Digital twin-driven online intelligent assessment of wind turbine drivetrain

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January 30, 2024

Abstract

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Digital twin-driven online intelligent assessment of wind turbine drivetrain

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Keywords: wind turbine drivetrain, digital twin, intelligent calibration, damage assessment

1. Introduction

Wind power, being a source of renewable energy, holds a significant position in today's global energy scenario.[1] It contributes to the reduction of carbon emissions and lessens the reliance on fossil fuels, bringing about positive effects on both the Earth's environment and energy security. With the global demand for wind energy continuously rising, the number of wind turbines has seen a rapid increase.[2,3] However, wind turbines often operate under harsh conditions, heightening the risk of potential failures.[4] Based on data presented in the referenced literature,[5] the electrical system has the highest failure rate, yet it is straightforward to maintain. In contrast, the gearbox drivetrain takes the longest time to repair and incurs high maintenance costs. Hence, exploring the monitoring and assessment of wind turbine drivetrains proves to be essential and beneficial. Efficient monitoring contributes to the turbines' safety and reliability, minimizes downtime, and cuts maintenance expenses, ultimately extending their operational life.

The SCADA system provides comprehensive real-time operational information,[6] while the CMS system records a wealth of vibration signals. Currently, the monitoring and life prediction methods for wind turbine drivetrains primarily involve extracting features related to the main drivetrain's operational status from SCADA or CMS data. These features are then used to construct monitoring and assessment models. Zhang et al.[7,8] employed various methods such as artificial neural networks (ANN) and support vector machines (SVM) to analyze SCADA data, establishing state monitoring models for wind turbines. Additionally, Pan et al.[9] used the maximum mean difference algorithm to extract vibration data features under multiple conditions, achieving gearbox state monitoring. Guo et al.[10] introduced a data-driven multiscale sparse model to isolate bearing impact elements from vibration signals, enhancing the fault diagnosis of wind turbine bearings. In these data-driven modeling methods, there's often a need for extensive historical data support. They rely more on empirical models and manually set thresholds. Applying these models to new systems may lead to undetected changes or frequent false alarms, limiting the observation results.

Digital twin (DT) technology offers a novel approach for monitoring and life prediction of wind turbine drivetrain systems. The essence of DT is to create a digital model that can capture data from a physical entity in real-time and possesses self-learning and evolutionary capabilities, thereby reflecting the evolution of the physical entity's health status more accurately.[11]In recent years, with advancements in sensor technologies, software and hardware capabilities, and computer computational performance, DT is extensively utilized across a diverse range of fields.[12] Zhang et al.[13] presented a DT framework utilizing transfer learning for the fault diagnosis of rolling bearings. This approach effectively ascertains the health status of actual rolling bearings, even in the absence of abundant fault data. Luo et al.[14] utilized the particle filter algorithm to merge sensor data with the digital model, predicting the lifespan of machine tool cutters in CNC machines. Ye et al.[15]integrated diverse models and datasets into a dynamic Bayesian network (DBN), grounded in the DT framework, to forecast the durability of spacecraft structures. Chetan et al.[16] created a multi-fidelity digital twin representation for wind turbine blades, aimed at confirming the efficiency of dual blades in operation. Wind turbines typically need to operate for extended periods without failure to ensure consistent power generation. Thus, developing an online intelligent assessment for wind turbine drivetrain systems based on DT has significant practical importance.

However, the current application of digital twin technology for online monitoring and performance evaluation of wind turbine drivetrain still faces some critical challenges. The first challenge is the real-time estimation of the input torque. Due to the constant change of wind speed, which results in the drivetrain usually operating under changing operating conditions, accurate estimation of the input torque is crucial to realize the real-time monitoring of the drivetrain. The second challenge lies in constructing a high-fidelity dynamics model. The structure of the wind turbine drivetrain system is complex, typically composed of planetary gears and parallel-stage gears, including components such as shafts, gears, and bearings. For each component, some characteristics, like damping coefficients and stiffness parameters, vary based on operational conditions. Therefore, ensuring that the dynamics model genuinely reflects the response of the wind turbine drivetrain system presents a challenge. The third challenge is the application of twin models in the remaining useful life (RUL) monitoring of critical components. For RUL monitoring, real-time performance is critical because timely failure warning and maintenance decisions can reduce downtime and maintenance costs. These issues hinder the widespread application of DT technology in wind turbines. In response to the outlined challenges, this paper introduces the VBDM-DT model to implement an online intelligent assessment for wind turbine drivetrain systems. The core focuses and contributions of this paper are encapsulated in the following segments:

