

Digital Twin-enabled predictive maintenance in wind, solar PV, hydropower, and battery energy storage systems: a review and maturity framework

Mohamad Fani Sulaima^a, Ashwini Kumar Pradhan^b, Radim Lenort^c, Robert Frischer^d, Ondrej Krejcar^{d,e}, Hamidreza Namazi^{a,d,*}

^a Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

^b School of Computing Science and Engineering, Galgotias University, Greater Noida 203201, India

^c Department of Production, Logistics and Quality Management, Skoda Auto University, Czech Republic

^d Research Center, Skoda Auto University, Czech Republic

^e Center for Basic and Applied Research, Faculty of Informatics and Management, University of Hradec Kralove, Hradec Kralove, Czechia

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ABSTRACT

The rapid digital transformation of energy systems is reshaping how renewable energy assets are monitored, maintained, and optimized across their operational lifecycles. Among emerging digital intelligence paradigms, Digital Twin (DT) technologies have gained prominence as dynamic cyber-physical systems that integrate real-time data, physics-based modeling, and artificial intelligence to enable predictive maintenance and reliability enhancement. This review synthesizes DT technologies applied to predictive maintenance in wind turbines, solar photovoltaic plants, hydropower facilities, and battery energy storage systems. Its novelty lies not only in framing DTs as decision-centric digital intelligence systems that connect sensing, analytics, and maintenance actions to sustainability-oriented outcomes, but also in proposing a Digital Twin Predictive Maintenance Maturity Framework. The framework structures the progression of DT-enabled maintenance from monitoring-oriented implementations toward diagnostic, prognostic, prescriptive, and increasingly autonomous maintenance ecosystems, while integrating architectural, analytical, operational, and deployment-related dimensions for comparative assessment and future research prioritization. The paper further examines enabling technologies, domain-specific implementations, key benefits, and major limitations, and identifies future directions related to explainable and trustworthy intelligence, federated DT ecosystems, autonomous maintenance, and standardized evaluation. Overall, the review positions DT-enabled predictive maintenance as a foundational enabler of intelligent, resilient, and sustainable renewable energy systems.

Introduction

The global transition toward low-carbon and sustainable energy systems has accelerated the deployment of renewable energy technologies such as wind turbines, solar photovoltaic (PV) plants, hydropower facilities, and battery energy storage systems. While these technologies are central to decarbonization strategies, their large-scale integration introduces new operational challenges related to reliability, maintenance cost, and long-term asset performance. Renewable energy assets are typically exposed to highly variable environmental and operational conditions, including fluctuating loads, extreme weather, thermal cycling, and complex grid interactions [1]. These factors accelerate

component degradation and increase the risk of unexpected failures, directly affecting system availability and economic viability.

Maintenance strategies, therefore, play a pivotal role in determining the sustainability of renewable energy infrastructures. Conventional corrective maintenance—performed after failure—results in extended downtime, safety risks, and costly emergency interventions [2]. Preventive maintenance, although more structured, relies on fixed schedules that often fail to reflect the actual health state of components, leading to premature replacements and inefficient resource use [3]. As renewable energy systems expand in scale and complexity, these traditional approaches are increasingly inadequate.

Recent advances in sensing, communication, and data analytics have

* Corresponding author at: Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia.

E-mail address: hamidreza.namazi@monash.edu (H. Namazi).

enabled a shift toward predictive maintenance, in which maintenance actions are triggered based on estimated degradation and failure probability rather than time-based schedules [4,5]. Within this paradigm, Digital Twin (DT) technology has emerged as a cornerstone of digital intelligence for energy systems. A Digital Twin is a continuously evolving virtual representation of a physical asset that synchronizes real-time operational data with computational models to mirror system behavior, diagnose anomalies, and forecast future states [6].

In the context of this review, digital intelligence refers to the integrated capability of a cyber–physical maintenance system to transform real-time data, virtual asset representation, predictive analytics, and domain knowledge into actionable maintenance insight. It should be distinguished from the Digital Twin itself, which primarily provides the synchronized virtual representation of the physical asset and its operating state. In contrast, digital intelligence denotes the higher-level functional layer that interprets DT-generated information, supports fault reasoning and remaining useful life estimation, and enables maintenance-oriented decision support under dynamic operating conditions. Thus, while a Digital Twin forms the structural and computational backbone of the system, digital intelligence describes the adaptive, predictive, and decision-enabling capability that emerges when sensing, modeling, analytics, and operational reasoning are tightly integrated.

The contribution of this review lies in advancing the understanding of Digital Twins not merely as virtual replicas or monitoring tools, but as the enabling backbone of decision-centric digital intelligence systems for predictive maintenance in renewable energy infrastructures. In this framing, the Digital Twin provides the real-time cyber–physical representation, synchronization, and model-based understanding of asset behavior, whereas digital intelligence refers to the higher-level capability to interpret asset states, infer degradation patterns, predict future failures, and support maintenance decisions in an adaptive and operationally meaningful manner. This distinction is important because DT architecture, AI analytics, prognostics, and decision support should not be treated as interchangeable terms; rather, they represent interconnected elements whose integration gives rise to digital intelligence. By adopting this perspective, the review moves beyond technology description and emphasizes how DT-enabled systems can support maintenance action, sustainability, and asset-level decision-making.

The main contributions of this review are threefold. First, it provides a structured cross-domain synthesis of Digital Twin–enabled predictive maintenance across wind turbines, solar photovoltaic systems, hydropower facilities, and battery energy storage systems. Second, it critically compares architectural layers, enabling technologies, reported benefits, and implementation challenges from the perspective of maintenance intelligence, deployment readiness, and practical applicability. Third, it proposes a Digital Twin Predictive Maintenance Maturity Framework that organizes the evolution of DT-enabled maintenance from basic digital monitoring to diagnostic, prognostic, prescriptive, and autonomous maintenance, thereby providing a structured basis for comparative assessment, benchmarking, and future research direction.

To clarify how the present review differs from prior literature surveys on Digital Twins in renewable energy and energy-system contexts, Table 1 compares the scope, methodological emphasis, principal contribution, and relative limitations of representative prior reviews with those of the present study. The comparison shows that the distinctive contribution of this paper lies in combining a cross-domain synthesis of DT-enabled predictive maintenance with a maturity-oriented framework for interpreting capability progression, deployment readiness, and future research priorities across wind, solar PV, hydropower, and battery energy storage systems.

The remainder of this paper is structured to ensure a coherent progression from conceptual foundations to practical implications. Section 2 introduces the Digital Twin concept through a layered digital intelligence architecture. Section 3 synthesizes DT applications across major renewable energy domains. Section 4 reviews enabling technologies that

underpin DT-driven predictive maintenance. Section 5 discusses the operational, economic, and sustainability benefits of DT adoption. Section 6 critically examines existing challenges and limitations. Section 7 presents the proposed Digital Twin Predictive Maintenance Maturity Framework. Section 8 outlines future research directions toward next-generation intelligent and sustainable DT ecosystems. Section 9 concludes the review.

Review methodology

This review was conducted using a structured narrative review approach to provide a transparent, reproducible, and thematically organized synthesis of the literature on Digital Twin–enabled predictive maintenance in renewable energy systems. The review was designed to capture both the breadth of recent developments and the foundational studies necessary to contextualize the evolution of Digital Twin concepts, predictive maintenance strategies, and supporting digital technologies in the energy sector.

The literature search was carried out across major scientific databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect, because these platforms provide broad coverage of engineering, renewable energy, industrial informatics, artificial intelligence, and cyber–physical systems research. To maintain both recency and conceptual depth, the review included peer-reviewed journal articles, relevant conference papers, and a limited number of seminal books and foundational publications where necessary to establish key concepts related to Digital Twins, predictive maintenance, and condition monitoring.

The search strategy was developed around combinations of keywords that reflect the core themes of the review. The main search terms included “Digital Twin,” “predictive maintenance,” “renewable energy,” “wind turbine,” “solar photovoltaic,” “hydropower,” “battery energy storage system,” “condition monitoring,” “fault diagnosis,” “remaining useful life,” “physics-based model,” “machine learning,” “edge computing,” “IoT,” and “cybersecurity.” These terms were used individually and in Boolean combinations to identify literature addressing both general Digital Twin frameworks and application-specific predictive maintenance solutions across renewable energy domains.

The review primarily emphasized literature published between 2018 and 2026, reflecting the rapid recent growth of Digital Twin research in intelligent energy systems during this period. The concentration of reviewed sources within these years also indicates that the field has progressed from early conceptual and enabling-technology studies toward more mature application-oriented research on predictive maintenance, system integration, and decision support in renewable energy systems. However, earlier foundational studies published before 2018 were also included where necessary to define the Digital Twin paradigm, establish the theoretical basis of predictive maintenance, or provide essential background on sensing, simulation, and reliability engineering. This approach ensured that the review remained both up to date and conceptually grounded.

After the initial search, duplicate records were removed, and the remaining sources were screened in two stages. First, titles and abstracts were examined to assess thematic relevance. Second, full-text screening was performed for sources that appeared directly relevant to the scope of the review. The inclusion criteria comprised sources that: (i) addressed Digital Twin architectures, models, or implementation frameworks; (ii) examined predictive maintenance, fault diagnosis, condition monitoring, or remaining useful life estimation; (iii) focused on renewable energy assets such as wind turbines, solar photovoltaic systems, hydropower facilities, or battery energy storage systems; and/or (iv) discussed enabling technologies such as IoT, edge/cloud computing, artificial intelligence, hybrid physics–data-driven modeling, interoperability, or cybersecurity in the context of DT-enabled maintenance. Sources were excluded if they: (i) discussed Digital Twins without meaningful relevance to maintenance or renewable energy applications;

Table 1

Comparison of the present review with representative prior review works on Digital Twins in renewable energy and energy-system contexts.

Prior Review	Main Scope	Review Type / Method	Main Contribution	Main Limitation Relative to This Review	Distinction of the Present Review
Prior DT review on renewable energy systems	Broad overview of DT applications in renewable energy	Narrative or systematic review	Summarizes DT concepts, architectures, and renewable energy use cases	Primarily descriptive; limited focus on predictive maintenance maturity, deployment readiness, or staged DT capability progression	The present review focuses specifically on predictive maintenance across wind, PV, hydropower, and BESS, and proposes a maturity framework that structures DT development from monitoring to autonomous maintenance
Prior AI-integrated DT review	DT combined with AI/ML across industrial or energy settings	Narrative review	Highlights the role of AI, data-driven models, and intelligent analytics in DT systems	Emphasizes AI integration but does not provide a maturity-oriented synthesis for predictive maintenance applications across renewable domains	The present review not only discusses AI as an enabling technology, but also integrates it into a comparative maturity model linked to maintenance intelligence, validation, and deployment readiness
Prior review on DT architecture / enabling technologies	DT layers, IoT, simulation, edge/cloud, and data infrastructure	Thematic review	Explains enabling technologies and layered DT architectures	Architecture-focused; does not distinguish how similar architectures may correspond to different maturity stages or maintenance capabilities	The present review treats architecture as a functional foundation and extends beyond it through a developmental maturity framework
Prior review on condition monitoring / predictive maintenance	Predictive maintenance methods with limited DT focus	Narrative or domain-specific review	Summarizes fault diagnosis, RUL estimation, and condition monitoring techniques	Focuses on maintenance analytics but lacks an integrative DT-centered maturity perspective across renewable energy assets	The present review links maintenance analytics explicitly to DT evolution and proposes six maturity levels from Digital Monitoring Twin to

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Table 1 (continued)

Prior Review	Main Scope	Review Type / Method	Main Contribution	Main Limitation Relative to This Review	Distinction of the Present Review
Prior domain-specific review (wind / PV / BESS / hydropower)	DT applications in one renewable domain	Domain-specific review	Provides deep domain insight for a specific asset class	Limited cross-domain comparison; limited ability to generalize maturity progression across renewable systems	Autonomous Maintenance Twin The present review provides a cross-domain comparison and identifies uneven maturity progression across four major renewable energy domains
Present review	DT-enabled predictive maintenance in wind, solar PV, hydropower, and BESS	Structured narrative review with comparative thematic synthesis	Cross-domain synthesis of DT applications, enabling technologies, benefits, and challenges; proposal of a Digital Twin Predictive Maintenance Maturity Framework		— Distinctive contribution lies in combining cross-domain predictive maintenance synthesis with a maturity-oriented framework for comparative assessment, benchmarking, and future research prioritization

(ii) addressed maintenance strategies without substantive linkage to Digital Twin technologies; (iii) lacked sufficient technical depth or scholarly relevance; or (iv) substantially duplicated findings already represented by other included references.

The final pool of selected sources was synthesized using a qualitative thematic approach. After full-text screening, the retained literature was grouped according to the main analytical dimensions of the review, namely Digital Twin concept and architecture, renewable energy applications, enabling technologies, benefits, challenges and limitations, and future research directions. Within each theme, the cited literature was examined comparatively based on its technical scope,

methodological emphasis, and relevance to DT-enabled predictive maintenance in renewable energy systems. In addition to thematic synthesis, the review was structured to identify recurring capability patterns, maturity differences, validation practices, and deployment constraints across renewable energy domains in order to support the development of a comparative maturity-oriented synthesis framework. This synthesis strategy enabled the review to identify major trends, recurring challenges, transferable design principles, and emerging research gaps across the literature.

