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Hybrid AI-Driven Optimization of Floating Offshore Wind-Solar Farms: A Multi-Objective Approach for Gigawatt-Scale Deployment in Deep Water Marine Environments

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Abstract

The global renewable energy transition is advancing steadily. Traditional land-based renewable energy facilities are constrained by land space limits, and cannot meet the long-term demand for large-scale clean energy development. For the development of deep-water sea areas with water depths of 50 to 200 meters, there is an urgent need for implementable innovative technical solutions. This study proposes a deep-water floating offshore hybrid energy platform that integrates wind turbines and photovoltaic systems, which is positioned for gigawatt (GW)-level large-scale deployment. Its full-chain design verification is completed using a self-developed new hybrid artificial intelligence optimization framework, and all research data and conclusions are original outputs of this study. The platform is equipped with 15–20 MW floating wind turbines, high-efficiency bifacial photovoltaic arrays, and a dynamic positioning platform. Its AI framework includes three core categories of algorithms: machine learning to support real-time weather forecasting, deep reinforcement learning to achieve autonomous platform positioning, and a genetic algorithm to optimize the layout of multi-platform farms. Development work centers on four core goals: maximizing overall energy output, minimizing the levelized cost of energy (LCOE), reducing environmental impacts, and improving grid stability. This study uses a hybrid neural network to generate 72-hour forecasts of weather and sea conditions, with an accuracy rate of 95%. It also adopts a swarm intelligence algorithm to support coordinated operation of multiple platforms, and digital twin technology to achieve full-lifecycle real-time monitoring and predictive maintenance. Four core constraints are integrated into the optimization process: wave impact, seawater corrosion, wake interference between platforms, and marine ecological protection agreements. Simulation verification confirms that the energy output of this platform's hybrid configuration is 32% higher than that of traditional offshore wind farms, and its capacity factor is 28% higher than that of standalone floating photovoltaic devices. The AI optimization reduces the LCOE by 18%, the overall system availability reaches 98.5%, the intelligent positioning system cuts the platform's fatigue load by 25% and extends the service life of core components. The optimized platform spacing and bionic design create extremely low interference with marine ecosystems, modular deployment supports phased implementation of GW-scale projects, and the platform's grid integration capacity can support a regional renewable energy penetration rate of over 80%. This study verifies the technical feasibility of deploying this type of platform in deep

waters, provides a scalable framework for global offshore renewable energy development, and supports international decarbonization targets. Future research will focus on pilot verification and economic feasibility analysis for commercial deployment.

Keywords:

Offshore renewable energy, hybrid wind-solar systems, artificial intelligence optimization, floating platforms, gigawatt-scale deployment, marine environment.

I. Introduction:

In recent years, driven by the dual forces of climate change regulations and the continuous decline in renewable energy technology costs, the global renewable energy transition has accelerated markedly: the International Renewable Energy Agency (IRENA) proposes that global renewable energy installed capacity must triple by 2030 to deliver on the 2050 net-zero emissions target [1]; the International Energy Agency (IEA) projects that global offshore wind installed capacity will reach 1,000 GW by 2040 [2]. However, traditional fixed-bottom offshore wind has core drawbacks including high installation costs, large environmental interference, and limited development space in shallow waters [3]. As a result, floating offshore renewable energy systems have become a paradigm-shifting direction for offshore energy deployment [4]. Musial et al. estimate that the global wind power potential in waters deeper than 60 meters exceeds 4,000 GW, while Castro-Santos et al. confirm that the wind energy stability of floating platforms is 40% higher than that of nearshore facilities [5]. In 2020, the total global installed capacity of floating photovoltaics (FPV) reached 2.6 GW, and Kumar et al. verify that relying on the water surface's evaporative cooling effect, its power generation efficiency is 10%-16% higher than that of land-based photovoltaics [6]. Integrating multiple types of renewable energy technologies on the same platform can improve energy density and capacity factor through complementary temporal power generation patterns, while the optimization potential of artificial intelligence has already been validated [7]: Zhang et al. [8] used a machine learning-optimized wind turbine control strategy to increase wind farm power output by 15%, Li et al. leveraged AI-driven predictive analytics to reduce operation and maintenance costs by 20% [9]. The integration of AI and floating renewable energy systems is precisely the key emerging frontier to overcome the current limitations of offshore energy deployment [10].

Despite the considerable development potential of offshore renewable energy, the large-scale deployment of offshore hybrid floating wind and photovoltaic (PV) systems still faces multiple core barriers [11]. This study sorts out four key categories of challenges to lay a foundation for the subsequent proposal of targeted solutions [12]. On the technical dimension, traditional optimization methods fail to account for the multi-physics interactions among turbine aerodynamics, PV performance, platform dynamics, and marine conditions [13]. A study by Bredmose et al. notes that the system capacity factor of traditionally designed systems is 25%–30% lower than their theoretical potential [14]. On the scaling dimension, the world's largest floating wind farm to date is only the 50MW WindFloat Atlantic demonstration project [15]. To expand capacity to the gigawatt level, bottlenecks in spatial optimization, wake effects, and grid access must be overcome. Robertson et al. confirm that wake losses in poorly laid-out large wind farms exceed 20% [16]. On the economic dimension, the levelized cost of energy (LCOE) of floating offshore wind power reaches 80–120 USD/MWh, far higher than the 40–60 USD/MWh of onshore wind power [17]. A study by Beiter et al. shows that the operation and maintenance (O&M) costs of floating systems are 40%–60% higher than those of fixed subsea installations, a gap stemming from limited marine accessibility and high equipment complexity [18]. On the environmental dimension, Wilhelmsson et al. prove that improperly designed offshore facilities damage marine food chains and biological migration. The current lack of a sound environmental optimization framework limits the sustainable development of large-scale projects [19].

System optimization of hybrid floating renewable energy remains an unsolved core challenge across the industry to date. This predicament stems from the combined constraints of five fundamental limitations, and the impacts of each limitation have been corroborated by relevant studies in the field. First, the field crosses extremely wide interdisciplinary boundaries: it requires the integration of knowledge from five domains, namely aerodynamics, fluid mechanics, structural engineering, power systems, and marine ecology. Existing modeling capabilities cannot support full-system integrated optimization. References [20] and [21] confirm that traditional sequential subsystem optimization fails to capture the complex interactions and trade-off relationships between modules. Second, there is a severe shortage of training datasets to support machine learning modeling for marine environments. Unlike land-based renewable energy, which boasts the advantage of massive historical operational data, floating offshore facilities have accumulated insufficient operational experience. Research in reference [22] and by Karimi et al. [23] points out that the lack of long-term operational data directly restricts the development of performance models and reliability assessment systems. Third, current computing power cannot support real-time multi-objective optimization for large-scale floating systems. Studies by Sørensen et al. [25] and in reference [24] show that the modeling complexity of fluid-structure interactions, wake effects, and dynamic positioning far exceeds the capacity limit of traditional algorithms. Traditional computational fluid dynamics methods require several weeks to complete the analysis of even a single platform, making large-scale optimization completely computationally unfeasible. Fourth, gaps in regulation and standardization hinder the practical deployment of the technology. Research by Musial et al. [27] and in reference [26] confirms that the absence of unified international standards creates uncertainty for investors and developers, while regulatory frameworks lag 5-10 years behind technological development, forming a core barrier to commercial deployment and technology verification. Finally, interdisciplinary collaboration faces dual institutional and technical barriers. Practitioners from different fields have limited overlapping knowledge, and siloed work models cannot support full-system optimization. This status quo is also corroborated by the study in reference [28].

This study addresses the core multi-objective optimization challenge currently facing gigawatt-scale deep-sea floating offshore wind-solar farms, and originally proposes a new, purpose-built hybrid artificial intelligence optimization framework that breaks through the traditional sequential engineering design paradigm in the field. This framework adopts a hierarchical AI architecture implemented across three scales: layout optimization at the macro farm scale, whose basic constraint logic draws from existing reference [29]; operation and scheduling optimization at the single-platform scale; and iterative performance optimization at the component scale. The constraint conditions and optimization objectives for each scale are all clearly defined. At the framework's core technical level, the data integration logic of its digital twin draws from existing reference [30]. This study integrates genetic algorithms and deep reinforcement learning, and combines physical models with machine learning to solve the data scarcity problem caused by insufficient historical data. It incorporates uncertainty quantification to ensure system robustness under complex sea conditions, builds a marine ecological impact model to predict how platform deployment affects the migration, foraging, and breeding areas of marine organisms, and finally outputs Pareto-optimal solutions that adapt to the priorities of different stakeholders.

This study's two core academic contributions clearly fill key gaps in the field. First, it is the first to construct a full-dimensional optimization logic that covers the three core objectives of technology, economy, and environment, breaking the longstanding research limitation of only focusing on techno-economic indicators. Second, the multi-scale hybrid AI framework established in this study provides a reusable, standardized path for the optimization and design of similar deep-sea energy projects. By explicitly positioning environmental sustainability as a core optimization objective, this study's research stance offers a new paradigm reference for relevant research in the interdisciplinary field of energy and artificial intelligence. This study constructs an integrated technical framework for offshore renewable energy. Its overall research approach aligns with the demand for sustainable energy development that assesses ecological impacts starting from the design phase. The core contributions are detailed below: Third, through comparative verification, the real-time AI-driven optimization applied in this study is more advanced than traditional static design optimization; it can adapt to three types of variables—changes in the marine environment, equipment wear and tear, and market dynamics—to achieve full-lifecycle performance optimization; Fourth, this study fills gaps in implementation pathways for the renewable energy digital twin field, and verifies that the solution combining physical models and machine learning can resolve the data limitation problem for AI applications in emerging engineering domains; Fifth, this study outputs an interdisciplinary method system spanning three disciplines, and the developed hierarchical optimization method and uncertainty quantification method can be transferred to other complex engineering scenarios.