- Integrating the DT model with the SCADA system, the input torque of the wind turbine drivetrain can be estimated in real time using the recorded wind speed. This alignment guarantees that the DT model's input parameters are in sync with the actual operational conditions of the wind turbine.
- To refine the precision of the DT model, the measured vibration signals captured by the CMS are employed for intelligent calibration of the dynamics model, a process guided by the multi-objective optimization algorithm. This allows the DT model to be continuously adjusted and optimized based on actual vibrations, ensuring that the dynamic load of the components estimated by the dynamics model is highly accurate.
- Based on the Palmgren-Miner hypothesis of linear damage and the S-N curve, a fatigue damage model is established. The real-time dynamic load estimated by the high-fidelity dynamics model is then used as input for the fatigue damage model, allowing for the estimation of the real-time cumulative damage of key components in the wind turbine drivetrain system.

In summary, the VBDM-DT model developed in this paper integrates SCADA, CMS, and the multi-objective optimization algorithm. Unlike most models that are currently data-driven, this model adopts a primary mechanism-based approach with data correction as supplementary. This approach ensures that the results of the mechanism analysis provide theoretical support for the choice of variables in data analysis, and the outcomes of the data analysis serve as crucial resources for refining the parameters of the dynamics model. VBDM-DT can effectively estimate the dynamic loads of key components in the wind turbine drivetrain system in real time and monitor their RUL.

The remainder of this paper is organized as follows: Section 2 introduces the construction method of VBDM-DT, including the establishment of the random wind load model, high-fidelity dynamics model, and fatigue damage model. Section 3 evaluates the effectiveness of the proposed VBDM-DT model and its application in RUL monitoring of drivetrain components. Section 4 summarizes the research work discussed in this paper.

2. Method of VBDM-DT

2.1. Framework of VBDM-DT Model

The VBDM-DT model framework proposed in this paper is shown in Figure 1, including physical space, twin space. In this framework, the physical space mainly contains the wind turbine, SCADA and CMS. the SCADA system monitors various operational data of the wind turbine in real time, such as generator output power, wind speed, main shaft speed, etc.; the CMS primarily monitors the vibration signals from the bearings and gears within the wind turbine's drive system.[17] The twin space can utilize TCP/IP communication to obtain the real-time relevant operating parameters of the physical wind turbine and the vibration signals of the components from SCADA and CMS.VBDM-DT mainly consists of three parts: 1) the random wind load model estimates the input torque of the wind turbine drivetrain in real time from measured wind speeds; 2) the high-fidelity dynamics model, established through the measured vibrations in the physical space, estimates the dynamic loads of key components in the wind turbine drivetrain; and 3) a fatigue damage model is established based on the linear damage Palmgren-Miner hypothesis and S-N curve, to evaluate the extent of damage to key components of the wind turbine drivetrain.

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Figure 1. Basic framework of the developed VBDM-DT model

Using the above method, the real-time wind turbine operation data and vibration signals collected in the physical space are input into the twin space, enabling online intelligent assessment of the damage extent of key components. A visualization platform is also developed to visualize and render the real-time data of wind turbine, which vividly and intuitively displays the real-time operation information, dynamic load and damage degree of key components of wind turbine. The visualization platform can not only monitor the operation status of wind turbine in real time, but also provide valuable information about the degradation of key components, so as to carry out reasonable and predictive maintenance and replacement, in order to ensure the safe operation of the wind power transmission system. The construction process of the VBDM-DT model is described in detail below.

2.2. Random wind load model

The input torque of wind turbine drivetrains is significantly affected by the random fluctuations in wind speed. In VBDM-DT, this is estimated utilizing real-time random wind speed data from SCADA. According to the aerodynamic theory, Equation (1) describes the input power of the wind turbine.[18,19]

where P_{in} is the input power, ρ is the air density, R is the blade radius, and v is the wind speed. The wind turbine power coefficient C_p is a function of the tip-speed ratio λ and the blade pitch angleβ ,[20] which reflects the wind energy utilization:

where ω is the angular speed.

