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Optimization and Improvement of Operation and Maintenance Efficiency of Condition Monitoring Technology for Offshore Wind Turbines

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ABSTRACT This study proposes an integrated condition-monitoring and predictive-maintenance framework for offshore wind turbines operating in harsh marine environments. To address the challenges of signal degradation, environmental interference, and limited fault-warning capability, a multi-source sensing architecture is developed based on risk-driven sensor deployment, edge-side signal fusion, and intelligent health assessment. Vibration, temperature, strain, and operational signals are adaptively processed through variance-weighted fusion and denoising strategies to improve data reliability. A CNN–LSTM hybrid model is employed for fault feature extraction and temporal degradation analysis, while a digital-twin-driven health assessment framework is used to quantify health indices and remaining useful life. Maintenance scheduling is further optimized by integrating equipment health conditions, resource constraints, and operational windows. Field validation in an offshore wind farm demonstrates that the proposed diagnostic model achieves a fault identification accuracy of 96.2%, while the predicted remaining useful life of the main bearing decreases from 180 days to 16 days before failure. The proposed framework establishes a closed-loop process linking signal acquisition, intelligent diagnosis, lifetime prediction, and maintenance decision-making, providing an effective engineering solution for reliable condition monitoring and intelligent operation of offshore energy systems.

INDEX TERMS condition monitoring, multi-source signal fusion, digital twin, predictive maintenance

I. INTRODUCTION

OFFSHORE wind power represents an important element in the clean energy system. Offshore wind turbines operate for extended periods in harsh marine environments, including high humidity, high salt spray, and high dynamic loads. This creates significant challenges for monitoring the condition of turbines and for maintenance [1,2]. Improving the reliability of monitoring technology, the accuracy in diagnosis, and the foresight in operations is directly and urgently required. These improvements ensure the safe and stable operation of units, and also reduce the total cost across the life cycle [3-5].

At present, technology for monitoring conditions in wind turbines at sea shows several important limitations.

The marine context produces corrosion in sensors and failure of these devices, creates interference in transmission of signals, and limits integrity and reliability of data that systems provide [6,7]. Signals from turbines during operation demonstrate patterns that differ across time, contain high levels of noise, and show coupling from multiple sources. These features present difficulties for methods used in the past to identify faults at early stages and to assess these faults in a measure that provides clear values [8,9]. Decisions for maintenance follow mainly from inspections that occur at set intervals and from repairs that follow after failures.

This approach cannot predict performance degradation trends. The limitation affects time when turbines stop without planning, affects how efficiently resources for maintenance receive allocation, and affects economics across the full period of operation [10,11].

To address the aforementioned issues, existing research has introduced various methods for improvement.

Sensor layout methods based on FMEA attempt to optimize measurement point configuration from the perspective of failure mechanisms [12,13]. Multi-source information fusion technologies, such as vibration and temperature fusion, aim to enhance data representation capabilities. Deep learning models such as CNN and LSTM are used for fault classification and trend extraction [14,15]. Digital twin technology achieves health status visualization through virtual-real mapping [16,17]. While these methods have made progress in specific areas, they still suffer from insufficient environmental adaptability, weak model generalization ability, and fragmentation in the monitoring-diagnosis-decision-making process. A closed-loop technical system covering data acquisition, condition assessment, and operation and maintenance scheduling has not yet been formed.

To solve the problems of fragmented condition monitoring, delayed diagnosis, and passive operation and maintenance of offshore wind turbines, this paper constructs an integrated technical system of "optimized monitoring – intelligent diagnosis – predictive operation and maintenance." This system first quantifies component risk priorities and regional equivalent stress through FMEA and environmental stress field analysis, establishes a sensor weight deployment matrix, and completes adaptive fusion and denoising preprocessing of multi-source signals at the edge side. Furthermore, a CNN-LSTM hybrid deep learning model is designed to achieve spatial extraction and temporal modeling of fault features; combined with a digital twin-driven physical degradation model, the health indices HI and RUL are quantified. Finally, by integrating lifetime prediction, resource constraints, and sea state windows, a multi-objective optimization model is established with economic efficiency, risk, and power generation loss as objectives, generating maintenance decision schemes and forming a life-cycle-oriented economic evaluation framework under pilot-scale operational conditions. This research is piloted and verified in an offshore wind farm, achieving simultaneous improvements in data acquisition reliability and fault diagnosis accuracy.

