

Digital Twin Technology for Renewable Energy Systems: Applications, Challenges, and Future Prospects

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Abstract

Renewable energy systems are increasingly deployed to support decarbonization and energy security, yet their operation remains challenged by intermittency, equipment degradation, grid instability, storage limitations, and the need for real-time decision-making. Digital twin technology offers a promising pathway for addressing these challenges by linking physical renewable energy assets with virtual models for monitoring, prediction, optimization, and control. This review examines the applications, enabling technologies, benefits, limitations, and future prospects of digital twin technology in renewable energy systems. A structured narrative review approach was adopted, in which 60 papers were initially considered and 44 studies were retained after screening for relevance to the scope of the study. The review shows that digital twins can support solar photovoltaic systems, wind turbines, battery storage units, hybrid microgrids, and smart grids through real-time monitoring, fault detection, power forecasting, predictive maintenance, battery health estimation, energy management, and grid optimization. However, practical deployment remains constrained by poor data quality, high implementation cost, cybersecurity risks, interoperability issues, model-validation challenges, and limited field testing. The review concludes that digital twin technology has strong potential to transform renewable energy systems from passively monitored assets into intelligent, adaptive, and actively managed energy systems. Future research should focus on affordable, scalable, secure, and field-validated digital twin frameworks, especially for developing countries where renewable energy adoption is growing but digital infrastructure remains limited.

Keywords: Digital twin, renewable energy, smart grids, solar photovoltaic systems, battery storage, microgrids.

1. Introduction

The global energy transition is increasingly being shaped by the need to reduce greenhouse gas emissions, improve energy security, and develop cleaner alternatives to fossil-fuel-based electricity generation. Renewable energy technologies such as solar photovoltaic systems, wind turbines, hydropower, biomass, geothermal systems, and hybrid renewable systems have become central to this transition because they offer pathways for lowering carbon emissions and diversifying energy supply. However, the shift to renewable energy is not simply a matter of replacing fossil fuels with cleaner technologies. It also requires reliable monitoring, intelligent control, accurate forecasting, efficient maintenance, strong policy support, and context-specific implementation. This is because renewable energy systems are affected by intermittency, weather variability, equipment degradation, grid instability, storage limitations, and economic constraints. Previous work on renewable energy barriers shows that adoption is limited by interconnected technical, economic, social, environmental, and policy challenges, including intermittency, high initial cost, limited storage capacity, public resistance, lifecycle impacts, and fragmented governance frameworks (Obuseh et al., 2025a).

The need for a more intelligent approach to renewable energy management becomes clearer when solar and wind energy are considered. These resources are naturally variable, and their output depends on environmental conditions such as solar irradiance, wind speed, temperature, humidity, shading, and seasonal changes. As renewable penetration increases, power systems must handle more uncertainty while still maintaining voltage stability, frequency stability, reliability, and power quality. This has made digital technologies more important in the energy sector. Digital twin technology has emerged as one of the most promising of these technologies because it provides a virtual representation of a physical asset, process, or system that can be updated using real-time or near-real-time data. Unlike ordinary simulation, a digital twin is not only used to model expected system behaviour; it is designed to remain connected to the physical system so that monitoring, prediction, diagnosis, optimization, and decision-making can be improved (Grieves & Vickers, 2017).

Digital twin technology has gained attention because renewable energy systems are becoming more complex, decentralized, and data-intensive. A modern renewable energy system may include solar panels, wind turbines, batteries, inverters, converters, sensors, smart meters, weather stations, controllers, communication networks, and grid-interface equipment. Managing these components manually or through fixed control assumptions is becoming less effective, especially where system performance changes continuously. Digital twins can help address this challenge by linking physical renewable energy assets with virtual models, artificial intelligence, machine learning, Internet of Things devices, cloud platforms, edge computing, and data analytics. This integration allows operators to detect faults, estimate system health, predict energy output, schedule maintenance, optimize storage operation, and support grid integration. Fuller et al. (2020) emphasized that digital twins depend on enabling technologies such as IoT, artificial intelligence, data analytics, and communication infrastructure, but also face open challenges related to modelling accuracy, data quality, interoperability, and cybersecurity.