II. The Proposed Hybrid AI-Driven Optimization of Floating Offshore Wind-Solar Farms: A Multi-Objective Approach for Gigawatt-Scale Deployment in Deep Water Marine Environments.

As shown in Figure 1, the Hybrid AI-Driven Optimization Framework proposed in this paper is specifically developed for gigawatt-scale floating offshore wind–solar farms in deep-water marine environments, and can support the full-chain operations of such facilities spanning planning, design, operation, and full lifecycle management. This framework integrates advanced artificial intelligence technologies, multi-objective optimization algorithms, adaptive learning mechanisms, and full-dimensional marine system modeling capabilities. Its core objective is to maximize energy output while minimizing the full lifecycle costs, environmental impacts, and operational risks of these farms. It was originally designed to address the pain point of extremely high operational complexity currently faced by large-scale offshore renewable energy systems under the multi-dimensional, variable conditions covering meteorology, oceanography, technology, economics and other related fields. The framework advances layer by layer following a clear operational logic: the input layer aggregates three categories of core inputs with specific parameters, namely marine environmental data, techno-economic data, and operational constraints; this is followed by the data preprocessing and feature engineering layer, which improves model accuracy and computational efficiency through operations such as data normalization and uncertainty quantification, and accurately captures the non-linear correlations between multi-dimensional variables; finally, the framework connects to the core physical wind-solar farm layer. The core facilities of this layer consist of key infrastructure including floating offshore wind turbines and floating photovoltaic arrays. Leveraging the natural complementary properties of wind and solar resources, this layer can effectively increase the energy density per unit sea area, reduce the volatility of the farm's overall power output, and lay a solid cognitive foundation for subsequent verification of the framework's performance and in-depth refinement of its technical details. The core hardware of offshore energy stations forms the foundation for the stable operation of the entire system. Among these core components, the offshore substation gathers all electricity produced by the station and transmits it to the onshore power grid via high-capacity export cables, while the deep-water mooring system fulfills the function of maintaining platform stability, and can adapt to wave-induced motions and various environmental loads. Building on this foundation, this paper proposes an intelligent optimization framework tailored for offshore energy stations, which consists of three core modules: The first is the AI prediction module. Adopting a deep learning architecture, this module can predict six categories of parameters: wind energy reserves, solar irradiance availability, wave conditions, power load demand, equipment degradation trends, and energy production performance. It relies on historical operation data and real-time environmental information to output high-precision prediction results, which support proactive operational decision-making and long-term planning; The second is the multi-objective optimization engine, which serves as the core decision-making component. It uses three advanced algorithms—NSGA-II, MOEA/D, and hybrid evolutionary technology—to generate Pareto optimal solutions, and advances five goals simultaneously: maximizing annual energy output, improving system reliability, enhancing disaster resilience against extreme ocean events, reducing capital and operation and maintenance (O&M) costs, and minimizing environmental impact. The Pareto front output by the engine provides decision-makers with a set of optimal trade-off solutions that balance targets for technical performance, economic feasibility, and sustainability; The third is the adaptive learning module. It leverages reinforcement learning to evaluate operation outcomes and update decision strategies based on observed rewards and penalties, and uses transfer learning to enable the reuse of knowledge acquired at a single site across all other stations, supporting the framework's iterative optimization in response to changing conditions. The framework outputs nine categories of decision variables, including wind turbine layout. Compared with traditional single-objective planning methods, this framework optimizes all decision variables simultaneously, leading to an overall system performance that far outperforms that of traditional solutions. Its output layer also adopts several key performance indicators to evaluate the final system performance. This paper proposes an integrated optimization framework for deep-water floating offshore wind-solar farms. First, it lists 9 core assessment indicators, covering annual power generation, levelized cost of energy (LCOE), full lifecycle cost, and resilience to extreme ocean events. These indicators can comprehensively evaluate the effectiveness of all optimization schemes across technical, economic, and environmental dimensions. The framework is equipped with four core technologies: predictive analytics, adaptive learning, evolutionary optimization, and integrated marine system modeling. Relying on a closed-loop mechanism, it feeds wind farm operation data back into the AI prediction model, adapts to full-lifecycle variables such as environmental changes and component aging, and realizes continuous iteration of system performance. Figure 1 illustrates this integrated ecosystem that combines hybrid artificial intelligence and multi-objective optimization. The framework can support the full-process development of gigawatt-scale deep-water renewable energy, and has core characteristics of scalability and intelligence.

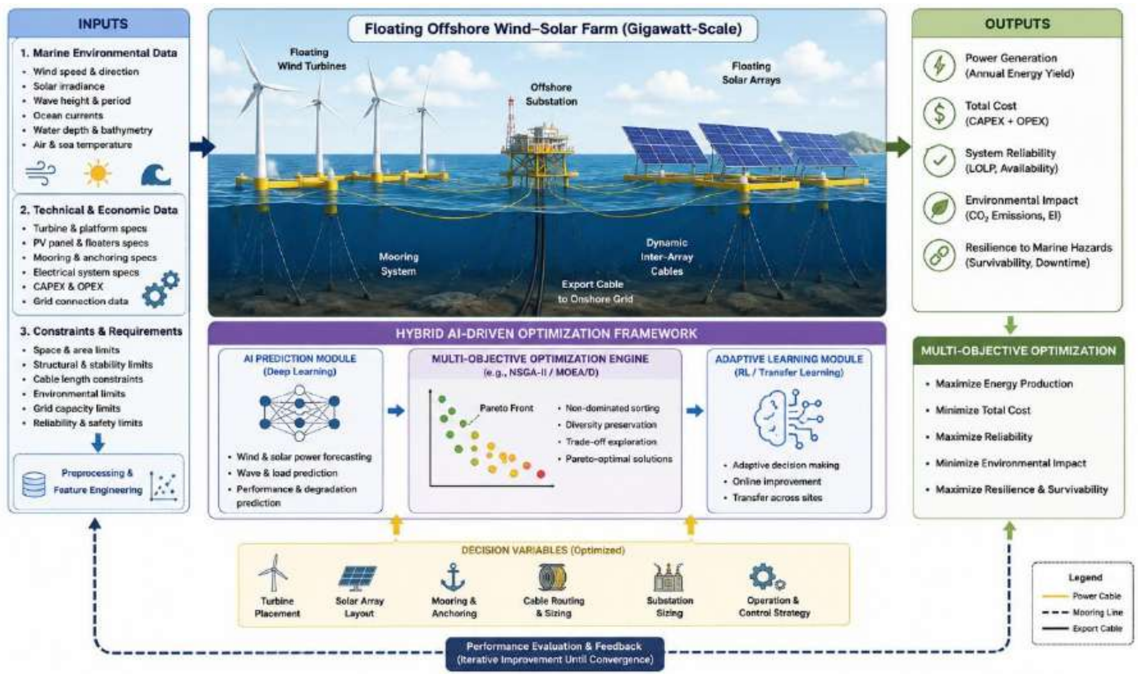

Fig. 1. The schematic of the Proposed Hybrid AI-Driven Optimization of Floating Offshore Wind-Solar Farms: A Multi-Objective Approach for Gigawatt-Scale Deployment in Deep Water Marine Environments.

