Offshore wind power digital twin modeling system for intelligent operation and maintenance applications

Ernu Zhang[1*], *Feng* Shen[1], *Siguang* Liu[2], *Gang* Chen[1], *Fuguo* Zhang[1], and *Shuo* Li[1]
[1]State Power Investment Corporation Research Institute, Beijing, China
[2]State Power Investment Corporation Jiangsu Electric Power Company, Nanjing, China

Abstract. Offshore wind power operates in a complex and harsh environment, while turbines continue to develop in the direction of large capacity and scale. Therefore, offshore wind power increasingly needs to reduce the overall operation and maintenance costs and improve the operation and control level of individual turbines and wind farms. Digital twin technology is intelligent, efficient and visual, and can provide intelligent services such as data analysis, fault diagnosis, performance evaluation and optimization suggestions for offshore wind power operation and maintenance. Relying on the digital twin five-dimensional model and its based prognostics health management method, a set of offshore wind power digital twin modeling system is deployed through the construction of data governance and maintenance fault recognition process. The system realizes the operation analysis and optimization of wind turbines, as well as the diagnosis and early warning of key equipment and field groups of wind turbines, which improves the management and control level of offshore wind power, improves the quality of operation and maintenance, optimizes the arrangement of offshore tasks, and reduces the cost of operation and maintenance. In the future, the system has great application prospects in predictive maintenance, quality improvement, efficient operation and maintenance of offshore wind power, providing support for the development of intelligent operation and maintenance of offshore wind power.

1 Introduction

Offshore wind power has outstanding advantages such as high wind speed, stable source, and good environmental effect, and has been well developed all over the world. The Global Wind Energy Report 2022 released by Global Wind Energy Council shows that in 2021, the global offshore wind power newly installed capacity of 21.1GW, a twofold increase year-on-year, and the proportion of the global new wind power installed capacity reached 22.5%, the largest increase in history.[1] In which, China has 16.9 GW of all newly installed offshore wind power capacity. Due to the offshore wind farm offshore distance, harsh operating environment, inspection and maintenance difficulties, the costs and risk level of offshore wind power operation and maintenance difficulties, operation and maintenance increased significantly. The development of wind turbines towards large capacity and scale has also further promoted the demand for offshore wind power to reduce overall operation and maintenance costs, and to improve the operation and control level of single machine and field group.

Digital twin technology matches real physical objects with virtual models and update them synchronously in real time, and provides intelligent services such as data analysis, fault diagnosis, performance evaluation, and optimization suggestion for offshore wind power operation and maintenance.[2] Digital twin technology is intelligent, efficient, and visible. The technology can support remote monitoring and early warning of equipment, and intelligent evaluation and optimization decision-making, thus effectively alleviating the difficulties of offshore wind power operation and maintenance of inconvenient transportation, complex marine hydro-logical and meteorological environments, and the lack of personnel operation and maintenance capabilities and experience. Due to the unique advantages of digital twin technology, its application has rapidly expanded in offshore wind power operation and maintenance. [3-8]

1.1 Origin and definition of digital twins

It is now widely believed that the concept of the digital twin was developed by Professor M.Grieves in a speech on Product Life-cycle Management (PLM) in 2003. In 2010, NASA (National Aeronautics and Space Administration) defined the Future Vehicle Digital Twin paradigm in order to address the need for simulation in the development of vehicles that cannot be flight tested in space. In March 2011, to address the issue of fighter air-frame maintenance, AFRL (U.S. Air Force Research Laboratory) also explicitly mentioned digital twins in a presentation.

The concept of digital twins has also gone through a period of development. In 2014, Professor M.Grieves

* Corresponding author: zhangernu@outlook.com

went into more depth on the definition of digital twin in Digital twin: manufacturing excellence through virtual factory replication, in which he claims that the digital twin consists of three components: the physical product in physical space; the virtual product in virtual space; and the data and information that connects the virtual to reality. [9] However, the structure of this definition is too shallow to meet the needs of increasingly complex industrial simulation. Today, the more widely accepted definition is that digital twin is a technology that fully utilizes data such as physical model sensor updates, operation history, etc., and integrates multi-disciplinary, multi-physical quantity, multi-scale, and multi-probability simulations so as to reflect the full-life-cycle process of the corresponding entity. [10]

