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Article

AI-driven digital twins for resilient wind turbines under extreme conditions

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Abstract: The increasing deployment of wind turbines in extreme environmental conditions, like high-altitude icing plateaus, introduces significant structural and operational challenges. Harsh conditions, including corrosion fatigue, ice-induced dynamic loads, and fluctuating wind forces, accelerate component degradation and increase maintenance demands. Traditional operation and maintenance (O&M) strategies struggle to adapt to these conditions, demanding a shift towards more proactive, adaptive and intelligent solutions. AI-driven digital twins (DTs) offer a transformative approach by integrating real-time monitoring, predictive analytics, and adaptive control to enhance turbine resilience. This study focuses on enhancing the resilience of onshore wind turbine towers in challenging environments using a digital twin (DT) framework. The case study investigates a 5 MW onshore wind turbine with a lattice-tubular hybrid (LTH) tower, subjected to highly variable wind and environmental loads. Through a DT framework integrating OpenFAST and OpenSees, the study combines multi-physics simulations with supervisory control and data acquisition (SCADA) and structural health monitoring (SHM) data to reconstruct wind-induced loads and predict fatigue deterioration in critical components, such as bolted ring-flange connections. The results demonstrate that the DT-enabled model updating significantly reduces estimated fatigue damage, improving structural reliability and enabling proactive maintenance under fluctuating conditions. Beyond the advances, challenges still remain, including data integration, real-time processing, and cost-effective deployment. Future works are highly advised to focus on refining AI models, enhancing sensor data accuracy, and developing standardized frameworks for DT applications in renewable energy. By addressing these challenges, AI-driven DTs can play a crucial role in the long-term sustainability and resilience of wind energy systems under extreme conditions.

Keywords: Artificial Intelligence (AI); Digital Twins (DTs); Wind Turbines; Extreme Condition; Resilience.

1. Introduction

1.1 Background and Challenges

Wind energy has become an essential pillar in the global transition to renewable energy, offering a sustainable solution to the growing energy demands while reducing dependence on fossil fuels [1]. As the deployment of wind turbines expands into more extreme environments, like high-altitude icing plateaus, new structural and operational challenges emerge, threatening long-term reliability and efficiency.

For instance, wind turbines in high-altitude icing plateaus must endure extreme cold, ice and snow accumulation, and increased dynamic loads from ice-induced vibrations, which can severely affect structural integrity. Ice accretion on blades alters aerodynamic performance, reduces efficiency, and increases loads on the drivetrain and tower, potentially leading to structural fatigue and unexpected failures [2–4].

The overall impact of extreme environmental conditions on onshore wind turbine structures is depicted in **Figure 1**, highlighting the challenges posed by icing, low temperatures, and fluctuating wind loads in such regions.

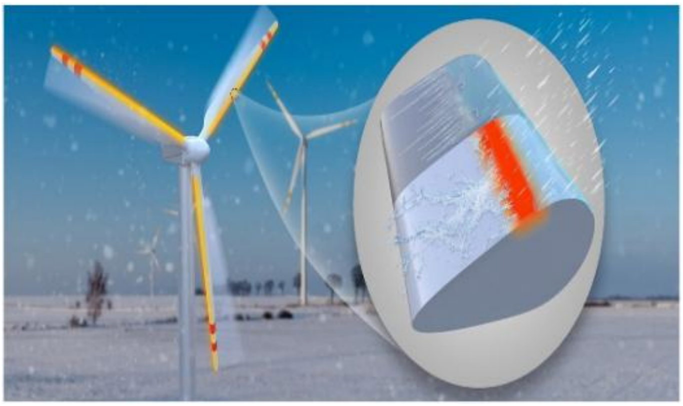


Figure 1. Onshore wind turbine structure in extreme conditions.

In these extreme environments, resilience becomes a crucial attribute for wind turbine systems. Here, the resilience refers to the ability of the turbine to withstand and adapt to harsh environmental conditions, ensuring long-term operational reliability despite the challenges posed by corrosion, fatigue, and extreme loading conditions [5]. Addressing these challenges requires a paradigm shift in wind turbine monitoring and maintenance strategies, moving from traditional reactive approaches to more proactive and adaptive solutions. Given the complexity of structural degradation in extreme environments, advanced technologies that enable real-time failure prediction, dynamic performance optimization, and improved structural resilience are essential. This growing need has driven increasing interest DTs, which hold the potential to revolutionize wind turbine O&M strategies by providing real-time insights and proactive management [6–8].

1.2 Motivation for DTs

Traditional O&M strategies, which rely on periodic inspections and reactive repairs, often fall short in extreme environments where corrosion, fatigue, and ice-induced vibrations accelerate structural degradation. These approaches are prone to delayed failure detection, high maintenance costs, and a lack of real-time adaptability, making them inefficient for ensuring turbine reliability in challenging conditions [9].

DTs offer a proactive solution, enabling real-time monitoring, predictive maintenance, and adaptive control. By continuously analyzing sensor data, DTs can detect early-stage damage, optimize maintenance schedules, and minimize downtime. The integration of AI further enhances decision-making capabilities, failure prediction, and performance optimization, ensuring that turbines remain resilient under harsh environmental conditions [10]. Beyond maintenance, DTs can dynamically adjust operational parameters based on real-time environmental loads, thereby reducing excessive stress, extending service life, and improving energy efficiency [11].

This work explores the role of AI-driven DTs in monitoring, managing, and optimizing wind turbine structures, emphasizing how these technologies can enhance resilience and long-term performance in extreme conditions, ultimately transforming traditional wind turbine operation and maintenance practices. Section 2 provides a State-of-the-Art Review, discussing the origin and development of DT technologies, the fundamentals enabling DTs, and the role of AI-driven DTs for resilient structures. Section 3 presents a case study of onshore Wind Turbine Towers, covering the engineering background, simulation and modelling, and the design optimization, followed by the results and discussion. Finally, Section 4 concludes with remarks, an exploration of challenges, and future directions for research.

2. State-of-the-Art Review

2.1 Origin and Development of DT Technologies

DT technology refers to virtual models that replicate physical assets in real-time, enabling advanced monitoring, simulation, and predictive analysis, often enhanced by AI [12]. The concept of DTs originated in aerospace engineering, where NASA pioneered its application to simulate spacecraft conditions and assess potential risks before missions [13]. The development of DTs has expanded to both civil infrastructure, such as buildings and bridges, where they integrate sensors and building information model for real-time SHM, predictive maintenance, and lifecycle management [14–16], and the renewable energy sector, where DTs optimize wind turbine performance by integrating SHM data and environmental sensors [17].