The relevance of digital twins to renewable energy systems is also linked to the broader sustainability debate. Renewable energy technologies are often described as clean because

they generate electricity with little or no direct emissions during operation. However, this description can be incomplete if the full life cycle of the system is ignored. Solar photovoltaic systems, for example, still involve raw material extraction, manufacturing, transport, installation, component replacement, storage systems, and end-of-life management. A recent life cycle assessment review of solar photovoltaic systems showed that the main environmental pressures of PV systems are often linked to manufacturing, storage, and end-of-life management rather than electricity generation alone, while methodological inconsistency and regional evidence gaps still weaken the reliability of broad sustainability claims (Obuseh et al., 2026).

This wider sustainability concern is important because digital twin technology can support renewable energy systems beyond ordinary performance monitoring. If properly implemented, it can help extend equipment lifetime, reduce unnecessary maintenance, improve fault detection, optimize energy yield, and support better lifecycle decision-making. For example, a digital twin of a PV plant can identify underperforming modules, track degradation, estimate cleaning needs, and support decisions on repair or replacement. A wind turbine digital twin can monitor blade stress, gearbox condition, vibration, and structural health. A battery digital twin can estimate state of charge, state of health, remaining useful life, and thermal behaviour. In this way, digital twins can contribute not only to technical performance but also to sustainability by reducing downtime, material waste, operational inefficiency, and premature component failure. Recent reviews confirm that digital twins are increasingly being applied across renewable energy domains, including solar, wind, hydro, and hybrid systems, and across lifecycle stages such as design, operation, maintenance, and end-of-life optimization (Mbasso et al., 2025).

The need for digital twin technology is particularly strong in developing countries, where renewable energy adoption is often constrained by weak infrastructure, limited technical capacity, high implementation cost, inconsistent policies, and poor data availability. Nigeria provides a good example. The country has strong solar energy potential, but the electricity sector continues to face unreliable supply, inadequate infrastructure, and heavy dependence on alternative fossil-fuel generators. A study on the viability of solar energy in Nigeria reported that the country receives nearly 290 days of sunlight annually, with average solar insolation ranging from about 4.0 kWh/m²/day in the southern coastal regions to 7.0 kWh/m²/day in the northern regions; however, affordability, awareness, technological barriers, and policy inconsistency remain major limitations to wider solar deployment (Alele et al., 2024).

At the same time, decarbonization itself must be treated as more than an emission-reduction agenda. A sustainable energy transition must also consider social equity, governance quality, economic resilience, institutional coordination, and regional realities. This is important because renewable energy expansion can fail to achieve long-term sustainability if it ignores affordability, community acceptance, policy stability, local capacity, and environmental trade-offs. A review on sustainability of decarbonization argued that many decarbonization policies focus heavily on environmental targets while giving insufficient attention to social justice, financial risk, governance coherence, and context-specific policy design (Obuseh et al., 2025b).

Digital twin technology therefore sits at the intersection of renewable energy, computing, sustainability, and smart infrastructure. Its relevance is not only in creating virtual models, but in enabling renewable energy systems to become more observable, predictable, adaptive, and controllable. For smart energy systems, the architecture of a digital twin must integrate physical assets, data acquisition systems, communication networks, virtual models, analytics platforms, and decision-support mechanisms. Aghazadeh Ardebili et al. (2024) showed that the successful deployment of digital twins in smart energy systems depends on appropriate architecture, enabling technologies, design choices, data integration, management strategies, and computational capacity.

The computing dimension of digital twins is also important because digital twins depend on real-time data processing, intelligent algorithms, and hardware-software integration. Renewable energy digital twins require the same kind of practical connection between software intelligence and physical devices that is seen in embedded and cyber-physical systems. In a related computing-based implementation, Okpeki et al. (2026) developed a MATLAB-Arduino voice-activated security door system using MFCC and GMM algorithms, achieving 96% recognition accuracy in quiet environments and 87% under moderate noise, while highlighting the importance of real-time adaptability and hardware-software integration. Although that study was not on renewable energy, it supports the broader argument that intelligent digital systems become more useful when software models are connected to physical devices under real operating conditions.