Fig. 1 summarizes the review workflow adopted in this study. It visually outlines the identification of literature from major scientific

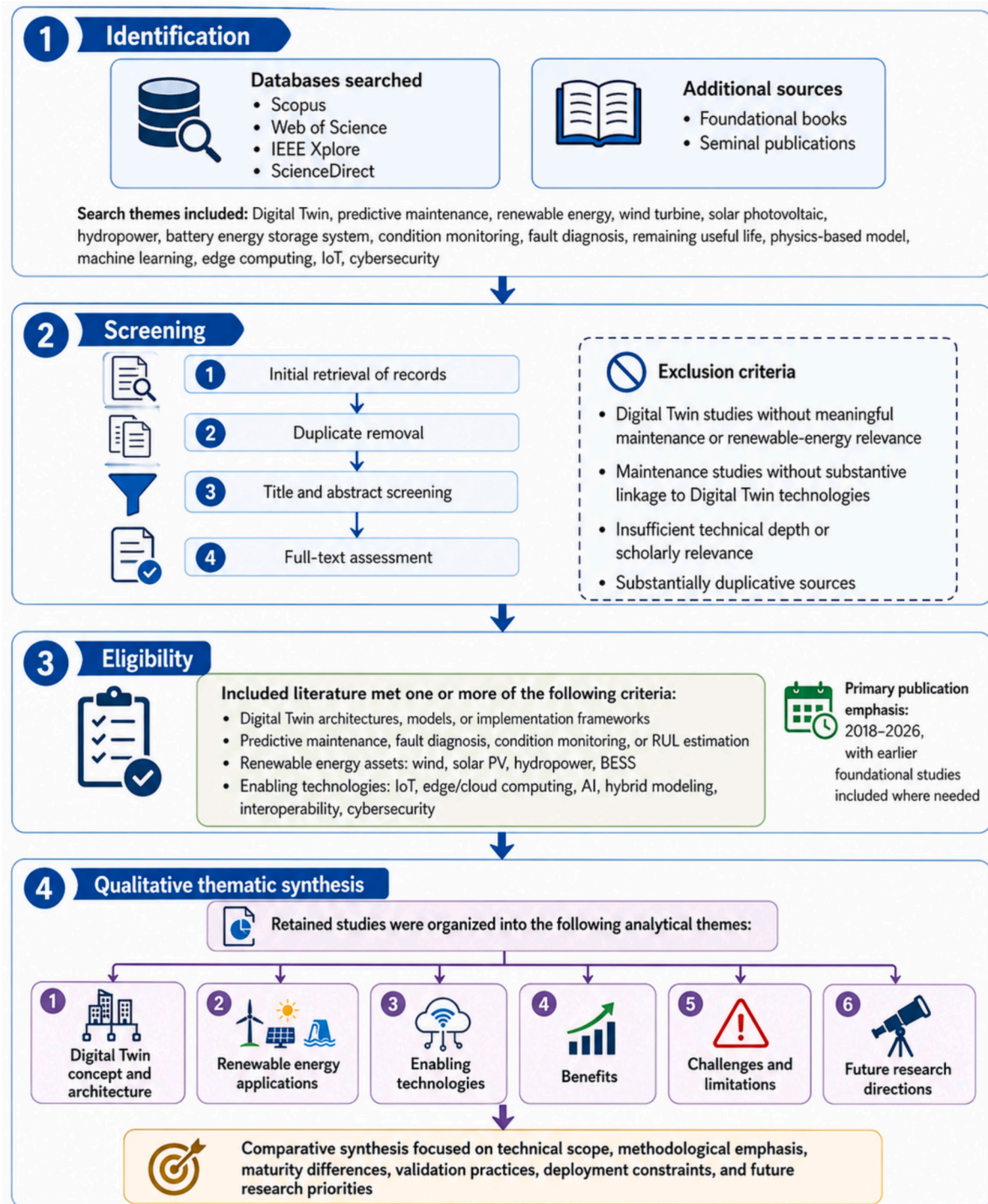


Fig. 1. PRISMA-style flowchart summarizing the literature search, screening, eligibility assessment, and qualitative thematic synthesis process used in this review.

databases and additional foundational sources, the removal of duplicate records, the two-stage screening process based on title/abstract review and full-text assessment, and the application of inclusion and exclusion criteria. The figure also shows how the retained literature was organized for qualitative thematic synthesis across the main analytical dimensions of the review.

Limitations of the review

Despite the structured methodology adopted in this review, several limitations should be acknowledged. First, the review may be affected by publication bias, since published studies are more likely to report successful implementations, positive predictive results, or promising DT applications than negative, inconclusive, or failed deployments. Second, database-related bias may also be present because the literature search was conducted through major indexed sources, namely Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Although these databases provide broad coverage of engineering and energy research, relevant studies indexed elsewhere, reported in industry documents, or published in less visible venues may not have been captured.

Third, the review focuses primarily on renewable energy applications involving wind turbines, solar photovoltaic systems, hydropower facilities, and battery energy storage systems. This means that some adjacent domains, narrower subfields, or cross-sector studies with only partial relevance to renewable energy predictive maintenance may have been excluded during screening. In addition, the review emphasizes English-language scholarly literature, which may limit the representation of region-specific or non-English contributions. Finally, the review is conducted in a field where standardized benchmarks, validation frameworks, and performance metrics remain underdeveloped. As a result, the comparability of reported results across studies is inherently limited, and conclusions regarding DT effectiveness, scalability, and transferability should be interpreted with appropriate caution. These limitations do not undermine the value of the review, but they do shape the scope, coverage, and generalizability of the synthesized findings. The proposed maturity framework should therefore be interpreted as a conceptually grounded synthesis of the reviewed literature rather than as a universally validated industrial standard, and its operational refinement will require future benchmarking and real-world validation. In addition, direct quantitative comparison across studies remains difficult because the reviewed literature varies substantially in asset type, sensing configuration, datasets, prediction targets, model structures, validation protocols, and reported performance metrics.

Digital Twin concept and architecture

Digital Twins (DTs) establish a cyber-physical framework in which physical renewable energy assets are continuously synchronized with their virtual representations for real-time monitoring and predictive analysis. By integrating sensing infrastructure, communication networks, simulation models, and data-driven intelligence, DT architectures enable the systematic capture of dynamic operating conditions and degradation mechanisms that are difficult to observe directly [7]. The layered architecture presented in this section serves as the functional foundation of DT-enabled predictive maintenance. It clarifies how physical systems, data flows, communication, modeling, service logic, and user interaction are organized, but it does not by itself indicate the maturity, autonomy, or deployment readiness of different DT implementations. A clear understanding of this layered architecture is therefore essential for assessing how Digital Twins support predictive maintenance, reliability enhancement, and informed decision-making in renewable energy systems, while also preparing the basis for the maturity-oriented synthesis developed later in the paper. The following subsections describe the key architectural layers and their functional roles.

Physical layer

The physical layer constitutes the foundation of a Digital Twin architecture, representing the tangible assets and hardware components operating in real-world renewable energy systems [8]. This layer typically includes wind turbine subsystems (blades, gearboxes, generators, towers), solar PV modules and inverters, hydropower turbines and generators, as well as battery energy storage units and balance-of-plant components. It also encompasses embedded sensing devices, actuators, and on-site controllers that enable continuous interaction between the physical and virtual domains. In the context of predictive maintenance, the physical layer serves as the source of ground truth, providing real-time operational signals that reflect degradation processes, fault evolution, and environmental stresses.

Extensive research has demonstrated that the fidelity of a Digital Twin is fundamentally constrained by the observability of the physical layer [9]. Early DT studies in wind energy emphasized structural and drivetrain monitoring using vibration sensors, strain gauges, temperature probes, and rotational speed measurements to capture fatigue accumulation and bearing wear [10]. More recent investigations have extended this sensing paradigm to include acoustic emissions, oil debris monitoring, fiber-optic strain sensing, and blade-embedded sensors, enabling the detection of early-stage damage mechanisms that are invisible to conventional SCADA systems [11,12]. In solar PV installations, the physical layer increasingly integrates thermal cameras, irradiance sensors, and distributed voltage and current monitors to capture localized faults such as hotspots, cell cracks, and bypass diode failures [13]. Similarly, hydropower DTs rely on pressure sensors, flow meters, shaft displacement probes, and temperature measurements to model cavitation, erosion, and misalignment phenomena [14].

From a systems perspective, the physical layer is no longer viewed as a static object but as a dynamically evolving entity whose behavior is influenced by operational conditions, environmental variability, and maintenance interventions [15]. Researchers have shown that Digital Twins capable of tracking component ageing must explicitly account for load histories, duty cycles, transient events, and extreme conditions such as gusts, grid faults, or thermal excursions [16,17]. This has motivated the deployment of high-resolution sensing infrastructure capable of capturing both steady-state and transient dynamics. In offshore wind and remote PV plants, physical-layer design is further complicated by accessibility constraints, power limitations, and harsh environments, driving research toward low-power wireless sensors, energy harvesting devices, and robust packaging strategies [18].

An important trend in the literature is the coupling of physical assets with embedded intelligence at the edge. Instead of functioning solely as passive data sources, modern physical layers increasingly host edge processors that perform preliminary diagnostics, anomaly screening, and data compression [19]. This reduces communication bandwidth requirements and enables faster responses to critical events. Studies in battery energy storage systems have demonstrated that embedding physical-layer thermal and electrochemical sensors significantly improves the accuracy of Digital Twin predictions for state-of-health and remaining useful life [20].

Despite these advances, the physical layer remains a major bottleneck in Digital Twin deployment. Sensor placement optimization, long-term sensor reliability, calibration drift, and retrofit feasibility for legacy assets continue to be active research challenges [21]. Nevertheless, the literature consistently affirms that a well-instrumented and intelligently designed physical layer is indispensable for realizing high-confidence, predictive Digital Twins in renewable energy systems [22].

Data acquisition layer

The data acquisition layer bridges physical assets and their virtual counterparts by continuously capturing, conditioning, and transmitting operational information [23]. This layer typically relies on a

combination of industrial Internet of Things (IoT) devices, supervisory control and data acquisition (SCADA) systems, and distributed monitoring platforms to collect multi-modal data streams. In Digital Twin-enabled predictive maintenance, data acquisition determines not only the temporal resolution of monitoring but also the scope of phenomena that can be digitally reconstructed, diagnosed, and forecast [24].

Prior research highlights that renewable energy systems generate heterogeneous data at vastly different sampling rates and granularities [25]. SCADA data, commonly sampled at intervals of seconds or minutes, provide system-level indicators such as power output, rotational speed, temperatures, and alarms [26]. In contrast, condition-monitoring sensors—such as accelerometers or acoustic emission sensors—produce high-frequency data capable of revealing incipient faults but at the cost of increased storage and processing demands [27]. Digital Twin studies in wind turbines have demonstrated that fusing high-frequency vibration signals with low-frequency SCADA data significantly enhances fault detection sensitivity while maintaining scalability [28]. Similar findings have been reported in PV systems, where combining electrical measurements with thermal image streams enables early identification of degradation patterns before substantial energy losses occur [29].

The literature increasingly emphasizes intelligent data acquisition strategies rather than brute-force data collection. Event-driven sensing, adaptive sampling, and compressed sensing techniques have been proposed to reduce data redundancy while preserving diagnostically relevant information [30]. For example, adaptive sampling schemes increase sensor resolution during abnormal operating conditions and revert to low-rate monitoring during normal operation [31]. In hydropower and battery systems, such approaches reduce sensor wear and energy consumption while extending monitoring coverage over long operational lifetimes.

Preprocessing and data conditioning are integral components of the data acquisition layer. Noise filtering, outlier removal, synchronization, and missing-data handling are essential to prevent error propagation into the Virtual Model Layer. Numerous studies have shown that improperly conditioned data can lead to model drift, false alarms, and degraded remaining useful life predictions [32]. Consequently, modern DT architectures often embed preprocessing pipelines at or near the data acquisition stage, particularly for real-time applications [33].

Another key theme in the literature is data provenance and traceability. Tracking sensor health, calibration status, and metadata has been identified as critical for long-term Digital Twin reliability [34]. In large renewable plants, where sensor replacements and maintenance actions are frequent, failure to account for metadata changes can corrupt historical datasets and invalidate trend analyses [35]. Emerging solutions incorporate standardized data schemas and semantic tagging to preserve contextual information throughout the DT lifecycle.

Overall, the data acquisition layer is transitioning from a passive data collection function to an intelligent, adaptive subsystem that actively supports predictive maintenance objectives. Its design strongly influences Digital Twin accuracy, robustness, and economic viability, making it a focal point of ongoing DT research and industrial innovation.

Communication layer

The communication layer enables bidirectional information flow between physical assets, data acquisition systems, and virtual models, forming the connective tissue of the Digital Twin architecture [36]. In renewable energy applications—often characterized by geographically dispersed and remotely located assets—communication performance directly affects synchronization accuracy, latency, scalability, and system resilience [37]. Communication infrastructure is widely recognized as both a critical enabler and a potential vulnerability in DT-driven predictive maintenance systems [38].

A wide range of communication technologies has been adopted across renewable energy Digital Twins. Short-range industrial protocols

such as OPC-UA and fieldbus systems are commonly used within turbines, substations, and battery containers for deterministic and secure data exchange [39]. At the plant and fleet levels, lightweight messaging protocols like MQTT have gained prominence due to their scalability and low overhead, particularly for IoT-based DT implementations [40]. For long-range connectivity, wireless technologies such as LoRaWAN are widely applied in remote PV plants and hydropower facilities, where low data rates are sufficient for condition monitoring and energy efficiency is paramount [41]. More recently, 5G networks have emerged as a promising solution for latency-sensitive DT applications, especially in offshore wind farms and autonomous inspection scenarios [42].