Figure 2 illustrates a DT framework for wind turbines, integrating various components of wind energy systems into a unified model. At the core of this framework is the interaction between the physical turbine and its digital counterpart, driven by AI to enhance operational efficiency and structural resilience. However, the widespread implementation of DTs for wind turbines is often hindered by data sparsity, as existing monitoring systems lack comprehensive coverage of all critical components across large wind farms.

Several key milestones have marked the evolution of DT technologies. The introduction of the Internet of Things (IoT) [18] allowed for seamless data collection from physical assets, while advancements in cloud computing facilitated large-scale data processing and storage [19,20]. More recently, AI has played a pivotal role in enhancing DT capabilities, enabling predictive maintenance, fault diagnosis, and adaptive control for wind turbines operating in extreme environments [21].

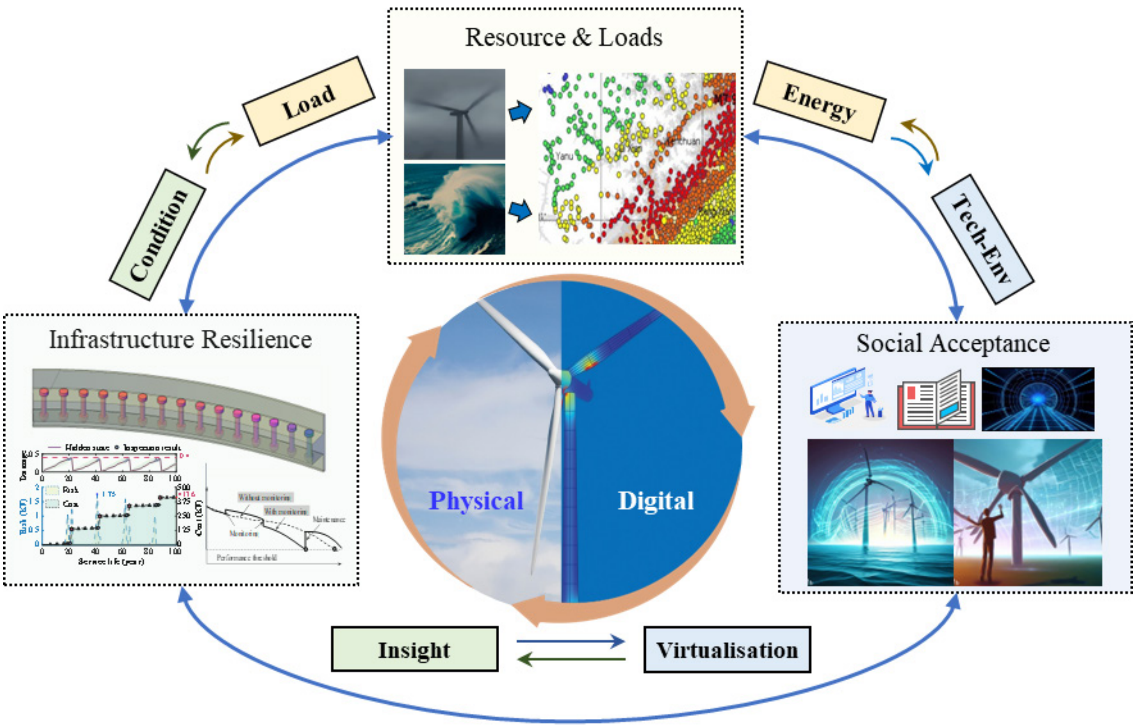


Figure 2. DT Framework for Wind Turbine Structures.

2.2 Fundamentals Enabling DTs

2.2.1 Artificial Intelligence

AI plays a pivotal role in enabling the functionality of DTs by facilitating advanced data analytics, predictive modelling, and intelligent decision-making. Machine learning algorithms analyse large datasets from wind turbine sensors to uncover patterns, detect anomalies, and predict failures before they occur, supporting proactive maintenance and enhancing turbine reliability [22]. Deep learning models, particularly convolutional and recurrent neural networks, are employed to process complex time-series data from SHM systems, improving fault detection and predictive maintenance strategies by identifying subtle damage indicators that may not be immediately obvious [23–25]. Reinforcement learning (RL)-based adaptive control strategies further optimize turbine performance in real-time by dynamically adjusting operational parameters, such as blade pitch and rotor speed, in response to changing environmental conditions, thereby improving efficiency and resilience [26].

In addition to AI techniques, computational resources such as edge computing [27,28], and specialized hardware like GPUs and FPGAs are crucial for supporting the large-scale data processing requirements of DTs. These technologies enable the real-time processing of vast datasets, ensuring that the DT models remain highly accurate and can effectively assess the resilience of wind turbines.

2.2.2 Data

Effective DT implementation relies on high-quality data acquisition from diverse sensing technologies. As shown in **Figure 3**, SHM sensors, including strain and vision sensors, provide real-time insights into the condition of critical components such as tower flanges and blades, enabling continuous structural assessment and early failure detection [29,30]. Additionally, acoustic emission-based sensing techniques have been successfully applied to various infrastructure monitoring tasks, such as rail track condition assessment [31]. Complementing these, environmental monitoring sensors, which measure wind speed, humidity, and temperature, capture external stressors that influence turbine performance and resilience to extreme weather and mechanical fatigue [32,33]. Wireless smart sensor networks (WSSN) have become an integral part of SHM systems, facilitating efficient measurement, assessment, and maintenance of civil infrastructure through real-time monitoring and data exchange [34].

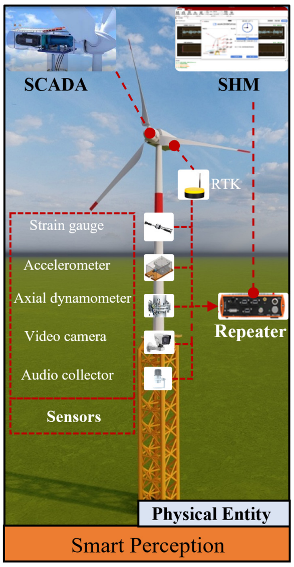


Figure 3. Monitoring framework for wind turbine support structures.