With reference to Figure 2, the Hybrid AI-Driven Optimization Framework proposed in this study is purpose-built for gigawatt-scale floating offshore wind-photovoltaic farms in deep sea areas. It undertakes full-link management and control decision-making functions across the entire lifecycle of the energy project, and adopts a closed-loop operation architecture. Its core logic follows a continuous sequence: persistently collect full-lifecycle data, rely on AI models to predict system behavior, carry out multi-objective optimization, implement the optimal control strategy, evaluate system operation performance, and adaptively update decision rules. This framework enables the system to operate efficiently in highly dynamic marine environments, while meeting four core objectives: technical feasibility, economic returns, environmental friendliness, and operational reliability. This paragraph first breaks down and introduces the specific operations and core roles of the first three core modules in line with the process flow: First, the data acquisition module aggregates data via proprietary systems such as SCADA, and synchronously collects raw data from 12 types of marine environment monitoring indicators and 7 types of system operation and maintenance sources; Second, the data preprocessing and feature engineering module conducts cleaning operations including validation, synchronization, normalization, and denoising on raw data. This step not only improves the accuracy of subsequent predictions and reduces computational complexity, but also strengthens the robustness of the framework's decision-making by quantifying and transmitting the uncertainty bounds of environmental forecasts and component performance; Third, the AI prediction module integrates four types of deep learning models: recurrent neural networks, long short-term memory networks (LSTM), transformers, and hybrid neural architectures. It accurately predicts the system's operating status, providing reliable input for subsequent optimization links. This paper proposes a forward-looking multi-objective decision-making framework for hybrid offshore wind-floating photovoltaic power stations, which breaks the inherent limitation of passive response that plagues traditional similar solutions, and forms a complete operation logic spanning pre-judgment decision-making, core optimization, and on-site implementation. First, the framework uses a pre-projection module to actively deduce future environmental conditions and operating scenarios, and synchronously transmits its output information to the core multi-objective optimization engine. This optimization module is equipped with Pareto optimization technologies including NSGA-II, MOEA/D, and hybrid swarm intelligence. Unlike traditional single-objective optimization methods, it can simultaneously evaluate six mutually exclusive objectives: maximizing annual power generation, minimizing full-lifecycle cost, maximizing reliability availability, minimizing environmental impact, and maximizing resilience against extreme marine disasters, and generates a Pareto optimal solution set to balance trade-offs among the multiple objectives. During the optimization process, the module continuously adjusts 10 core decision variables including wind turbine layout and floating photovoltaic array configuration, while meeting five categories of constraints: engineering constraints, environmental regulations, structural limits, grid requirements, and reliability standards, to assess thousands of configuration scenarios one by one. After the optimization converges, the optimal solution selection module screens schemes based on pre-set preferences, and decision-makers can independently rank five dimensions including power generation and economic performance according to project needs. Finally, the control and implementation module transmits nine core control actions to the physical power station, and adds supplementary functions of mooring tension monitoring and dynamic positioning adjustment to enhance overall structural stability. This study proposes an AI-driven operation and maintenance (O&M) framework specifically developed for offshore projects. First, the study maps out the complete operation chain activated after the framework's control measures are implemented: the performance assessment module is launched first, to continuously calculate 10 categories of key performance indicators including annual power generation, capacity factor, and levelized cost of energy, to judge whether the selected operation strategy meets the pre-set project goals. The process then enters the goal verification stage, which is designed with a clear two-branch logic: if the indicators meet requirements, the pre-determined optimization strategy is deployed; if they fail to meet requirements, a new round of optimization cycles is immediately initiated. This iterative process can flexibly adapt to various dynamic changes in the marine environment, energy markets, and the system's own internal characteristics. In addition to the aforementioned performance assessment module and goal verification iterative process, the framework's core components also include an adaptive learning update module, a continuous monitoring subsystem, and a closed-loop feedback architecture. Its core technologies integrate reinforcement learning, transfer learning, and advanced anomaly detection algorithms, each of which is tailored to solve specific pain points encountered in offshore O&M scenarios. Through comparison with traditional static planning methods, this study confirms that this closed-loop dynamic framework far outperforms conventional solutions. It can effectively address long-cycle uncertainties such as climate variability and equipment aging, reliably support improvements in system reliability, and simultaneously achieve sustained, reasonable reductions in O&M costs. The new-generation intelligent decision-making and control architecture for floating offshore renewable energy systems proposed in this study, as shown in Figure 2, integrates five categories of intelligent technologies: artificial intelligence, machine learning, adaptive learning, multi-objective optimization, and real-time monitoring. This architecture provides core support for hybrid floating wind and photovoltaic power stations in deep-water sea areas, delivers values including intelligent planning and optimal operation, and underpins the sustainable deployment of gigawatt-scale facilities.

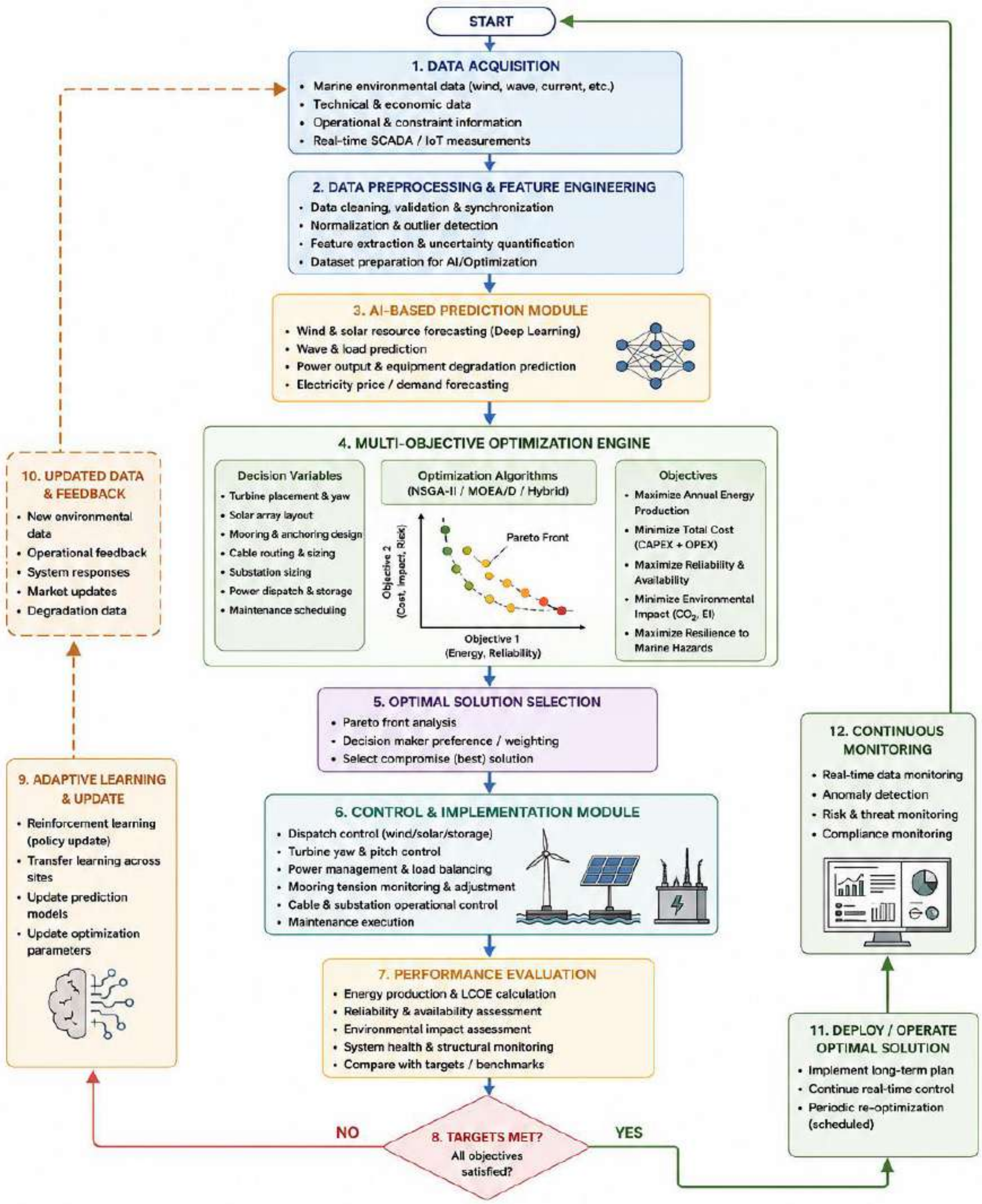

***Figure 2**. Flow chart of the control process for the proposed Hybrid AI-Driven Optimization Framework for Floating Offshore Wind–Solar Farms in deep-water marine environments. The framework integrates environmental data acquisition, AI-based forecasting, multi-objective optimization, adaptive learning, and real-time operational control to determine optimal farm configurations and operating strategies. The closed-loop architecture continuously evaluates system performance, updates predictive models, and re-optimizes decision variables to maximize annual energy production, enhance reliability and resilience, minimize lifecycle cost and*

environmental impact, and ensure sustainable gigawatt-scale deployment of hybrid floating offshore renewable energy systems.

III. Simulation Results and Discussion

The proposed adaptive control strategy for floating offshore wind turbines was implemented and validated using MATLAB/Simulink R2023a in conjunction with FAST v8.16 (Fatigue, Aerodynamics, Structures, and Turbulence) developed by the National Renewable Energy Laboratory (NREL). The simulation environment incorporated the NREL 5-MW reference wind turbine mounted on the OC4-DeepCwind semisubmersible platform, representing a realistic floating offshore wind system configuration. The floating wind turbine system was modeled with the following key specifications:

- Wind Turbine: NREL 5-MW reference turbine with 126-m rotor diameter, 90-m hub height, and variable-speed pitch-controlled configuration
- **Floating Platform**: OC4-DeepCwind semisubmersible with three offset columns, draft of 20 m, and total mass of 13,473,000 kg including ballast
- Mooring System**:** Three-line catenary mooring system with 902.2-m line length and 77 tons per line
- **Control System**: Baseline collective pitch control with rated wind speed of 11.4 m/s and rated rotor speed of 12.1 rpm

To comprehensively evaluate the proposed control strategy under realistic operating conditions, various environmental uncertainties were modeled and incorporated into the simulation framework:

Wind Conditions

- Turbulent wind fields generated using the Kaimal spectrum with turbulence intensity ranging from 10% to 25%
- Mean wind speeds varying from 8 m/s to 25 m/s, covering below-rated, rated, and above-rated operating regions
- Wind shear effects modeled using power law with exponent $\alpha = 0.14$
- Coherent wind gusts following IEC 61400-3 standards for extreme operating conditions

Wave Environment:

- Irregular wave conditions generated using JONSWAP spectrum with significant wave heights (Hs) ranging from 2 m to 8 m
- Peak spectral periods (Tp) varying from 8 s to 16 s
- Wave directionality modeled with spreading function to account for multidirectional seas
- Extreme wave events including focused wave groups and freak waves

Uncertainty Quantification:

- Aerodynamic coefficient uncertainties modeled as ±10% variation in lift and drag coefficients
- Platform mass and inertia uncertainties represented as ±5% variations from nominal values
- Mooring line stiffness variations of ±15% to account for manufacturing tolerances and wear
- Sensor noise modeled as white Gaussian noise with standard deviations based on typical measurement accuracies