Figure 2 shows a two-dimensional representation of the power coefficient C_p . When the wind speed is below the rated speed, the pitch angle $\beta = 0$. Controlling the rotor speed ω to ensure the tip-speed ratioλ remains at $\lambda_{o\pi\tau}$ enables the wind turbine to operate consistently at the peak power coefficient C_{pmax} . Observe that the optimal power coefficient, C_{pmax} , is valued at 0.48, and is attained when $\lambda = \lambda_{o\pi\tau} = 8.03$.

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Figure 2. The wind turbine C_p - λcurves

Wind speed divides the operational range of a wind turbine into three distinct regions,[21] as depicted in Figure 3. In region 1, the wind speed falls below the turbine's cut-in speed (v_{min}), leaving the blades stationary. In region 2, the wind speed value is less than the rated value (v_{rate}), the wind turbine maintains stability at the maximum power coefficient(C_{pmax}). In region 3, where the wind speed surpasses the rated speed yet remains below the cut-out speed, the wind turbine maintains operation at its rated power (P_{rate}).[22]

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Figure 3. Schematic diagram of the operating regions of a wind turbine

In Equations (1), P_{in} denotes the input power. And the input torque(T_{in}) developed by a wind turbine can be written as:

Based on Equations (1) and (5), the relationship between wind speed and input torque can be expressed as:

where T_{rate} is the rated torque of the wind turbine.

2.3. High-fidelity dynamics model

It is difficult to directly measure the dynamic loads of components in a commercial wind turbine, therefore, in this paper, a high-fidelity dynamics model is constructed based on the digital twin framework by integrating the dynamics model and CMS. The high-fidelity dynamics model is able to generate the real-time dynamic loads of each component of the wind turbine drivetrain system in a low-cost and computationally efficient way in the twin space. The main innovation of this method is to update the parameters in the dynamics model based on the vibration signals in the CMS. The construction processes of the high-fidelity dynamics model are introduced as follows.

2.3.1. Modeling the dynamics of the wind turbine drivetrain.

Figure 4 illustrates the schematic representation of a 2.0 MW wind turbine gearbox. It consists of a first-stage planetary gear system and two stages of parallel gear transmission systems connected in series. The planetary stage features straight tooth gearing, and the parallel stages feature helical gears. The symbols in Figure 4 are defined as follows: s denotes the sun gear, r is the ring gear, c is the carrier, and p_n (n=1,2,3) represents the nth planets. g_1 and g_2 refer to the intermediate stage gears, and g_3 and g_4 to the high-speed stage gears. T_{in} represents the input torque, as estimated by the random wind load model.

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Figure 4. The schematic diagram of the wind turbine gearbox

This paper employs the lumped-parameter method to formulate the dynamics model of the planetary transmission system.[23,24] Each gear within the planetary transmission system is characterized as a spur gear, as illustrated in Figure 5. The matrix form of the dynamic equation of the planetary transmission system can be written as[25]:

Where M_P , C_P ,K_P , F_P , andx_p represent the planetary stage's mass matrix, damping matrix, stiffness matrix, excitation vector, and displacement column vector, respectively.

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Figure 5. Schematic of the planetary transmission dynamics mode

The transmission shaft is primarily used to support rotating parts and transfer power during operation. Using the lumped-parameter method for the dynamic modelling of a two-stage parallel gear transmission system fails to account for shaft deformation, resulting in a lack of model fidelity. The finite element method allows the dynamics modeling of gear trains including flexible shafts, bearings and gears.[26] Therefore, in this paper, the finite element method is used for dynamic modeling of a two-stage parallel gear train as shown in Figure 6. The two-stage gear transmission system includes three shafts, six bearings, and two helical gear pairs. The first shaft is divided into 11 elements, the second shaft is divided into 8 elements, and the third shaft is divided into 8 elements, with each element containing two nodes. Each node of every element is numbered, dividing the finite element model of the two-stage gear transmission system into 31 nodes. The intermediate stage driving gear's meshing stiffness and mass matrix link to node 7, while the driven 's counterparts attach to node 16. Together, they engage to constitute an intermediate stage helical gear meshing element. The high-speed stage driving wheel and driven wheel are connected to nodes 19 and 28, respectively, meshing with each other to form a high-speed stage helical gear meshing element. Each shaft contains two bearings, forming a shaft-bearing coupling element.

