Chapter 7

Digital Twin Frameworks for AI-Driven Wind Turbine Monitoring and Predictive Maintenance

Nguyen Duc Thuan
http://orcid.org/0000-0002-5749-5409
Hanoi University of Science and Technology, Vietnam

ABSTRACT

The rapid digitalization of renewable energy systems has made digital twin technology a transformative approach for modeling, monitoring, and optimizing wind turbines. This chapter presents a framework for an AI-powered digital twin that integrates multi-physics modeling, machine learning, and real-time data synchronization. It develops detailed aerodynamic, mechanical, electrical, structural, and thermal models forming a hybrid simulation grounded in physics. Artificial intelligence methods, from machine learning to physics-informed neural networks, enhance fault detection, anomaly diagnosis, and life prediction. A small-scale turbine simulation validates the framework, showing real-time operation, improved torque prediction, and precise anomaly detection. The discussion highlights future directions in multi-agent wind farm twins, uncertainty quantification, explainable AI, and self-evolving models, outlining a roadmap toward autonomous and trustworthy digital energy ecosystems.

1. INTRODUCTION

The global transition toward renewable energy has brought wind power to the forefront as one of the most sustainable and rapidly expanding sources of clean

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electricity (Gielen et al., 2019). Modern wind turbines have evolved into highly complex electromechanical systems that integrate aerodynamic, mechanical, electrical, and control subsystems (Yousefzadeh & Ahmadi Kamarposhti, 2024). As the scale of deployment grows, from individual turbines to geographically distributed wind farms, maintaining reliability and maximizing energy yield have become crucial (McKenna et al., 2016). The increasing penetration of wind energy in power grids also imposes stringent requirements on predictive maintenance, fault diagnosis, and operational optimization (R. K. Pandit et al., 2023). Achieving these goals demands a level of system observability, modeling, and intelligence far beyond that of traditional supervisory control and data acquisition (SCADA) systems.

As wind farms expand in both scale and geographical dispersion, the operational landscape becomes increasingly complex. Offshore wind installations, now exceeding 60-story structures and located tens of kilometers from shore, operate under harsh conditions involving salt corrosion, humidity, severe turbulence, and difficult accessibility (Hassani & Dackermann, 2023). These constraints significantly increase the cost of corrective maintenance, making proactive health assessment essential. Moreover, the variability of wind resources and the intermittency of renewable generation pose additional challenges for grid stability, further motivating the need for intelligent monitoring systems capable of anticipating failures before they propagate into power-quality disruptions or grid imbalance events (Kull et al., 2025; Saleh et al., 2024). The convergence of these industrial pressures underscores why modern wind energy systems require monitoring paradigms far more advanced than the legacy SCADA-based frameworks.

Conventional monitoring frameworks, typically based on SCADA and condition monitoring systems (CMS), provide valuable but limited insights into turbine health. They operate primarily through threshold-based alarms derived from aggregated signals such as rotor speed, wind velocity, temperature, or vibration RMS (R. Pandit et al., 2023). However, these systems often suffer from insufficient temporal resolution, restricted sensor coverage, and weak adaptability to complex degradation dynamics (Tautz-Weinert & Watson, 2017). As a result, they struggle to detect early-stage faults, handle sensor drift, or adapt to changing environmental conditions. The limitations of such rule-based systems are especially evident when dealing with nonlinear and coupled phenomena, such as gearbox wear under fluctuating wind loads or blade fatigue influenced by turbulence intensity (Da Silva et al., 2025).

Beyond their sensing limitations, SCADA and conventional CMS architectures are fundamentally constrained by their one-directional data pipelines and low-level processing capabilities. They lack the architectural flexibility needed to integrate physics-based models, high-rate vibration streams, or edge-level analytics in real time (Wang et al., 2026). As wind turbines increase in rating, moving toward 10–20 MW offshore units, the resulting data ecosystem becomes too rich and complex for

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