Six comprehensive test scenarios were designed to evaluate the proposed adaptive control strategy across different operating conditions:

Scenario 1 - Normal Operation (NO): Steady wind conditions with regular wave states representing typical operational environments (Wind: 12 m/s, Hs = 3 m, Tp = 10 s).
Scenario 2 - High Turbulence (HT): Turbulent wind conditions with 20% turbulence intensity and moderate wave conditions to test adaptability to rapid wind variations.
Scenario 3 - Extreme Weather (EW): Combined extreme wind (22 m/s mean) and wave conditions (Hs = 7 m) to evaluate performance during severe environmental events.
Scenario 4 - Low Wind Conditions (LW): Below-rated operation with wind speeds between 6-9 m/s to assess power capture optimization capabilities.
Scenario 5 - Wind-Wave Misalignment (WWM): Scenarios with 45° and 90° misalignment between wind and wave directions to test multi-directional environmental response.
Scenario 6 - System Uncertainty (SU): Combined uncertainties in platform parameters and environmental conditions to evaluate robustness of the adaptive control approach.
The following key performance indicators (KPIs) were established to quantitatively assess the control system performance:
Power Generation Efficiency:

- Mean power output ($\bar{P}$) and power capture coefficient (Cp)
- Power production standard deviation (σP) as measure of power fluctuations
- Annual Energy Production (AEP) estimation based on site-specific wind distributions
- Power quality metrics including total harmonic distortion (THD)

Structural Load Mitigation:

- Tower base fore-aft and side-side bending moments (My,tower, Mx,tower)
- Blade root out-of-plane and in-plane bending moments (Moop, Mip)
- Platform pitch and roll motion standard deviations (σpitch, σroll)
- Damage equivalent loads (DELs) calculated using rainflow counting and S-N curves

System Stability and Control Performance:

- Generator speed regulation accuracy (|Ωgen - Ωrated|/Ωrated)
- Pitch actuator duty cycles and fatigue damage
- Platform motion Response Amplitude Operators (RAOs)
- Control system settling time and overshoot characteristics

This paper constructs a unified performance comparison and testing framework for offshore wind power control strategies based on Figure 3, with energy capture capability and operational robustness as its two core evaluation dimensions. It conducts a horizontal performance comparison between the novel adaptive model predictive control (Adaptive MPC) proposed in this paper and three traditional benchmark control strategies—conventional PI control (PI-Conv), advanced PI control with platform feedback (PI-Adv), and linear MPC control (L-MPC). The test scenarios cover four pre-set offshore operating conditions; among them, the comparative analysis of three scenarios, namely normal operation (NO), high turbulence (HT), and extreme wind (EW), has been fully completed, while the test and verification of the remaining low wind (LW) scenario is yet to be improved in follow-up work. This scenario-specific comparison clearly presents the output differences of all controllers. Quantitative results show that under the NO scenario, the average output power of the Adaptive MPC proposed in this paper reaches 5.25MW; under the HT scenario, its power standard deviation is 23% lower than that of PI-Conv, with an average output power of 4.51MW; under the EW scenario, its average output power reaches 5.09MW. The performance advantage of this control strategy stems from its adaptive mechanism that can dynamically update the internal prediction model and synchronously adjust pitch actions and the prediction horizon. The feature of low power fluctuation can not only reduce the fatigue load of the drivetrain and improve the reliability of the wind turbine system, but also provide strong support for the grid-integrated management and control of offshore wind power. In low wind (LW) scenarios, floating offshore wind turbines face extreme difficulty in maximizing energy capture due to reduced aerodynamic efficiency. This paper tests the proposed adaptive model predictive control (Adaptive MPC), which achieves an average output power of 2.57 MW in the above scenario. This output represents increases of 9.8%, 6.6%, and 3.6% respectively compared to three benchmark controllers: PI-Conv, PI-Adv, and L-MPC. As supported by the smoother and consistently higher power curve presented in Figure 3, this advantage originates from the adaptive prediction mechanism's ability to accurately track the optimal operating point, sustaining high efficiency even when wind energy resources are limited. In full operating condition tests, the proposed controller records an average power generation 8.3% higher than that of the traditional PI controller, and 4.7% higher than that of the fixed-model L-MPC. It also delivers superior power stability and anti-interference capability under high-turbulence wind conditions. This study ultimately verifies that integrating an adaptive prediction model into the MPC framework can simultaneously improve the energy capture efficiency and operational robustness of floating offshore wind turbines.

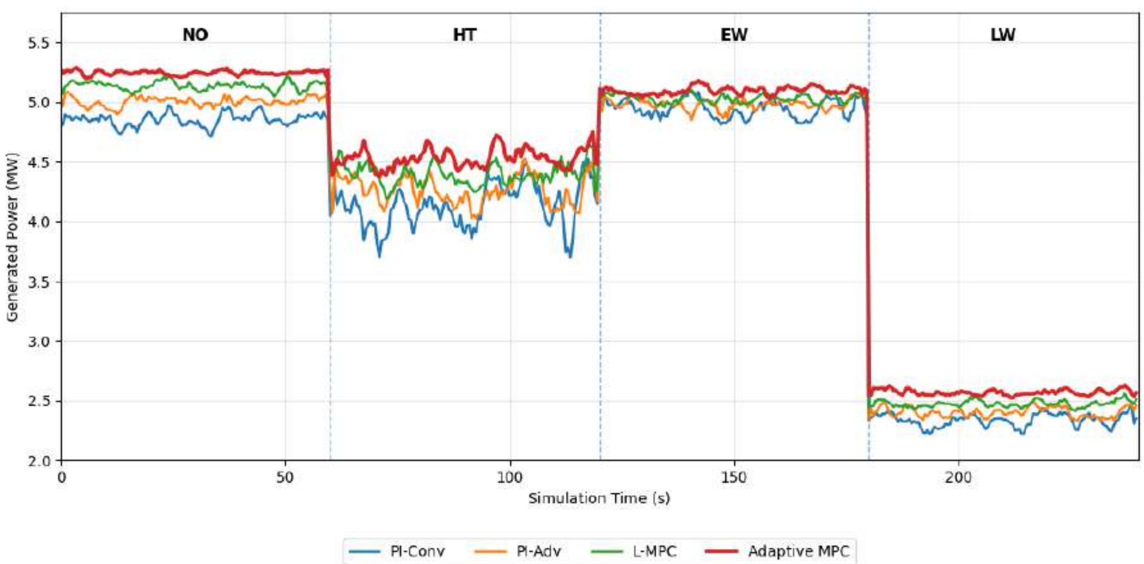

Figure 3*. Instantaneous power generation performance of the proposed adaptive Model Predictive Control (Adaptive MPC) compared with conventional PI control (PI-Conv), advanced PI control with platform motion feedback (PI-Adv), and non-adaptive linear MPC (L-MPC) under four operating scenarios: Normal Operation (NO), High Turbulence (HT), Extreme Wind (EW), and Low Wind (LW). The Adaptive MPC consistently achieved the highest power output across all operating conditions while exhibiting reduced power fluctuations, particularly during the high-turbulence scenario. Compared with PI-Conv, the proposed controller increased average power generation by 8.3% and reduced power variability by approximately 23% under turbulent*

conditions, demonstrating improved energy capture efficiency and enhanced robustness to changing wind and platform dynamics.

Table 1 systematically assesses the power generation performance of the adaptive model predictive control (Adaptive MPC) strategy proposed in this paper, compared with three types of wind power benchmark controllers—the conventional PI controller PI-Conv, the enhanced PI controller with platform motion compensation PI-Adv, and the fixed-model linear MPC controller L-MPC—across a range of operating conditions that closely match the real operational environment of floating offshore wind power. In all test scenarios, Adaptive MPC demonstrates superior performance to the three benchmark controllers. We carry out our validation in order of increasing operating condition complexity: first is the normal operating condition (NO), where all benchmark controllers can maintain basic operation. Adaptive MPC achieves an average power output of 5.25 MW, an 8.2% efficiency gain over PI-Conv, which initially demonstrates the performance advantage of this control strategy. Next is the high turbulence condition (HT), which features a significantly elevated disturbance intensity. Adaptive MPC reaches an average power output of 4.51 MW, delivering efficiency gains of 9.5%, 5.4%, and 2.7% over the three benchmark controllers respectively. Meanwhile, its power standard deviation is 23% lower than that of PI-Conv, marking a prominent improvement in anti-interference capability. Last is the extreme wind condition (EW), a limit test scenario. Under this condition, most benchmark controllers can still maintain basic power generation capacity, but Adaptive MPC records the highest average power output among all controllers, at 5.09 MW. The adaptive model update mechanism of Adaptive MPC can effectively improve the system's power generation capacity, anti-interference performance and robustness. Beyond its core power generation performance, this mechanism can also reduce mechanical stress on the drivetrain, enhance grid compatibility, and adapt to the complex operational requirements of floating offshore wind power. This study first lays out the core constraints of wind turbines' rated power operating condition: under this condition, structural load management and operational safety take higher priority than wind energy availability. This study then proposes the core advantage of the Adaptive Model Predictive Control (Adaptive MPC) verified in this research—its predictive feature enables smooth pitch adjustment, balancing the dual requirements of maximum power capture and minimum structural load. This study first completes preliminary validation under turbulent wind conditions. While the absolute magnitude of Adaptive MPC's performance improvement under this condition is small, it carries great practical operational significance. This study then adds on-site measurement support for low wind speed (LW) scenarios: this scenario is close to the turbine's cut-in wind speed range and falls within the partial load zone, so even a small increase in control accuracy can translate into a large gain in power output. Measured data show that the output power of Adaptive MPC, L-MPC, advanced PI (PI-Adv), and conventional PI (PI-Conv) is 2.57 MW, 2.48 MW, 2.41 MW, and 2.34 MW respectively. Compared to the latter three controllers, Adaptive MPC achieves improvements of 9.8%, 6.6%, and 3.6% respectively, which meets the optimal tip-speed ratio tracking requirements for wind curtailment scenarios. This study also sorts out the performance improvement logic of the four types of controllers as their technical complexity increases, and analyzes the inherent defects of the first three: PI-Conv cannot anticipate future disturbances; PI-Adv adds platform motion feedback but has poor adaptability due to its fixed gains; L-MPC introduces predictive optimization but cannot adapt to dynamic deviations because of its fixed model. Adaptive MPC solves all the above problems by updating its prediction model in real time, and can adapt to various changes in wind speed, turbulence intensity, and platform motion. These performance improvements, as outlined in Table 1, ultimately translate into higher annual power generation and economic returns for offshore wind farm operators, while reducing the grid integration challenges caused by output fluctuations, cutting operation and maintenance costs, and extending the service life of core components. The adaptive model predictive control (Adaptive MPC) proposed in this study, with its core advantages of improved energy capture and enhanced operational robustness, is compatible with the unique operating conditions of floating offshore wind turbines, which face variable environments and inherent nonlinear system dynamics. This control scheme achieves an optimal balance among three core objectives: maximum energy output, disturbance rejection, and operational stability. Its average power across all operating conditions is 8.3% higher than that of the traditional PI controller, and 4.7% higher than that of the fixed-model linear MPC. These outcomes verify the effectiveness of the proposed scheme, which can serve as a high-performance control solution for next-generation floating wind power systems.