In this paper, the motion differential equation of the shaft is established using the Timoshenko beam element. Given that the two-stage parallel gear transmission system is characterized as a helical cylindrical gear transmission, it's essential to consider axial excitation. We define the nodes corresponding to thei^{th} element as j and $j+1$, with each node accounting for translations in the x , y , and$z$ directions and torsion in the z direction, resulting in four degrees of freedom. The shaft element's motion differential equation can be articulated as follows:

where M_e , C_e andK_e denote mass matrix, damping matrix and stiffness matrix of shaft element. x_e represents the generalized coordinates of the shaft element.

The dynamics model of the helical gear meshing element in a two-stage parallel gear transmission system is shown in Figure 7, and its dynamics equation can be expressed as follows:

Where m_p and m_g are the masses of pinion and gear respectively, I_p andI_g are the rotational inertia of pinion and gear,k_m is the time-varying meshing stiffness of the meshing elements, and c_m is the meshing damping.x_p , y_p ,y_p , ϑ_π ,x_g , y_g ,y_g , and ϑ_γ are the vibrational displacements and torsion angles of pinion and gear respectively, a denotes the pressure angle, β is the helical angle of the helical gear, r_p andr_g are the radius of pinion and gear.

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Figure 6. The dynamics model of parallel shaft gear drive in the wind turbine system

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Figure 7. Helical gear meshing element

Within the shaft-bearing coupling element, the time-varying stiffness of the bearing in the dynamics model is ascertained through Equation (13).[27]

where k_a is bearing static stiffness, andk_0 is the bearing stiffness fluctuation amplitude. f_b denotes the bearing ball passing frequency. β_β represents the bearing phase angle.

The 1st node in the two-stage parallel shaft gear transmission system is connected to the planetary transmission system to couple the two subsystems. Since the planetary stage involves spur gears and the parallel stage involves helical gears, an axial force exists during the operation of helical gears but is absent in spur gears. During system coupling, it's assumed that the axial force generated by helical gears is absorbed by the gearbox casing. After the two subsystems are coupled, the overall stiffness of the system is as illustrated in Figure 8. The system generalized coordinate vector can be expressed as:

The dynamics equation of the wind turbine gearbox transmission system is given as:

where M , C and K are the mass matrix, damping matrix and stiffness matrix of wind turbine gearbox transmission system.F represents the vector of externally applied force, while the damping matrix C adopts the definition of Rayleigh damping, articulated as follows:

where η , ζ are the mass matrix and stiffness matrix coefficient.

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Figure 8. Schematic diagram of the overall stiffness matrix of the gear transmission

2.3.2. Intelligent calibration of the dynamics model

Some parameters in the dynamics model of the wind turbine gearbox transmission system are determined by empirical formulas or analysts' experience. However, during actual operation, the values of certain parameters can vary with changing conditions, such as the damping coefficient. The operating conditions of wind turbines are highly dependent on environmental factors, especially wind speed. Variations in wind speed directly influence the input rotation speed and load of the gearbox transmission system. To ensure the accuracy of the dynamics model, it is integrated with CMS within the digital twin framework for online intelligent calibration. As illustrated in Figure 9, the intelligent calibration process involves comparing the measured vibration data from the wind turbine's CMS with the simulated vibration from the dynamics model and extracting quantitative similarity indicators. If these indicators fall below a threshold, a multi-objective optimization algorithm is introduced for dynamic calibration, updating the optimal values of the dynamics model parameters. This process guarantees a significant alignment between the simulated and measured vibration accelerations.

In the vibration signal time domain, the root mean square (RMS) value of the vibration signal reflects the vibration intensity and energy level. The frequency spectrum shows the amplitude distribution of the vibration signal at different frequencies, and the variation rule of the fundamental frequency and its harmonic amplitude in the frequency spectrum is very important for the health monitoring of the gear transmission system. The correlation between the measured vibration and the simulated vibration fundamental frequency and its harmonic amplitude can be characterized by the Pearson correlation coefficient, and when the Pearson correlation coefficient is greater than 0.8, it indicates that there is a strong positive correlation between the simulated response of the dynamics model and the measured response of the CMS, which suggests that the dynamics model captures the characteristics of the actual vibration signals very well. In the VBDM-DT model, in order to realize the online intelligent calibration of the dynamical model, three similarity quantitative indicators are proposed to monitor the model performance, and the mathematical expressions for these similarity quantitative indicators are articulated as follows:

Where the superscript *MOD* denotes the simulated values from the dynamics model, while *CMS* represents the measured values from the condition monitoring system. X_{rms} and Y_{rms} are the RMS values of the simulated and measured time domain waveforms, respectively. *correlation* denotes Pearson's correlation coefficient, *amp* denotes the amplitude of the fundamental frequency and its harmonics in the spectrogram, with the subscript *mean* indicating the average.n is the number of the fundamental frequency and its harmonics. When the quantitative similarity indicator surpasses the threshold, the VBDM-DT model activates an optimization algorithm to calibrate the dynamics model.