Despite the growing body of research on digital twins, several gaps remain. Many studies still focus on conceptual frameworks, simulation models, or laboratory prototypes, while fewer demonstrate long-term field deployment in real renewable energy environments. There is also limited integration between digital twin research and sustainability assessment, especially in terms of cost, lifecycle impact, cybersecurity, interoperability, and suitability for developing countries. Existing studies often discuss solar, wind, battery, microgrid, and smart-grid applications separately, but fewer papers draw these areas together to explain how digital twins can support renewable energy systems as complete cyber-physical and sustainability-oriented systems. Recent work on digital twins for renewable energy and smart grids confirms that digital twins have strong potential for modernizing sustainable grids, but also identifies challenges related to high renewable penetration, energy storage integration, vehicle-to-grid operation, cybersecurity, and practical implementation (Al-Shetwi et al., 2025).

Based on these gaps, the novelty of this review lies in presenting a broad but integrated discussion of digital twin technology for renewable energy systems, with attention to applications, enabling technologies, benefits, limitations, and future prospects. Unlike studies that focus only on one technology, this review brings together solar PV systems, wind energy systems, battery storage, hybrid renewable systems, microgrids, and smart grids. It also links technical applications with wider concerns such as sustainability, policy relevance, developing-country challenges, lifecycle thinking, and practical deployment. In doing so, the review contributes to the literature by showing that digital twin technology should not be treated merely as a modelling tool, but as a decision-support framework for improving the reliability, efficiency, and sustainability of renewable energy systems.

2. Materials and Method

2.1 Review Design and Search Strategy

This review adopted a structured narrative review approach to examine existing research on digital twin technology for renewable energy systems. The approach was considered suitable because the study was not intended to follow a strict systematic review protocol, but to provide a broad and critical synthesis of the applications, challenges, and future prospects of digital twins across renewable energy technologies. Relevant studies were sourced from reputable academic databases and scholarly platforms, including Google Scholar, Scopus, ScienceDirect, IEEE Xplore, SpringerLink, Wiley Online Library, and MDPI. These sources were selected because they provide access to peer-reviewed publications in renewable energy, computing, smart grids, cyber-physical systems, and sustainability research.

The search focused on studies that addressed digital twin technology either from a conceptual, technical, or application-based perspective. Foundational papers were considered where they explained the meaning, evolution, classification, architecture, and enabling technologies of digital twins. Recent studies were also considered where they examined digital twin applications in solar photovoltaic systems, wind energy systems, battery storage systems, hybrid renewable systems, microgrids, smart grids, energy management, predictive maintenance, fault diagnosis, and renewable energy integration. In addition, a few related studies on renewable energy sustainability, decarbonization, solar energy viability, and barriers to renewable energy adoption were included to provide broader context for the review.

2.2 Study Selection and Synthesis

A total of 60 papers were initially considered during the literature search. After screening for relevance and alignment with the scope of the study, 44 papers were retained and used for the review, while 16 papers were excluded because they were either outside the focus of digital twin technology, not sufficiently related to renewable energy systems, or did not provide useful insight into the themes addressed in this paper. The retained papers were selected because they contributed directly to the understanding of digital twin concepts, renewable energy applications, enabling technologies, system monitoring, predictive maintenance, energy management, smart grid integration, sustainability, and implementation challenges.

The selected studies were examined and grouped around the major themes of the review. These themes included the conceptual understanding and evolution of digital twin technology, digital twin architecture and enabling technologies, applications in solar photovoltaic systems, applications in wind energy systems, battery storage and hybrid renewable systems, microgrid and smart grid applications, reported benefits, limitations, and research gaps. The findings were synthesized narratively to identify recurring patterns, major contributions, practical limitations, and future research directions. This method allowed the review to move beyond a simple summary of existing studies and instead draw broader insights on how digital twin technology is shaping the development and operation of renewable energy systems.