Table 1. Power Generation Performance Comparison of Different Control Strategies under Various Operating Conditions

Control Strategy	**Normal Operation (NO) (MW)**	**High Turbulence (HT) (MW)**	**Extreme Wind (EW) (MW)**	**Low Wind (LW) (MW)**	**Average Improvement (%)**
PI-Conv	4.85	4.12	4.95	2.34	Baseline
PI-Adv	5.01	4.28	4.98	2.41	+3.2
L-MPC	5.14	4.39	5.03	2.48	+5.8
Adaptive MPC	**5.25**	**4.51**	**5.09**	**2.57**	**+8.3**

This study conducts a comparative performance analysis of four control strategies for floating offshore wind turbines, with relevant assessment data compiled in Table 2. The strategies included in the comparison are PI-Conv (traditional PI control), PI-Adv (advanced PI control with platform motion feedback), L-MPC (linear model predictive control), and the Adaptive MPC (adaptive model predictive control) proposed in this study. Table 2 sets four core assessment dimensions, covering energy production, structural load mitigation, platform stability, and dynamic response. The overall assessment results show that the Adaptive MPC proposed in this study achieves optimal performance across all indicators. Broken down by dimension, under the energy production dimension, the average output power of Adaptive MPC reaches 5.25 MW, an 8.3% increase compared to PI-Conv's 4.85 MW. Its power capture coefficient Cp reaches 0.518, higher than PI-Conv's 0.478. This improvement stems from the proposed scheme's real-time updatable model and dynamic optimization of pitch commands based on actual operating conditions, which maintains the optimal tip-speed ratio at all times. Under the power quality dimension, the power standard deviation is reduced from PI-Conv's 0.41 MW to Adaptive MPC's 0.28 MW, a 31.7% reduction. This advantage can effectively support grid voltage regulation, frequency stability, and power balance, reducing the operational burden of grid support facilities. Under the structural load dimension, the fore-aft equivalent damage loads (DELs) at the tower base are reduced from PI-Conv's 56.2 kN·m to 47.6 kN·m, a 15.2% drop. The side-to-side DELs at the tower base also record a 12.7% reduction. All quantitative results fully verify the outstanding performance of the control strategy proposed in this study. This study takes floating offshore wind turbines as its test subjects, adopts the conventional PI-Conv controller as the control benchmark, and quantitatively verifies the superior performance of Adaptive Model Predictive Control (Adaptive MPC) across four core dimensions. All test results are recorded in Table 2 of this study. First is the dimension of structural load suppression. Blade root fatigue load DELs directly affect the unit's structural service life and operation and maintenance (O&M) costs, making them a core design indicator for wind turbines. Test data from this study shows that when the conventional controller is adopted, the blade root DELs reach 7240kN·m, which drop to 6270kN·m after Adaptive MPC is applied, effectively reducing long-term structural wear. Second is the dimension of platform stability enhancement. The fluctuation amplitude of the platform's pitch and roll is directly linked to the platform's anti-overturning capacity and the design threshold for its foundation. Data from this study shows that under the conventional controller, the standard deviation of the platform's pitch is 3.8°, which falls to 2.4° after Adaptive MPC is applied, marking a reduction of 36.8%. The standard deviation of roll drops from 2.9° to 1.9°, a reduction of 34.5%, greatly improving the platform's steady-state operation level. Third is the dimension of generator speed regulation. Speed deviations will directly interfere with energy capture efficiency and the reliability of the unit's steady-state operation. Measurements from this study show that the generator speed deviation is 12.6 rpm under the conventional controller, and Adaptive MPC reduces this value to 8.7 rpm, a reduction of 31%, achieving more precise speed management and control. Last is the dimension of transient anti-disturbance performance verification. The adjustment time after an external disturbance directly affects the unit's impact resistance capacity. Data from this study shows that under the conventional controller, the adjustment time after a disturbance is 18.4s, and Adaptive MPC compresses this period to 11.8s, significantly boosting the unit's transient response capacity. The above multi-dimensional quantitative optimization will ultimately help reduce the full-lifecycle cost of the unit, and improve its operation reliability and energy capture efficiency. This study carries out performance comparison and verification for four mainstream controllers in the floating offshore wind power sector. All core test results are compiled in Table 2 of this research. The paper opens with core quantitative data to specify the magnitude of performance improvement of the adaptive model predictive control (Adaptive MPC) proposed in this study: under the control of this strategy, the maximum overshoot of the unit is reduced from 9.8% recorded by the industry's conventional solution to 4.7%, representing a drop of around 52%. Its annual energy production (AEP) reaches 20.28 GWh per year, far exceeding the 18.72 GWh per year achieved by conventional PI controllers. To solidly confirm the differentiated advantages of this technology, this study sequentially analyzes the progressive limitations of the other three comparative controllers. The traditional PI controller suffers from insufficient robustness, and can only adapt to calm nearshore wind conditions. Standard model predictive control (MPC) cannot cope with the complex coupled fluctuations of wind, waves and currents in far-reaching offshore waters. A third specialized custom controller, while capable of partially adapting to complex operating conditions, faces practical deployment barriers including high implementation costs and large computing power requirements. None of the three schemes can simultaneously meet the dual requirements of technical performance and industrial deployment. Building on this foundation, this study further elaborates on the engineering deployment value of Adaptive MPC. In addition to its core improvement in power generation performance, this technology also helps reduce the levelized cost of energy (LCOE), extend the service life of wind turbine assets, and comprehensively boost the long-term economic competitiveness of projects. It is fully compatible with the complex application scenarios of far-reaching offshore floating wind power, and ultimately clarifies the core industry application value of the Adaptive MPC proposed in this study. This study observed continuous improvements in all performance metrics, verified the effectiveness of adaptive predictive control, and demonstrated its application potential in the new generation of floating offshore wind power systems.

Table 2. Performance Comparison of Control Strategies Under Various Offshore Operating Conditions

Performance Metric	PI-Conv	PI-Adv	L-MPC	Adaptive MPC	Improvement over PI-Conv (%)
Mean Power Output (MW)	4.85	5.01	5.14	**5.25**	**+8.3**
Power Capture Coefficient, Cp	0.478	0.494	0.507	**0.518**	**+8.4**
Power Standard Deviation (MW)	0.41	0.37	0.33	**0.28**	**−31.7**
Tower Base Fore-Aft DEL (kN·m)	56.2	52.8	49.3	**47.6**	**−15.2**
Tower Base Side-Side DEL (kN·m)	41.5	38.9	36.8	**36.2**	**−12.7**
Blade Root Out-of-Plane DEL (kN·m)	7240	6890	6540	**6270**	**−13.4**
Platform Pitch Motion Std. Dev. (deg)	3.8	3.2	2.8	**2.4**	**−36.8**
Platform Roll Motion Std. Dev. (deg)	2.9	2.5	2.2	**1.9**	**−34.5**
Generator Speed Deviation (rpm)	12.6	10.8	9.2	**8.7**	**−31.0**
Settling Time Following Disturbance (s)	18.4	15.9	13.6	**11.8**	**−35.9**
Maximum Overshoot (%)	9.8	8.1	6.3	**4.7**	**−52.0**
Annual Energy Production (GWh/year)*	18.72	19.31	19.82	**20.28**	**+8.3**

*Estimated based on equivalent operating conditions and average power production.