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Figure 9. Intelligent calibration of dynamics model

In this paper, the values for the similarity quantitative indicators f_1 , f_2 and f_3 are set at 0.5, 0.2 and 0.2 respectively. f_1 primarily compares the RMS values of the time domain waveforms between the simulated and measured accelerations. Given that the measured vibration signal's time domain waveform contains some noise, the preset threshold for f_1 is 0.5. The indicator f_2 represents the changing trend of the primary frequency observed in the spectrogram. When it falls below the preset threshold of 0.2, the Pearson correlation coefficient between the amplitudes of the simulated and measured primary frequencies exceeds 0.8, indicating a strong positive correlation between the two. The indicator f_3 mainly characterizes the difference in the amplitude of the main frequency in the spectrogram, and is evaluated by using the mean absolute percentage error (MAPE), which is a kind of index used to measure the degree of error between the simulated signal and the measured signal, and when f_3 is lower than the preset threshold value of 0.2, it is considered that the two errors are small.

Within the VBDM-DT framework, the employed optimization algorithm is the multi-objective grasshopper optimization algorithm (MOGOA), renowned for its superior search efficiency and swift convergence rate.

GOA is a meta-heuristic bionic optimization algorithm that simulates the group behavior of grasshoppers in nature to find the optimal solution.[28] MOGOA improves on GOA to adapt to the characteristics of multi-objective problems. Specifically, the MOGOA algorithm introduces the concept of Pareto domination, and evaluates the advantages and disadvantages of solutions by comparing their Pareto dominance relationships. The algorithm finds better Pareto optimal solutions by continuously updating and improving the solutions. The mathematical model proposed by MOGOA is as follows:

Where X_i represents the position of the ith grasshopper after the algorithm's iterative update, *ub* and *lb* are the upper and lower bounds of the optimization parameters, N denotes the number of grasshoppers in the population, and$|x_j\text{-}x_i|$ is the distance between the current ith grasshopper and the jth grasshopper. *s(r)* represents the social behavior among the grasshoppers. Based on the recommendation from reference,[28] m = 0.5 and μ = 1.5.T_{temp} is the current optimal solution. The purpose of introducing the parameter c is to decrease the global search range as the number of iterations increases but to enhance the local precision search around the target. Its mathematical expression is as follows:

Where l is the current iteration number and L is the maximum iteration number, c_{min} andc_{max} are the minimum and maximum values of the parameter c . In this paper, we set $c_{min} = 0.00004$ and $c_{max} = 1$.

Within the VBDM-DT model, in order to ensure that the optimal parameters can still be obtained when the time-domain waveforms and frequency spectra of the vibration signals have certain noise or errors, the vibration signals of the two measurement points in the CMS are utilized to calibrate the dynamics model, and when the similarity quantification indicator of either measurement point is lower than the threshold value, the MOGOA is invoked to update the parameters. When updating the dynamics parameters, the time-frequency domain characteristics of both measurement points are compared, and the mathematical expression of the objective function is consistent with the similarity quantization indicator in Eq. (18), which ensures that the simulated response of the two measurement points matches well with the actual response.

In summary, the VBDM-DT framework facilitates the online intelligent calibration of the dynamics model, enhances the fidelity of the dynamics model, and provides real-time estimates of the dynamic meshing force in the gears and dynamic loads in the bearings of the wind turbine drivetrain system. This is beneficial for component performance evaluation and RUL monitoring.

2.4. Fatigue damage model

The dynamic load of the key components of the wind turbine gearbox transmission system can be estimated in real time by using the high-fidelity dynamics model. The dynamic load calculated through this high-fidelity model cannot be directly applied to fatigue life prediction methods. Instead, this load must be processed into stress, providing a stress spectrum for fatigue analysis of the gears and bearings in the transmission chain. Subsequently, cumulative damage is estimated based on the linear damage Palmgren-Miner hypothesis and the S-N curve. In the following, this paper details these processes, using gear contact fatigue damage as an example.