A simple publication trend analysis was also carried out to show the yearly distribution of the selected studies. The result, presented in Figure 1, shows that most of the selected publications were produced in recent years, especially between 2024 and 2026. This reflects the growing research interest in digital twin technology for renewable energy systems, particularly in areas such as smart grids, solar PV monitoring, wind turbine maintenance, battery health estimation, microgrid control, and real-time energy optimization. The year-wise distribution of the selected studies is presented in Figure 1.

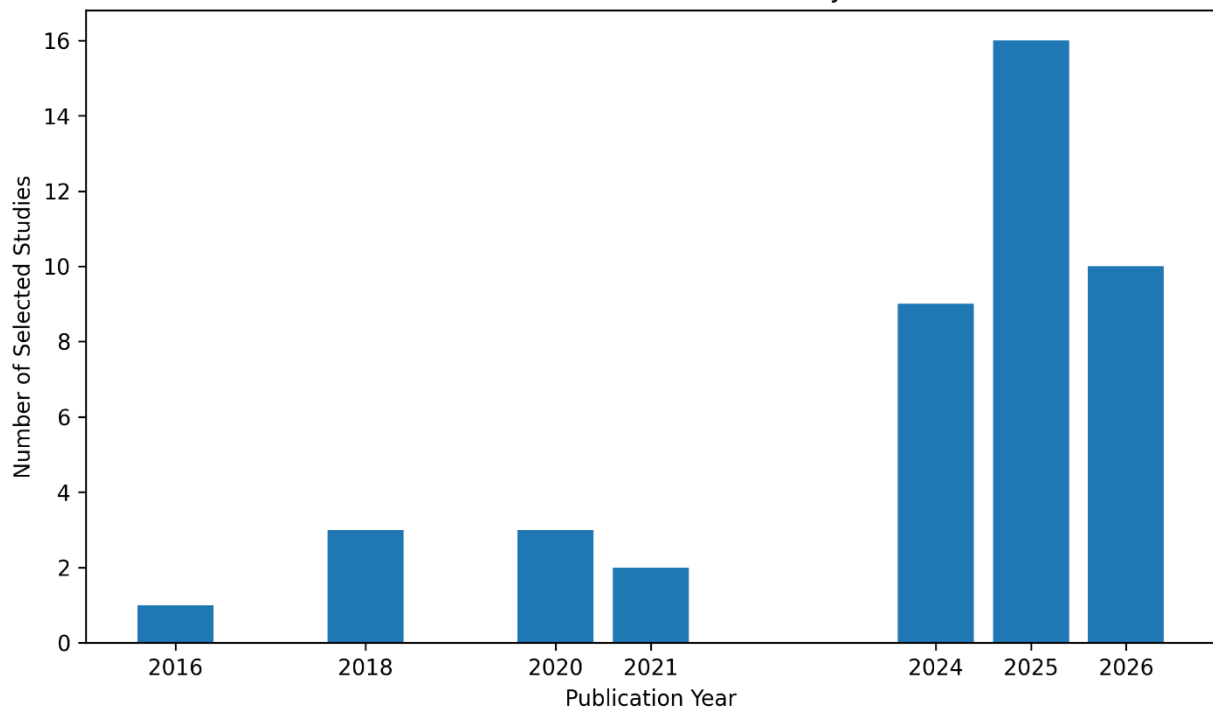


Figure 1. Distribution of selected studies by year.

The distribution shows that digital twin research in renewable energy systems has expanded strongly in recent years. While earlier studies from 2016, 2018, 2020, and 2021 provided the conceptual and methodological foundation for digital twin technology, the higher number of studies from 2024 to 2026 indicates a shift toward practical applications in clean energy systems, smart grids, battery storage, hybrid microgrids, and renewable energy integration. This trend supports the relevance of the present review, as it captures both the foundational development of digital twin technology and its recent expansion into renewable energy applications.