Research has shown that communication latency and packet loss can significantly compromise Digital Twin fidelity [43]. Delayed or incomplete data streams result in desynchronized virtual models, reducing the accuracy of fault diagnosis and remaining useful life estimation. To address this, several studies propose edge-to-cloud architectures in which preliminary analytics are performed locally, and only distilled information is transmitted to centralized DT platforms [44]. This hierarchical communication strategy reduces bandwidth usage while maintaining situational awareness. Event-based communication, where data transmission is triggered by anomalies rather than continuous streaming, has also been demonstrated to be effective in reducing network congestion [45].

Cybersecurity is a dominant theme in communication-layer research. As DTs rely on continuous connectivity, they introduce expanded attack surfaces for cyber threats such as spoofing, denial-of-service attacks, and data manipulation. The literature highlights that compromised communication channels can lead to erroneous predictive maintenance decisions, unnecessary shutdowns, or unsafe operating conditions [46]. Consequently, secure communication protocols, encryption schemes, authentication mechanisms, and intrusion detection systems are increasingly integrated into DT communication frameworks [47]. Emerging research explores blockchain-based communication logs and zero-trust architectures to enhance trustworthiness and auditability [48,49].

Interoperability presents another persistent challenge. Renewable energy plants often consist of equipment from multiple vendors using proprietary protocols and data formats. Communication-layer research has therefore focused on middleware solutions and standardized data models that enable seamless integration across heterogeneous systems [50]. Without such abstraction layers, Digital Twins remain tightly coupled to specific hardware configurations, limiting portability and scalability.

In summary, the communication layer is far more than a transmission conduit; it actively shapes the responsiveness, robustness, and security of Digital Twin systems. Advances in wireless networking, edge communication strategies, and secure protocols continue to play a decisive role in enabling reliable DT-based predictive maintenance across renewable energy infrastructures.

Virtual model layer

The virtual model layer represents the analytical core of the Digital Twin, where physical reality is abstracted, simulated, and forecast through computational models. This layer integrates physics-based simulations, data-driven analytics, and hybrid modeling approaches to replicate the operational behavior and degradation dynamics of renewable energy assets. The literature broadly agrees that the predictive power of a Digital Twin is governed by the fidelity, adaptability, and interpretability of this virtual representation [51].

Early Digital Twin formulations relied predominantly on physics-based models such as finite element analysis (FEA) for structural components and computational fluid dynamics (CFD) for aerodynamic and hydrodynamic processes. In wind energy, such models have long been used to analyze blade loading, fatigue accumulation, and tower dynamics. Hydropower DT studies similarly employ CFD to simulate

cavitation and flow-induced vibrations [52]. While these models provide deep physical insight, their high computational cost limits their applicability for real-time predictive maintenance.

To overcome this limitation, the literature has increasingly shifted toward data-driven and machine learning-based models. Supervised learning algorithms, deep neural networks, and probabilistic models have been widely adopted to identify fault signatures, predict remaining useful life, and model nonlinear degradation processes [53,54]. In PV systems, data-driven DTs have proven effective for inverter failure prediction and performance loss estimation under variable irradiance and temperature conditions [55]. Battery DTs leveraging machine learning have significantly improved state-of-health estimation by learning complex electrochemical aging patterns that are difficult to express analytically [56].

More recent research emphasizes hybrid physics-machine learning models as a unifying solution. These models embed physical constraints within learning architectures, combining the generalization capability of machine learning with the interpretability and extrapolation strength of physics-based formulations. Studies consistently demonstrate that hybrid DTs outperform purely data-driven models under data scarcity, non-stationarity, and rare failure events—conditions commonly encountered in renewable energy systems [57]. Such hybrid approaches are particularly important for long-term predictive maintenance, where models must remain reliable despite evolving operating conditions.

Model updating and synchronization are central challenges in the virtual model layer. The literature highlights the need for continuous parameter adaptation as components age, undergo maintenance, or experience environmental shifts [58]. Techniques such as online learning, Bayesian updating, and digital twin calibration are increasingly incorporated to prevent model drift [59]. Additionally, uncertainty quantification has emerged as a critical research topic, enabling maintenance decisions that account for prediction confidence rather than relying on deterministic outputs [60].

Overall, the virtual model layer has evolved into a sophisticated, multi-disciplinary environment where simulation, AI, and domain knowledge converge. Its ongoing development is pivotal for advancing Digital Twin-based predictive maintenance from descriptive monitoring toward fully prognostic and decision-support systems.

Service layer

The service layer operationalizes the insights generated by the Digital Twin, translating complex simulations and predictions into actionable maintenance intelligence. This layer interfaces directly with asset management systems, maintenance planners, and operational decision-making processes. In the literature, the service layer is widely regarded as the value-realization component of Digital Twin architectures, where analytical capability is transformed into tangible reliability and economic benefits [61].

Core services provided by DT platforms include fault detection, anomaly diagnosis, remaining useful life estimation, and maintenance scheduling optimization. Numerous studies across wind, solar, hydro-power, and battery systems demonstrate that DT-based services outperform traditional threshold-based monitoring by identifying early degradation patterns before critical failure thresholds are crossed [62,63]. For example, predictive maintenance services for wind turbine gearboxes integrate vibration-based fault indicators with Digital Twin simulations to forecast failure timelines, allowing maintenance actions to be scheduled during low-wind periods [64]. Similar service-level benefits have been reported for inverter replacement planning in PV plants and thermal management interventions in battery systems [65].

Beyond diagnostics, the service layer increasingly supports prescriptive maintenance. Rather than merely predicting failures, modern DT services evaluate multiple intervention scenarios and recommend optimal actions based on cost, safety, downtime, and resource availability. Optimization algorithms embedded within the service layer

balance competing objectives such as minimizing maintenance cost while maximizing asset availability. Fleet-level DT services extend this capability by prioritizing maintenance across multiple assets, considering spare-part logistics and workforce constraints.

Visualization and explainability are critical functions of the service layer. Studies emphasize that maintenance engineers are more likely to trust DT outputs when predictions are accompanied by interpretable indicators, trend explanations, and uncertainty ranges [66]. Consequently, service-layer research has expanded to include explainable AI techniques that highlight contributing factors behind predicted failures. This is particularly important in safety-critical renewable energy systems, where opaque decision logic can hinder adoption.

Integration with enterprise systems is another major theme in DT service-layer research. Effective service layers interface with computerized maintenance management systems (CMMS), enterprise resource planning (ERP) tools, and energy management platforms. Such integration ensures that DT insights influence real maintenance actions rather than remaining isolated within analytical dashboards. Interoperability challenges persist, but standardized APIs and service-oriented architectures are increasingly proposed as solutions.

In summary, the service layer transforms Digital Twins from analytical models into operational tools. Its maturity largely determines whether DT technologies deliver measurable improvements in reliability, cost efficiency, and asset lifespan within renewable energy systems.

User interface layer

The user interface (UI) layer represents the human-Digital Twin interaction point, where complex analytical outputs are communicated to operators, engineers, and decision-makers. Although often treated as a secondary consideration, the UI layer is increasingly recognized as a critical determinant of Digital Twin adoption and effectiveness in predictive maintenance [67]. A technically advanced DT system fails to deliver value if its insights cannot be intuitively understood and acted upon by human users.

Traditional DT interfaces rely on dashboards displaying key performance indicators such as temperature trends, vibration levels, predicted remaining useful life, and alarm states [68]. Studies in wind and PV maintenance show that well-designed dashboards reduce cognitive load and improve response time during abnormal events [69]. However, as DT models become more complex, there is a growing emphasis on advanced visualization techniques that convey uncertainty, temporal evolution, and spatial distribution of faults [70]. Heat maps, degradation trajectories, and probabilistic failure envelopes are increasingly used to support maintenance planning.

Recent research explores immersive interfaces using augmented reality (AR) and virtual reality (VR). These approaches allow technicians to visualize hidden internal states—such as stress distribution in turbine blades or thermal gradients in battery packs—overlaid directly onto physical assets. AR-enabled DT interfaces have been shown to improve inspection efficiency, reduce human error, and accelerate training [71]. In offshore and remote renewable energy sites, such interfaces are particularly valuable for supporting less experienced personnel.

Explainability and interaction are central themes in UI-layer studies. Modern interfaces increasingly allow users to query the Digital Twin, explore “what-if” scenarios, and adjust assumptions to understand model behavior. This interactive capability fosters trust and encourages proactive engagement with DT insights rather than passive monitoring. Additionally, role-specific interfaces are often proposed, where high-level managers, maintenance engineers, and data scientists access tailored views aligned with their responsibilities [72].

In conclusion, the user interface layer plays a vital role in bridging advanced Digital Twin analytics and practical maintenance action. Its thoughtful design enhances usability, trust, and organizational readiness—factors that are as crucial as technical accuracy in the successful

deployment of DT-based predictive maintenance systems.

The layered structure of Digital Twin architectures—including physical assets, data acquisition, communication, virtual modeling, service, and user interface layers—and their respective roles in predictive maintenance are summarized in Table 2.

Although the layered architecture provides a useful functional view of DT-enabled predictive maintenance systems, implementations that share similar layers may still differ substantially in sensing depth, model sophistication, prognostic capability, validation rigor, decision autonomy, and industrial readiness. This limitation motivates the maturity-oriented framework proposed later in the manuscript, which extends beyond structural composition to interpret the developmental progression of DT-enabled maintenance systems across renewable energy domains.

Digital Twin applications in renewable energy predictive maintenance

Digital Twin applications in renewable energy systems translate architectural concepts into domain-specific predictive maintenance solutions. While the core DT framework remains consistent, each renewable technology presents distinct operational dynamics, failure modes, and data characteristics that shape how Digital Twins are implemented and utilized. This section reviews major application domains and synthesizes how DTs enhance maintenance intelligence across different renewable energy assets.

Wind turbines

Wind turbines constitute the most extensively studied application domain for Digital Twin-based predictive maintenance. In wind energy, mechanical subsystems—particularly gearboxes, bearings, and shafts—are especially well suited to DT modeling because their degradation is strongly coupled to variable operational loading. A consistent finding across wind-focused studies is that combining vibration-based condition monitoring with physics-based drivetrain models improves the early detection of abnormal loading patterns, fatigue accumulation, and incipient faults beyond what SCADA data alone can provide

Table 2
Layered Digital Twin Architecture and Functions for Predictive Maintenance.

Digital Twin Layer	Components	Data	Function
Physical Layer	Renewable assets, sensors, actuators, controllers	Vibration, temperature, strain, electrical signals	Captures real-time operational behavior and degradation processes
Data Acquisition Layer	IoT devices, SCADA systems, preprocessing pipelines	Time-series data, thermal images, event logs	Data conditioning, synchronization, and quality assurance
Communication Layer	OPC-UA, MQTT, wireless networks, 5G/LoRaWAN	Streaming and event-driven data	Enables real-time data transfer and DT synchronization
Virtual Model Layer	Physics-based models, machine learning models, hybrid models	Health states, remaining useful life estimates, uncertainty	Fault diagnosis and degradation forecasting
Service Layer	Diagnostics, prognostics, optimization services	Maintenance recommendations	Maintenance planning and decision support
User Interface Layer	Dashboards, visualization tools, AR/VR interfaces	Visual health indicators and trends	Human-Digital Twin interaction and interpretability

[73,74]. These DTs are frequently enhanced with data-driven models to capture nonlinear interactions between wind conditions, control actions, and component wear, leading to significantly extended fault warning horizons.

Blade-related DT applications are also widely documented. Extensive experimental and numerical studies show that aeroelastic DTs integrating aerodynamic load simulations with structural response data can detect damage mechanisms such as crack initiation, delamination, erosion, and icing [75]. When coupled with strain sensing, acoustic emission monitoring, or image-based inspection data, these DTs support condition-based blade maintenance and reduce unnecessary inspections, particularly in offshore installations where access is limited.

Generator and power electronics monitoring represents another mature DT application area. Multiple investigations report that thermal-electromagnetic DTs can effectively capture insulation aging, converter stress, and cooling system degradation under fluctuating wind and grid conditions [76]. Such DTs enable early detection of overheating and abnormal electrical behavior, which are among the leading causes of turbine downtime.

More recent studies extend DT applications to full-turbine and wind-farm levels. Integrated DTs combining structural dynamics, drivetrain behavior, and control system models support holistic integrity assessment and maintenance prioritization across fleets [77]. Farm-level DT implementations further enable risk-based scheduling, lifetime consumption tracking, and health-aware operational strategies.

Overall, the literature shows that DTs substantially improve reliability, availability, and maintenance efficiency in wind energy systems, and from a maturity perspective, wind energy appears to be among the more advanced renewable domains in DT-enabled predictive maintenance, particularly in diagnostic and prognostic applications involving drivetrain, blade, and generator monitoring. Some recent studies also suggest movement toward prescriptive maintenance and fleet-level decision support, although fully autonomous maintenance capability remains limited [78].

Solar photovoltaic (PV) systems

Digital Twin applications in solar PV systems primarily address performance degradation, fault localization, and inverter reliability. A broad range of studies report that module-level DTs based on electrical, thermal, and environmental models can accurately distinguish between normal performance fluctuations and degradation-driven losses [79]. By integrating irradiance, temperature, and IV-curve data, these DTs capture degradation mechanisms such as soiling, encapsulant aging, interconnect degradation, and cell mismatch.