The definition of digital twin has been further expanded with the increased demand for digital twin models in terms of application domain expansion, integration with emerging IT technologies, realization of information-physical data fusion, realization of multi-domain and multi-level services, pervasive industrial inter-connectivity, and dynamic multi-dimensional multi-temporal and spatial-temporal scale models. Tao Fei et al. proposed the concept of five-dimensional model of digital twins in 2019. [11]

1.2 Five-dimensional model of digital twins

Five-dimensional model of digital twins includes the dynamic connection between each other of the physical entity, virtual entity, service, twin data and the above models, whose expression is shown in Equation (1). [12]

$$MDT = f(PE, VE, Ss, DD, CN) \tag{1}$$

In which: MDT denotes the digital twin model reference architecture. PE denotes physical entity, VE denotes virtual entity, Ss denotes service, DD denotes twin data, and CN denotes the connection between components.

According to equation (1), the structure of the digital twin five-dimensional model is shown in Figure 1.

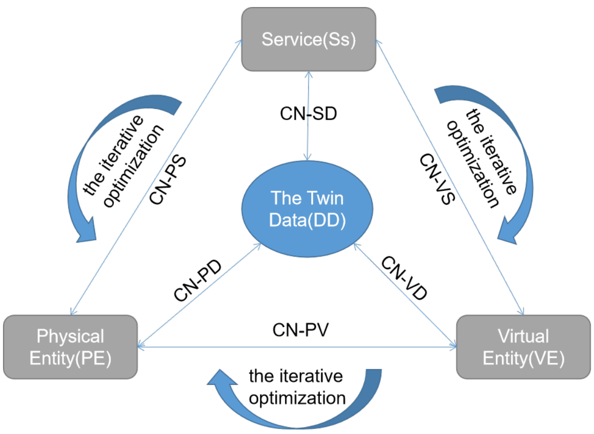


Fig. 1. Structure of Digital Twin Five-dimensional Model: The model relies on the DD to form the links of PE, VE, and Ss in the run to achieve the iterative optimization of the PE and the VE.

MDT is a common reference architecture. The twin data (DD) integrates and fuses the information data and physical data. Services (Ss) service-oriented encapsulation of various types of data, models, algorithms, simulations, results, etc. required for different domains, different levels of users, and different businesses in the process of digital twin application. Connectivity (CN) realizes pervasive industrial interconnection between physical entities, virtual entities, services and data. Virtual Entity (VE) portrays and describes physical entities in multiple dimensions, spatial scales, and time scales. The five-dimensional model, which is an important guide for the landing of digital twins, can be directly mapped or transformed into a service-oriented software architecture in engineering applications.

For the accurate construction of the digital twin system of offshore wind turbine, the five-dimensional model is applied. Fig.2 shows the specifics of the digital twin system model for offshore wind power based on the five-dimensional modeling architecture, where the different elements of the five-dimensional model are subdivided.

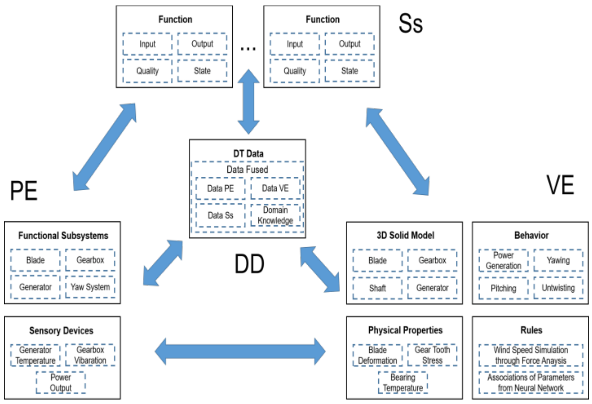


Fig. 2. Specifics of the Digital Twin System Model for Offshore Wind Power Based on the Five-dimensional Modeling Architecture: Blue double arrows represent connections.

1.3 Digital twin-driven PHM methodology

Based on the five-dimensional digital twin model of offshore wind turbines, Tao Fei et al. proposed a digital twin-driven prognostics health management (PHM) methodology, which is applied to intelligent operation and maintenance of offshore wind power. [13] The PHM method based on the digital twin five-dimensional model can utilize continuous virtual-real interaction, information-physical fusion data, and virtual model simulation verification to enhance the information-physical fusion in the process of equipment condition monitoring and fault prediction, so as to improve the accuracy and effectiveness of the PHM method.

The method consists of three phases: observation, analysis and decision.