3. Review of Digital Twin Technology in Renewable Energy Systems

3.1 Conceptual Understanding and Evolution of Digital Twin Technology

Digital twin technology has become an important concept in the digital transformation of engineering and energy systems. At its simplest level, a digital twin can be described as a virtual representation of a physical object, process, or system that is connected to the real

system through data. However, it is not enough to define a digital twin as just a computer model. A normal simulation may show how a system is expected to behave, but a digital twin is expected to maintain a living connection with the physical system through data exchange, monitoring, prediction, and feedback. This makes the digital twin more useful for real-time decision-making than ordinary modelling or simulation (Grieves & Vickers, 2017).

The concept first gained attention in product lifecycle management, where virtual representations were used to support design, production, operation, maintenance, and disposal of complex products. This lifecycle view is important because engineering systems do not fail only during operation; many failures begin from design choices, material selection, production defects, poor maintenance planning, or weak operational control. Therefore, digital twin technology provides a way of linking the different stages of a system's life so that decisions made at one stage can be understood in relation to their effects at another stage (Tao et al., 2018).

A major issue in the literature is that the term digital twin is sometimes used loosely. Some studies describe any virtual model as a digital twin, even when there is no real-time connection between the physical system and the virtual representation. To avoid this confusion, digital twin studies often distinguish between a digital model, a digital shadow, and a true digital twin. A digital model has little or no automatic data exchange with the physical system, while a digital shadow receives data from the physical system but may not send feedback or decisions back. A true digital twin requires a stronger level of integration between the physical and virtual systems (Kritzinger et al., 2018).

This distinction is especially important in renewable energy systems because many studies still remain at the level of modelling and simulation. For example, a PV simulation model that predicts output under different irradiance and temperature conditions may be useful, but it does not automatically become a digital twin unless it is linked to real system data and updated as the physical PV system operates. In this sense, the digital twin should be viewed not merely as a model, but as a data-driven decision-support system that improves understanding of how a physical asset behaves under real operating conditions (Jones et al., 2020).

The development of digital twin technology has also been shaped by advances in enabling digital technologies. Internet of Things devices, sensors, cloud computing, artificial intelligence, machine learning, big data analytics, and communication networks have made it easier to collect, transfer, process, and interpret real-time data from physical systems. Without these technologies, the digital twin would remain only a static virtual model with limited operational value (Fuller et al., 2020).

From a modelling perspective, digital twins may be developed using physics-based models, data-driven models, or hybrid models. Physics-based models are useful because they describe system behaviour using known scientific and engineering principles. Data-driven models, on the other hand, can learn patterns directly from operational data. Hybrid models combine both approaches and are often more suitable for complex engineering systems where physical laws are known but real-world behaviour is affected by uncertainty, degradation, weather variation, and operational disturbances (Rasheed et al., 2020).

The movement of digital twin technology into renewable energy systems is linked to the changing nature of modern power systems. Renewable energy assets such as solar PV systems, wind turbines, battery storage units, inverters, and microgrids operate under variable environmental and electrical conditions. Their performance depends on factors such as irradiance, wind speed, temperature, load demand, component ageing, and grid interaction. As a result, renewable energy systems require continuous monitoring and intelligent management rather than fixed design assumptions alone (Aghazadeh Ardebili et al., 2024).

In solar PV systems, for instance, digital twins can help track performance losses caused by dust accumulation, shading, module mismatch, inverter faults, and degradation. In wind energy systems, they can support blade monitoring, gearbox diagnosis, turbine control, and predictive maintenance. In battery energy storage systems, they can assist in estimating state of charge, state of health, thermal behaviour, and remaining useful life. These applications show that digital twin technology is not limited to one renewable energy technology but can support different assets across design, operation, maintenance, and lifecycle management (Mbasso et al., 2025).

Despite its growing relevance, digital twin technology should not be presented as a perfect solution to all renewable energy problems. Its performance depends on the quality of data collected from the physical system, the accuracy of the virtual model, the reliability of the communication infrastructure, and the ability of operators to convert digital insights into practical decisions. Where data are poor, sensors are limited, or models are not properly validated, the digital twin may produce misleading results rather than useful intelligence (Semeraro et al., 2021).