Thermal-imaging-enhanced DTs are especially prominent in PV research, where combining infrared measurements with electrical performance models improves detection of localized faults such as hotspots, microcracks, and bypass diode failures [80]. These DTs enable targeted interventions at the string or module level, reducing yield losses and maintenance costs in large-scale PV plants.

Inverter-focused DT research is also extensive. In inverter-oriented PV applications, DTs that capture component-level stress accumulation, thermal cycling, and harmonic effects are particularly effective for predicting degradation of capacitors, power semiconductor devices, and control electronics [81,82]. Machine learning-augmented DTs improve remaining useful life estimation for inverters, enabling condition-based replacement strategies that avoid unplanned outages [83].

At the plant level, DTs integrating meteorological forecasts, shading analysis, and degradation models are widely reported [84]. Such DTs support predictive maintenance planning, performance benchmarking, and optimization of cleaning and inspection schedules. Fleet-level implementations further enable early identification of underperforming assets across geographically distributed PV installations. Collectively, the literature confirms that DT-driven predictive maintenance significantly enhances operational transparency and long-term

performance sustainability in PV systems [85].

In maturity terms, PV-oriented DT applications can be regarded as moderately developed, with notable strengths in fault localization, performance degradation tracking, and inverter prognostics. However, compared with wind and some emerging BESS applications, most PV implementations remain less advanced in prescriptive maintenance capability, autonomy, and large-scale deployment integration.

Hydropower systems

Hydropower systems represent a long-standing but increasingly active application area for Digital Twin technologies, particularly for turbine wear, hydraulic performance, and structural safety assessment. In hydropower systems, DTs that couple flow simulations with pressure, vibration, and acoustic measurements are especially effective in capturing cavitation dynamics, erosion progression, and efficiency losses in hydraulic turbines [86,87]. These DTs enable early identification of damaging operating regimes and support maintenance strategies that mitigate wear without major hardware modification.

Electromechanical DT applications for generators, shafts, and bearings are also extensively reported. A recurring pattern in hydropower research is that integrating electromagnetic and structural models with vibration and temperature data improves detection of misalignment, imbalance, and insulation degradation [88]. Such DTs reduce reliance on periodic manual inspections and enhance fault localization accuracy in complex shaft-line systems.

Beyond rotating machinery, DTs are increasingly applied to civil infrastructure associated with hydropower plants. Multiple investigations report the use of large-scale structural DTs that integrate finite element models with water level, stress, displacement, and environmental data to monitor dam safety and long-term material degradation [89,90]. These applications extend predictive maintenance from individual components to entire hydropower systems.

From a maturity standpoint, hydropower DTs show strong development in asset-specific modeling, hydraulic performance analysis, and structural health monitoring [91,92], but their maturity remains uneven across sub-assets and application contexts. In particular, mature monitoring and simulation capabilities are more evident than standardized prognostic, prescriptive, or autonomous maintenance implementations across integrated hydropower systems.

Battery energy storage systems (BESS)

Battery Energy Storage Systems have become a major focus of Digital Twin research due to their rapid deployment and sensitivity to aging and safety risks [93]. BESS-oriented DT frameworks commonly combine electrochemical or equivalent-circuit models with operational measurements to estimate state of charge, state of health, and internal degradation parameters [94]. These DTs enable continuous tracking of capacity fade and resistance growth under realistic cycling and environmental conditions.

Data-driven enhancements to battery DTs are widely documented. Across BESS studies, integrating machine learning with physics-based representations consistently improves degradation modeling and remaining useful life prediction, particularly under variable load profiles [95]. Hybrid DTs are repeatedly shown to outperform purely empirical approaches, especially for long-term prognostics and early fault detection.

Thermal DTs receive strong attention in the literature due to safety considerations. Extensive experimental and modeling studies show that real-time thermal DTs can detect abnormal heat generation, cooling inefficiencies, and spatial temperature gradients that precede thermal runaway events [96,97]. DT-informed thermal management strategies have been reported to enhance both safety and lifespan [98].

At the system and fleet levels, DTs are increasingly applied to optimize maintenance and operation of large-scale storage installations.

Aggregated DT outputs enable anomaly detection across populations, capacity planning, and health-aware dispatch strategies [99]. Overall, the existing literature confirms that Digital Twins play a critical role in enabling safe, reliable, and economically sustainable battery energy storage systems. In comparative maturity terms, BESS represents one of the most rapidly advancing DT domains, especially in state-of-health estimation, degradation prognostics, and safety-aware thermal management. Nevertheless, despite this rapid progress, the field still faces important challenges related to validation consistency, interoperability, and standardization for large-scale industrial deployment.

Taken together, the reviewed studies show that Digital Twin implementations vary significantly across renewable energy domains in both technical emphasis and maintenance purpose. Wind energy DTs are dominated by the need to monitor mechanically complex rotating components under highly variable loading, making structural, aero-elastic, and drivetrain prognostics especially important. In contrast, PV-oriented DTs focus more strongly on electrical-thermal fault localization, inverter ageing, and performance degradation under environmental exposure. Hydropower DTs differ further by requiring integration across hydraulic, electromechanical, and civil infrastructure layers, thereby extending predictive maintenance beyond machinery to long-life structural assets. BESS DTs are more strongly shaped by electrochemical degradation, thermal runaway risk, and the need for continuous state-of-health and safety estimation. These contrasts suggest that the maturity, architecture, and practical value of DT-based predictive maintenance depend heavily on domain-specific degradation physics, sensing accessibility, safety implications, and maintenance decision horizons.

To make these domain-specific differences more explicit, Table 3 presents a cross-domain comparison of Digital Twin applications, asset types, dominant degradation mechanisms, DT modeling priorities, predictive maintenance outcomes, and relative maturity characteristics across major renewable energy technologies.

Although the reviewed studies enable meaningful cross-domain comparison at the level of DT purpose, model emphasis, and maintenance role, direct benchmarking of predictive performance remains limited because the literature uses heterogeneous datasets, sensing configurations, prediction targets, validation protocols, and reporting metrics. As a result, comparisons across domains should be interpreted cautiously, particularly when considering quantitative performance claims or industrial deployment readiness.

Enabling technologies for DT-driven predictive maintenance

The effectiveness of Digital Twins in predictive maintenance relies on the coordinated advancement of several enabling technologies spanning sensing, computation, analytics, simulation, and cybersecurity. A substantial body of published research demonstrates that Digital Twins are not standalone solutions but integrative frameworks that synthesize these technologies into a coherent cyber-physical system [100]. This section reviews the key enabling technologies that underpin DT-driven predictive maintenance in renewable energy systems and summarizes how existing studies leverage them to enhance reliability, scalability, and decision-making accuracy.

Internet of Things (IoT) and advanced sensing

IoT technologies form the backbone of Digital Twin implementations by providing continuous, real-time data streams from physical assets. Extensive research across renewable energy sectors highlights that dense and heterogeneous sensing is essential for capturing early degradation signatures that precede failures [101]. Studies consistently report that IoT-based sensor networks—comprising vibration, temperature, pressure, strain, electrical, acoustic, and environmental sensors—enable high observability of complex systems such as wind turbines, PV plants, hydropower units, and battery storage systems

Table 3

Cross-domain comparison of Digital Twin applications for predictive maintenance across major renewable energy systems.

Renewable Energy Domain	Asset Type	DT Modeling Focus	Dominant Degradation / Failure Mechanisms	Predictive Maintenance Outcome	Relative Maturity Characteristic
Wind Energy	Gearboxes, blades, generators	Structural, aeroelastic, and thermal DTs	Fatigue, bearing wear, blade damage, icing	Early fault detection, reduced downtime, improved maintenance efficiency	Relatively advanced, especially in diagnostic and prognostic DT applications
Solar Photovoltaic	Modules, inverters	Electrical–thermal DTs	Hotspots, microcracks, inverter aging	Targeted replacement, performance recovery, improved operational transparency	Moderately developed, with strengths in fault localization and inverter prognostics
Hydropower	Turbines, shafts, dams	CFD-based, electromechanical, and structural DTs	Cavitation, erosion, misalignment, structural degradation	Reduced forced outages, improved safety assessment, long-term asset management	Uneven maturity across sub-assets; stronger in monitoring and simulation than in standardized prognostics
Battery Energy Storage Systems	Cells, packs, cooling systems	Electrochemical–thermal DTs	Capacity fade, resistance growth, overheating	Safety-aware maintenance, life extension, health-aware operation	Rapidly advancing, especially in SOH estimation, degradation prognostics, and safety-oriented DT applications

[102,103].

A large body of work demonstrates that IoT technologies allow DTs to move beyond periodic inspections toward continuous condition awareness. In wind and hydropower systems, distributed vibration and pressure sensing supports early detection of fatigue, cavitation, and misalignment [104]. In PV systems, IoT-enabled electrical and thermal sensors enable real-time tracking of module mismatch, inverter stress, and performance degradation [105]. Battery systems benefit from embedded voltage and temperature sensing combined with impedance-based measurements to monitor electrochemical aging and safety-critical conditions [106].

Multiple studies emphasize the importance of smart and adaptive sensing strategies. Rather than uniform data collection, IoT-enabled DTs increasingly employ event-triggered sensing, adaptive sampling, and context-aware activation to focus resources on high-risk operating conditions [107]. These approaches reduce data redundancy, communication overhead, and sensor wear while preserving diagnostic sensitivity. Research also highlights the role of low-power wireless sensors and energy-harvesting devices in enabling long-term monitoring of remote or offshore renewable assets [108].

Interoperability and scalability are recurrent themes in the IoT literature. Standardized data formats, semantic descriptions, and device abstraction layers are widely reported as prerequisites for integrating heterogeneous IoT devices into unified DT platforms [109]. Overall, prior studies clearly establish IoT and advanced sensing as fundamental enablers that determine the resolution, responsiveness, and long-term viability of DT-driven predictive maintenance.

Edge and cloud computing infrastructure

Edge and cloud computing technologies play a central role in managing the computational demands of Digital Twin frameworks. The literature widely reports that DTs generate and process large volumes of multi-modal data while running complex simulations and predictive models, necessitating scalable and flexible computing infrastructure [110]. Cloud platforms are commonly used to host high-fidelity simulations, fleet-level analytics, and long-term historical data storage, whereas edge computing addresses latency, bandwidth, and reliability constraints [111].

Numerous studies demonstrate that edge computing enables preliminary diagnostics, feature extraction, and anomaly detection to be performed close to the physical asset [112]. This is particularly valuable for time-critical applications such as fault detection in wind turbine drivetrains, inverter protection, or battery thermal monitoring. Edge-based DT implementations reduce communication delays and allow continued operation even under intermittent connectivity, a frequent challenge in offshore wind farms and remote hydropower sites [113].

Cloud-based DT architectures are extensively reported for large-scale optimization and predictive analytics. These environments support

computationally intensive tasks such as multi-physics simulations, ensemble machine learning training, uncertainty quantification, and fleet-level maintenance scheduling. Cloud-enabled DTs are particularly valuable for cross-asset comparison, benchmarking, and centralized decision-making across geographically distributed renewable installations [114].

Hybrid edge–cloud architectures are increasingly emphasized as best practice. A common conclusion across recent studies is that intelligently partitioning DT functionality across edge and cloud layers improves scalability and robustness while balancing computational cost. Research also explores containerization, microservices, and virtualization to increase portability and ease deployment across different renewable platforms [115].

Taken together, these studies indicate that advanced computing infrastructure is not merely supportive but structurally integral to DT-driven predictive maintenance, directly influencing responsiveness, scalability, and economic feasibility.

Artificial intelligence and machine learning

Artificial intelligence and machine learning are among the most extensively studied enabling technologies for Digital Twins. Across the reviewed renewable energy domains, AI methods significantly enhance DT capabilities for fault detection, degradation modeling, and remaining useful life estimation [116,117]. Machine learning models are widely used to capture nonlinear system behavior, handle noisy data, and identify complex patterns that are difficult to encode analytically [118].

Supervised, unsupervised, and semi-supervised learning techniques have all been reported in DT frameworks. Unsupervised approaches are particularly highlighted for anomaly detection in systems where labeled fault data are scarce [119]. Deep learning models, including convolutional and recurrent architectures, are widely applied to vibration signals, thermal images, and time-series operational data [120]. Reinforcement learning is increasingly explored for maintenance decision optimization and condition-aware control strategies [121].

At the same time, purely data-driven approaches remain limited by data dependency, model opacity, and weak generalization under changing operating conditions [122]. As a result, hybrid physics–ML models are a dominant research trend. A strong trend in recent works is the embedding of physical constraints, degradation laws, or simulation outputs within learning architectures to improve robustness, interpretability, and data efficiency. These hybrid DTs are repeatedly shown to outperform standalone AI models in long-term predictive maintenance tasks [123].

Recent research further highlights the importance of explainable and trustworthy AI within DT frameworks. Techniques for feature attribution, uncertainty estimation, and confidence quantification are increasingly integrated to support decision transparency [124]. Overall, published studies make it clear that AI is most effective when tightly

coupled with physical modeling rather than used in isolation.

High-fidelity simulation and physics-based modeling

Physics-based simulation remains a cornerstone of Digital Twin technology, particularly for capturing multi-physics interactions and extrapolating system behavior beyond observed data. The literature documents widespread use of finite element analysis, computational fluid dynamics, thermal–electrical modeling, and electrochemical simulation across renewable energy DT applications [125]. These models provide interpretable representations of stress, flow, heat transfer, and degradation mechanisms.