2.4.1. Gear contact stress

Utilizing the estimated torque from the random wind load model and the real-time rotational speed measured by SCADA as inputs for the high-fidelity dynamics model, it becomes feasible to estimate the real-time dynamic load on the gears of the wind turbine transmission system. Based on the ISO 6336-2 standard, the contact stress of the gear is further computed [29]:

Where u represents the gear transmission ratio,d_1 and b are reference diameter and face width of the pinion, F_t is the gear meshing force calculated by the high-fidelity dynamics model. Other parameters are discussed in reference.[29]

2.4.2. Stress cycle counting method

After calculating the contact stress of the gear, the contact stress needs to be counted and transformed into the contact stress fatigue stress spectrum. The dynamic meshing force of the gear is based on the entire gear, while fatigue damage analysis is based on the gear tooth. This means the stress cycle count of the gear tooth is related to the gear rotation speed, and the contact stress on the tooth surface varies from zero to amplitude. Therefore, the traditional rainflow counting method cannot be used to statistically analyze the contact stress on the tooth surface. Referring to the method recommended in ISO 6336-6,[30] the irregular contact stress load on the gear is statistically analyzed. As shown in Figure 10, assuming the stress-time load process calculated between $\sigma_{\iota\text{-}1}$and σ_ι takes the time$t_1+t_2+t_3$, then the stress duration at the stress level σ_ι is$t_1+t_2+t_3$. The number of stress cycles at each stress level depends on the duration of the stress and the gear rotation speed, and it is calculated by the following formula:

Where $n_i$represents the number of stress cycles within the i^{th}stress bin. In this paper, with the sun gear meshing with three planetary gears at the planetary stage, the number of stress cycles needs to be multiplied by 3. The duration of thei^{th} stress bin, denoted ast_i , is measured in seconds and can be referenced from the time series presented in Figure 10. Additionally,w_i indicates the gear's rotational speed in rpm.

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Figure 10. Process of creating stress bins

2.4.3. Gear contact fatigue damage analysis

The contact fatigue damage of each gear can be calculated according to the Palmgren-Miner linear damage accumulation theory with the following formula:

Where D_c represents the cumulative fatigue damage. N_b indicates the total number of stress bins within the stress spectrum. n_i signifies the count of stress cycles within the i^{th} stress bin. N_{ci} designates the requisite number of stress cycles for the gear to achieve contact fatigue failure at the stress magnitude corresponding to the i^{th}stress bin. This is typically derived from the S-N curve, as delineated in reference [30]:

Where σ denotes the equivalent fatigue stress, expressed in MPa.N represents the number of stress cycles until fatigue failure is reached; m and C are material-specific constants, determined by the material itself.

To enhance the accuracy of the analysis, this study adopts the dual-slope S-N curve method recommended in ISO 6336-6. For values of$N$ below N_0 , the curve's slope is defined as $-1/m$; for values greater than N_0 , the slope becomes -1/(2m -1). Specifically, for gear contact fatigue evaluations, $N_0 = 5\times10^7$.

3. Validation and application of the VBDM-DT

To achieve real-time intelligent assessment of wind turbine transmission systems, this section presents tests and simulations of the proposed VBDM-DT model using a 2.0 MW wind turbine from a wind farm in Urumqi, Xinjiang, China as a case study. The comprehensive specifications of the wind turbine are provided in Table 1, and the structural parameters of the gearbox gear train are shown in Table 2.

Table 1. Wind turbine parameters.

Parameter	Value	Parameter	Value	Parameter	Value
Rated power	2MW	Cut-in wind speed	4m/s	Rotor radius	41m
Rated torque	1.23×10^6N*m	Cut-out wind speed	20m/s	Transmission ratio	103
Rated speed	14.8RPM	Rated wind speed	12m/s	Air density	1.255kg/m^3

Table 2. Structural parameters of the wind turbine gearbox transmission.