Beyond data collection, efficient transmission and processing are essential for real-time decision-making. Edge computing plays a crucial role by enabling localized data processing, reducing latency, and improving the responsiveness of adaptive control strategies. By ensuring that high-quality data is processed rapidly and accurately, edge computing enhances predictive modelling, AI-driven diagnostics, and overall turbine reliability, minimizing failure risks and optimizing long-term performance.

2.3 The Role of AI-Driven DTs for Resilient Structures

AI-driven DTs play a critical role in enhancing the resilience of wind turbine structures through continuous condition assessment, operational control, repowering, and lifespan extension strategies.

2.3.1 Condition Assessment

Condition assessment is crucial for ensuring the long-term reliability and operational efficiency of wind turbine structures. DT technology, combined with AI-driven predictive analytics, enables real-time monitoring and early fault detection, thereby enhancing structural performance and reducing maintenance costs.

Wind turbine condition monitoring relies on a combination of SCADA, condition monitoring systems (CMS), and DT-based simulations. SCADA provides operational data, while CMS integrates sensor-based structural health monitoring. Advanced methodologies such as fuzzy synthetic assessment and k-means clustering algorithms further refine condition assessment by classifying turbine working conditions and optimizing alarm thresholds [35,36]. A data-informed dynamic approach (DIDA) can be established for the real-time structural condition assessment of aging towers by integrating both prior knowledge from prediction and simulation models and posterior observations from in-situ health monitoring and inspections. For instance, bolt deterioration is highly prone to fatigue cracking, a failure mode that significantly impacts the long-term stability of wind turbine towers. **Figure 4** illustrates how the DIDA framework enables resilience assessment by continuously updating the structural condition of in-service wind towers based on real-time monitoring and historical degradation patterns. This approach enhances predictive maintenance strategies by dynamically calibrating fatigue life estimations and providing insights into future structural evolution.

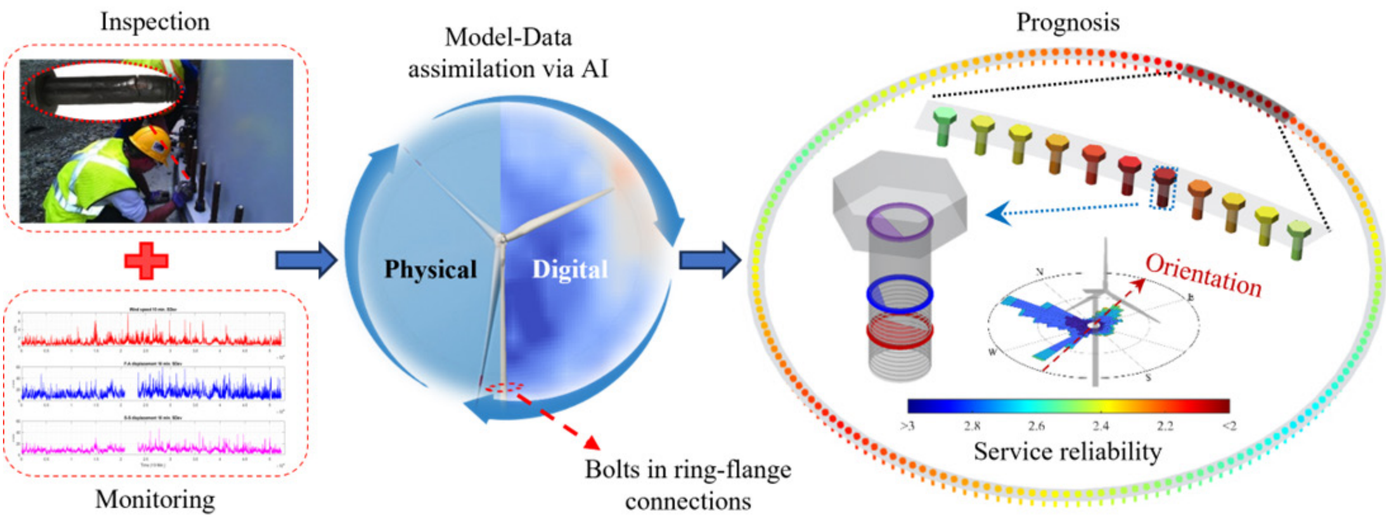


Figure 4. AI-based structural condition assessment of wind turbines (illustrated with bolted ring-flange connections).

DT-based condition assessment further enhances predictive maintenance capabilities. These virtual models integrate real-time load monitoring, stress analysis, and degradation modelling to estimate the remaining useful life (RUL) of critical components such as drivetrain shafts and wind turbine gearboxes. Studies show that DT-informed fatigue assessments significantly reduce uncertainty in failure prediction and maintenance scheduling [37–39].

Additionally, real-time adaptation of control strategies based on condition assessment findings has proven to minimize operational risks. AI-enhanced diagnostic models help mitigate dynamic loads, reducing fatigue damage accumulation by as much as 40% in certain cases [40].

2.3.2 Operational Control

Operational control strategies, particularly those involving AI and DTs, are crucial for optimizing wind turbine performance by adjusting parameters like blade pitch and rotor speed in response to changing environmental conditions. These dynamic adjustments maximize efficiency while reducing excessive wear on key components. AI-driven adaptive control systems help balance loads across the turbine structure, minimizing fatigue risk and extending the lifespan of critical parts such as blades and towers.

AI and DT technologies enable turbines to respond to real-time data, adjusting operational parameters to enhance performance and protect structural integrity, as depicted in **Figure 5**. For example, Yao et al. demonstrated that an optimized active power dispatching strategy could reduce fatigue loads by up to 57.1% during de-loading operations, highlighting the effectiveness of AI-driven adjustments in mitigating damage [41]. Similarly, Jensen et al. showed that optimized power reference controls could reduce damage equivalent load by up to 58.9%, showcasing the impact of predictive control mechanisms [42].