II. OFFSHORE WIND TURBINE CONDITION MONITORING AND INTELLIGENT OPERATION AND MAINTENANCE TECHNOLOGY SYSTEM

A. OPTIMIZATION OF MULTI-SOURCE MONITORING DATA ACQUISITION FOR OFFSHORE ENVIRONMENTS

Offshore wind turbines operate in environments that experience extensive humidity, salt spray and impact loads. Therefore, the quality of the monitoring system's data source is critical in assessing wind turbine health [18,19]. The process of optimizing the monitoring data acquisition process begins logically with the failure mode effect analysis mapping out how environmental stressors effect the failure mechanisms of key wind turbine components, and then follows by determining what sensors best collect data for all of the various combinations of sensor outputs occurring at the same time [20,21]. The full configuration of the sensor layout is completed using a quantification model as well as generating an overall consistent output of multiple source signals using edge-side computing.

Sensor configuration constructs core constraints through risk priority values. Failure risk is represented by the Risk Priority Number (RPN), defined as the product of severity S, occurrence O, and detectability D. This index is introduced from failure mode and effects analysis to quantify the relative criticality of turbine subsystems under combined environmental and operational stress. These three are quantified dimensionless parameters, reflecting the intensity of damage consequences, the potential trigger frequency, and the difficulty of the monitoring system capturing state changes, respectively. The RPN value is used to determine the signal type, the number of measurement points, and the sampling bandwidth.

$$RPN = S \cdot O \cdot D \tag{1}$$

The environmental stress field of the wind turbine drive train, blades, and tower is measured by the equivalent stress σ_e, which is composed of the superposition of wind load, wave load, and temperature cyclic load to ensure that each measuring point maintains a stable response under long-term action. The monitoring domain is first discretized according to drivetrain, blade, and tower load transmission paths. Equivalent stress fields obtained from structural analysis are used to identify long-term stress concentration zones, ensuring that candidate measurement locations correspond to mechanically critical nodes rather than abstract risk rankings. The sensor weight expression for the monitoring area is as follows:

$$w_i = \frac{RPN_i}{\sum_{j=1}^{n} RPN_j} \tag{2}$$

In Formula (2), w_i is the relative importance of the i-th monitored object; RPN_i is its corresponding risk value; n is the number of monitored objects. The risk priority number and the equivalent stress field are jointly introduced into the deployment matrix, where structural load paths determine admissible sensor locations and the risk index modulates sampling density within mechanically meaningful regions.

After the measuring points are configured, the multi-source data are fused in real time at the edge node at the bottom of the wind turbine tower. The original signal is weighted by the noise variance σ_n^2 and the measurement variance σ_m^2, and the fusion estimate is obtained according to $\hat{x}$.

$$\hat{x} = Kz_1 + (1 - K)z_2, \quad K = \frac{\sigma_m^2}{\sigma_m^2 + \sigma_n^2} \tag{3}$$

In Formula (3), z_1 and z_2 are the synchronous sampling values of the structural vibration and operating condition monitoring channels, respectively, and K is the fusion coefficient. This process completes denoising, alignment, and coarse feature extraction at the edge, outputting a signal stream with a unified time reference and stability index, providing a consistent basis for the input of the cloud-based health assessment model.