The observation phase mainly ensures that the VE are updated in real time with the PE and correspond accurately, and makes judgment when inconsistencies arise. It includes three steps: digital twin modelling and calibration, model simulation and interaction, and consistency judgement. In order to achieve the goal of the observation phase, the VE must be able to realize the interactive update of the real-time status and working conditions of the PE. However, due to the different manufacturers of wind turbine equipment, the complexity of the control model, and the independence of the data in different processes such as equipment design, infrastructure and commissioning, real-time monitoring, maintenance and repair, etc., the VE must be able to realize the interactive update of the PE real-time status and operating conditions. Therefore, in order to achieve the goal of the observation phase, data governance is required to map the components in the PE to the corresponding data of the different processes, and then to map them to the components of the VE by mirroring the reverse establishment.

The analysis phase mainly realizes the identification and traceability of fault states. It includes three steps: degradation detection, inconsistency caused judgement, identification and prediction of fault cause. This stage can track the degradation process in PE operation and provide early warning. At the same time, when the PE and the VE produce inconsistency, it can determine whether a fault occurs by comparing with the historical data under the same operating conditions and trace the fault. However, the realization of the above functions requires the extraction of warning features from historical data, fault correlation and fault traceability analysis, and the generation of fault knowledge bases and risk bases. This requires model training and knowledge base construction, and fusion of fault features, fault modes, and fault causes through neural networks to build an AI-based maintenance fault recognition process.

The decision-making phase will select the appropriate maintenance strategy among various preset scenarios based on the fault types and causes obtained in the analysis phase, which will be implemented in the VE to verify the effect, and then in the PE to finalize the O&M process.

It can be found that the application of digital twin in offshore wind power intelligent O&M requires data governance of offshore wind power and the application of artificial intelligence to construct the maintenance fault recognition process. In the following section, the construction methods of data governance and maintenance fault recognition process for offshore wind power will be described in detail, and the process of constructing the digital twin model will be specified.

2 Offshore wind power digital twin modeling system

In order to meet the requirements of implementing digital twin-driven PHM methodology so as to realize intelligent operation and maintenance, and to solve the problems of inconvenient transportation, complex marine hydrological and meteorological environments, and the lack of personnel ability and experience in the operation and maintenance of offshore wind power, a set of offshore wind power digital twin modeling system has been developed. The system consists of three parts: data governance, construction of maintenance fault recognition process, and construction of digital twin model.

2.1. Data governance

First, the data objects to be governed is identified to perform data governance. Types of data that related to different physical entities of offshore wind power liker blade, generator, gearbox, yaw system, etc. was analyzed. Eventually, four types of data were confirmed: equipment design data, infrastructure commissioning data, real-time status data and maintenance & repair data.

Second, in order to unify these four types of data, types of wind turbine data coding were studied, including monitoring point code, KKS code (Kraftwerk-Kennzeichensystem, or Power Plant Signage System), equipment code, and equipment fault code, that are carried out to record these four types of data in the operation system and maintenance system of offshore wind power. The internal logic of these codes was sorted out and integrated to the data corresponding to a specific device in the wind turbine. Finally, by integrating these devices, the virtual entities form the primary equipment, secondary equipment, and operation system model were formed.

The detailed structure of the data governance is shown in Figure 3.

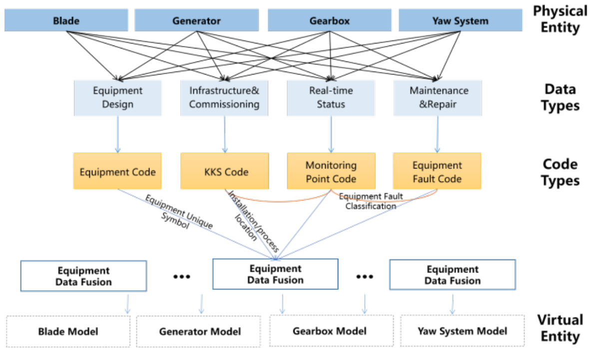


Fig. 3. Data Governance Structure: Utilizing the correspondence of data encoding to realize the mapping of each component in the PE to the corresponding type of data of different processes, and then establishing the mapping to each component of the VE by mirroring inverse.