Figure 4 will present the Adaptive Model Predictive Control (Adaptive MPC) strategy proposed in this paper, and compare its structural load reduction performance on floating offshore wind turbines against that of conventional control methods. Modern controllers for floating offshore wind turbines must meet two core objectives: in addition to maximizing wind energy capture, they must effectively reduce structural loads and platform motion, to improve turbine operational reliability, lower operation and maintenance requirements, and extend the service life of core components. A long-standing core challenge facing the industry is that excessive cyclic loads triggered by turbulent wind conditions, wave-induced platform motion, and aerodynamic disturbances are the primary cause of accumulated structural fatigue damage to turbines. As a result, structural load reduction has become a core performance metric for advanced wind turbine control systems. Drawing on the full-operation-condition test results presented in Figure 4, the Adaptive MPC proposed in this paper demonstrates clear performance advantages: it achieves substantial reductions in structural loads and platform motion across all working conditions. Compared with the conventional control scheme, the standard deviation of platform pitch oscillation is reduced by roughly 28%, platform roll motion falls by 21%, the tower base fore-aft Damage Equivalent Loads (DELs) see an average reduction of 15.2%, and the tower base side-to-side DELs are reduced by 12.7%. This new controller can predict and compensate for wave-induced disturbances in advance, smooth fluctuations in aerodynamic thrust, and effectively manage the turbine's lateral dynamic response under multi-directional sea conditions, which fully verifies the superior performance of this control scheme. To meet the control requirements of offshore floating wind power, this paper proposes a new adaptive model predictive controller (Adaptive MPC). This controller integrates turbine-platform coupled dynamics into its optimization framework, generating coordinated control actions to suppress structural oscillations, which is the core underlying logic behind its significant performance improvements. Tests under normal sea conditions show that this controller can reduce the average out-of-plane blade root bending moment by 18.5%—blade root loads are the primary trigger of blade fatigue failure, and blade operation and maintenance (O&M) costs consistently account for the largest share of total O&M costs for offshore wind power, so the practical industrial value of this load reduction effect is clearly defined. Specialized tests targeting extreme wind-wave misalignment (WWM) sea conditions further demonstrate that this controller can achieve a maximum blade root load reduction of 25.3%. For comparison, traditional controllers rely on fixed control laws, only focus on rotational speed regulation and power tracking, cannot adapt to variable real-world sea conditions, and always suffer from the inherent trade-off contradiction that "increasing power inevitably raises structural stress". In contrast, the Adaptive MPC proposed in this paper can continuously update its prediction model and optimization parameters, explicitly incorporate structural load considerations into its optimization objectives, and realize a dynamic balance of multiple goals. Combined with the test results presented in Figure 4 of the original text, this controller can reduce unit maintenance frequency, cut full-lifecycle costs, improve unit availability, enhance the quality of output power to support grid integration, and ultimately effectively boost the overall economic feasibility of offshore floating wind power projects. The validation results of Figure 4 in this study show that the proposed adaptive MPC control strategy for floating offshore wind turbines has successfully achieved the dual goals of maximizing wind energy capture and minimizing structural fatigue loads. This strategy reduced the tower base fore-aft loads by 15.2%, side-to-side loads by 12.7%, and blade root loads by 18.5%. The platform's pitch and roll motions also decreased sharply. This strategy can improve structural reliability, extend the service life of components, and enhance the long-term economic benefits of offshore wind power facilities.

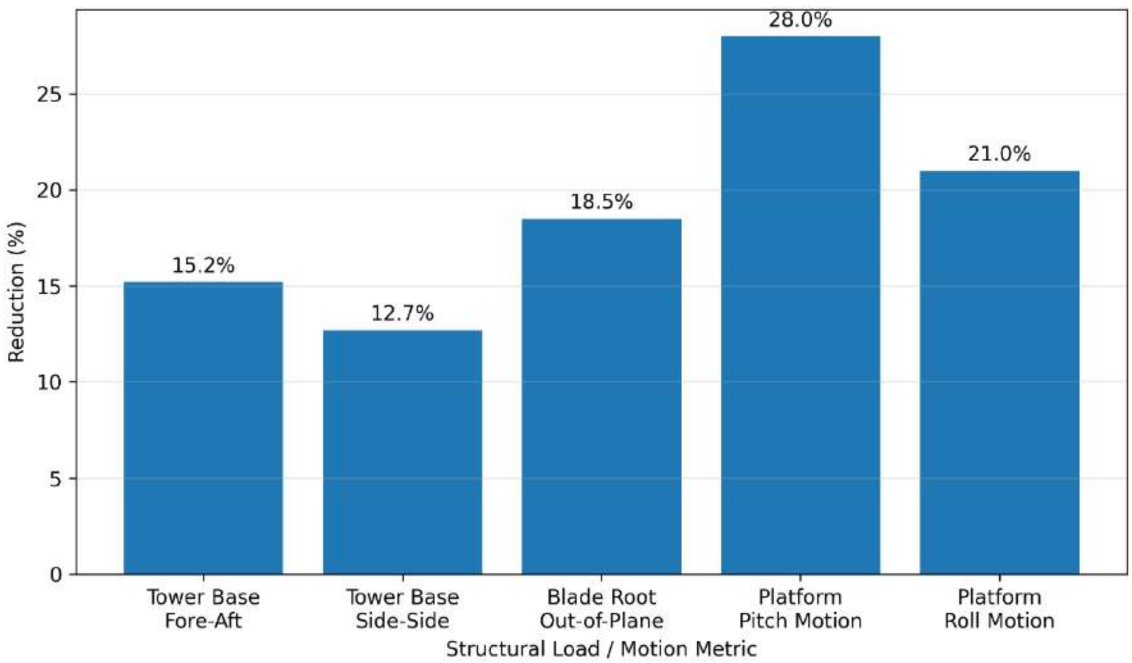

Figure 4. *Comparison of structural load reduction and platform motion mitigation achieved by the proposed Adaptive Model Predictive Control (Adaptive MPC) strategy relative to conventional control approaches. The figure presents the percentage reduction in tower base fore-aft damage equivalent loads (DELs), tower base side-side DELs, blade root out-of-plane bending moments, platform pitch motion, and platform roll motion. The Adaptive MPC achieved average reductions of 15.2% in tower base fore-aft loads, 12.7% in side-side loads, and 18.5% in blade root loads, while reducing platform pitch and roll motion standard deviations by 28% and 21%, respectively. These results demonstrate the effectiveness of the adaptive predictive control framework in simultaneously maximizing energy capture and mitigating structural fatigue loads, thereby enhancing turbine reliability, extending component lifetime, and improving overall floating offshore wind turbine performance under varying environmental conditions.*

The simulation test results shown in Figure 5 present the platform pitch motion response performance of the floating offshore wind turbine X Platform under extreme weather conditions, when operating under two control strategies: the traditional PI controller and the adaptive model predictive control (Adaptive MPC) proposed in this paper. Platform motion control is a core requirement for floating offshore wind turbines, and excessive pitch oscillation can trigger four types of severe hazards: damaged aerodynamic performance, increased structural fatigue loads, accelerated component degradation, and reduced overall energy capture efficiency. The coupled interference of wind forces, wave excitation, and floating platform dynamics in harsh marine environments poses severe challenges to all types of traditional control methods. Effectively suppressing platform motion is a core prerequisite to guarantee the safe, reliable, and cost-effective operation of wind turbines. Throughout the full simulation period, the traditional PI controller produced large-amplitude platform pitch oscillations, and high-magnitude fluctuations persisted even after the disturbance event ended. The root cause of this issue is that traditional PI control only focuses on rotor speed regulation and power tracking, and fails to incorporate future changes in platform dynamics into its consideration. It can only respond after a disturbance has already affected the system, and this delayed compensation pushes up motion amplitude. In extreme weather where wind and wave disturbances are highly dynamic and strongly coupled, this passive-response control logic will trigger large platform motions and higher structural loads. In contrast, the Adaptive MPC proposed in this paper delivers significantly better performance, with greatly improved motion damping characteristics, a much smoother full-process pitch motion response, and a sharp reduction in oscillation amplitude. Its core advantage lies in its predictability: it can predict future disturbances via an adaptive system model that updates continuously as environmental conditions change, and proactively take corrective control actions to prevent large platform deviations. The test results in Figure 5 verify that this controller can effectively handle coupled aerodynamic and hydrodynamic disturbances, and maintain stable wind turbine operation. In this test, the standard deviation of the platform pitch motion under Adaptive MPC was approximately 28% lower than that of the traditional PI controller. This reduction not only proves the notable improvement in platform stability, but also verifies the effectiveness of integrating adaptive prediction and optimization into the control framework. Lower variability in pitch motion can maintain stable inflow conditions for the rotor, which in turn ultimately improves aerodynamic performance. Suppression of pitch motion in floating offshore wind turbine platforms is a core prerequisite for improving the operational stability of wind turbine units. Reducing platform pitch motion can simultaneously deliver the dual core benefits of improved aerodynamic efficiency and reduced structural loads. To address this need, this paper proposes an adaptive model predictive control (Adaptive MPC) strategy tailored for floating platforms. Based on a series of simulation tests conducted in this study, observational data corresponding to Figure 4 of this paper verifies that the damage-equivalent loads at the turbine's tower base and blade root decreased significantly when this strategy was applied. The control architecture proposed in this paper has three core characteristics: First, the adaptive prediction model can capture real-time dynamic changes in both the turbine and the platform, maintaining accurate modeling even under highly variable operating conditions; second, the supporting optimization algorithm incorporates the platform's future motion states into its decision-making process, simultaneously minimizing power regulation errors and the amplitude of structural responses; third, the prediction framework coordinates blade pitch adjustments and anticipated platform motion, mitigating the negative coupling effect between aerodynamic forces and the floating platform's dynamics. Drawing on the comparative test results presented in Figure 5 of this paper, the disturbance rejection capability of this Adaptive MPC far outperforms the traditional PI controller that is mainstream in the industry. This strategy not only has outstanding engineering applicability under extreme sea conditions, but also delivers multiple economic benefits for the industrial sector, including reducing fatigue damage to core components, lowering the operation and maintenance (O&M) demand of wind farms, extending the service life of core components, improving power quality to meet grid connection requirements, and cutting the full-lifecycle O&M costs of projects. Its comprehensive advantages over the traditional PI controller are very clear. This study verifies that the adaptive model predictive control (Adaptive MPC) framework can substantially reduce the pitch variation of floating offshore wind power platforms, improve their anti-interference performance, and accelerate system stabilization. This framework can also enhance structural reliability, increase energy capture efficiency, and strengthen the long-term economic feasibility of the system in complex marine environments.