Data acquisition optimization shifts sensor deployment from empirical point placement to quantifiable risk-stress joint planning, ensuring high availability of the acquisition link under wave impact, wind shear, and temperature abrupt disturbances [22,23]. The data stream after edge fusion maintains reliable stability in terms of noise suppression, missing data compensation, and dynamic consistency, laying the foundation for the convergence performance of subsequent intelligent diagnosis and life prediction.

B. HEALTH STATUS ASSESSMENT MODEL BASED ON DEEP LEARNING AND DIGITAL TWINS

Offshore wind turbines are subjected to long-term random wind and wave excitation, and their vibration, temperature, and yaw-related signals exhibit strong nonlinearity and temporal coupling characteristics [24,25]. The health status assessment uses the unified signal stream output by the edge nodes as input to construct a diagnostic model composed of convolutional and long short-term memory structures. Joint features are formed by spatial pattern extraction and temporal dependency characterization, and then the health index is quantified and RUL is predicted by a digital twin model [26,27].

The convolutional structure takes the instantaneous physical pattern of the input sequence as its core objective, and forms a local feature map by sliding a one-dimensional convolutional kernel along the time axis [28,29]. Let the input signal sequence be $x(t)$, the convolutional kernel weights be $h(k)$, and the output feature map $y(t)$ be:

$$y(t) = \sum_{k=1}^{m} h(k)x(t-k+1) \tag{4}$$

In Formula (4), m is the kernel length. Convolution operations enhance the weak vibration modes in the early stages of instability, enabling early signs such as bearing raceway damage, abnormal gear meshing, and yaw load shift to form stable spatial representations.

The feature sequences extracted by the convolutional layers are input into the long short-term memory (LSM) structure in the form of hidden states. The LSM structure uses input gates, forget gates, and output gates to nonlinearly control the hidden states, effectively memorizing slow-changing processes such as sudden wind speed changes, power fluctuations, and load accumulation during wind turbine operation [30-31]. The core quantity for updating the hidden states is:

$$h_t = f_t \odot h_{t-1} + i_t \odot \tilde{c}_t \tag{5}$$

In Formula (5), h_t is the current hidden state; h_{t-1} is the hidden state at the previous time step; f_t is the forget gate; i_t is the input gate; $\tilde{c}_t$ is the candidate state; the symbol $\odot$ is element-wise multiplication. This update mechanism maintains the continuity of structural damage evolution under high noise and non-stationary signal conditions, ensuring that the trend term of the degradation signal remains smooth and stable within the prediction domain.

The high-dimensional feature vector output by the diagnostic model is input into the digital twin model and mapped to the mechanical response and health degradation path of the wind turbine structure in a virtual-real synchronous manner [32,33]. The digital twin in this framework represents a virtual structural state space driven jointly by measured loads, stress responses, and material damage evolution. It updates stress–damage parameters online using field data, maintaining consistency between physical measurements and the virtual degradation trajectory. The digital twin constructs a degradation function using equivalent stress σ_e and material damage variable D_s, and the health index is measured as:

$$HI = 1 - D_s(t) \tag{6}$$

In Formula (6), HI is the health level of the structure at time t, and $D_s(t)$ evolves driven by historical loads, stress amplitudes, and environmental conditions during the calculation. The degradation state is continuously updated under time-varying loads, and the resulting virtual trajectory is used to estimate damage rate evolution and remaining useful life [34,35].

The deep learning diagnostic architecture and the digital twin degradation model are synchronized through dual channels: data flow and parameter flow. The deep learning architecture is responsible for the accurate extraction of high-dimensional features, while the digital twin constrains feature evolution through stress–damage coupling and load-driven parameter updating. Together, they form a convergent and consistent health assessment result within the prediction domain, ensuring the stability and reliability of early fault identification, degradation tracking, and lifetime prediction in high-noise marine environments. The health index is defined as a normalized structural degradation indicator reflecting the cumulative damage state, while the RUL is obtained from the time-varying degradation rate estimated by the digital twin under the current load and stress trajectory. Therefore, a moderate health index value does not imply a long remaining lifetime when the degradation rate enters an accelerated regime, and the RUL may decrease sharply even when the normalized health level has not yet approached zero.