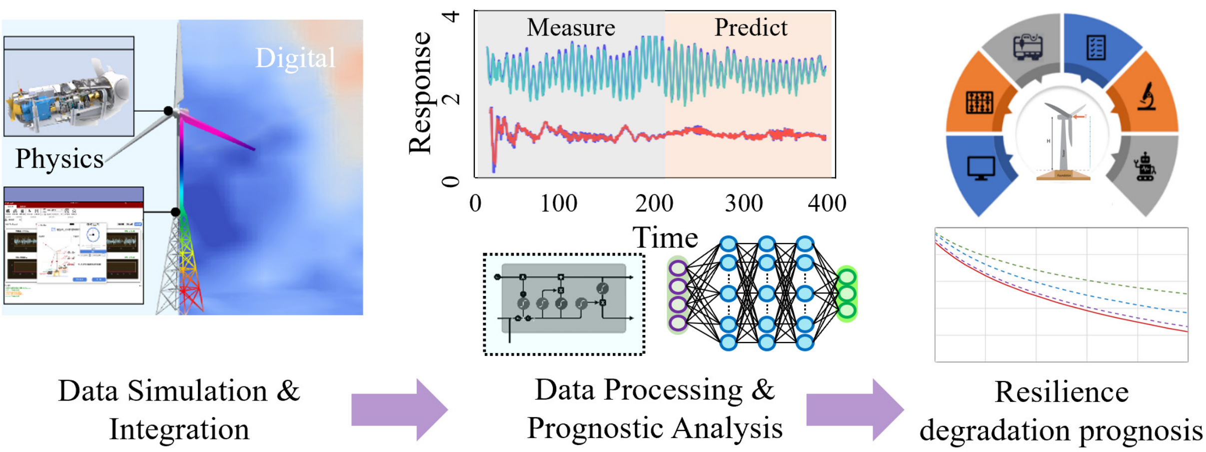


Figure 5. Data-driven method for onshore wind turbine structures under extreme conditions.

These strategies also help manage loads on the turbine structure. Pan et al. proposed a virtual inertia control strategy that mitigates fatigue loads from frequency regulation, reducing stress on turbine components [43]. Kipchirchir et al. found that optimized control could lower dynamic structural loads on rotor blades by 10.7% and on towers by 36.2%, contributing to longer turbine lifespans [11].

Additionally, real-time damage assessment integrated with de-rating control methods has proven effective in reducing damage accumulation. Njiri et al. reported a 40% reduction in damage accumulation, further emphasizing the role of AI and

DTs in enhancing turbine durability [44]. These advancements demonstrate that operational control, powered by AI and DTs, is key to improving turbine performance and extending component lifespans.

2.3.3 Repowering and Lifespan Extension

Repowering is a comprehensive process that upgrades or replaces aging wind turbine components, such as blades, generators, and controllers, to enhance performance, efficiency, and energy output, thereby extending the lifespan of wind farms. This strategy enables wind farms to leverage technological advancements without requiring new sites, which is particularly beneficial as prime wind energy locations become scarce or costly. With advancements in turbine technology, including larger, more efficient blades and advanced energy conversion systems, repowering significantly boosts the energy production of existing turbines. By integrating DTs, operators can simulate and predict turbine performance, ensuring data-driven decisions that optimize repowering efforts and enhance the economic viability of wind farms. **Figure 6** illustrates the integrated process of repowering, highlighting its potential and challenges. The schematic representation emphasizes key strategies such as increasing turbine height, strengthening structural components, and implementing advanced control technologies like SCADA and tuning control. It also contrasts outdated configurations with modern repowered designs, demonstrating how repowering serves as a unified approach to optimizing wind energy capture and extending operational lifespan.

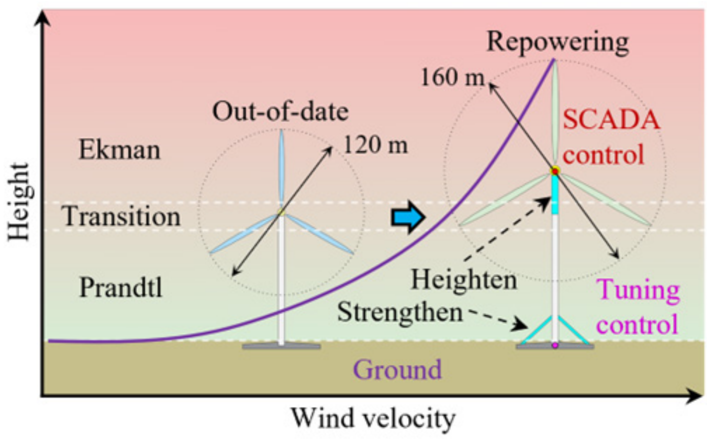


Figure 6. Schematic representation of repowering potential, process, and challenges.

For example, in Germany, repowering has been a crucial strategy due to the aging wind turbine fleet. Researches indicate that repowering old turbines with modern, larger-capacity models significantly enhances energy production. In some cases, repowered wind farms have shown an increase in energy output by up to 110% compared to their baseline performance in 2021, depending on geographical and technological factors [45]. Similarly, in Denmark, repowering efforts have replaced aging turbines with more efficient models, leading to an increase in capacity factor by close to 10% and a reduction in reactive power consumption [46]. Additionally, life cycle assessment (LCA) studies have shown that the environmental benefits of repowering outweigh its impacts. The process significantly offsets carbon emissions by increasing renewable energy generation. For instance, an LCA study found that the carbon footprint of decommissioning old turbines and installing new ones is clearly offset by the long-term reduction in emissions due to higher efficiency [47].

Moreover, repowering is often more socially acceptable than constructing new wind farms because it utilizes existing sites, reducing land-use conflicts and preserving established grid connections. This strategy aligns with broader national energy goals, such as Germany's plan to phase out coal-based electricity by 2038, where repowering is expected to play a significant role in maintaining and expanding wind energy contributions [45]. Overall, repowering is proving to be a vital tool in ensuring the continued viability and expansion of wind energy, balancing economic feasibility, environmental benefits, and social acceptance.

2.3.4 Enhancing Structural Resilience

Beyond operational enhancements, DTs facilitate structural optimization by enabling data-driven design improvements and real-time structural adaptation. By integrating finite element analysis with real-time sensor data, DTs enable engineers to refine wind turbine support structures, enhancing their load-bearing efficiency and fatigue resistance. For floating offshore wind turbines, DTs assist in optimizing mooring configurations, reducing dynamic responses to wave and wind loads, and improving platform stability under extreme weather conditions [48]. Moreover, AI-driven DTs enable automated topology optimization, identifying optimal material distributions and geometric configurations to maximize structural resilience while minimizing weight and construction costs [49]. Additionally, the integration of remote sensing technologies, such as drones and autonomous robots, enhances maintenance efficiency by reducing human exposure to hazardous conditions [50].