Therefore, the evolution of digital twin technology can be understood as a movement from passive modelling to active, intelligent, and data-connected system management. In renewable energy systems, this shift is valuable because it supports better forecasting, fault detection, predictive maintenance, energy management, and operational planning. However, the literature still suggests that many applications remain at conceptual, simulation, or prototype level, especially in developing energy markets where cost, digital infrastructure, technical expertise, and data availability remain serious barriers. This creates a clear need for further research on practical implementation, affordability, cybersecurity, interoperability, and sustainability assessment of digital twin-enabled renewable energy systems (Qi & Tao, 2018).

3.2 Digital Twin Architecture and Enabling Technologies

The architecture of a digital twin is usually built around the relationship between the physical system, the virtual system, and the data connection that keeps both sides synchronized. In renewable energy systems, the physical layer may include solar PV modules, wind turbines, battery storage units, power converters, inverters, sensors, meters, protection devices, and grid-interface equipment. This layer is important because the quality of the digital twin depends first on how accurately the real system is observed. If the physical system is poorly instrumented, the digital twin may become only a theoretical model rather than a reliable operational tool (Kabir et al., 2024).

The second part of the architecture is the data acquisition and communication layer. This layer collects operating data such as voltage, current, temperature, irradiance, wind speed, battery state of charge, power output, fault signals, and load demand. These data are usually obtained through sensors, smart meters, SCADA systems, IoT devices, and weather-monitoring units. For renewable energy systems, this layer is particularly important because solar and wind outputs are not constant; they change with environmental and operating conditions. Therefore, the data layer allows the digital twin to move beyond fixed assumptions and reflect the real behaviour of the energy asset (Aghazadeh Ardebili et al., 2024).

The virtual modelling layer is the analytical centre of the digital twin. It converts the collected data into a useful virtual representation of the physical system. Depending on the purpose of the twin, the virtual model may be physics-based, data-driven, or hybrid. Physics-based models are useful when the behaviour of the system can be described using electrical, thermal, mechanical, or aerodynamic equations. Data-driven models are useful when historical and real-time data are available for learning patterns. Hybrid models are often more suitable for renewable energy systems because they can combine engineering knowledge with machine learning to handle uncertainty, degradation, weather variation, and operational disturbances (Rasheed et al., 2020).

Another important layer is the data processing and intelligence layer. This is where artificial intelligence, machine learning, big data analytics, and optimization algorithms are used to interpret system behaviour and support decisions. In solar PV systems, this layer may be used for fault detection, power forecasting, dust estimation, and degradation tracking. In wind energy systems, it may support blade monitoring, gearbox diagnosis, and predictive maintenance. In battery storage systems, it can assist in state of charge estimation, state of health prediction, thermal monitoring, and remaining useful life estimation. This shows that the intelligence layer gives the digital twin its practical value, because raw data alone cannot improve system performance unless they are converted into useful insight (Mbasso et al., 2025).

Cloud computing and edge computing also play important roles in digital twin implementation. Cloud computing provides large storage capacity and computational power for simulation, long-term data analysis, and system-wide optimization. However, relying only on cloud platforms may create delay, data-transfer cost, and privacy concerns. Edge computing addresses part of this problem by processing some data closer to the physical asset, making it useful for fast control, real-time monitoring, and local decision-making. In renewable energy systems, this is important because faults, sudden weather changes, and battery safety issues may require quick responses rather than delayed cloud-based analysis (Fuller et al., 2020).

The final part of the architecture is the decision-support and feedback layer. This layer transforms the output of the virtual model into practical actions such as maintenance scheduling, control adjustment, fault alarms, energy dispatch, battery charging strategy, inverter control, or grid-support decisions. A digital twin becomes more valuable when it does not only describe the condition of a renewable energy system, but also helps operators decide what to do next. This makes feedback and decision support essential, especially in

systems such as microgrids and smart grids where several energy sources, storage units, and loads must be coordinated in real time (Thwe et al., 2025).