C. DATA-DRIVEN PREDICTIVE OPERATION AND MAINTANANCE DECISION GENERATION AND EVALUATION

O&M (Operation and Maintenance) decisions are based on health indices and RUL trends. A scheduling model is established using a multi-dimensional parameter domain comprised of resource constraints, work windows, spare parts inventory, and sea conditions to provide a unified solution for "when to repair," "what to repair," and "how to repair" key components. The model uses a decision vector u to represent the set of maintenance actions to be executed, including personnel allocation, vessel deployment, and task sequence. O&M costs, downtime losses, and health risks are weighted to form the overall objective function:

$$J = \alpha C(u) + \beta L(u) + \gamma R(u) \tag{7}$$

In Formula (7), $C(u)$ is the cost of O&M actions; $L(u)$ is the power generation loss caused by downtime; $R(u)$ is the risk term caused by health degradation; α, β, γ are weighting coefficients.

When offshore wind turbines operate, information about status requires transmission that occurs continuously between systems that provide monitoring, systems that conduct analysis, and systems that allow response for operation and maintenance. This process provides the basis for describing the main approach to obtaining data from wind turbines, to conducting processing of data, and to providing response for operation and maintenance. The overall relationship between these elements appears in Figure 1.

Figure 1 presents the development of information about status in the system, using flow of data as the main element. The layer that obtains data focuses on the turbine for wind, showing status of operation and conditions in the environment using different forms of signals for observation. The processing layer performs time alignment, normalization, and feature stabilization on incoming signals, forming a unified data stream for fault identification. The results from diagnosis move to the part of the system that makes decisions, and information about status changes to provide a basis for decisions about operation and maintenance, creating a relationship that is direct between actions for maintenance and the conditions of operation that are actual for the equipment. The results from actions for maintenance affect the status of operation for the turbine for wind in a way that is reverse, and this produces a closed form of information in a loop, Maintenance actions update system states, forming a closed-loop link between condition perception and operational response.

The decision vector u, obtained after solving the operation and maintenance model, undergoes a full life-cycle economic assessment before execution, measuring the planned benefits and costs in the form of discounted net present value. The assessment results and the optimized u are linked, ensuring that short-term maintenance decisions are consistent with long-term economic goals. Predictive maintenance forms a stable closed loop under this mechanism: data collection determines input quality; health assessment determines risk boundaries; scheduling model determines resource allocation; economic assessment determines strategy convergence, enabling offshore wind turbines to maintain high availability and low total life cycle cost in highly dynamic sea conditions and highly corrosive environments.

III. OFFSHORE WIND FARM PILOT APPLICATION AND PERFORMANCE VERIFICATION

A. VERIFICATION OF IMPROVED MONITORING AND DIAGNOSTIC CAPABILITIES

In the offshore wind farm pilot application, focusing on the issues of insufficient data quality and limited stability of diagnostic models in the condition monitoring link, the effectiveness of multi-source monitoring signal acquisition and the performance of intelligent diagnostic algorithms are systematically verified simultaneously. At the monitoring level, the effective acquisition level of key component operating signals is compared and evaluated by optimizing sensor configuration and edge-side data fusion mechanisms. At the diagnostic level, under unified data input conditions, various typical machine learning and deep learning models are introduced to compare fault identification performance. The relevant results are presented comprehensively in the form of improved data availability and differences in model performance, as shown in Figure 2.