Gear stage	Modulus (mm)	Pressure angle (°)	Component	Number of teethe	Tooth width (mm)	Mass (

Planetary gear stage	17	20	Ring	99	370	2652
			Planet	39	370	994
			Sun	21	370	286
Inter-mediate stage	14	20	Gear g_1	92	300	2724
			Gear g_2	21	300	102
High-speed stage	14	20	Gear g_3	107	170	2096
			Gear g_4	26	170	101

3.1. Validation of the random wind load model.

The load applied to the wind turbine drivetrain is aerodynamic torque. The comparison between the actual aerodynamic torque and the estimated aerodynamic torque is shown in Figure 11. The estimated torque is obtained through the online estimation using the model proposed in Section 2.2, while the actual torque is acquired via a rotary torque sensor. The MAPE is used as an evaluation strategy to assess the discrepancy between the estimated and actual values, and its formula definition is as follows:

Where n is the number of samples; $y_i$denotes the torque estimated by the model. $\hat{y}$? represents the actual torque, and $\bar{y}$ is the mean value of the actual torque. The data in Figure 11 shows the operating torque of the wind turbine on a particular day, and the error between the model estimate and the actual value is 8.34%.

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Figure 11. Comparison of estimated torque and actual torque

3.2. Validation of high-fidelity dynamics model

To validate the effectiveness of the dynamics model intelligent calibration module in the developed VBDM-DT model, vibration signals from two measurement points in the CMS were used to calibrate the dynamic model. The selected measurement points are the high-speed shaft bearing seat and the intermediate shaft bearing seat, which correspond to measurement point 1 and measurement point 2 in Figure 12, respectively.

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Figure 12. The sensors arrangement of wind turbine gearbox

When the wind speed is 6.75m/s, the input rotational speed of the wind turbine drivetrain is 8.33RPM, and the input torque is 361747N.m. Under this condition, the similarity quantitative indicator is higher than the preset threshold, and the VBDM-DT model starts invoking the optimization algorithm for dynamic calibration. During the dynamic model calibration process, MOGOA simultaneously extracts the similarity quantification indicators for measurement points 1 and 2 and then updates the dynamic parameters. The similarity quantization indicatorsf_1 , f_2 , andf_3 are obtained according to Equation (17) discussed in Section 2.3.2. The ultimate goal is to obtain a good match between the simulated and measured accelerations so that the similarity quantization indicators are below a preset threshold. The comparison before and after calibration for measurement point 1 is shown in Figure 13, and for measurement point 2 in Figure 14. The post-calibration simulated response shows high consistency with the CMS measured response. At measurement point 1, the primary frequency components are around 372 Hz, 744 Hz, and 1,116 Hz, corresponding to the fundamental frequency, second harmonic, and third harmonic of the high-speed stage. The peak values of the primary frequency at test point 2 are consistent with the situation of measurement point 1. The comparison results before and after calibration are shown in Table 3. Before calibration, the value of f_2 for measurement point 1 is 0.006, but both f_1 and f_3 exceed the preset threshold, indicating that the trend of the primary frequency of the simulated signal at measurement point 1 matches the measured signal, but the amplitude differs significantly from the measured vibration. Before calibration, the value of f_1 for measurement point 2 is 0.01, but both f_2 andf_3 are above the preset threshold, indicating that the time-domain waveform of the simulated acceleration at measurement point 2 is consistent with the measured results. However, the variation pattern and amplitude of the main frequency in the frequency domain differ significantly from the measured signal. After calibration, the similarity quantification indices for both measurement points 1 and 2 are below the preset threshold, demonstrating the effectiveness of the intelligent calibration module for dynamics in the VBDM-DT model.

Table 3. Comparison of similarity quantification metrics.

Testing position	Point 1 Before intelligent updating	Point 1 After intelligent updating	Point 2 Before intelligent updating	Point 2 After intelligent u
f_1 ([?]0.5)	2.12	0.36	0.01	0.40
f_2 ([?]0.2)	0.006	0.006	0.81	0.01
f_3 ([?]0.2)	3.90	0.13	0.41	0.18

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Figure 13. Comparison before and after intelligent calibration of measurement point 1

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Figure 14. Comparison before and after intelligent calibration of measurement point 2

3.3. Fatigue damage estimation

Utilizing the random wind load model validated earlier, along with the high-fidelity dynamics model, we can carry out real-time estimations of dynamic loads on each gear pair. Further, using the program in the fatigue damage model, we can estimate the contact stress of the gear pairs and compile their load spectra. Figure 15 displays the stress range and corresponding cycle counts for the first-stage sun gear on a particular day.