By integrating machine learning and real-time sensor data, DTs enable dynamic adaptation of operational parameters, ensuring optimal wind turbine performance under varying environmental conditions. Through continuous monitoring and anomaly detection, DT-based systems can identify early signs of component degradation, allowing for timely interventions that minimize downtime and extend asset lifespan. Furthermore, the incorporation of remote sensing technologies, such as drones and autonomous robots, enhances maintenance efficiency by reducing human exposure to hazardous conditions. This proactive approach not only improves cost-effectiveness but also strengthens the resilience and sustainability of wind farms [51].

3. Case Study: Prognostic Digital Twinning of Onshore Wind Turbine Towers

In this study, prognostic digital twinning refers to a digital twin paradigm that integrates probabilistic load prediction, model updating, and fatigue-damage evolution to support forward-looking assessment of structural performance.

3.1 Engineering Background

In order to further illustrate the proposed DT framework, a case study has been carried out on an onshore wind turbine with LTH towers, which is regarded as the possible next-generation onshore wind turbines in exploring the rich wind resource at escalating heights [52]. As illustrated in **Figure 7**, the tower structure features a hub height of 180 meters, consisting of a bottom lattice section (0–82.5 m), a top tubular section (87.5–180 m), and a connecting transition piece (82.5–87.5 m). Due to commercial confidentiality, the specific parameters of the turbine used in this project cannot be disclosed. Nevertheless, according to recent studies, onshore hybrid or lattice towers with hub heights around 180 m are typically equipped with 5.5 MW class turbines [53–55], indicating that the adopted configuration remains representative for tall onshore systems. In this work, the NREL 5 MW reference turbine [56], a widely validated and openly available benchmark model, is employed for the subsequent analysis to demonstrate the proposed DT methodology. Similar practices have also been reported in the literature [52], where standard reference models were used as substitutes for confidential industrial configurations to ensure research transparency and comparability.

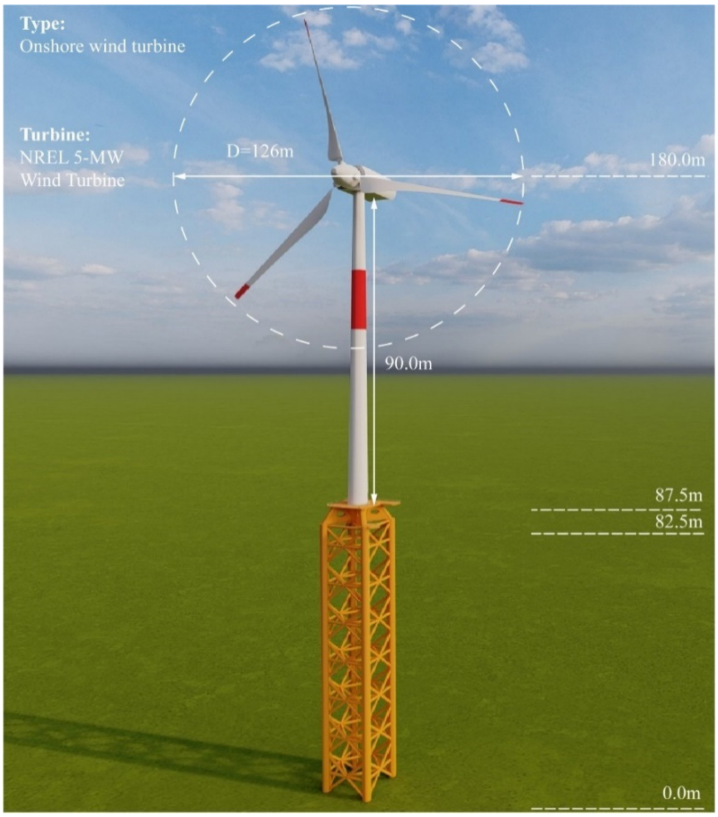


Figure 7. The schematic diagram of the LTH tower.

The deployment site experiences highly variable environmental conditions, including fluctuating wind speeds, temperature changes, and seasonal factors. These conditions impose significant stresses on the tower structure and its connections. Fatigue in bolted ring-flange connections becomes a critical concern, as these components are subjected to cyclic loading and environmental exposure, leading to potential premature failure. Such challenges highlight the importance of advanced monitoring and control systems to assess structural integrity, mitigate fatigue damage, and optimize maintenance strategies, ultimately improving the operational reliability and lifespan of the turbine.

3.2 Wind Field

Wind speed conditions ranging from 3.4 m/s to 23.4 m/s were examined in 2 m/s intervals to capture a range of operational scenarios. A representative case with a mean wind speed of 11.4 m/s is selected to demonstrate the key modeling parameters. Given that the site is located in a region characterized by moderately rough terrain, all relevant wind field parameters are adopted from reference [57]. At hub height, the mean wind speed follows a power law profile with an exponent of 0.20 and a surface roughness length of 0.03 m. The corresponding turbulence intensity reaches 17.377%, with a standard deviation of 1.981 m/s. To maintain spatial coherence, the IEC model is employed with coherence parameters of (12.0, 0.000353) applied to all velocity components. The turbulence length scale is set to 42.0 m, and the integral length scale for the longitudinal (u) component is 340.2 m. **Figure 8(a)** displays the wind speed variation at hub height, while **Figure 8(b)** presents the spatial and temporal distribution of the full wind field. The wind simulation utilizes a 31×31 grid with a time resolution of 0.1 seconds, yielding 700 seconds of usable data. To ensure data quality, the first 100 seconds, typically affected by transient behaviour, are excluded, and the interval from 100 to 700 seconds is retained for further analysis.