2.2. Construction of maintenance fault recognition process

Combining model training, knowledge base construction and neural network fusion, the offshore wind power maintenance fault recognition process is constructed. The overall process consists of four parts: (1) Equipment structural breakdown & acquisition data processing: the complex wind turbine system is disassembled until the minimum repairable parts. (2) Fault mode and impact analysis: Locate the failure modes of the corresponding Minimum Repairable Parts and analyze their failure effects. Based on the data accumulated in this section, AI is applied to perform fault correlation analysis. (3) Root cause analysis: Locate the cause of the fault based on fault traceability analysis. Based on the data accumulated in this part, AI is applied to obtain risk matrix to realize the identification and early warning of operational risks. (4) Maintenance strategy development and execution: Based on the cause of the fault, the corresponding maintenance strategy is made. Meanwhile, based on the data accumulated by root cause analysis, AI is applied to form maintenance knowledge base, which is combined with the maintenance strategy to form the final output maintenance strategy.

The detailed structure of the maintenance fault recognition process is shown in Figure 4.

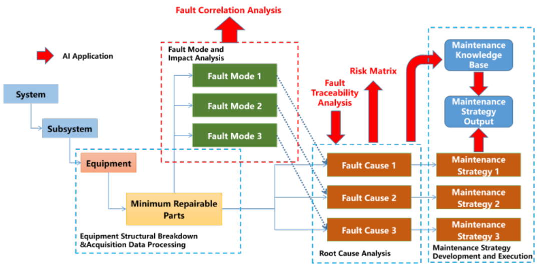


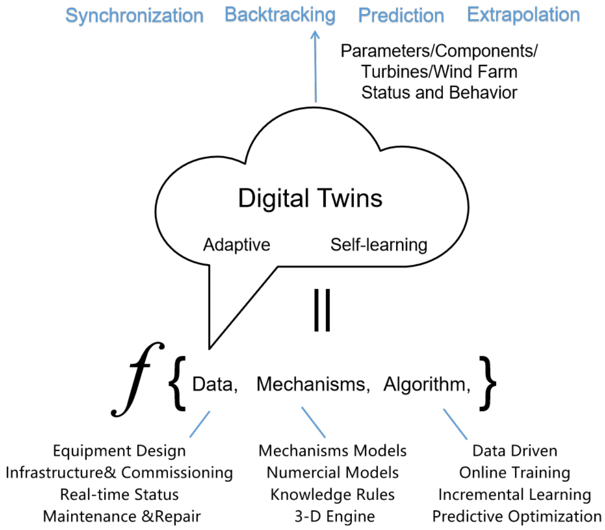
Fig. 4. Maintenance Fault Recognition Process Structure: Building a maintenance knowledge base and risk matrix for degradation and fault model training, and performing fault correlation analysis and fault traceability analysis through neural network fusion.

2.3. Construction of digital twin model

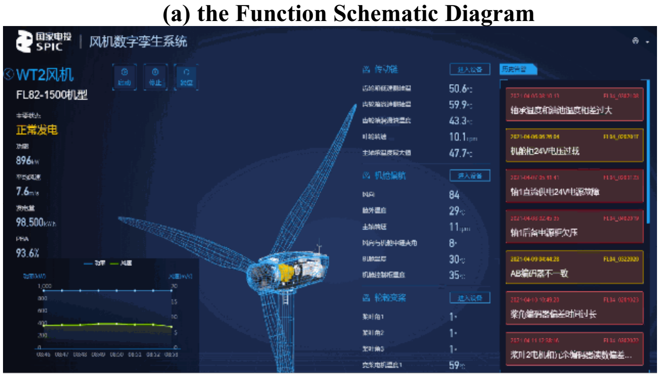
After the development of data governance and maintenance fault recognition process described in the previous section, a digital twin system for offshore wind power based on five-dimensional model is constructed. The digital twin model is deployed in the offshore wind farm of SPIC (State Power Investment Corporation) Jiangsu Company.

Based on the data-driven and mechanism, the multi-source data-driven mechanism model is constructed, thus realizing the mapping between the physical and virtual entities of the wind turbine. On this basis, the digital twin of the wind turbine is constructed, which can be synchronized with the wind turbine entity in real time, and has the ability to deduce and predict the operation of the equipment, which can support the diagnosis and early warning of the equipment, and help to improve the quality and efficiency of wind turbine production.

Figure 5 is the function schematic diagram and display interface of offshore wind power digital twin system.



(a) the Function Schematic Diagram



(b) Display Interface

Fig. 5. The Function Schematic Diagram (a) and Display Interface (b) of Offshore Wind Power Digital Twin System Function Schematic Diagram: The offshore wind power digital twin system is deployed in the offshore wind farm of SPIC Jiangsu Company. By assembling data, mechanisms and algorithms, digital twins with adaptive and self-learning capabilities are constructed, capable of synchronizing, back-tracing, predicting, and extrapolating the behavior of parameters, components, turbines, and wind farm status and behaviors. The language of the display interface is Chinese.