As shown in Figure 2(a), the monitoring data exhibits a consistent improvement trend after optimization. The availability of main bearing vibration signals improves from 93.4% to 98.7%; gearbox vibration improves from 91.6% to 98.3%; generator temperature and yaw system angle signals reach 99.2% and 99.0% respectively;

tower strain signals improve from 90.8% to 97.6%. The availability indicator in this study characterizes long-term continuity of usable monitoring streams rather than intrinsic transmission reliability. This change reflects that the reconfiguration of sensor locations combined with corrosion-resistant packaging, reduced cable exposure, and stabilized edge acquisition conditions decreases long-term signal dropout and maintenance-related data loss under offshore environments. The improvement demonstrated in Figure 2(a) characterizes data availability and continuity rather than intrinsic signal purity. On this basis, the denoising and feature stabilization effects observed in Figure 2(b) are attributed to the combined action of edge-side preprocessing, variance-weighted fusion, and model robustness, instead of being directly caused by increased availability alone. The separation between acquisition continuity and noise suppression clarifies that availability enhances the effectiveness of subsequent signal processing, while the reduction of noise influence is realized at the fusion and modeling stages.

B. PROSPECTIVE VALIDATION OF PREDICTIVE MAINTENANCE

During the long-term operation of offshore wind turbines, the operating state of key components evolves over time under the combined effects of random wind loads, structural vibrations, and the marine environment. This section evaluates the time evolution of the health index and rolling RUL prediction under real operating conditions. The assessment reflects continuous degradation tracking and online updating of lifetime estimates. The results that are relevant are shown as changes in the measure of health and RUL across time, and these appear in Figure 3.

In Figure 3, it is evident that the main bearing health index continues to deteriorate with continued usage.

Initially (60 days post initial operation), this index decreases from 1.000 to 0.928, suggesting that at this point in time (60 days), the primary degradation characteristics of the component are gradual. This continues with the gradual build-up of fatigue throughout continued operation (120

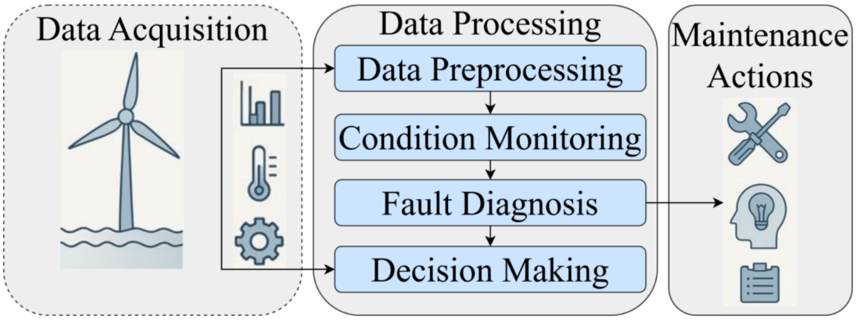

FIGURE 1. Schematic diagram of intelligent status monitoring and operation and maintenance decision-making for offshore wind turbines

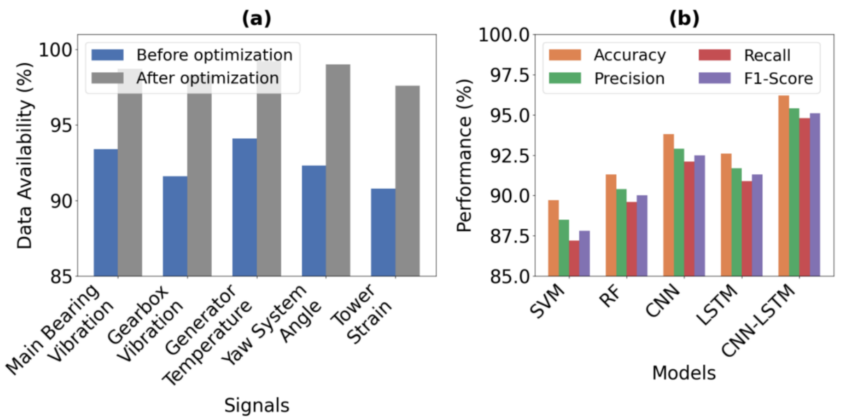

FIGURE 2. Verification of improved availability of offshore wind turbine monitoring data and comparison of multi-model diagnostic performance. (a) Comparison of monitoring signal data availability before and after optimization ; (b) Comparison of performance indicators of different diagnostic models