Despite this layered structure, digital twin architecture should not be seen as a fixed design that works the same way in every renewable energy application. A digital twin for a single PV module may require fewer sensors and simpler models than a digital twin for a wind farm, battery energy storage system, or grid-connected hybrid microgrid. The architecture must therefore be designed according to the purpose of the system, the level of data available, the required accuracy, and the type of decision to be supported. This is why recent literature increasingly treats digital twins as flexible cyber-physical frameworks rather than one-size-fits-all software tools (Kim et al., 2025).

The architecture of a digital twin for renewable energy systems depends on the effective integration of physical assets, real-time data, communication networks, virtual models, intelligent analytics, and decision-support mechanisms. The enabling technologies do not work separately; they complement one another. Sensors and IoT devices provide data, communication networks transmit data, cloud and edge platforms process data, artificial intelligence extracts meaning from data, and feedback systems convert digital insight into operational action. However, the strength of the architecture also creates its weakness, because poor data quality, weak connectivity, high implementation cost, cybersecurity risks, and lack of interoperability can reduce the practical usefulness of digital twins in renewable energy systems.

3.3 Digital Twin Applications in Solar Photovoltaic Systems

Solar photovoltaic systems are highly suitable for digital twin application because their performance is strongly affected by changing environmental and operating conditions. Solar irradiance, module temperature, shading, dust accumulation, inverter behaviour, cable losses, and component ageing can all cause the actual output of a PV system to differ from its expected output. For this reason, digital twins are increasingly being explored as tools for linking real-time PV operating data with virtual models that can monitor, predict, and diagnose system behaviour. A PV digital twin therefore goes beyond ordinary PV simulation because it is expected to represent the physical system dynamically and update its behaviour as new data are received (Zhao et al., 2024).

One of the major applications of digital twins in PV systems is power-output prediction. Accurate PV power forecasting is important because solar generation is intermittent and depends on weather conditions that change throughout the day. By combining historical PV data, weather information, and intelligent prediction models, digital twins can improve the ability of operators to estimate future energy generation. This is particularly useful for grid-connected PV plants, smart buildings, and microgrids where solar power must be coordinated with load demand, storage, and grid supply. In this direction, transformer-based digital twin models have been proposed to improve the prediction of PV output under uncertain operating conditions (Zhao et al., 2024).

Digital twins are also useful for fault detection and diagnosis in PV systems. PV faults may occur at module, string, converter, inverter, sensor, or communication level. When these

faults are not detected early, they can reduce energy yield, increase downtime, and create safety concerns. A digital twin can help by creating a reference behaviour for the PV system and comparing this reference with real measured values. If the measured output deviates significantly from the expected output, the system can identify possible abnormal conditions. Hong and Pula (2024) applied a digital twin approach with a PSO-optimized shifted-window transformer for PV fault diagnosis, showing how intelligent models can strengthen fault identification in PV systems.

Recent studies have also connected digital twin technology with machine learning techniques for more accurate PV fault classification. This is important because different PV faults can produce similar symptoms, making diagnosis difficult when only basic threshold methods are used. Machine learning-based digital twins can learn from normal and abnormal operating patterns, allowing them to classify faults more intelligently. Nasri et al. (2025) proposed a digital twin-based kernel random forest framework for fault detection and diagnosis in grid-connected PV systems, highlighting the growing role of hybrid digital twin and AI methods in improving PV reliability.

Another important application is energy management in buildings and distributed PV systems. As more buildings adopt rooftop PV systems for self-consumption, there is a need to understand how PV generation interacts with household or building energy demand. Digital twins can support this by modelling the behaviour of the PV system and helping to optimize energy use. Dimitrova-Angelova et al. (2025) compared mathematical modelling and neural network approaches for photovoltaic digital twins in smart buildings, showing that PV digital twins can support energy management by improving the representation of PV generation under real operating conditions.