3 Application of offshore wind power digital twin system in intelligent operation and maintenance

The offshore wind power digital twin modeling system deployed in the offshore wind farm of SPIC Jiangsu Company provides intelligent O&M services, and thus generate substantial revenue. The application on a typical 4MW model with a capacity of 300MW offshore wind farm create an annual value of RMB 31.703 million in the dimensions of replacement / maintenance and power generation enhancement. The system benefits the offshore wind power O&M in two fields: 1) intelligent analysis & optimization, 2) intelligent diagnosis & warning. The following sections will separately introduce specific application in both fields.

3.1. Offshore wind power intelligent analysis & optimization application

Three typical applications of the offshore wind power digital twin modeling system in intelligent analysis & optimization will be introduced followed: offshore wind farm energy efficiency analysis, yaw diagnostics and optimization, wind farm wake flow control & optimization.

3.1.1. Offshore wind farm energy efficiency analysis.

In order to optimize the energy efficiency of wind turbines, an offshore wind turbine energy efficiency analysis system was designed to establish a refined model based on digital twins for power generation performance assessment of offshore wind turbines, and dynamically track the trend of wind turbine performance degradation. The system is able to effectively identify the equipment status and obtain the power generation and power characteristics of wind turbines, thus reducing the failure rate, increasing the running time and improving the efficiency of turbine capacity. Figure 6 shows the digital twin wind turbine energy efficiency analysis system architecture.

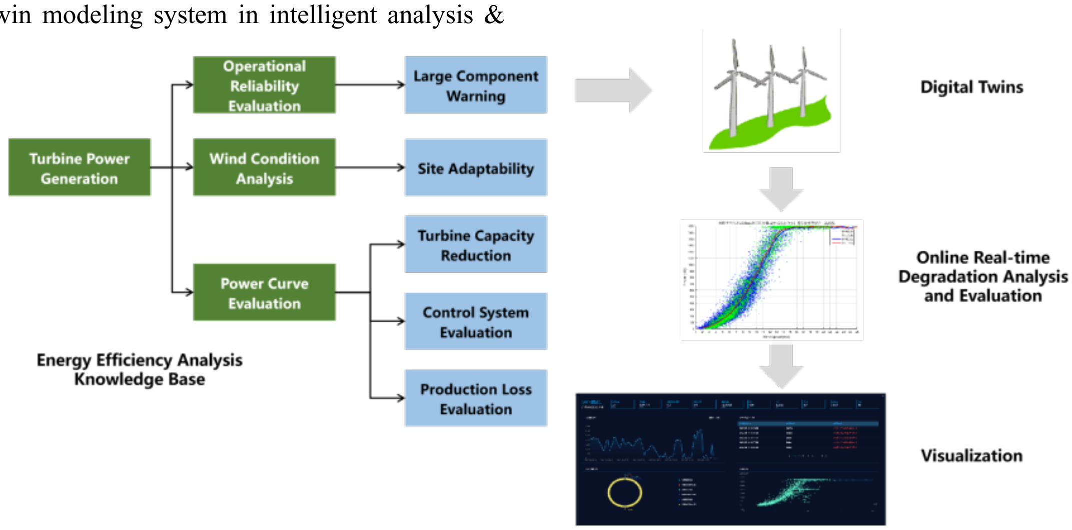


Fig. 6. the Digital Twin Wind Turbine Energy Efficiency Analysis System Architecture: Based on the established data base map and digital twin base, the system further integrates the mechanism + data-driven digital twin modeling technology to form a digital twin for identifying turbine degradation; based on the real-time data of wind farms, it realizes online real-time degradation analysis and evaluation of wind turbine performance, and adapts to follow the degradation of the turbine and diagnose the causes of degradation.

3.1.2. Yaw diagnostics and optimization

SCADA (Supervisory Control And Data Acquisition) based regular manual analysis of wind turbine yaw has real-time and high efficiency, and can avoid the loss of downtime, but the method still requires experienced technicians to carry out regular manual analysis, which is time-consuming and labor-intensive. [14] Relying on the maintenance fault recognition process, a digital twin based yaw prediction model is developed, which is constructed by fusing the yaw wind fault mechanism with the SCADA data of the wind turbine to realize the diagnosis and optimization of wind turbine yaw. Figure 7 shows the decision-making architecture of the digital twin based yaw prediction model.