High-fidelity simulations are particularly effective for modeling blade fatigue, cavitation erosion, thermal hotspots, and battery aging dynamics [126]. Such models are especially valuable for predictive maintenance because they allow exploration of hypothetical scenarios, extreme loading events, and long-term degradation pathways that may not be directly observable in operational data.

Given their computational cost, many works focus on model reduction and surrogate modeling techniques. Reduced-order models, response surfaces, and digital surrogates trained on simulation data are widely reported as effective compromises between accuracy and real-time feasibility [127–129]. These approaches enable physics-informed DTs that can operate continuously while retaining physical interpretability.

Cybersecurity, data integrity, and trustworthy DT operation

Cybersecurity is increasingly recognized as a critical enabling technology for Digital Twin deployment. DTs introduce expanded attack surfaces because they rely on continuous connectivity, cloud integration, and communication networks [130]. Compromised DTs can lead to incorrect maintenance decisions, unsafe operating conditions, or cascading failures in interconnected energy systems.

Recent studies have focused on vulnerabilities such as data tampering, false-data injection, unauthorized access, and denial-of-service attacks targeting DT infrastructures [131]. Proposed mitigation strategies include encrypted communication channels, authentication mechanisms, intrusion detection systems, and secure data management protocols. Blockchain-based approaches are frequently reported for ensuring data integrity, traceability, and tamper resistance within DT ecosystems [132].

Trustworthiness and validation are also emphasized as critical concerns. Another recurring concern is the need for continuous verification of DT outputs, monitoring of model drift, and assessment of uncertainty to prevent overreliance on inaccurate predictions. Privacy-preserving techniques, including federated learning and secure multi-party computation, are increasingly explored to protect sensitive operational data while enabling collaborative analytics [133].

Overall, the literature confirms that robust cybersecurity and trust mechanisms are indispensable for safe and scalable DT-driven predictive maintenance, particularly as renewable energy systems become more interconnected and autonomous.

Each enabling technology discussed in this section contributes to specific Digital Twin capabilities while simultaneously addressing known limitations related to data availability, computational scalability, interpretability, and cybersecurity, as summarized in Table 4.

From a methodological standpoint, the reviewed DT studies can be broadly grouped into three modeling categories: physics-based approaches, data-driven approaches, and hybrid physics–data-driven approaches. Physics-based models provide interpretability and mechanistic consistency, data-driven models offer flexibility in capturing nonlinear patterns from operational data, and hybrid models aim to combine these strengths for more robust predictive maintenance under uncertainty and changing operating conditions. This taxonomy is important because the relative use of these model classes influences DT

Table 4

Enabling Technologies for Digital Twin–Driven Predictive Maintenance and Addressed Limitations.

Enabling Technology	Role	DT Capability Enabled	Limitation
IoT and Advanced Sensing	Continuous, multi-modal condition monitoring	High observability of degradation	Limited sensor coverage in legacy assets
Edge and Cloud Computing	Distributed analytics and scalable computation	Low-latency and large-scale DT operation	Bandwidth and computational constraints
Artificial Intelligence and Machine Learning	Learning nonlinear degradation patterns	Fault detection and RUL prediction	Data dependency and model opacity
Physics-Based Simulation	Mechanistic system representation	Interpretability and extrapolation capability	High computational cost
Cybersecurity Technologies	Secure communication and data protection	Trustworthy DT operation	Vulnerability to cyber attacks

maturity, validation requirements, and deployment readiness across renewable energy domains.

The enabling technologies reviewed in this section do not contribute equally across all stages of DT development. Basic monitoring-oriented implementations may rely primarily on sensing, connectivity, and simple analytics, whereas higher-maturity stages increasingly require hybrid modeling, uncertainty-aware artificial intelligence, secure edge–cloud coordination, explainability, and interoperable service integration. Accordingly, these technologies should be understood not only as isolated enablers, but also as progression factors that determine how far a DT system can evolve from descriptive monitoring toward prescriptive and increasingly autonomous maintenance.

Fig. 2 visually summarizes the methodological taxonomy discussed in this section by comparing the three principal Digital Twin modeling approaches—physics-based, data-driven, and hybrid physics–data-driven—across the four renewable energy domains covered in the review. It highlights how each model class is used in relation to domain-specific predictive maintenance tasks, including structural and thermal behavior analysis, fault detection, anomaly identification, state estimation, remaining useful life prediction, and safety assessment. The figure is intended as a qualitative synthesis of modeling patterns reported in the reviewed literature rather than as a quantitative benchmark.

Benefits of Digital Twins in predictive maintenance

Across the reviewed literature, Digital Twin–driven predictive maintenance is associated with several transformative benefits for renewable energy systems by enabling a shift from reactive or schedule-based maintenance to proactive, condition-aware decision-making [134]. One of the most widely reported advantages of DTs is their ability to detect faults at very early stages by continuously comparing real-time operational data with expected system behavior derived from virtual models [135]. This model-based consistency checking allows DTs to identify subtle deviations associated with incipient mechanical, electrical, thermal, or electrochemical degradation that often remain undetected by conventional threshold-based monitoring. As a result, DTs provide significantly longer warning horizons for emerging failures, improving the accuracy of remaining useful life predictions under variable and non-stationary operating conditions.

These enhanced prognostic capabilities directly translate into reduced unplanned downtime and lower maintenance costs. A recurring finding is that DT-enabled predictive maintenance minimizes emergency repairs by enabling maintenance actions to be scheduled during

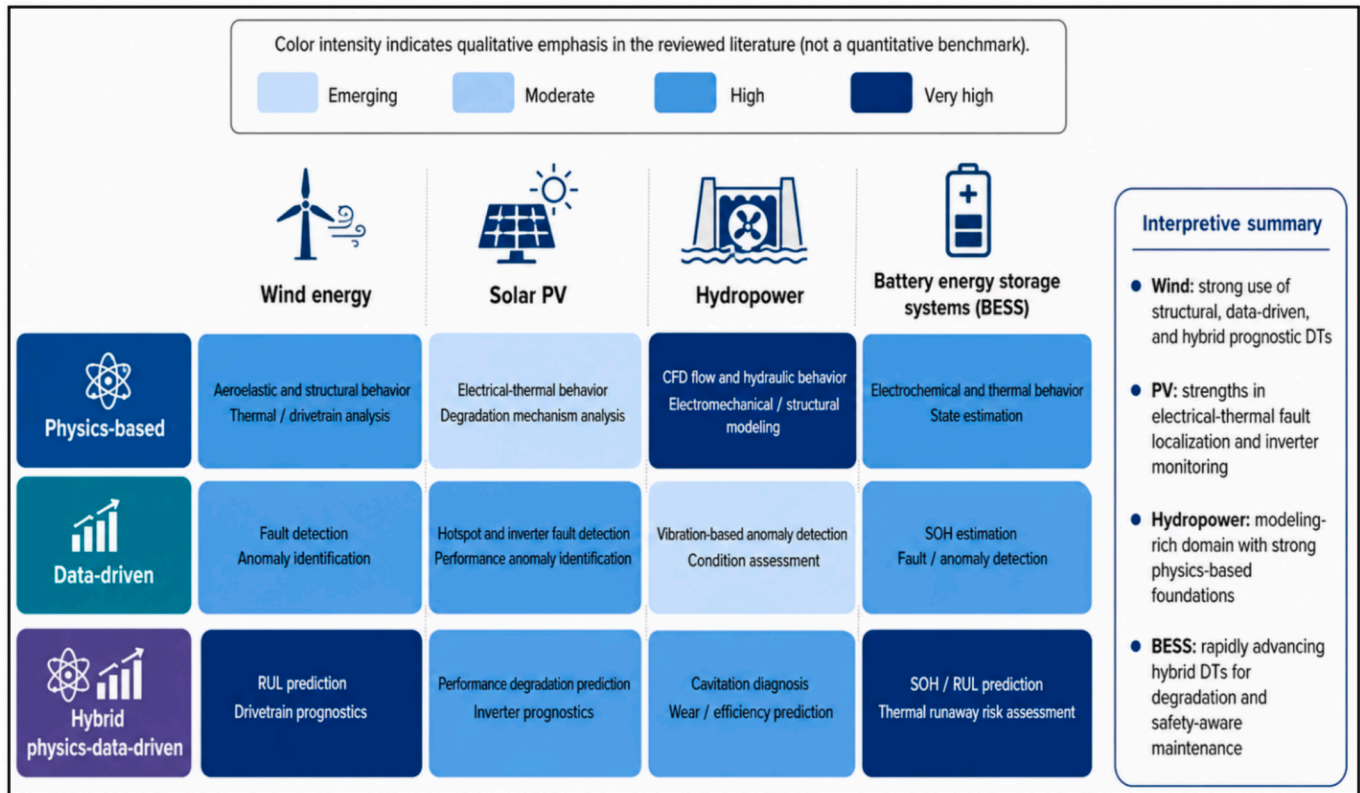


Fig. 2. Qualitative heatmap of Digital Twin modeling approaches across wind energy, solar photovoltaic systems, hydropower, and battery energy storage systems.

planned outages or low-demand periods [136]. Instead of relying on conservative preventive replacements, DTs support optimized intervention timing that maximizes component utilization while avoiding catastrophic failure [137]. At the fleet level, DT-based risk assessment enables maintenance prioritization across multiple assets, ensuring that limited resources are allocated to components with the highest predicted failure probability or economic impact. This coordinated, data-driven approach is shown to significantly reduce maintenance expenditure and improve asset availability.

Another major benefit highlighted across studies is the extension of asset lifespan and long-term performance sustainability. By continuously monitoring degradation trends and identifying damaging operating regimes, DTs support health-aware operational strategies that reduce cumulative fatigue, thermal stress, and aging effects [138]. Such strategies include adaptive load management, derating under adverse conditions, and optimized thermal control, all of which contribute to slowing degradation without sacrificing system reliability. For long-lived renewable infrastructure, DTs thus play a key role in deferring capital replacement, improving return on investment, and maintaining stable performance over extended lifetimes.

From a sustainability and energy-performance standpoint, these benefits should be linked to measurable operational and environmental indicators rather than discussed only in conceptual terms. DT-enabled predictive maintenance can support environmental sustainability by extending asset lifetime, reducing failure-driven component replacement, lowering maintenance-related material usage, and minimizing waste associated with avoidable degradation and unplanned failures. Moreover, by detecting faults early and supporting health-aware operational adjustments, DTs can reduce energy losses caused by degraded system performance, improve availability, and thereby enhance lifecycle resource efficiency. Relevant indicators for assessing these gains include asset lifetime extension, replacement frequency, maintenance-related waste, spare-parts utilization, avoided energy loss, availability improvement, and lifecycle efficiency improvement.

Safety enhancement emerges as a critical complementary benefit of DT-based predictive maintenance. Across safety-critical applications, early detection of hazardous conditions—such as overheating in battery systems, excessive vibration in rotating machinery, or structural over-stress in large installations—reduces the probability of sudden failures that could endanger personnel or infrastructure [139]. DTs further support risk-informed decision-making by quantifying uncertainty in health predictions and enabling simulation of extreme or fault scenarios, thereby strengthening contingency planning and operational resilience [140].

At the organizational level, DTs also improve maintenance planning, logistics, and decision support. Predictive insights derived from DTs enable more accurate spare-part forecasting, workforce scheduling, and coordination between operational and maintenance teams. At strategic levels, DT-informed analytics support long-term asset management decisions, including refurbishment planning, life-extension programs, and technology upgrades. By providing a unified, continuously updated view of asset health, Digital Twins enhance transparency, cross-functional collaboration, and confidence in maintenance decisions. Collectively, these reported benefits explain the growing adoption of Digital Twin technologies as foundational tools for predictive maintenance in modern renewable energy systems.

From an economic and asset-management standpoint, the benefits of DT-enabled predictive maintenance should be interpreted not only in qualitative terms but also through explicit ROI and cost-benefit analysis. While DT adoption can improve availability, reduce emergency maintenance, extend service life, and enhance maintenance efficiency, these gains must be evaluated against the required investments in sensors, connectivity, data infrastructure, model development, computing capability, and cybersecurity. The economic viability of DT deployment is therefore context dependent and influenced by asset age, failure risk, maintenance strategy, accessibility, and scale of operation. Relevant indicators for such assessment include payback period, lifecycle cost savings, downtime-loss avoidance, reduction in maintenance

expenditure, inventory optimization, and asset lifetime value improvement. Where sufficiently reported, such outcomes may also have implications for broader energy-management performance through improved asset availability and reduced performance losses associated with degradation and unplanned outages.

Although many studies report improvements in diagnostic performance, reduced unplanned downtime, maintenance efficiency, and cost-related outcomes, these gains are often reported using different metrics, time horizons, asset classes, and validation settings, which limits direct cross-study quantitative comparison. In this sense, DT-enabled predictive maintenance should be understood not only as a digitalization strategy, but also as an operational approach that can influence energy-system performance through improved availability, reduced performance losses, stronger maintenance efficiency, and more favorable lifecycle asset outcomes.

The benefits discussed in this section arise from the closed-loop nature of Digital Twin-enabled predictive maintenance, in which sensing, modeling, analytics, and maintenance actions are continuously integrated.