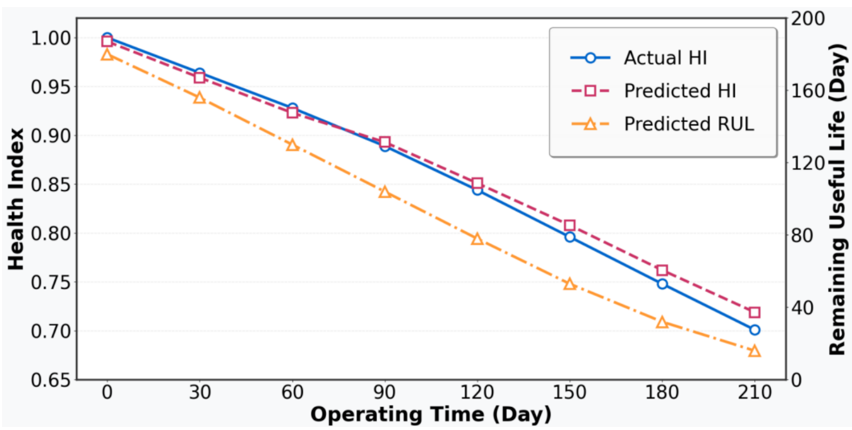

FIGURE 3. Main bearing health degradation process and RUL prediction results versus operating time curves

days) and an overall decrease in the main bearing health index at this point to 0.844 that closely corresponds to the gradual development of internal failure caused by prolonged alternating loads over time, followed by a pronounced downward trend in the health index at 210 days, reaching 0.701, indicating that cumulative damage has entered a non-linear evolution stage. At this stage, although the normalized health index remains above mid-scale, the degradation rate inferred from the digital twin increases markedly under sustained load and stress accumulation. Correspondingly, the predicted remaining useful life decreases from its initial estimate of 180 days to a short-term horizon of 16 days, reflecting the model's response to accelerated damage propagation rather than to the absolute value of the health index itself. The predictive maintenance approach developed in this study effectively captures and characterizes the evolution of degradation and identifies the risk of component failure in advance while under operating conditions.

C. COMPARISON OF KEY OPERATION AND MAINTENANCE EFFICIENCY INDICATORS

Under long-term operation conditions of offshore wind turbines, the impact of different operation and maintenance strategies on work execution results is often reflected in multiple dimensions such as task completion quality, execution stability, and emergency response performance. Under the same wind farm and turbine configuration conditions, the experiment compiles operation and maintenance records over a continuous operating cycle, comparing and analyzing the execution results of key operation and maintenance tasks under four operation and maintenance scenarios: periodic maintenance, monitoring and optimization, predictive maintenance, and intelligent scheduling. The relevant data is all derived from statistical summaries of field work orders and operation and maintenance logs, and after being processed using a unified standard, they are used to characterize the structural differences in operation and maintenance performance under different strategies.

As shown in Figure 4, different operation and maintenance scenarios exhibit relatively clear hierarchical characteristics in terms of various task execution indicators. In the scheduled maintenance scenario, the on-time maintenance and successful maintenance rates remain at 79.2% and 82.6%, respectively, while the completion rate corresponding to rework is 73.9%, reflecting that operation and maintenance activities in this mode rely more on fixed-cycle scheduling, and task execution is easily affected by changes in on-site conditions.

With the introduction of monitoring and optimization strategies, the planned execution and on-time maintenance rates both increase to 81.6% and 83.5%, indicating that enhanced status awareness helps reduce planning deviations. In the predictive maintenance scenario, the rework and successful maintenance rates increase to 83.6% and 89.3%, respectively, showing that early identification of degradation trends has a direct effect on reducing repetitive work. The intelligent scheduling scenario maintains an overall leading position in all indicators, with on-time maintenance reaching 92.4%, planned execution reaching 90.2%, and emergency response remaining at 88.3%. This change is closely related to the improved matching degree of resource allocation and work windows. A comprehensive comparison shows that after the operation and maintenance strategy evolved from passive to data-driven, the stability and consistency of task execution results are systematically improved, verifying the practical effect of the intelligent operation and maintenance system in improving operation and maintenance efficiency.