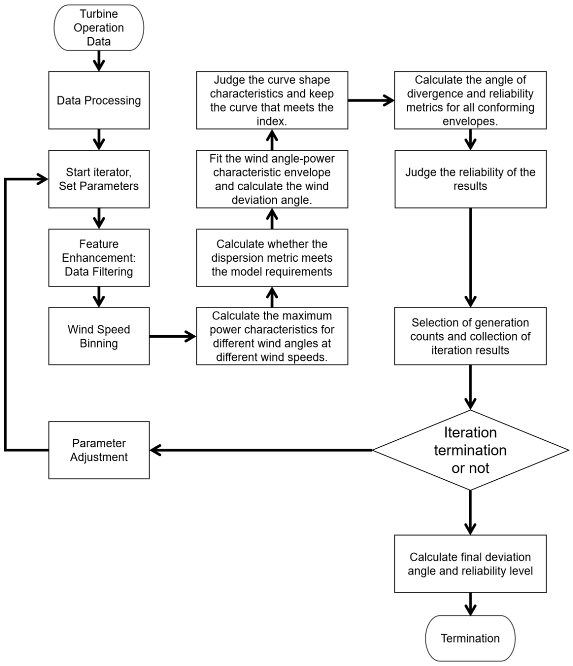


Fig. 7. the Digital Twin Based Yaw Prediction Decision-making Architecture: Without adding new sensors, the deviation of yaw-to-wind incorrectness is predicted based on wind speed, wind angle, wind energy utilization factor or power, and the current yaw system wind incorrectness is warned in real time based on the prediction results, and the health value and fault level are evaluated.

3.1.3. Wind farm wake flow control and optimization

Wind turbine wake flow drastically reduces the overall power generation of wind farms, affects the economics of wind farms, increases the fatigue load of wind turbines, and shrinks the service life of wind turbines. [15] Due to the low sea level roughness and small wake attenuation, the wake of a single wind turbine is longer, and the superimposed effect of the wake is larger; at the same time, due to the complexity of the atmospheric wind field, the structure of the real wake field is variable, which poses a challenge for the accurate assessment of the wind turbine wake.

Currently, most of the existing studies analyze the characteristics of wind turbine wake flow through wake flow model and numerical simulation of computational fluid dynamics, or use wind measurement LiDAR to detect the wind field in the field and invert the wake flow field. [16] The industry does not yet have a mature intelligent control capability for wake flow.

Using the offshore wind power digital twin system, based on the simulated wake condition data synchronized in the digital twin virtual entity, the simulation of wake loss, wind speed, active power, and corresponding orientation is realized, and the yaw optimization strategy is selected according to the simulated power generation efficiency, and the wake control is realized through the field-level controller. The architecture of wake flow control and optimization system is shown in Figure 8.

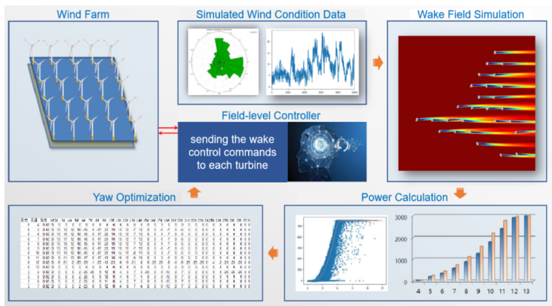


Fig. 8. Wind Farm Wake Flow Control and Optimization System Architecture: According to the machine layout and wind measurement data, the wake condition table of the whole field is formulated. According to the wake condition table, the calculation of wake loss, wind speed, active power, and nacelle orientation corresponding to each condition is completed, and the dynamic database of wind speed, wind direction, turbulence, and nacelle orientation corresponding to each unit is generated and used for wake control strategy. The field-level controller communicates with the whole field turbines, monitors the state of the whole field turbines, and sends the wake control commands to each turbine.

3.2. Offshore wind power intelligent diagnosis & warning application

For the operation diagnosis and early warning of key equipment of single wind turbine, the gearbox temperature early warning system is constructed with the transmission system as the object. Meanwhile, for the overall operation of the wind farm, the digital twin system of single wind turbine is assembled to establish the field group early warning system.