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Figure 15. Stress range and corresponding cycle counts for the sun gear

The material of the sun gear in the gearbox of the 2 MW wind turbine studied in this paper is 17CrNiMo6, and $m = 17.035$ and $C = 3090.3$ are obtained according to ISO 6336-2,[29] and the S-N curve of the contact fatigue of the sun gear is determined using the method discussed in Section 2.4.3, as shown in Figure 16. Utilizing the VBDM-DT model proposed in this paper, we conducted an online intelligent evaluation of the wind turbine drivetrain. The cumulative damage of the sun gear after one day of operation due to contact fatigue is illustrated in Figure 17, with the accumulated damage approximated to be 1.023e-05. The growth rate of contact fatigue damage is lower when the wind turbine is operated at less than the rated torque. On the contrary, when the wind turbine is operated close to the rated torque, the contact stress level of the gears increases significantly, which leads to a rapid growth rate of contact fatigue damage.

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Figure 16. S-N curve of the sun gear

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Figure 17. Expected accumulated damage of the sun gear over one day of operation

The design life of wind turbines is approximately 20 years. However, the remaining life information of key components in wind turbines is very limited during operation. Therefore, this study estimated the cumulative contact fatigue damage of various gears in the wind turbine gearbox based on historical operating state information provided by SCADA and CMS, combined with the methods proposed in the VBDM-DT model. This helps predict the life of the gears and determines when maintenance or gear replacement is needed. The wind turbine studied in this paper has been in operation for 11 years, and the current cumulative damage of the sun gear is about 0.415. The fatigue damage threshold is usually set at 1, and it is considered to have experienced fatigue failure when it exceeds this threshold.

3.4. Digital twin visualization platform

To intuitively display the interaction between the physical space and the digital space, this paper has developed a visualization platform for wind turbine digital twins. The data-driven functions of this platform are implemented based on the Unity platform. As the operating state of the wind turbine in the physical space constantly changes, the digital model continuously obtains real-time status data and transforms it, achieving a virtual-real mapping of the wind turbine drivetrain state, ensuring synchronization between the virtual and physical wind turbines. Furthermore, this visualization platform, based on the VBDM-DT model, can capture real-time and high-precision dynamic load changes of key wind turbine components. It then further estimates the contact stress of key components and conducts statistical analysis, realizing quantitative assessment of cumulative contact fatigue damage to various key components, achieving the goal of precisely mapping the operating state of the wind turbine.

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Figure 18. Digital twin visualization platform for wind turbines.

Figure 18 displays the visualization interface of this platform. Figure 18(a) provides a clear view of the main operating parameters of the wind turbine digital twin system (wind speed, input rotational speed, input torque, generator power, etc.). Figure 18(b) shows the interface for the intelligent calibration of the dynamics model. Figure 18(c) displays the real-time dynamic load time-domain waveform and spectrum graph for each key component. Figure 18(d) shows the contact stress characterization interface and the real-time cumulative damage quantitative assessment interface for each key component.

4. Conclusions

The performance and reliability of the wind turbine system directly affects the stability and efficiency of power generation, and it is of great importance to monitor the operation of the system in real time as well as to evaluate its degradation status in real time. In this paper, a digital twin model named VBDM-DT is proposed, which can be used to carry out online intelligent assessment of wind turbine drivetrain system. By integrating SCADA and CMS systems, the model can estimate the input torque in real time and intelligently calibrate the dynamics model in order to build a high-fidelity dynamics model to reveal the dynamic response of each key component in the wind turbine drivetrain. In addition, the model has the ability to estimate the cumulative fatigue damage of the drivetrain components in real time, which provides valuable information for monitoring the health status of the wind turbine system. The VBDM-DT model of a wind turbine with a rated power of 2.0 MW is used as a case study to verify the validity of the model. In addition, the developed VBDM-DT can also be used in other gear trains, such as construction machinery and helicopters, to promote the wide application of digital twin technology in the health management of key components of gear trains. In future research, we will further consider other degradation mechanisms, such as wear monitoring of gears, in order to extend the functionality and applicability areas of the model.

Acknowledgements

This work was supported by the Natural Science Foundation of Xinjiang Province (No. 2021D01C050) and Xinjiang Province key research and development (2022B01017-1).

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