D. COMPREHENSIVE EVALUATION OF TECHNICAL AND ECONOMIC BENEFITS

During the long-term operation of offshore wind turbines, the acquisition of status information, the characterization of degradation trends, and the organization of operation and maintenance resources all contribute to the economic performance of the system. This effect is not isolated but exhibits a synergistic evolutionary characteristic as functional modules are gradually integrated. This paper selects annual operating data from the same wind farm under unified operating boundary conditions to quantitatively characterize different integration stages: basic operation and maintenance, monitoring enhancement, predictive introduction, and scheduling coordination. Through unified dimensionless processing, multi-dimensional technical and economic indicators are mapped to the same evaluation space. The correlation and changes among various indicators during the system capability evolution process are shown in Figure 5.

As can be observed from Figure 5, with the increase in the degree of system integration, the various technical and economic indicators show a consistent but uneven improvement. During the periodic maintenance stage, the cost efficiency index remains at 0.46, and the operational reliability index is 0.41, reflecting that fault exposure is mainly constrained by the maintenance cycle, and unplanned shutdowns have a significant impact on economic efficiency. After introducing monitoring optimization, the operational reliability index increases to 0.56, a higher increase than the cost efficiency index of 0.54. This difference stems from the direct effect of enhanced state awareness on early anomaly identification, while the investment in the monitoring system itself weakens the cost improvement. There is a rise in the reliability index to 0.71 during this predictive optimization stage and an increase in the power generation efficiency index to 0.66. This suggests that, as the trend of degradation has moved forward, the number of sudden failures occurred less frequently and the negative impact of downtime loss on power generation has been greatly reduced. In entering the intelligent scheduling stage, the performance index of LCOE (Levelized Cost of Energy) has increased to 0.78, and the performance index of investment efficiency has increased to 0.72. This indicates that, with the help of monitoring and forecasting data, the optimal allocation of windows to perform maintenance, resources to support operations, and plan strategic operation activities together compresses the total life cycle cost structure. The overall movement from a very dispersed bubble distribution to a centralized bubble distribution illustrates that, within the temporal scope and operational boundary of the pilot dataset, the progressive integration of monitoring, prediction, and scheduling functions forms a coherent technical–economic coupling trend. The observed aggregation of indicators reflects a consistent improvement tendency under the tested conditions, rather than a completed full life-cycle economic characterization.

IV. CONCLUSION

This paper addresses the challenges of operating and maintaining offshore wind turbines in high humidity and high salt spray environments, proposing the application of corrosion-resistant technical coatings and fiber-reinforced composite structures as integral components of the solution. By leveraging advanced material science to enhance structural durability, the proposed framework ensures the long-term relia-

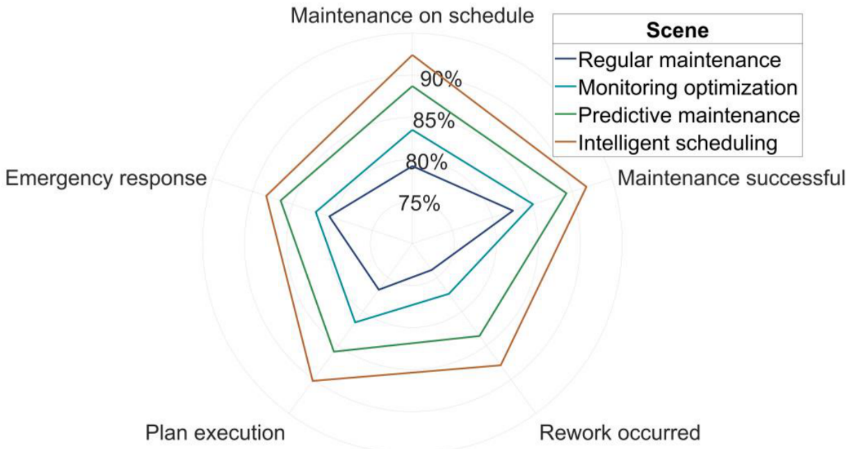

FIGURE 4. Comparative analysis of operation and maintenance task execution results under different operation and maintenance scenarios