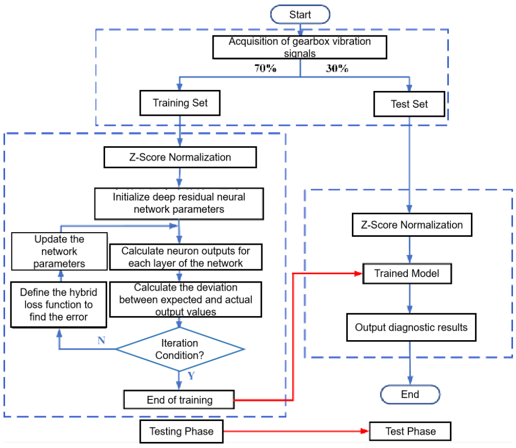
3.2.1. Offshore wind turbine gearbox temperature warning system

Wind turbine transmission system as one of the most important equipment of the wind turbine, it is easy to fail in the harsh environment and high load operation. Transmission system initial damage is not easy to detect, long-term neglect of these damages can easily cause the entire gear box, main shaft, etc. scrapped, resulting in significant property losses.

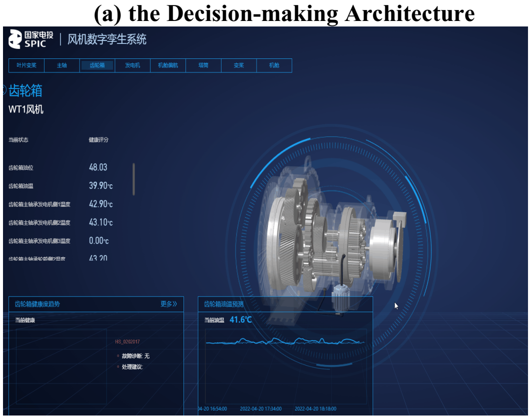
Commonly used fault diagnosis methods for wind turbine transmission system include the fault diagnosis method based on oil and fluid data and the fault diagnosis method based on acoustic emission data. [17][18] The former obtains information on wear particles entering the mechanical lubrication system with the help of iron spectrum analyzers and spectral analyzers to determine the wear condition, but it is difficult to meet the timely demand for fault diagnosis. The latter determines the type and degree of failure of wind turbine gearboxes by detecting the difference in the frequency of elastic waves, but this method requires the installation of additional sensors, which is costly and susceptible to noise interference.

Based on the wind turbine digital twin technology, we study the real-time monitoring and diagnosis & fault early warning technology, make full use of the existing sensor data of the wind turbine and artificial intelligence algorithms, and carry out a pilot project in the wind turbine gearbox to realize the diagnosis and early warning of the abnormal temperature of the gearbox. We designed a gearbox temperature early warning system based on SCADA and vibration data combined with digital twins, and developed the fault characteristics embedded in vibration signals and SCADA data through reasonable algorithms to accurately locate the fault site and fault degree, and visualized them in the digital twin gearbox model.

Figure 9 shows the decision-making architecture and display interface of the gearbox temperature warning system based on SCADA and vibration data combined with digital twin.



(a) the Decision-making Architecture



(b) Display Interface

Fig. 9. the Decision-making Architecture (a) and Display Interface (b) of Gearbox Temperature Warning System: The gearbox temperature warning system is deployed in the offshore wind farm of SPIC Jiangsu Company. The language of the display interface is Chinese.

3.2.2. Field group early warning system

Integrating the energy efficiency analysis, deterioration diagnosis and fault early warning results of the maintenance fault recognition process in the digital twin system of single wind turbines, the field group early warning system is constructed, which realizes the evaluation of the overall health state of the wind farm, the analysis of power generation efficiency, and the ability to identify outlying groups of units in the wind farm.

The specific functions of the field group early warning system is shown in Figure 10.

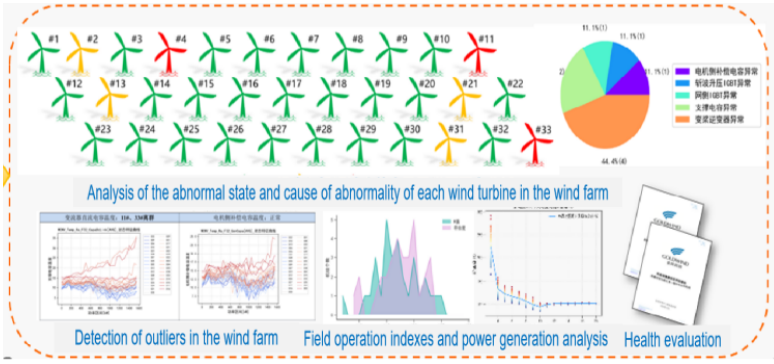


Fig. 10. Specific Functions of Field Group Early Warning System: Including abnormality analysis, detection of outliers, operation indexes and power generation analysis and health evaluation.