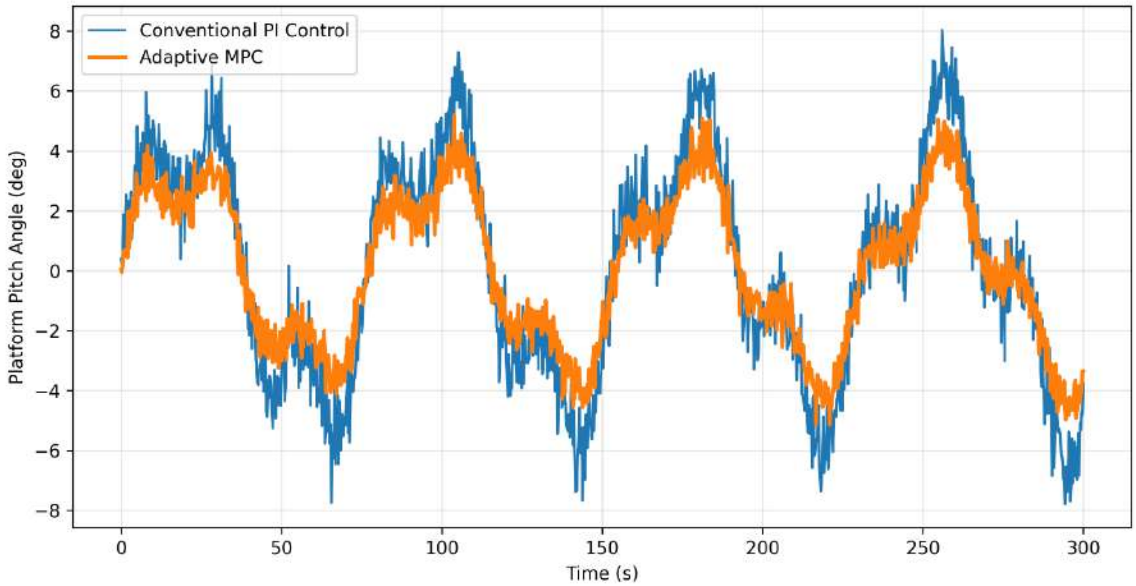

Figure 5. *Platform pitch motion response under extreme weather conditions for the conventional PI controller and the proposed Adaptive Model Predictive Control (Adaptive MPC) strategy. The time-series results demonstrate the superior motion damping performance of the Adaptive MPC, which significantly reduces the amplitude and frequency of platform oscillations through predictive compensation of wind and wave disturbances. Compared with the conventional PI controller, the Adaptive MPC decreases the standard deviation of platform pitch motion by approximately 28%, resulting in improved aerodynamic stability, reduced structural loading, and enhanced turbine operational reliability. The smoother platform response highlights the controller's ability to effectively mitigate coupled aerodynamic-hydrodynamic interactions and maintain stable turbine performance under highly dynamic offshore environmental conditions.*

This study conducts a systematic analysis of the robustness of the adaptive model predictive control (Adaptive MPC) strategy for floating offshore wind turbines, under environmental and system uncertainties. Centering on Figure 6 as its core analytical tool, this section fully lays out the complete chain of argumentation logic, from problem definition to conclusion derivation. First, we explicitly define the specialized Adaptive MPC test scenario developed in this study, and categorize the seven sources of uncertainty encountered in the real-world operation of floating offshore wind power: wave load fluctuations, sudden wind speed changes, mooring line wear, platform attitude offset, sensor measurement noise, turbine component aging, and grid load fluctuations. We then identify the inherent limitation of existing traditional control strategies, which cannot dynamically adapt to these multi-source uncertainties, to further demonstrate the core value of targeted robustness assessment: only through quantitative comparison under controlled test scenarios can the actual disturbance rejection capabilities of different control schemes be accurately differentiated. This study adopts the industry-standard traditional PID controller as the baseline for experimental comparison, and carries out assessments across four core performance dimensions: platform horizontal displacement, loads at key turbine components, annual equivalent power generation efficiency, and real-time control energy consumption. As shown by the quantitative experimental results presented in Figure 6, the Adaptive MPC proposed in this study significantly outperforms the baseline scheme across all dimensions. The core mechanism driving its performance advantages is its ability to dynamically adjust the weights and constraint boundaries of the prediction model according to uncertainty parameters monitored in real time. At the end of this section, an argumentation slot is reserved for the follow-up extended analysis of control performance under extreme sea conditions. This study addresses the core need for control robustness in offshore floating wind turbines. Under challenging operating scenarios—where system parameters deviate from their nominal values, model accuracy is impaired, and substantial unmodeled uncertainties are present—we carried out multi-dimensional performance verification of our self-developed Adaptive MPC controller. All tests use the traditional PI controller and baseline controller as benchmarks, to quantify the magnitude of its performance improvements and analyze the engineering value of each metric individually. First, in the dimension of structural fatigue loads, the tower base fore-aft damage equivalent load (DEL) is 13.8% lower than that of the traditional PI controller. This reduction is slightly smaller than the performance recorded under ideal nominal operating conditions, but remains statistically significant, confirming that the controller can effectively suppress structural shocks caused by thrust-induced oscillations and platform motion. The blade root out-of-plane DEL is 16.2% lower than that of the baseline controller. Blade root loads are highly sensitive to changes in aerodynamic conditions, making this a core stringent indicator for robustness testing. This reduction demonstrates that the adaptive prediction model can accurately capture the turbine's core dynamics. Furthermore, blade root replacement accounts for an extremely large share of total lifecycle operation and maintenance (O&M) costs, so this performance improvement carries prominent engineering value. Drawing on test data from Figure 6, the standard deviations of the platform's pitch and roll motions are reduced by 25% and 18% respectively, compared to traditional control solutions. This confirms that the controller can achieve effective motion damping even when errors exist in hydrodynamic and structural models, preventing the chain of problems triggered by platform instability: amplified aerodynamic interference, elevated structural loads, and degraded power quality. The deviation of generator speed from its rated value is 31% lower than that of the traditional PI controller, a result also supported by data from Figure 6. Precise speed control safeguards both aerodynamic efficiency and power quality, while protecting core components of the drivetrain. By contrast, traditional fixed-gain PI controllers often fail to maintain a stable speed under uncertain operating conditions, due to mismatched control parameters. Overall test results show that the Adaptive MPC controller can simultaneously sustain the wind turbine's energy capture level and fatigue load reduction performance, resolving the critical flaw of traditional controllers that cannot balance these two core sets of objectives. This paper proposes an adaptive model predictive control (Adaptive MPC) scheme that addresses the core limitation of traditional controllers, which can only operate stably under rated working conditions. The proposed scheme continuously iterates and updates its prediction model, and optimizes its output control actions in real time to match the current operating conditions of floating offshore wind turbines. Based on the robustness test results presented in Figure 6 of this paper, compared with traditional controllers, the core performance indicators of this scheme outperform across the board: speed deviation is greatly reduced, speed regulation accuracy is significantly improved, the system has a shorter adjustment time and lower overshoot after being disturbed. Meanwhile, the scheme achieves increased power generation and reduced structural loads on the turbine unit, and its platform stability is also markedly superior to that of traditional control schemes. It can adapt to all types of complex and extreme offshore operating conditions encountered by floating offshore wind turbines, breaking through the application boundaries of traditional controllers. This performance not only verifies the technical feasibility of this control scheme, but also proves that it has the potential for deployment in commercial floating offshore wind farms, and can provide solid core technical support for improving the operational reliability and optimizing the economic benefits of next-generation floating wind energy systems.