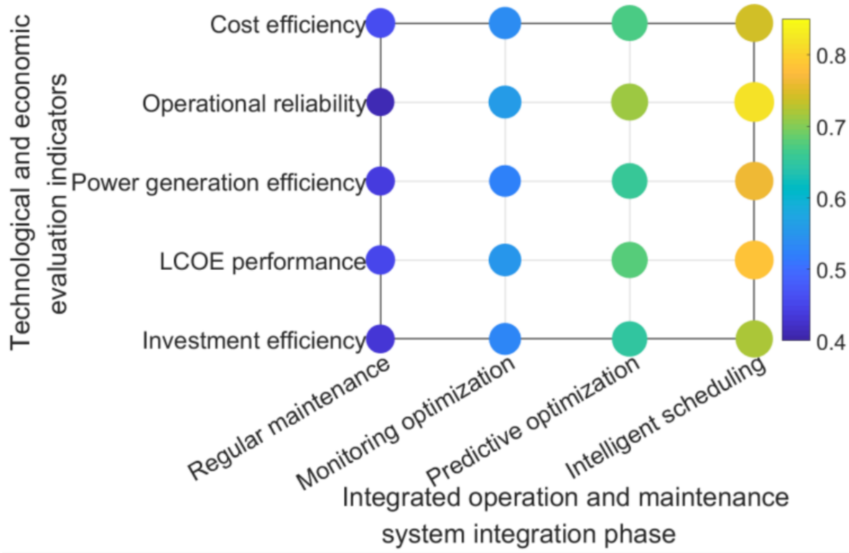

FIGURE 5. Bubble matrix diagram of technical and economic indicators at different integration stages of the integrated intelligent operation and maintenance system

bility of turbine components against extreme marine degradation: an optimized configuration method driven by risk and environmental stress; a convolutional neural network (CNN)-long short-term memory network (LSTM) fusion diagnostic model; a predictive operation and maintenance decision-making process utilizing digital twins (DT). The system is validated in real-world wind turbine conditions. Analyses of the effect of operation and maintenance execution on operation and maintenance have been carried out, and the results are as follows: the predictive operation and maintenance model developed through scheduling coordination has produced an on-time maintenance rate of 92.4%. The results of the analysis indicate that, within the limited operational horizon of the offshore pilot application, the integrated technological system exhibits a consistent positive influence on operation and maintenance efficiency and associated economic tendencies.

Limitations of the study include having a limited pilot scale, an insufficient number of extreme long-term sea state datasets, and a need for more verification of the resulting generalized cross-wind farm capabilities from the model. Accordingly, the economic evaluation presented in this study is intended to reflect short- to medium-term operational behavior and system interaction characteristics, rather than to constitute a finalized full life-cycle economic validation. Future research could focus on collaborative models of multi-wind farm data while developing a deeper integration of high-performance material fatigue mechanisms with data models to perform long-term economic impact assessments. This approach will enhance the engineering application of intelligent monitoring by synchronizing the structural degradation cycles of fiber-reinforced composites with predictive operation and maintenance technologies.

AUTHOR CONTRIBUTIONS

Conceptualization –Yilei Ouyang and Wei Liang; methodology – Yilei Ouyang and Wei Liang; investigation – Yilei Ouyang and Wei Liang; writing-original draft preparation – Yilei Ouyang and Wei Liang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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