Importantly, the benefits of DT-enabled predictive maintenance are not expected to be uniform across all implementation levels. Lower-maturity DT systems may provide improved condition awareness and earlier fault detection, whereas higher-maturity systems are more likely to deliver robust prognostics, optimized maintenance planning, resource coordination, and adaptive operational decision support. Thus, many of the economic, operational, and sustainability gains discussed in this section are closely linked to the maturity of the DT implementation rather than to DT adoption in a generic sense.

Challenges and limitations

Despite the strong potential of Digital Twin (DT) technologies for predictive maintenance in renewable energy systems, the literature also shows that their practical deployment remains constrained by a series of interconnected technical, operational, economic, and organizational barriers. Although many studies report improved fault detection, health assessment, and maintenance planning, these benefits are often demonstrated under controlled conditions, with well-instrumented assets, stable communication infrastructure, and relatively mature digital environments. In real industrial settings, however, DT performance is shaped by trade-offs among model fidelity, sensing depth, computational feasibility, interoperability, trustworthiness, and deployment cost. As a result, the main limitations of DT-based predictive maintenance should not be viewed as isolated technical issues, but as coupled constraints that affect scalability, robustness, and real-world transferability.

Data scarcity, incompleteness, and quality issues

A fundamental challenge in DT development is the availability, consistency, and representativeness of operational data. Many renewable energy assets, particularly legacy wind farms, rural PV installations, and ageing hydropower facilities, were not originally designed with DT-oriented monitoring in mind and therefore lack the sensing density or measurement quality required for reliable model calibration and prognostics. Even when sensors are present, the literature repeatedly reports practical issues such as noise contamination, missing data segments, calibration drift, asynchronous measurements, and environmental disturbances, all of which reduce the reliability of DT outputs. Sparse fault-event data further complicate the development of predictive models, especially for rare but high-impact failures such as gearbox collapse, inverter burnout, or thermal runaway.

This challenge has broader methodological implications. While data-driven DTs often perform well when trained on abundant, high-quality datasets, their reported success may not generalize to poorly instrumented or data-poor environments. In this sense, the literature reveals a

clear tension between algorithmic sophistication and data realism: more advanced models do not necessarily yield more robust maintenance intelligence when the underlying data are incomplete, biased, or operationally unrepresentative. This is especially important in renewable energy systems, where degradation is strongly influenced by variable environmental and load conditions.

High model complexity and computational burden

Another major limitation lies in the complexity of DT models and the computational resources required to operate them continuously. High-fidelity DTs often combine multi-physics simulation, data assimilation, uncertainty estimation, and AI-based prediction, which can significantly improve interpretability and diagnostic depth. However, the literature also makes it clear that such gains come at a cost. More detailed models require greater computational power, more frequent calibration, and more demanding synchronization between physical and virtual layers. These requirements become particularly restrictive in real-time or fleet-level deployments involving large numbers of geographically distributed assets.

This creates one of the central trade-offs in the DT literature: higher model fidelity may enhance physical realism and predictive accuracy, but it can also reduce responsiveness, scalability, and economic feasibility. In practice, many industrial applications may require reduced-order or hybrid representations rather than fully detailed twins. Thus, the challenge is not simply to build more accurate DTs, but to identify the appropriate balance between model sophistication and operational practicality.

Integration of heterogeneous, multi-source data streams

Renewable energy systems generate highly heterogeneous data streams, including vibration signals, thermal images, electrical measurements, SCADA logs, meteorological variables, acoustic emissions, and structural response data. In principle, integrating these sources can improve fault sensitivity and system awareness. In practice, however, the literature highlights substantial integration difficulties. Differences in sampling rates, data formats, temporal alignment, metadata standards, and uncertainty characteristics complicate the creation of coherent and synchronized DT environments.

Although multi-modal fusion is frequently presented as a strength of DT architectures, the reported benefits are not always straightforward. Richer data ecosystems increase observability, but they also raise pre-processing demands, increase system complexity, and create more opportunities for error propagation across the DT pipeline. This means that more data do not automatically translate into better predictive maintenance performance. Without robust synchronization, feature extraction, and data governance mechanisms, the integration of multi-source data can undermine rather than improve DT reliability.

Lack of standardization and industry-wide DT frameworks

The literature consistently identifies fragmentation as a major barrier to DT adoption in renewable energy systems [68]. Current DT implementations are often tailored to specific assets, vendors, sensing infrastructures, and software ecosystems, which limits portability and cross-platform reproducibility. The absence of widely accepted standards for data structures, communication protocols, model validation, benchmark testing, and lifecycle management makes it difficult to compare DT solutions across studies or assess their readiness for industrial deployment.

This lack of standardization has deeper consequences than technical inconvenience. It slows technology transfer, complicates regulatory acceptance, and weakens confidence in reported performance claims. A DT that performs well in one pilot environment may not be easily transferable to another asset class or operator context. As a result, the

field still lacks a sufficiently unified methodological foundation to support broad industrial scaling. The future progress will depend not only on technical innovation, but also on the development of shared frameworks for interoperability, verification, and performance benchmarking.

Cybersecurity vulnerabilities and data privacy risks

As DTs depend on continuous data exchange across sensing systems, communication networks, edge devices, and cloud platforms, they also introduce significant cybersecurity exposure. The literature points to a wide range of vulnerabilities, including false-data injection, spoofing, denial-of-service attacks, unauthorized access, ransomware, and manipulation of predictive outputs. In safety-critical renewable energy environments, such attacks are not merely information-security concerns; they can directly affect maintenance decisions, asset availability, and operational safety.

A central tension emerges here between connectivity and trustworthiness. The same high-connectivity architectures that enable real-time synchronization, centralized analytics, and fleet-level coordination also expand the attack surface and increase system dependence on secure communication and authentication. Likewise, cloud-based DT ecosystems may improve scalability and accessibility, but they can create additional concerns related to data privacy, ownership, and competitive sensitivity, especially in multi-plant or multi-stakeholder environments. The literature therefore suggests that cybersecurity should not be treated as an auxiliary design layer, but as a structural requirement of DT deployment.

High initial deployment costs and economic barriers

The financial dimension of DT adoption remains one of the most persistent implementation constraints. Deploying a DT ecosystem typically requires investment in sensing infrastructure, communication networks, computing resources, software integration, and model development, in addition to ongoing costs for maintenance, recalibration, and cybersecurity management. While many studies emphasize the long-term economic value of predictive maintenance, the literature also makes clear that the return on investment is highly context dependent. Factors such as asset age, failure frequency, maintenance culture, site accessibility, and operator scale strongly influence whether DT deployment becomes economically justified.

This reveals a recurring gap between technological promise and business feasibility. Highly sophisticated DT systems may be technically attractive, yet economically impractical for small and medium-sized operators or for assets with limited residual life. In such cases, the optimal solution may not be a full-scale DT, but a simplified or modular implementation aligned with the economic profile of the asset. Consequently, the literature increasingly points to the need for scalable and retrofittable DT strategies rather than one-size-fits-all digitalization models.

Limited availability of skilled workforce and organizational readiness

DT implementation is not solely a technical challenge; it is also an organizational one. Effective deployment requires expertise that spans multiple disciplines, including sensing, simulation, AI, data engineering, maintenance planning, power systems, and cybersecurity. Many renewable energy operators, however, do not yet possess teams with this breadth of capability. The literature therefore identifies workforce readiness as a major adoption bottleneck, particularly in organizations where digital systems remain weakly integrated into maintenance workflows.

Beyond technical skill shortages, organizational culture also matters. DTs are most valuable when their outputs are trusted, interpreted correctly, and incorporated into actual maintenance decisions. Yet resistance to new digital tools, lack of training, and poor coordination

between engineering, operations, and maintenance teams can reduce the practical utility of DT-generated insights. This means that even technically robust DT systems may underperform if organizational processes are not redesigned to support their use. Accordingly, implementation readiness should be evaluated as a socio-technical issue rather than a purely engineering one.

Drift, degradation over time, and validation difficulties

A further limitation concerns the long-term stability and verifiability of DT models. Renewable energy assets evolve continuously as they age, undergo repairs, experience environmental variability, and operate under changing load profiles. If the DT is not regularly recalibrated, its predictions may gradually diverge from the actual system, leading to model drift and declining predictive value. The literature increasingly recognizes that maintaining DT accuracy over time is often more difficult than achieving high initial accuracy [35].

Validation is equally challenging. Many published studies evaluate DT models using retrospective datasets, simulated conditions, or limited pilot implementations, but few provide long-duration real-world validation across diverse operating scenarios. Ground-truth failure events are often rare, and controlled experimental validation is typically impractical for critical infrastructure. As a result, claims regarding prognostic accuracy, fault detection sensitivity, or remaining useful life performance are not always directly comparable across studies. This weakens the evidential basis for universal deployment claims and reinforces the need for standardized validation methodologies and uncertainty-aware performance assessment.

Critical synthesis of trade-offs and practical constraints

Taken together, these findings show that the limitations of DT-based predictive maintenance cannot be reduced to a simple list of technical obstacles. Rather, the field is shaped by several recurring trade-offs. Higher-fidelity models may improve interpretability and diagnostic detail, but they can also undermine real-time feasibility. Denser sensing networks can increase fault observability, but they also raise deployment cost and maintenance complexity. Advanced AI methods may improve predictive performance, yet they may reduce transparency and increase dependence on high-quality labeled data. Similarly, cloud-connected architectures enhance centralized intelligence and scalability, but they also heighten communication dependence and cybersecurity risk.

Reported outcomes are not fully uniform across renewable energy domains. Some studies present DTs as highly effective tools for early fault detection, maintenance optimization, and life extension, whereas others highlight limited transferability under sparse data conditions, legacy infrastructure constraints, or low-maturity digital environments. These differences suggest that DT effectiveness is strongly context dependent and shaped not only by model design, but also by asset characteristics, infrastructure quality, organizational capability, and economic constraints. Therefore, no single DT configuration should be regarded as universally optimal. The real challenge is to design DT systems whose sensing architecture, computational depth, model structure, cybersecurity provisions, and operational integration are proportionate to the requirements of the target application.

To synthesize the critical issues discussed above, Table 5 summarizes the principal challenges and limitations of Digital Twin-based predictive maintenance in renewable energy systems and their implications for practical deployment. The table emphasizes that successful DT implementation depends not only on technical model performance, but also on resolving broader constraints related to data availability, scalability, standardization, cybersecurity, economic viability, organizational readiness, and long-term validation.

In summary, the challenges associated with Digital Twin-based predictive maintenance extend beyond isolated technical limitations

Table 5

Key Challenges and Limitations of Digital Twin–Based Predictive Maintenance in Renewable Energy Systems.

Challenge Category	Challenge	Implications for DT Deployment
Data availability and quality	Sparse failure data, missing measurements, sensor noise, and data inconsistency	Reduced accuracy of fault detection and RUL prediction
Model complexity and computational burden	High-fidelity multi-physics and AI models require significant computing resources	Limited real-time capability and scalability
Multi-source data integration	Heterogeneous data types with different sampling rates and formats	Increased system integration complexity
Lack of standardization	Absence of unified DT frameworks, benchmarks, and protocols	Limited interoperability and slow industrial adoption
Cybersecurity and data privacy	Vulnerability to cyber attacks, data tampering, and unauthorized access	Risk to operational safety and decision reliability
Economic and cost barriers	High initial investment in sensors, infrastructure, and computing	Uncertain return on investment
Workforce and organizational readiness	Shortage of interdisciplinary expertise and resistance to change	Slow DT adoption and suboptimal use
Model drift and validation	Degradation-induced model mismatch and lack of ground truth data	Declining long-term prediction reliability

and reflect broader tensions among accuracy, scalability, cost, interpretability, trustworthiness, and deployability. Persistent barriers include data scarcity, model complexity, integration of heterogeneous data sources, lack of standardization, cybersecurity and privacy risks, economic uncertainty, organizational readiness constraints, and long-term model drift and validation difficulties. Taken together, these challenges suggest that DT-enabled predictive maintenance should not be assessed as a binary distinction between the presence and absence of Digital Twin technology. Rather, implementations should be understood as occupying different maturity positions defined by their sensing robustness, model depth, predictive capability, decision-support functionality, trustworthiness, and deployment readiness. This need for structured differentiation motivates the introduction of a Digital Twin Predictive Maintenance Maturity Framework, which is proposed in the following section as a synthesis tool for interpreting the developmental progression of the field.

Proposed Digital Twin predictive maintenance maturity framework

The preceding sections have shown that Digital Twin (DT)–enabled predictive maintenance in renewable energy systems cannot be adequately understood through architecture, application domain, or enabling technology alone. Although many studies report promising advances in fault detection, degradation monitoring, remaining useful life estimation, and maintenance planning, the reviewed literature also reveals substantial variation in sensing depth, model sophistication, validation rigor, decision-support capability, and deployment readiness across renewable energy domains. As a result, DT implementations should not be viewed as equivalent merely because they share common architectural elements. Rather, they should be interpreted as occupying different stages of maturity in the evolution from digital monitoring toward intelligent, adaptive, and potentially autonomous maintenance ecosystems. To address this need for structured differentiation, this section proposes a Digital Twin Predictive Maintenance Maturity Framework for renewable energy systems.

The purpose of the framework is threefold. First, it provides a conceptual structure for organizing the developmental progression of DT-

enabled predictive maintenance beyond descriptive classification. Second, it offers a comparative basis for interpreting differences among DT implementations across wind turbines, solar photovoltaic systems, hydropower facilities, and battery energy storage systems. Third, it supports benchmarking and future research prioritization by clarifying which technological, analytical, and operational capabilities are associated with different stages of maturity. In contrast to the layered architecture presented in Section 2, which explains how a DT system is functionally organized, the maturity framework proposed here focuses on how DT capability develops from basic digital visibility to increasingly predictive, prescriptive, and autonomous maintenance intelligence.

