of fluid-structure coupling. The other parameters and boundary conditions in the computational fluid dynamics of this case are set as shown in Table 4.

Table 4. Fluid-solid coupling calculation parameters and boundary parameters.

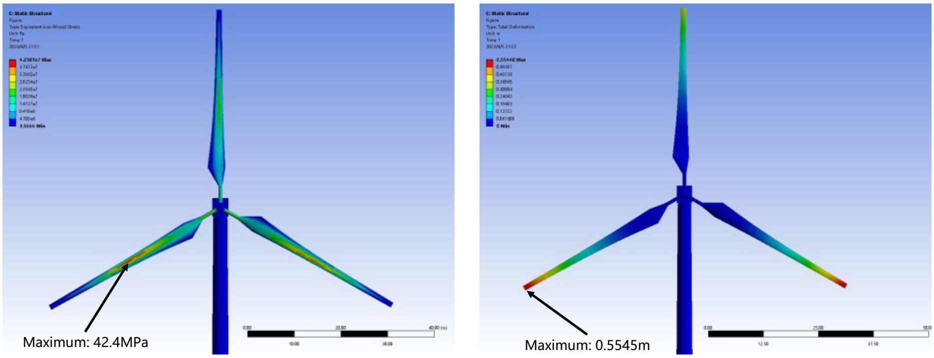
Surface boundary	**Calculation time step**	**Rotation speed**	**Inlet speed**	**Air properties**
No Slip	0.01s	17rpm	20m/s	25℃, 1atm

It should be ensured that the equivalent force of the blade under load does not exceed the material damage limit [12]. The equivalent force is limited as:

$$\sigma_{max} \leq [\sigma] = \frac{\sigma_s}{\gamma} \tag{9}$$

where: σ_{max} is the maximum stress of the blade, $[\sigma]$ is the permissible stress, σ_s is the yield stress of the material, γ is the safety factor.

As shown in Figure 3, the maximum stress value is 42.4 MPa, and when the safety factor γ is 3 and the material yield stress is 220 MPa, the maximum stress value of the blade is 57.82% of the allowable stress. The elastic deformation of the blade reaches its maximum value at the tip of the blade, which is 0.5545 m.



a) Stress b) Deformation

Figure 3. Wind turbine blade stress-strain calculation results.

4.4. Maintenance Activity

Combining the data-mechanism fusion results for wind turbine blade maintenance for the operation of wind turbine No. 3 of this wind farm in December 2021.

According to the fusion model results, the maximum stress value at the area near the blade r/R=0.6 in the strong wind condition can reach more than 50% of the permissible stress. The percentage of time when the wind speed is greater than 17 m/s is 24.0%. Long time of this structural load and strong wind and weak wind high-frequency alternating conditions are more likely to lead to cracks in the blade leaf area, bringing safety risks to wind turbines.

Table 5 shows the maintenance activities optimally arranged in this paper. The blue background shows the newly added maintenance activities based on the fusion modeling results. Comparing with the original wind farm maintenance strategy, it can effectively predict the blade maintenance demand and optimize the existing maintenance activity arrangement, which has certain guiding significance for the blade maintenance of wind farms.

Table 5. Wind turbine maintenance activity arrangement.

Date	Maintenance system	Maintenance type	Maintenance content
2021.11.07	Gearbox	Daily maintenance	Cooling system leakage, coupling wear alignment, etc.
2021.11.08	Generator	Daily maintenance	Coolant refill, cooling line leakage, nut torque, etc.
2021.12.13	Blade	Monthly examination	Blade appearance inspection
2021.12.26	Blade	Monthly examination	Leaf root baffle, cover plate inspection
2022.01.06	Wind turbine	Annual examination	General inspection of gearbox, electrical inspection of generator
2022.01.08	Wind turbine	Annual examination	Nacelle and tower inspection

5. Conclusion

This paper proposes a data-physical fusion modeling method for wind turbine maintenance, which is applied to the maintenance of wind turbine blades. A data-driven algorithm is constructed based on a time-series data prediction model. The physical model based on fluid-solid coupling wind turbine is constructed. Using a strategy based on updating the fluid-solid coupling boundary conditions to construct a data-physical fusion model. Based on the simulation results, a maintenance strategy is designed under the constraints of site personnel, spare parts, and meteorological conditions. The wind turbine blade conditions are predicted more accurately, shortening the maintenance cycle and optimizing maintenance activities. The maintenance method can be extended to other complex equipment in industry, and the reduced-order model (ROM) can be used to design the drive mechanism model in the future.

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References

[1] Jung J, Broadwater RP. Current status and future advances for wind speed and power forecasting. Renewable and Sustainable Energy Reviews. 2014;31:762-777.
[2] Wang TY, Han QK, Chu FL and Feng ZP. Vibration based condition monitoring and fault diagnosis of wind turbine planetary gearbox: A review. Mechanical Systems and Signal Processing. 2019;126:662-685.
[3] Hsu JY, Wang YF, Lin KC, Chen MY, Hsu JHY. Wind turbine fault diagnosis and predictive maintenance through statistical process control and machine learning. IEEE Access. 2020;8:23427-23439.
[4] Garan M, Tidriri K, Kovalenko I. A data-centric machine learning methodology: Application on predictive maintenance of wind turbines. Energies. 2022;15(3):826.
[5] Wang JJ, Liang YY, Zheng YH, Gao RX and Zhang FL. An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples. Renewable Energy. 2020;145:624-650.
[6] Sanchez HE, Escobet T, Puig V, Odgaard PF. Health-aware model predictive control of wind turbines using fatigue prognosis. International Journal of Adaptive Control and Signal Processing. 2018;32(4):614-627.

[7] Shen YJ, Song Z and Kusiak A. Enhancing the generalizability of predictive models with synergy of data and physics. Measurement Science and Technology. 2022 Mar;33(3):034002.
[8] Park J, Park J. Physics-induced graph neural network: An application to wind-farm power estimation. Energy.2019 Nov;187:115883.
[9] Schroder L, Dimitrov NK, Verelst DR, Sorensen JA. Using transfer learning to build physics-informed machine learning models for improved wind farm monitoring. Energies. 2022 Jan;15(2):558.
[10] Memarzadeh G and Keynia F. A new short-term wind speed forecasting method based on fine-tuned LSTM neural network and optimal input sets. Energy Conversion and Management. 2020 Jun;213:112824.
[11] Ageze MB, Hu YF, Wu HC. Comparative study on uni- and bi-directional fluid structure coupling of wind turbine blades. Energies. 2017 Oct;10(10):1499.
[12] Peeters M, Santo G, Degroote J, Van Paepegem W. Comparison of shell and solid finite element models for the static certification tests of a 43 m wind turbine blade. Energies. 2018 Jun;11(6):1346.