4 Conclusion

Based on digital twin technology, using big data, artificial intelligence and other advanced digital technologies, the offshore wind power digital twin modelling system realizes the operation analysis and optimization of wind turbines, as well as the diagnosis and early warning of wind turbine key equipment and field groups, improves the management and control of offshore wind power, improves the quality of operation and maintenance, optimizes the arrangement of tasks at sea, and reduces the cost of operation and maintenance. According to the existing benefits, based on the total installed wind power capacity of 3,582MW of SPIC as of October 2021, it can create at least hundreds of millions of RMB value per year in the dimensions of replacement/maintenance and power generation enhancement.

The system can be further expanded and has a wide range of application prospects in the future: by reasonably adjusting the turbine operation and maintenance strategy, the wind farm operation and maintenance mode can be changed from reactive maintenance of failures to predictive maintenance, which effectively improves the safety and economy of the overall operation of the units; the application of quality improvement and efficiency enhancement based on digital twins is expected to increase the annual power generation of wind farms by more than 1 percent, thereby contributing to zero-carbon emission, which has high-social benefits; linking energy efficiency analysis, deterioration diagnosis, and early warning results with the work order system in the future can locate factors affecting power generation and support efficient operation, maintenance and repair.

Acknowledgement: Science and Technology Project "Research and Application of Digital Twin Key Technology for Smart Power Plant" (126001JX0120230743).

References

1. J. Lee, F. Zhao, Global Wind Report 2022, (Global Wind Energy Council, 1000 Brussels,2022)
2. C. Yang, Comprehensive Analysis and Evaluation of the Operation and Maintenance of Offshore Wind Power Systems: A Survey. Energies . 2023, 16, 5562. (2023)
3. Y. Wang. Research on digital twin technology of large-scale offshore wind power flexible direct transmission system. J. Phys.: Conf. Ser. 2450, 012046. (2023)
4. J. Walker, Digital twins of the mooring line tension for floating offshore wind turbines to improve monitoring, lifespan, and safety. J. Ocean Eng. Mar. Energy. 8, 1-16. (2021)
5. M. Wang, Recent progress on reliability analysis of offshore wind turbine support structures considering digital twin solutions. Ocean. Eng. 232, 109168. (2021)
6. A. Haghshenas, Predictive digital twin for offshore wind farms. Energy. Inform. 6, 1-26. (2023)
7. J. Jorgensen, Requirements for the application of the Digital Twin Paradigm to offshore wind turbine structures for uncertain fatigue analysis. Comput. Ind. 145, 103086. (2023)
8. D. Augustyn, Reliability Updating of Offshore Wind Substructures by Use of Digital Twin Information. Energies. 14, 5859. (2021)
9. M. W. Grieves Digital twin: manufacturing excellence through virtual factory replication. White paper. 1(2014), 1-7. (2015)
10. E. Glaessgen, D. Stargel, The digital twin paradigm for future NASA and US Air Force vehicles. in Proceedings of 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference, Honolulu, Hawaii, USA, April 23-26, (2012), 1818
11. T. Fei, Five-dimension digital twin model and its ten applications.CIMS, 25(1), 1-18. (2019)
12. M. W. Grieves, J. Vickers, Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems, (Transdisciplinary Perspectives on Complex Systems, Springer, 2017)
13. T. Fei, M. Zhang, Digital twin driven prognostics and health management for complex equipment. Cirp. Ann-Manuf. Techn. 67, 169-172. (2018)
14. J. Dai, Effect investigation of yaw on wind turbine performance based on SCADA data. Energy, 149, 684-696. (2018)
15. L.J. Vermeer, Wind turbine wake aerodynamics. Prog. Aerosp. Sci. 39(6-7), 467-510. (2003).

16. R. Nash, Wind turbine wake control strategies: A review and concept proposal. Energy Convers. Manage. 245, 114581. (2021)
17. B. Yu, A review of the application of oil analysis in condition monitoring and life prediction of wind turbine gearboxes. Insight. 63(5), 289-301. (2021)
18. Y. Zhang, Planet gear fault localization for wind turbine gearbox using acoustic emission signals. Renew. Energy. 109, 449-460. (2017)