The proposed framework is also intended to function as a technology-readiness classification lens by distinguishing not only analytical capability, but also the relative deployment maturity of DT-enabled predictive maintenance implementations across renewable energy domains.

Rationale and framework structure

The need for a maturity-oriented synthesis arises from several recurring patterns identified throughout the review. First, current DT literature is highly heterogeneous: some studies focus mainly on real-time monitoring and anomaly detection, whereas others incorporate hybrid simulation, prognostics, optimization, fleet-level coordination, or safety-aware control. Second, the reported benefits of DT deployment are not uniform; simpler implementations may improve condition awareness, while more advanced ones may support prescriptive maintenance planning or health-aware operational decision-making. Third, the practical usefulness of DTs depends not only on algorithmic performance, but also on interoperability, uncertainty awareness, cybersecurity, and organizational readiness. These observations suggest that DT-enabled predictive maintenance evolves through qualitatively different stages rather than through a single linear increase in model complexity.

Accordingly, the proposed framework organizes DT maturity into six levels: (1) Digital Monitoring Twin, (2) Condition-Aware Twin, (3) Diagnostic Twin, (4) Prognostic Twin, (5) Prescriptive Twin, and (6) Autonomous Maintenance Twin. These stages are distinguished not only by what the DT can observe or predict, but also by the depth of model integration, the role of decision support, the degree of human involvement, the rigor of validation, and the readiness of the implementation for operational deployment. The framework is therefore intended as a comparative and developmental synthesis rather than as a rigid standard. Its value lies in making explicit that higher maturity is not defined by data volume or AI sophistication alone, but by the coordinated advancement of sensing, modeling, analytics, explainability, operational integration, and trustworthiness.

Fig. 3 provides a qualitative visualization of the relative maturity of Digital Twin–enabled predictive maintenance across major renewable energy domains using the six-level framework proposed in this section. It highlights how the reviewed literature positions wind energy, solar photovoltaic systems, hydropower, and battery energy storage systems differently along the progression from monitoring-oriented implementations toward diagnostic, prognostic, prescriptive, and more advanced autonomous maintenance capability. The figure is intended as a qualitative synthesis of the comparative findings reported earlier in the review, rather than as a quantitative benchmark.

Level 1: digital monitoring twin

The first maturity level corresponds to the Digital Monitoring Twin. At this stage, the DT functions primarily as a synchronized digital representation of the physical asset for real-time visibility and state tracking. Its main purpose is to aggregate operational data from sensors, SCADA platforms, and basic monitoring infrastructure into a coherent

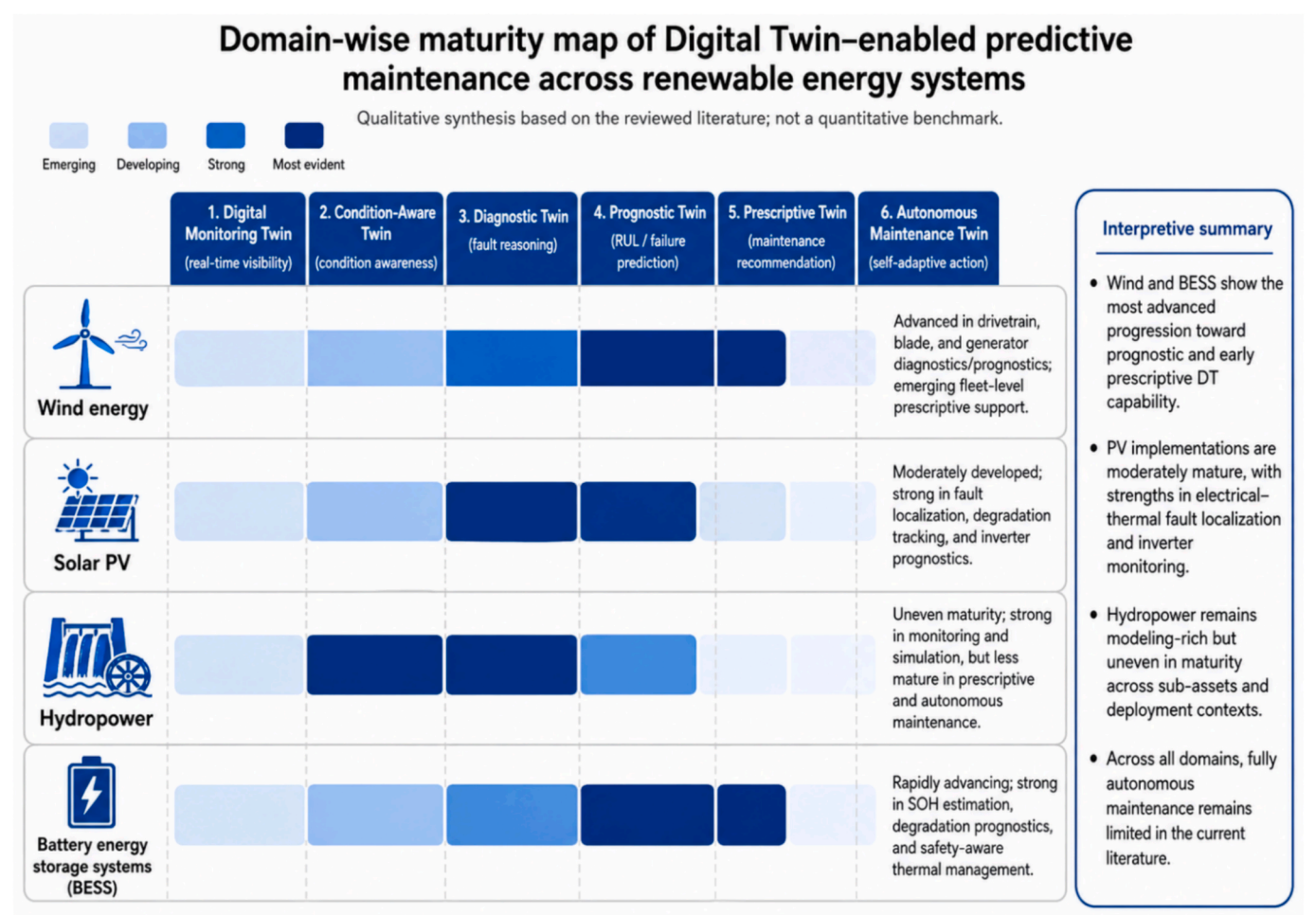


Fig. 3. Domain-wise maturity map of Digital Twin-enabled predictive maintenance across renewable energy systems based on the proposed six-level maturity framework.

virtual environment that reflects current asset status. Implementations at this level typically emphasize data acquisition, connectivity, visualization dashboards, and threshold-based event detection rather than deep analytical inference.

In renewable energy systems, Level 1 DTs are often observed in applications where the main goal is to improve situational awareness of turbines, PV installations, hydropower equipment, or battery systems without yet enabling robust fault reasoning. The corresponding analytical depth is limited, and model behavior is often descriptive rather than predictive. Human operators remain central to interpretation, while validation tends to focus on data consistency, communication reliability, and representation fidelity. Although this level provides only limited maintenance intelligence, it constitutes a critical foundation because it establishes the digital observability, synchronization, and data infrastructure required for more advanced DT capability.

Level 2: condition-aware twin

The second maturity level is the Condition-Aware Twin, in which the DT moves beyond passive monitoring toward basic interpretation of asset condition. At this stage, the system integrates sensor signals, event indicators, and elementary analytics to identify abnormal patterns, degradation signatures, or departures from expected operating behavior. The emphasis is typically on anomaly detection, health-state screening, and early warning rather than root-cause diagnosis or future failure prediction.

This level is especially relevant in renewable energy contexts where

fault labels are sparse and where the practical priority is to identify abnormal operation early enough to trigger inspection or closer observation. Condition-Aware Twins often rely on signal processing, feature extraction, statistical monitoring, or unsupervised learning methods. In PV systems, for example, they may identify hotspots, abnormal string behavior, or inverter irregularities; in wind and hydropower systems, they may detect unusual vibration, temperature, or pressure patterns; in BESS, they may identify early thermal or electrochemical deviation. The DT at this stage improves condition awareness significantly, but maintenance action remains largely reactive-to-alert rather than diagnostically informed. As such, human interpretation is still essential, and uncertainty treatment is usually limited.

Level 3: diagnostic twin

The third maturity level corresponds to the Diagnostic Twin. Here, the DT no longer only flags abnormal behavior, but also supports structured fault identification and root-cause reasoning. This stage requires tighter integration among sensing data, model-based interpretation, and domain-specific knowledge so that observed deviations can be associated with likely failure mechanisms, degradation pathways, or subsystem interactions. Diagnostic Twins therefore mark an important transition from detection to explanation.

In practical terms, Level 3 DTs may combine vibration analysis, thermal behavior, electrical signatures, or hydraulic response with machine learning classifiers, physics-based fault models, or hybrid reasoning strategies. Wind turbine applications at this level often focus

on gearbox, blade, and generator fault diagnosis; PV systems may diagnose module mismatch, hotspot origin, or inverter degradation; hydropower systems may identify cavitation, misalignment, or shaft-related abnormalities; and BESS applications may diagnose capacity fade patterns, abnormal heat generation, or internal resistance growth. Compared with lower levels, the key advance here is that maintenance planning becomes more informed because operators gain insight into what kind of fault is developing rather than merely knowing that the system is behaving abnormally. Validation also becomes more demanding, since the credibility of diagnostic recommendations depends on correct fault attribution rather than just anomaly sensitivity.

Level 4: prognostic twin

The fourth maturity level is the Prognostic Twin, in which the DT gains the capability to estimate future degradation trajectories, remaining useful life, or failure probability under evolving operating conditions. This level is especially important because predictive maintenance, in the strict sense, depends on more than fault detection or diagnosis; it requires the ability to anticipate how asset health will evolve and when intervention should be considered. Level 4 therefore represents a major step from maintenance awareness to maintenance foresight.

Prognostic Twins typically rely on hybrid combinations of historical condition data, degradation models, simulation outputs, and uncertainty-aware predictive analytics. Their strength lies in transforming present asset health information into forward-looking maintenance intelligence. In renewable energy systems, this may include forecasting drivetrain wear in wind turbines, inverter ageing in PV systems, cavitation progression in hydropower equipment, or capacity fade and thermal risk in BESS. At this stage, uncertainty quantification becomes significantly more important because future predictions are inherently probabilistic and sensitive to changing load, environment, and maintenance history. Accordingly, a higher-maturity DT is not defined simply by producing future estimates, but by doing so in a way that is explainable, calibrated, and operationally interpretable. Prognostic Twins therefore offer stronger support for maintenance scheduling, resource preparation, and risk-aware operational planning.

Level 5: prescriptive twin

The fifth maturity level is the Prescriptive Twin. At this stage, the DT does not merely estimate future failure risk, but actively evaluates alternative maintenance and operational responses in order to recommend optimal interventions. Prescriptive capability requires the integration of diagnostic and prognostic outputs with decision models that account for cost, downtime, risk, safety, spare-part availability, operational priorities, and sometimes fleet-level coordination. This level thus moves beyond predictive intelligence toward decision-oriented maintenance optimization.

In renewable energy applications, Prescriptive Twins may recommend intervention timing, inspection prioritization, derating strategies, thermal management adjustments, or coordinated maintenance scheduling across multiple assets. The practical value of this stage is particularly high because it translates DT outputs into actionable recommendations rather than leaving interpretation entirely to human experts. However, this also increases the importance of explainability, uncertainty communication, and integration with maintenance management systems. A prescriptive recommendation must be trusted, operationally feasible, and aligned with broader asset-management constraints. As a result, Level 5 maturity depends not only on model capability, but also on enterprise integration, workflow compatibility, and robust evaluation of decision quality. Prescriptive Twins therefore represent a transition from predictive analytics to intelligent maintenance planning.

Level 6: autonomous maintenance twin

The sixth maturity level corresponds to the Autonomous Maintenance Twin. This stage represents the most advanced and still largely aspirational form of DT-enabled predictive maintenance, in which the system participates in closed-loop maintenance and operational adaptation with limited human intervention. At this level, DT outputs are not only used to support human decisions, but are increasingly connected to automated workflows, robotic inspection platforms, adaptive control actions, digital work orders, or self-optimizing asset-management logic. The Autonomous Maintenance Twin thus represents the convergence of monitoring, diagnosis, prognosis, prescription, and execution.

In renewable energy systems, fully autonomous maintenance remains uncommon, but emerging pathways are visible. Examples include DT-guided robotic blade inspection in wind systems, automated thermal-risk response in battery installations, adaptive derating or dispatch decisions informed by DT health estimation, and integrated digital ecosystems linking fault prediction to inspection scheduling and maintenance execution. Nevertheless, the maturity of this level should not be overstated. Autonomous capability requires much more than advanced algorithms: it depends on high-confidence validation, secure and resilient communication infrastructure, explainable decision pathways, human override mechanisms, cybersecurity assurance, and governance structures for high-consequence intervention. For this reason, Level 6 should be interpreted as a future-oriented maturity target rather than as the current norm in renewable energy DT deployment.