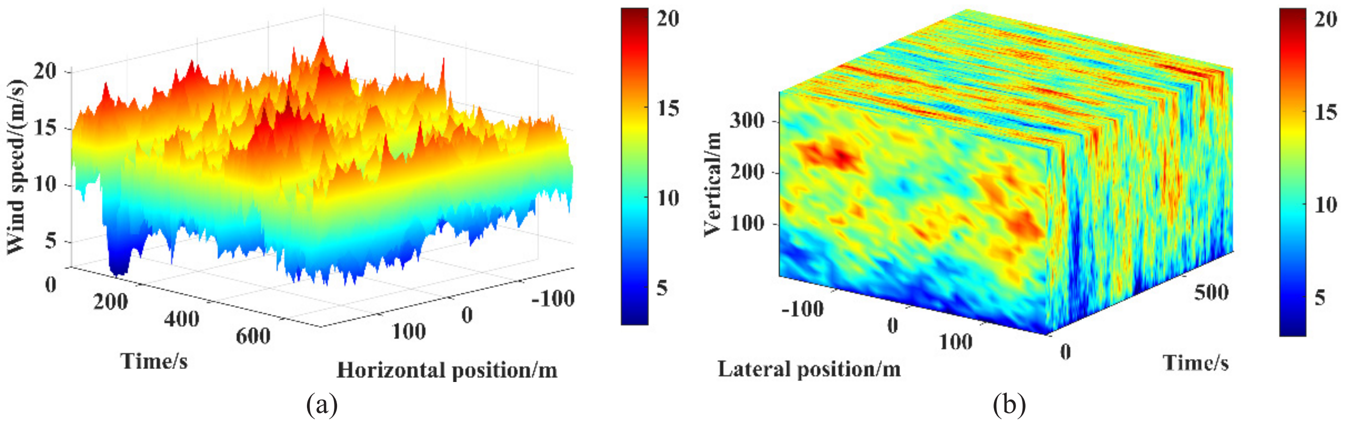


Figure 8. Wind speed characteristics at hub height and full-field distribution: (a) wind speed at hub height; (b) full-field wind speed distribution.

3.3 Data Preparation and DT Model

To demonstrate the feasibility of the proposed DT framework, a comprehensive numerical and data-driven workflow is developed for the LTH wind turbine tower. The framework integrates aerodynamic simulation, structural response analysis, virtual sensing, and model updating into a unified closed-loop information system. The goal is to replicate, in a virtual environment, the physical behavior and degradation process of the tower under realistic operating conditions, thus enabling continuous performance assessment and fatigue damage evaluation (**Figure 9**).

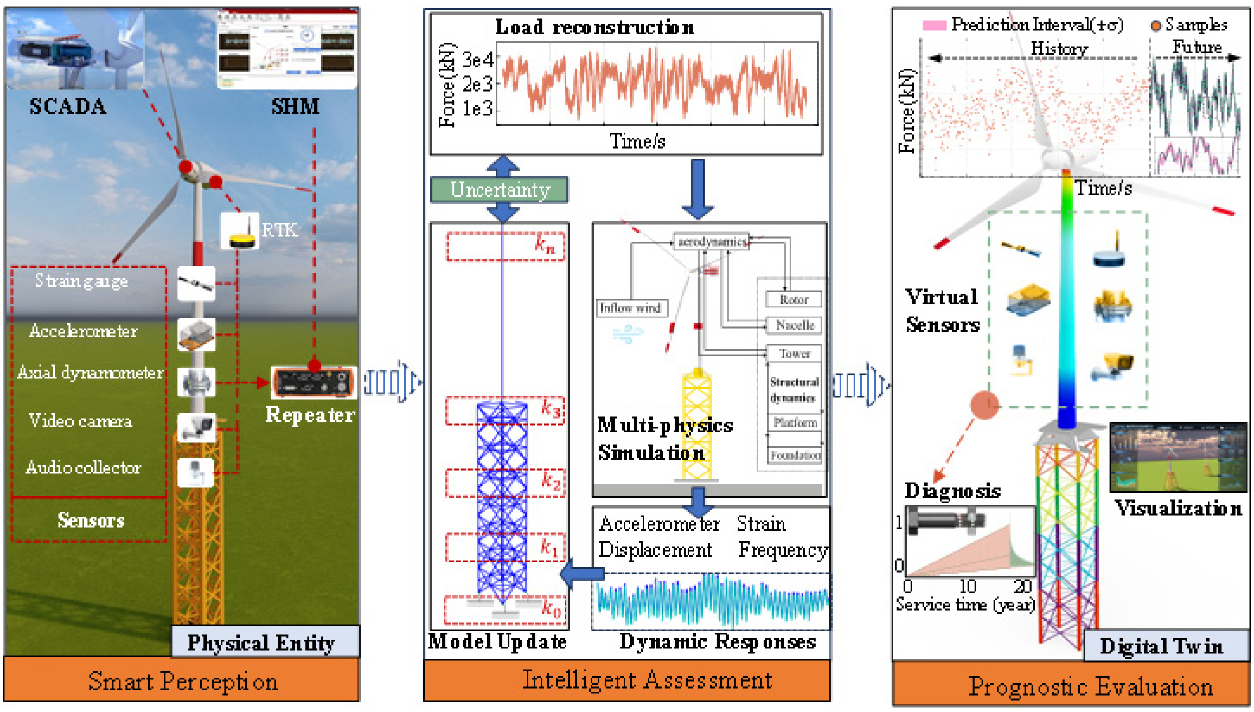


Figure 9. The DT framework for LTH wind turbine towers.

3.3.1 Multi-Physics Simulation and Data Synthesis

The DT begins with multi-physics numerical simulation that combines OpenFAST and OpenSees to generate synthetic SCADA and SHM data. The OpenFAST platform models the aerodynamic, mechanical, and control subsystems of the 5 MW reference wind turbine. The tubular section of the tower and the rotor–nacelle assembly are defined following standard OpenFAST configurations, while the lattice section is represented through the SubDyn module, which performs high-fidelity computation for substructure dynamics.

At each time step, OpenFAST calculates the unsteady aerodynamic loads, rotor thrust, torque, and bending moments at the tower base, taking into account stochastic turbulent wind inputs derived from site-specific Weibull distributions. These time-series load components are then transferred to the OpenSees structural model via a data-exchange interface developed for sequential coupling. This integrated simulation produces artificial datasets that emulate field measurements, including tower-top displacement, nacelle acceleration, axial strain, and power output. These synthetic SCADA and SHM data serve as the virtual observation layer of the DT, providing inputs for both model calibration and subsequent fatigue-damage analysis. The approach allows the numerical twin to operate as a proxy for a real turbine, maintaining the same data structure and time-synchronization protocol used in operational monitoring systems.