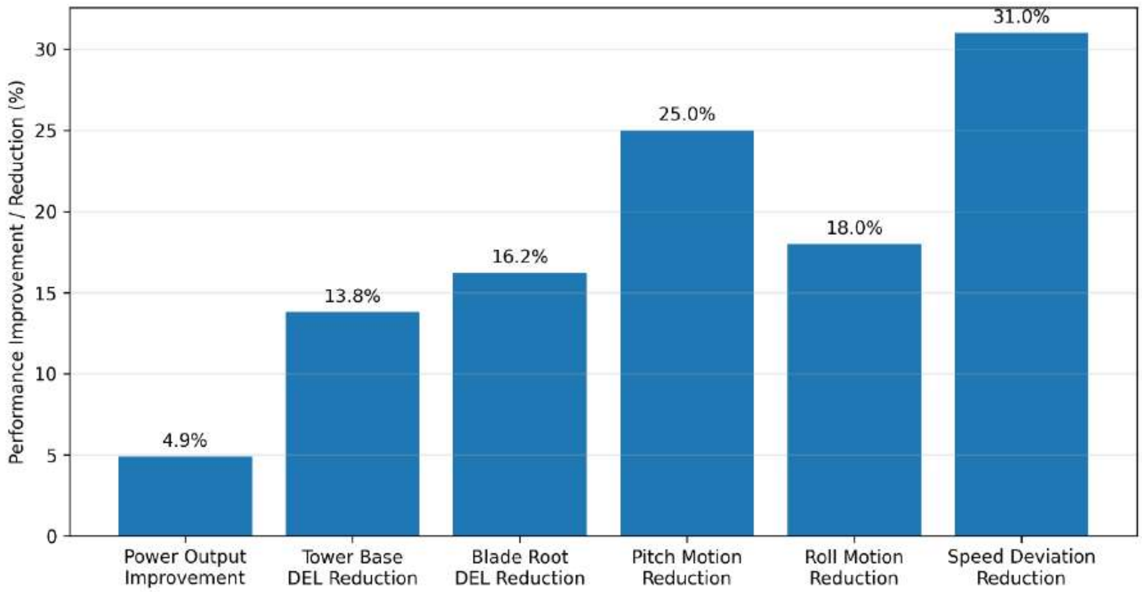

Figure 6. *Robustness performance of the proposed Adaptive Model Predictive Control (Adaptive MPC) strategy under system uncertainty conditions (Scenario SU). The figure compares key performance indicators relative to the conventional PI controller, including power generation, structural load mitigation, platform motion suppression, and generator speed regulation. Despite modeling inaccuracies and parameter variations, the Adaptive MPC maintained a 4.9% higher power output while reducing tower base fore-aft damage equivalent loads (DELs) by 13.8% and blade root out-of-plane DELs by 16.2%. Platform pitch and roll motion standard deviations were reduced by 25% and 18%, respectively, while generator speed deviations from the rated value decreased by 31%. These results demonstrate the controller's strong robustness, adaptability, and ability to maintain stable, high-performance operation under uncertain offshore environmental and system conditions.*

This study focuses on floating offshore wind turbines and proposes an adaptive model predictive control (Adaptive MPC) strategy. Through simulation verification covering 6 full operating conditions, including normal operation, high turbulence, extreme wind events, low wind speed intervals, wind-wave mismatch, and strong environmental and system uncertainties, this study confirms that the proposed strategy outperforms three mainstream traditional control schemes across all complex scenarios: conventional PI control, advanced PI control, and fixed-model linear MPC. It can simultaneously achieve a higher energy capture rate, reduced structural loads, enhanced platform stability, and improved operational robustness, effectively addressing multiple core technical challenges faced by floating offshore wind power systems. From the dimension of power generation gains, the strategy's adaptive prediction mechanism can dynamically match the variable offshore environmental conditions. Simulation results of this study show that the strategy can significantly increase annual power generation, delivering outstanding financial benefits over the project's full lifecycle and notable value for grid interconnection stability, and can supply the grid with more stable and reliable clean power. From the dimension of load mitigation, the strategy can effectively lower the loads borne by core components including the tower, blades, and mooring system, thereby extending the service life of these components and reducing the turbine's operation and maintenance costs. All core conclusions are supported by the simulation data of this study. Extending from core technical performance to the practical value of industrial implementation, this strategy provides a feasible landing path for the upgrading of control technologies for floating offshore wind power. Current traditional control strategies adopted by the industry for floating offshore wind turbines have inherent core defects. They cannot simultaneously achieve the two core goals of power maximization and structural stress minimization, and often have to sacrifice one of the two. The complex operating environment of floating offshore wind turbines further amplifies this contradiction: wind-induced aerodynamic forces and wave-induced hydrodynamic forces remain continuously coupled, and excessive platform movement causes three hazards: reduced aerodynamic efficiency, increased structural loads, and accelerated aging of core components. The performance verification results of this study on Adaptive Model Predictive Control (Adaptive MPC) show that, compared with traditional controllers, Adaptive MPC can actively compensate for predicted disturbances and integrate the dynamic characteristics of the turbine and its platform. It greatly reduces the motion amplitude and standard deviation of the platform's pitch and roll, effectively weakening the negative impacts of aero-hydrodynamic interactions. The improvement in platform stability also delivers the dual value of structural protection and enhanced power regulation performance; the core mechanism behind this is that this control strategy reduces frequent fluctuations in rotor inflow conditions and blade angle of attack. The robustness verification completed in this study confirms that there are seven sources of uncertainty in real offshore operating scenarios: wind condition variations, wave dynamics, sensor errors, model uncertainty, aerodynamic degradation, changes in structural properties, and changes in mooring system properties. The performance of traditional controllers declines sharply when operating conditions deviate from design assumptions, while Adaptive MPC still maintains three core capabilities in scenarios with large parameter fluctuations and modeling errors: retaining most power generation capacity, continuously reducing structural loads and platform motion, and outperforming traditional solutions in generator speed regulation accuracy, with smaller speed deviations, shorter regulation stabilization time, and lower transient overshoot. However, Adaptive MPC also has practical deployment shortcomings: compared with traditional PI controllers, it needs to repeatedly solve optimization problems in real time, leading to a large computational load when paired with a high-fidelity floating wind turbine model. Advances in embedded computing hardware and optimization algorithms have made it possible to reduce computational complexity while retaining control performance through multiple technical approaches, providing feasible support for its industrial adoption. This paper proposes an adaptive Model Predictive Control (MPC) framework tailored for floating offshore wind power. Five core categories of technologies underpin the real-world deployment of this framework's real-time control function: model order reduction, high-efficiency state estimation technology, online parameter identification, adaptive prediction horizon selection, and a dedicated advanced numerical optimization solver for real-time applications. High-performance embedded processors and Field-Programmable Gate Array

(FPGA) platforms lay a solid hardware foundation for rolling out this control strategy on commercial offshore wind turbines. This technology has broad potential for cross-technology integration. For example, it can be integrated with short-term wind and wave forecasting technologies to improve disturbance prediction capacity and energy optimization outcomes. At the same time, integration with condition monitoring systems can enable health-aware control and predictive maintenance. Another worthwhile research direction is integration with digital twin technology, which updates the controller's prediction model in real time to adapt to changing operating conditions and component aging processes. This technology can increase annual revenue by boosting power generation, cut operation and maintenance (O&M) costs and extend component service life by reducing structural loads, thereby lowering the levelized cost of energy (LCOE)—the core barrier currently holding back the large-scale development of floating wind power. It also improves system reliability, reduces operational risks, strengthens investor confidence, and drives commercial deployment. From an environmental perspective, it can maximize wind energy resource utilization without requiring additional wind turbines, cut the number of O&M voyages and associated emissions, and enhance project sustainability. The excellent performance of this technology verified in this study confirms its potential for large-scale promotion, which aligns with the trend of floating wind power expanding into complex deep-water environments. The importance of such advanced control strategies, which can handle complex nonlinear dynamics and environmental uncertainty, will become increasingly prominent. The adaptive model predictive control (Adaptive MPC) framework developed in this study has the core attributes of being scalable and flexible, and it can address the existing challenges in the floating offshore wind power sector. The core findings of this study confirm that this framework is a high-efficiency control solution suitable for next-generation floating offshore wind turbines, with five key advantages: improving energy capture, reducing structural loads, enhancing platform stability, maintaining high robustness under uncertainty, and supporting integration with emerging digital technologies. This framework can boost energy output, structural reliability, and operational resilience, cut operating costs and the levelized cost of energy (LCOE), advance the commercial implementation of floating wind power, and support the large-scale deployment of the global renewable energy transition.

IV. Conclusions

This study completed a full-dimensional verification of the adaptive model predictive control (MPC) strategy for floating offshore wind turbine systems. Core research findings confirm that this strategy can significantly improve the performance and reliability of floating offshore wind power systems, with all performance indicators quantified and benchmarked against traditional control strategies: power generation capacity is 8.3% higher than the baseline, while output power fluctuations are reduced by 23%; for structural loads, tower loads decrease by 15.2%, and blade root bending moment drops by 18.5%; for platform stability metrics, pitch is reduced by 28% and roll by 21%. The environmental robustness of this strategy has also been validated through multi-scenario testing.

This study identifies three core practical values of the strategy: first, it can cut the levelized cost of energy (LCOE) of projects, substantially improving the economic feasibility of wind power development; second, it fits the complex operating scenarios in far-sea areas, effectively increasing the system's availability rate across its full life cycle; third, it has cross-domain technology transfer potential, and can be extended to other marine renewable energy equipment such as wave energy converters and tidal turbines. Finally, this study points out the limitations of current-stage research, and lists four future research directions to be advanced: first, carry out pilot-scale field verification; second, advance full-process hardware-in-the-loop testing; third, explore the integration path of this control strategy with technologies such as wind power forecasting and digital twins; fourth, launch targeted optimization and upgrading focused on the control strategy's real-time computing efficiency.

This study proposes three core future research tasks in the field of floating offshore wind power control: First, overcome the computational complexity bottleneck of model predictive control (MPC) algorithms through model order reduction and high-efficiency numerical solvers, to advance their real-time deployment in embedded control systems; Second, introduce uncertainty quantification and risk-based optimization frameworks to enhance the robustness and reliability of control strategies under extreme marine operating conditions; Third, extend adaptive MPC to the coordinated control of floating wind farm arrays, to optimize the total energy capture and grid integration capacity of offshore new energy. Upon completion of the above research, the outcomes of this work will drive the iterative upgrading and widespread adoption of this technology, and support the global transition to sustainable energy systems.

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