Cross-level assessment dimensions

To make the maturity framework analytically useful, each level should be interpreted across several recurring dimensions rather than as a purely descriptive label. The first is sensing and data richness, which captures the breadth, quality, and robustness of monitoring inputs. Lower maturity levels may function with limited sensing and simple data streams, whereas higher maturity levels require richer, multi-modal, and more reliable data environments. The second is model depth, ranging from descriptive representations and simple analytics to hybrid physics-AI models with uncertainty awareness and adaptive updating. The third is maintenance intelligence function, which evolves from visibility and anomaly awareness to diagnosis, prognosis, prescription, and eventually autonomous response.

A fourth dimension is decision autonomy, which reflects the degree to which DT outputs are merely observed, operationally interpreted, recommended, or directly linked to action. A fifth is validation rigor, since higher maturity stages demand stronger benchmarking, uncertainty calibration, and real-world reliability evidence. A sixth is trustworthiness and cybersecurity, which become increasingly critical as DTs move closer to maintenance execution and operational decision-making. Finally, deployment scale and organizational integration distinguish asset-level prototypes from plant-level, fleet-level, or enterprise-integrated implementations. Together, these dimensions clarify that maturity is multi-factorial and that progress in one dimension does not necessarily imply equivalent advancement in others.

Cross-domain interpretation of the framework

When interpreted through the proposed framework, the reviewed renewable energy domains exhibit uneven maturity profiles. Wind energy appears among the more advanced domains, particularly in diagnostic and prognostic DT applications involving gearboxes, blades, and generators, with some emerging movement toward prescriptive maintenance and fleet-level coordination. BESS also appears to be advancing rapidly, especially in health estimation, degradation prognosis, and safety-aware thermal management, although validation consistency and standardization remain significant challenges. By contrast, PV-oriented

DT applications often show moderate maturity, with strengths in fault localization, performance degradation tracking, and inverter prognosis, but more limited evidence of higher-level prescriptive or autonomous deployment. Hydropower DTs demonstrate strong asset-specific modeling and structural monitoring capabilities, yet their maturity remains uneven across sub-assets and operating contexts, particularly when moving beyond monitoring and diagnosis toward integrated maintenance intelligence.

These differences indicate that DT maturity is strongly influenced by domain-specific degradation physics, sensing accessibility, operational criticality, and maintenance horizon. Domains with stronger access to high-frequency condition data and clearer fault signatures may progress faster toward diagnostics and prognosis, whereas domains characterized by sparse data, long asset life, or complex civil infrastructure may advance more unevenly. The proposed framework is valuable precisely because it captures these differences without reducing all DT applications to a single notion of digital advancement. Instead, it allows the field to recognize that renewable energy DTs can be technically sophisticated in some dimensions while still remaining limited in autonomy, validation, or industrial readiness.

To further consolidate the proposed framework, Table 6 summarizes the defining characteristics of each maturity stage in terms of its principal maintenance function, typical analytical capability, decision-support role, and deployment profile. This summary provides a compact comparative view of how DT-enabled predictive maintenance evolves from basic digital monitoring to increasingly autonomous maintenance capability across renewable energy systems.

Significance of the proposed framework

The significance of the proposed Digital Twin Predictive Maintenance Maturity Framework lies in its ability to transform the review from a descriptive survey into a structured synthesis of technological progression. Rather than treating DT-enabled predictive maintenance as a uniform category, the framework clarifies how different implementations vary in purpose, capability, and readiness. This helps address the common ambiguity in the literature between monitoring, diagnosis, prognosis, optimization, and autonomy, and provides a more explicit vocabulary for comparing studies across renewable energy domains.

The framework also offers practical value for future benchmarking and deployment strategy. Researchers can use it to position new DT studies more clearly, identify missing capability layers, and design evaluation strategies appropriate to the maturity level being claimed. Practitioners can use it to assess where a given implementation currently stands and what technical or organizational developments would be required to progress toward more advanced maintenance intelligence. In this sense, the framework should be understood not as a rigid

industrial standard, but as a conceptually grounded synthesis tool derived from the reviewed literature. Its operational refinement will require future benchmarking, broader validation, and domain-specific adaptation. Nonetheless, it provides a much-needed structure for interpreting the developmental progression of DT-enabled predictive maintenance in renewable energy systems and for guiding the field toward more intelligent, trustworthy, and scalable maintenance ecosystems.

Future research directions

The future development of Digital Twin (DT)-enabled predictive maintenance in renewable energy systems should be interpreted through the maturity progression outlined in Section 7 rather than as a flat collection of independent research topics. While the literature demonstrates substantial progress in sensing, modeling, diagnostics, and prognostics, the reviewed studies also show that implementations remain uneven in capability, validation rigor, autonomy, and industrial readiness across renewable energy domains. Accordingly, future research should focus not only on improving individual DT components, but also on enabling the systematic transition from lower-maturity monitoring-oriented DT systems toward prescriptive, adaptive, and increasingly autonomous maintenance ecosystems.

A first priority is the establishment of standardized validation, benchmarking, and interoperability frameworks. The maturity framework proposed in this review highlights that many current DT implementations remain limited not by a lack of algorithmic sophistication, but by insufficient comparability, inconsistent validation practice, and weak portability across platforms and domains. Future work should therefore prioritize benchmark datasets, common performance metrics, uncertainty-aware evaluation criteria, and interoperable data and communication standards for DT-enabled predictive maintenance. In particular, future studies should report DT performance using more standardized quantitative criteria, including prediction accuracy, fault-detection sensitivity, remaining useful life error, downtime reduction, maintenance-cost savings, availability improvement, avoided energy loss, and lifecycle value indicators. These developments are essential for moving from fragmented proof-of-concept studies toward reproducible, quantitatively comparable, and industry-trusted DT systems.

A second major direction is the advancement of trustworthy hybrid modeling architectures that combine physics-based knowledge with artificial intelligence. As DT systems progress toward higher maturity levels, accurate condition awareness alone becomes insufficient; robust prognostics, interpretable decision support, and adaptive optimization require models that remain reliable under non-stationary operating conditions, sparse fault data, and changing degradation pathways. Future research should therefore strengthen hybrid physics-machine learning models, uncertainty quantification, explainable AI, and

Table 6
Maturity Levels and Defining Characteristics of DT-Enabled Predictive Maintenance in Renewable Energy Systems.

Level	Maturity Stage	Main Function	Typical Analytical Capability	Decision Role	Deployment Characteristic
1	Digital Monitoring Twin	Real-time asset visibility and synchronization	Data acquisition, visualization, threshold monitoring	Human observation	Asset-level monitoring with limited maintenance intelligence
2	Condition-Aware Twin	Early detection of abnormal behavior	Signal processing, anomaly detection, health-state screening	Human-interpreted alerting	Condition awareness with basic fault sensitivity
3	Diagnostic Twin	Identification of fault type and likely cause	Fault classification, root-cause reasoning, hybrid interpretation	Maintenance support	More informed inspection and fault localization
4	Prognostic Twin	Prediction of degradation trajectory and remaining useful life	RUL estimation, degradation forecasting, uncertainty-aware prediction	Predictive maintenance planning	Forward-looking maintenance intelligence
5	Prescriptive Twin	Recommendation of optimal interventions	Maintenance optimization, scenario evaluation, risk-cost trade-off analysis	Decision recommendation	Integration with maintenance planning and operational strategy
6	Autonomous Maintenance Twin	Closed-loop adaptive maintenance execution	Self-updating intelligence, automated coordination, adaptive response	Semi-autonomous or autonomous action	Advanced, highly integrated, and still largely emerging deployment stage

confidence-aware prognostic systems that can support maintenance decisions transparently and safely in renewable energy environments.

Another critical research direction concerns resilient and adaptive sensing infrastructures. The proposed maturity framework implies that movement toward higher DT capability depends strongly on the quality, robustness, and contextual richness of sensing and data acquisition. However, many renewable assets—particularly remote, legacy, or offshore systems—continue to operate under sensing limitations, communication interruptions, and data inconsistency. Future work should thus focus on adaptive sensing strategies, robust sensor placement, low-power monitoring systems, online recalibration methods, and multi-modal data fusion mechanisms that can preserve DT reliability under real-world operational constraints.

Secure and scalable edge-cloud DT infrastructures also represent a central enabler of future maturity progression. Higher-level DT implementations require not only advanced analytics, but also dependable coordination among distributed sensing, local intelligence, cloud-based computation, and maintenance service integration. Future studies should therefore develop architectures that allocate computation intelligently across edge and cloud layers while ensuring low latency, cybersecurity, resilience to network disruption, and privacy-aware coordination across geographically distributed renewable assets. In this context, secure communication and trustworthy data governance should be treated as structural requirements of advanced DT deployment rather than secondary technical add-ons.

The economic and organizational dimensions of DT adoption also require much greater research attention. The maturity framework proposed in this review suggests that higher DT maturity is associated not only with stronger technical capability, but also with greater demands in infrastructure, validation, workforce expertise, and operational integration. Future work should therefore move beyond technical demonstration toward lifecycle cost-benefit analysis, scalable deployment models, retrofittable solutions for legacy assets, workforce-readiness strategies, and governance structures that support real maintenance adoption. Without such work, the transition from research-grade DT systems to industry-ready maintenance ecosystems will remain limited.

At more advanced stages of DT maturity, future research should increasingly examine federated DT ecosystems and coordinated decision-making across renewable energy networks. Rather than treating turbines, PV arrays, hydropower units, and battery systems as isolated assets, future DT frameworks should support fleet-level health management, cross-asset prioritization, maintenance-resource coordination, and resilience-aware operational planning. Achieving this vision will require progress in distributed intelligence, hierarchical modeling, interoperability, privacy-preserving analytics, and system-level uncertainty management.

Finally, the highest maturity stages envisioned in the proposed framework point toward semi-autonomous and autonomous maintenance ecosystems in which DTs interact with robotic inspection systems, digital work planning tools, and adaptive operational control. Although fully autonomous DT-enabled maintenance remains largely aspirational at present, future research should begin to address the technical and governance conditions under which such systems can be implemented safely and responsibly. This includes human-in-the-loop decision design, explainable recommendation systems, repair verification, robotic coordination, and formal safeguards for high-consequence maintenance decisions.

Overall, future research should be guided by the recognition that DT-enabled predictive maintenance evolves through distinct maturity stages rather than through isolated technological advances. Near-term work should prioritize validation, interoperability, trustworthy modeling, robust sensing, and secure infrastructure. Medium-term efforts should strengthen scalable deployment, cross-domain comparability, and economically viable operational integration. Longer-term research can then support the emergence of federated, adaptive, and increasingly autonomous maintenance ecosystems across renewable

energy systems. In this way, the maturity framework proposed in this review provides not only a conceptual synthesis of the current field, but also a structured roadmap for its future development.

Conclusion

Digital Twin (DT) technologies are increasingly reshaping predictive maintenance strategies in renewable energy systems by enabling a shift from static, schedule-based maintenance toward dynamic, data-driven, and model-informed decision-making. Across wind turbines, solar photovoltaic systems, hydropower facilities, and battery energy storage systems, the reviewed literature shows that DTs can enhance condition awareness, support fault diagnosis, improve degradation tracking, and strengthen maintenance planning under complex and variable operating conditions. At the same time, the review also shows that DT-enabled predictive maintenance remains uneven in maturity across domains, with substantial differences in sensing depth, modeling sophistication, prognostic capability, validation practice, decision autonomy, and deployment readiness.

The contribution of this paper lies not only in synthesizing the state of the art across major renewable energy domains, but also in advancing a more structured interpretation of how DT-enabled predictive maintenance develops. In particular, the review has emphasized that Digital Twins should be understood not merely as virtual replicas or monitoring tools, but as the enabling backbone of decision-centric digital intelligence systems for maintenance-oriented reasoning and action. Building on this perspective, the paper proposed a Digital Twin Predictive Maintenance Maturity Framework that organizes the progression of DT-enabled maintenance from basic digital monitoring toward diagnostic, prognostic, prescriptive, and increasingly autonomous maintenance ecosystems. This framework constitutes the main conceptual novelty of the paper and provides a structured basis for comparative assessment, benchmarking, and interpretation of technology readiness across renewable energy applications.

The review further demonstrates that the practical value of DTs depends not only on architecture or algorithmic performance in isolation, but also on the integration of enabling technologies, the quality and reliability of sensing and communication infrastructure, the trustworthiness of predictive models, the robustness of cybersecurity provisions, and the economic and organizational conditions of deployment. The reported benefits of DT-enabled predictive maintenance—such as earlier fault detection, reduced downtime, improved safety, extended asset lifetime, and stronger sustainability performance—should therefore be interpreted in relation to implementation maturity rather than as uniform outcomes of DT adoption in general.

Overall, this paper shows that the future of DT-enabled predictive maintenance in renewable energy systems will depend on progress toward more validated, interoperable, explainable, secure, and scalable maintenance intelligence ecosystems. In this context, the proposed maturity framework offers not only a synthesis of the current field, but also a roadmap for its future development. By linking architecture, applications, enabling technologies, benefits, limitations, and future priorities within a unified maturity-oriented perspective, the paper provides a clearer conceptual foundation for advancing Digital Twin research and deployment in intelligent, resilient, and sustainable renewable energy systems.

CRedit authorship contribution statement

Mohamad Fani Sulaima: Writing – review & editing. **Ashwini Kumar Pradhan:** Writing – original draft. **Radim Lenort:** Writing – review & editing, Funding acquisition. **Robert Frischer:** Writing – review & editing. **Ondrej Krejcar:** Writing – review & editing. **Hamidreza Namazi:** Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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