3.3.2 Framework Configuration and Data Flow

The DT framework operates through a hybrid sequential-coupling architecture between OpenFAST and OpenSees, enabling bidirectional data exchange and model synchronization. OpenFAST first computes the aerodynamic and operational loads under varying wind speeds, yaw angles, and turbulence intensities. These computed loads are then applied as boundary conditions in OpenSees to determine the structural response of the LTH tower, including time-varying displacements, stresses, and internal forces. The simulation results, together with virtual sensor data, are continuously stored in a shared database that serves as the central communication hub of the DT. This sequential coupling approach avoids the high computational cost of fully coupled aeroelastic simulation while maintaining sufficient accuracy for fatigue analysis. To ensure consistency between aerodynamic excitation and structural response, stiffness coefficients and modal parameters are periodically updated and synchronized between the two platforms. Through this process, the DT framework is capable of reconstructing load paths, estimating fatigue-damage evolution.

3.3.3 Virtual Sensing and Monitoring-Data Integration

To replicate field-level monitoring while maintaining practical efficiency, a hybrid virtual–physical sensing configuration is implemented within the simulation framework. Instead of dense instrumentation, the strategy relies on multi-modal and complementary measurements to achieve full-field observation with limited sensor deployment. Real-time kinematic (RTK) [58] receivers are positioned at the tower top and transition segment to provide high-accuracy displacement and tilt tracking. Accelerometers are distributed along the tower axis to record vibration responses, supporting modal identification and dynamic amplification analysis. Strain gauges are installed on representative sections of the tubular segment, rather than at bolted joint interfaces, to monitor axial and bending strains of the tower wall. These strain data, when combined with displacement and acceleration responses, allow indirect estimation of sectional bending moments and shear forces.

The synthetic signals produced by the virtual sensors are merged with SCADA records (e.g., rotor speed, pitch angle, power output) to establish a unified multi-source monitoring dataset. This dataset forms the observation layer of the DT, serving for model validation, fatigue-indicator computation, and data-driven parameter updating. In addition, the DT framework enables iterative optimization of sensor placement, identifying the most informative measurement points to balance accuracy and cost. This approach ensures efficient monitoring coverage and lays the groundwork for subsequent studies on DT-driven sensor layout optimization currently under development by the authors.

3.3.4 Model Updating and Load Prediction

Model updating and short-term load prediction are implemented as core functionalities within the proposed AI-driven prognostic digital twinning framework. Beyond traditional load reconstruction, this case study employs the Bayesian Dynamic Linear Model (BDLM) as a probabilistic machine-learning approach to predict key mechanical indicators of the LTH tower, specifically the top bending moment and shear force, using the reconstructed load histories as inputs (detailed in [59]), as shown in **Figure 10**. In this model, the state variables describe the evolving mechanical responses of the tower, while the observation model statistically relates these states to the available monitoring data. Both the state transition and observation processes are governed by Gaussian noise assumptions, enabling the BDLM to capture temporal correlations and quantify uncertainty in the dynamic system.

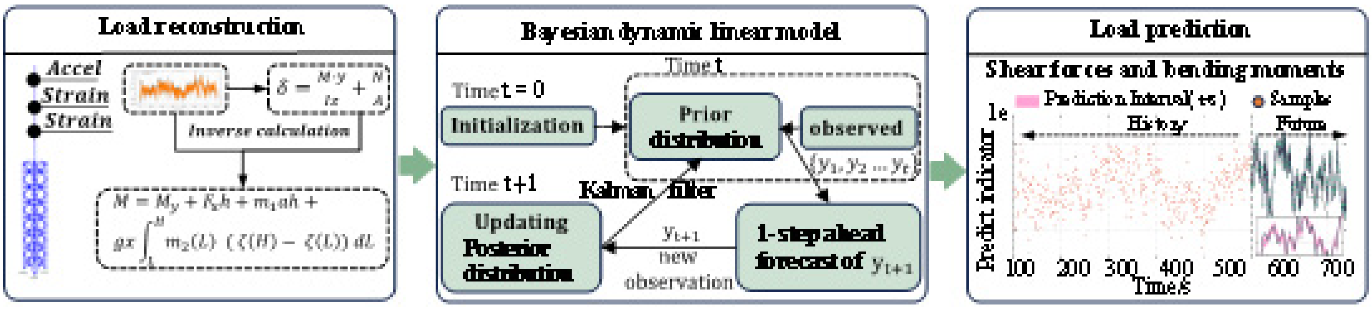


Figure 10. The load prediction flowchart.

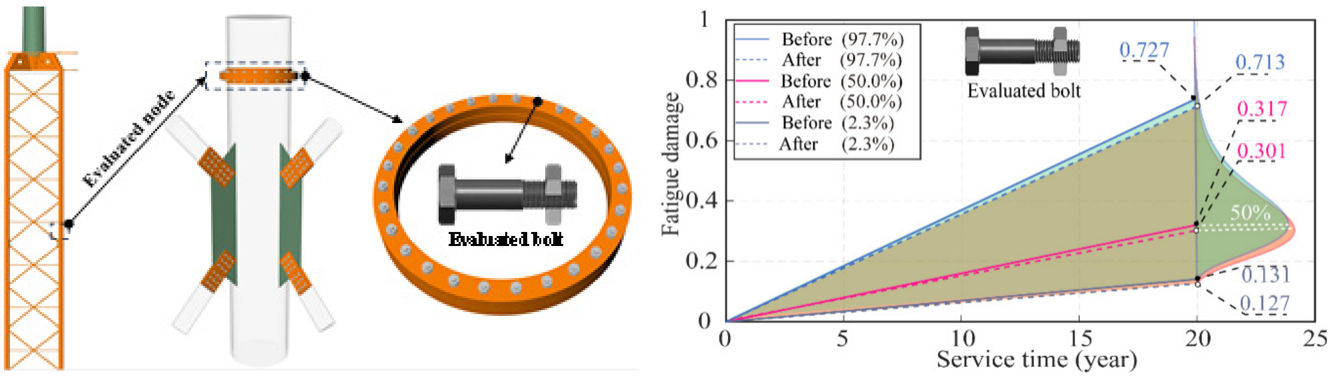
During operation, predictions are sequentially updated as new monitoring data become available through a Kalman-type recursive estimation procedure, which continuously refines both the state and its associated uncertainty. Within the DT, the BDLM prediction loop is fully integrated with the numerical twin: reconstructed load histories provide baseline shear-force and bending-moment profiles; the BDLM then generates short-term forecasts with uncertainty bounds; these forecasts are compared against the monitoring dataset, and the resulting discrepancies inform parameter adjustments in the structural model, such as stiffness and connection flexibility. The updated parameters are subsequently synchronized with the OpenSees simulation for verification, thereby completing the iterative updating cycle.

By combining BDLM-based probabilistic prediction with data-driven model correction, the DT framework achieves continuous refinement of both structural-state estimation and key model parameters, while explicitly quantifying predictive uncertainty. This approach enhances the adaptability and robustness of the DT, ensuring reliable tracking of the tower's mechanical behavior under varying operational conditions.

3.4 Results and Discussion

Figure 11 presents the fatigue assessment results of the bolted ring-flange connections in the LTH wind turbine tower. As shown in **Figure 11(a)**, the evaluated bolts are located at the interface between the tubular section and the transition segment, where axial forces and bending moments induced by wind loading are concentrated. Owing to their fatigue-sensitive nature, these bolts are selected as representative components for evaluating the proposed DT framework.

Figure 11(b) compares the predicted fatigue damage before and after DT-based model updating under different survival probabilities (97.7%, 50%, and 2.3%), representing conservative, median, and lower-bound fatigue life estimates, respectively. Prior to model updating, the fatigue damage coefficients exhibit a noticeable spread across survival probabilities, indicating sensitivity to uncertainty in reconstructed loads and model parameters. After updating, fatigue damage is consistently reduced at all probability levels, with the damage factor decreasing from 0.727 to 0.713 at the conservative (97.7%) survival level. All predicted damage values remain well below the critical threshold of 1.0, confirming a low risk of fatigue failure within the evaluated service period.



(a) (b)

Figure 11. (a) The diagram of bolts; (b) Comparison of fatigue life before and after model update for bolts with different survival rates.

Beyond the reduction in fatigue damage, **Figure 11(b)** provides direct evidence of improved robustness in fatigue prediction. Compared with the initial model, the updated damage estimates show a narrower spread across survival probabilities, indicating reduced variability in predicted fatigue life. This contraction of probability-dependent damage reflects the effectiveness of the DT-based updating process in mitigating key uncertainty sources, including sensor noise, modelling assumptions, and stochastic wind-field variability. In particular, the BDLM accounts for observation noise and model uncertainty through probabilistic state estimation, while stochastic wind-field simulation and sequential updating enable adaptation to fluctuating operating conditions.

From a sensitivity perspective, the reduced separation between fatigue damage estimates at different survival probabilities implies that variations in input conditions lead to smaller deviations in fatigue prediction after model updating. As a result, the proposed DT framework delivers more stable and reliable fatigue assessments without the need for a separate deterministic sensitivity analysis. Validated on a 5 MW onshore wind turbine with an LTH tower, the framework supports robust fatigue evaluation of critical bolted connections under uncertain and variable operating conditions, thereby enabling proactive maintenance planning and resilience-oriented operation.

4. Discussion

The case study in Section 3 validates the proposed AI-driven prognostic digital twinning framework under controlled, simulation-based conditions. By integrating probabilistic load prediction, sequential model updating, and fatigue assessment, the digital twin demonstrates its capability to provide robust fatigue prognosis for critical bolted connections in an LTH wind turbine tower.

It is acknowledged that the current implementation relies on virtual sensors that provide synchronized and noise-free monitoring signals. While this assumption is appropriate for methodological validation, real-world deployment is challenged by sparse and noisy sensing, data heterogeneity, and high computational demand.

To bridge this gap, **Figure 12** summarizes the transition from simulation-based digital twins to field-deployable implementations by explicitly linking deployment challenges, enabling strategies, and practical DT functionalities. As illustrated, challenges such as sparse and noisy sensing, data heterogeneity, and computational latency can be addressed through optimized sensor layouts, virtual–physical sensing fusion, probabilistic modelling, and edge–cloud collaborative computing. These strategies support key field-deployable DT capabilities, including online model updating, real-time fatigue prognosis, scalable DT networks, and O&M decision support.

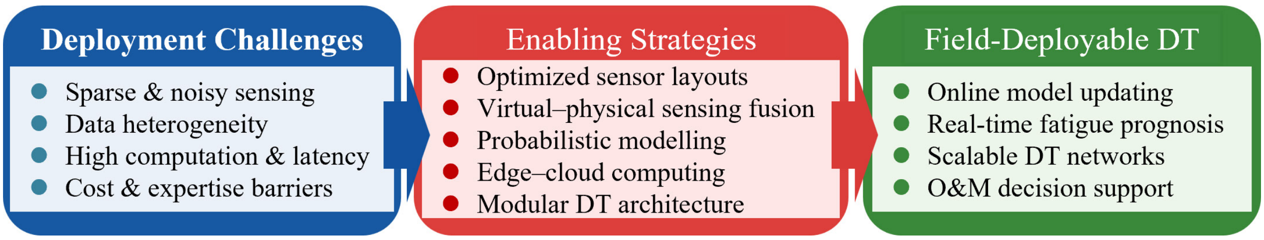


Figure 12. Transition from simulation-based DTs to field-deployable DTs for wind turbine structures.

Within this context, the probabilistic structure of the proposed framework provides a suitable foundation for extending the DT toward real-world applications involving uncertain and imperfect monitoring data.

5. Conclusion

• AI-driven DTs represent a promising direction for improving the resilience and reliability of wind turbines under extreme environmental conditions. By integrating artificial intelligence, SHM, and multi-physics simulation, DTs enable continuous condition assessment, predictive maintenance, and adaptive control. The review confirms that AI techniques, particularly probabilistic learning and adaptive control, provide a solid foundation for resilience-oriented digitalization in wind energy systems;

• Building on these insights, this study develops an AI-assisted DT framework for LTH wind turbine towers. The framework couples OpenFAST and OpenSees for aero-structural simulation, incorporates virtual sensing for data generation, and employs the BDLM for probabilistic load prediction and model updating. This approach effectively links physical behavior with numerical representation, ensuring consistent parameter synchronization and efficient computation;

• The case study on a 5 MW onshore turbine demonstrates that the proposed DT framework can accurately capture dynamic responses and fatigue evolution. After model updating, the predicted fatigue damage of bolted connections was notably reduced, verifying improved stiffness calibration and reduced uncertainty in load estimation. Overall, the framework achieves real-time adaptability and predictive capability, supporting proactive maintenance and enhanced structural resilience of wind turbine towers;

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