Digital twins can further support intelligent monitoring and maintenance planning. Instead of waiting for a PV module or inverter to fail before action is taken, the digital twin can help detect early signs of performance decline. This is useful for identifying underperforming modules, abnormal temperature rise, shading effects, dust-related losses, or inverter irregularities. Patrick (2026) developed a solar-panel digital twin prototype for intelligent monitoring, fault detection, and fault classification, demonstrating how even small-scale PV systems can benefit from real-time digital representation.

However, the application of digital twins in PV systems still faces practical limitations. Many PV digital twin studies focus on simulation, small testbeds, or prototype systems, while fewer studies demonstrate long-term field deployment in large-scale PV plants under real environmental stress. In addition, effective PV digital twins require accurate sensors, clean data, reliable communication, validated models, and sufficient computational resources. Where these conditions are weak, the digital twin may produce unreliable results. Recent reviews on PV digital twins therefore emphasize that although the technology has strong potential for monitoring, prediction, fault diagnosis, and maintenance, its wider adoption still depends on solving issues related to cost, scalability, interoperability, and real-world implementation (Elnosh et al., 2026).

Digital twin technology is becoming an important tool for improving the operation and reliability of solar PV systems. Its main value lies in its ability to connect real-time field data

with virtual models for performance monitoring, output prediction, fault diagnosis, maintenance planning, and energy management. Nevertheless, its success in PV applications will depend on how well researchers and operators move from laboratory-based models to practical, affordable, and scalable systems that can operate reliably in real PV environments.

3.4 Digital Twin Applications in Wind Energy Systems

Wind energy systems are another major area where digital twin technology has gained strong research attention. This is because wind turbines are large, expensive, mechanically complex, and usually exposed to harsh environmental conditions. Their operation is affected by changing wind speed, turbulence, temperature, mechanical loading, vibration, fatigue, and grid conditions. As a result, wind turbines require continuous monitoring and intelligent maintenance strategies to reduce failure risk and improve availability. Digital twins are useful in this context because they can combine real-time turbine data with virtual models to monitor performance, detect faults, and support maintenance decisions (Olatunji et al., 2021).

One important application of digital twins in wind energy is condition monitoring. Wind turbines contain several critical components, including blades, gearbox, generator, bearings, drivetrain, tower, and foundation. Failure in any of these components can lead to costly downtime and loss of energy production. A digital twin can monitor turbine behaviour by receiving data from vibration sensors, temperature sensors, strain gauges, SCADA systems, and power-output measurements. This allows the virtual model to compare normal and abnormal operating conditions and detect early signs of deterioration before complete failure occurs (Kandemir et al., 2024).

Digital twins are also valuable for predictive maintenance in wind turbines. Traditional maintenance may be scheduled at fixed intervals or performed after a fault has occurred, but this approach can either waste resources or allow hidden faults to grow. Predictive maintenance uses data to estimate when a component is likely to fail so that maintenance can be planned before serious damage occurs. In wind energy systems, this is particularly important because some turbines are installed offshore or in remote locations where inspection and repair are expensive. Recent research has shown that digital twin models can support predictive maintenance by combining real-time data, simulation, and degradation analysis for more reliable maintenance planning (Khazaeli Moghadam, 2024).

Another major application is structural health monitoring, especially for offshore wind turbines. Offshore turbines are exposed to wind, wave, current, and structural loading, making their foundations, towers, and blades vulnerable to fatigue and damage. A digital twin can help estimate the structural response of the turbine under real operating conditions, even when sensor data are limited. This is important because it is not always practical or economical to install sensors on every structural location. Jiang and Chen (2025) proposed a graph neural network-based digital twin for real-time and high-fidelity structural health monitoring of offshore wind turbines, showing the growing role of advanced AI models in wind-turbine safety assessment.

Wind-turbine blades are also a key focus of digital twin research. Blades are continuously exposed to aerodynamic forces, rain erosion, lightning, icing, fatigue, and mechanical stress.

Small blade defects can reduce aerodynamic efficiency and may develop into more serious structural problems if not detected early. Digital twins can support blade monitoring by linking sensor data, aerodynamic models, and fault-diagnosis algorithms. This makes it possible to identify abnormal vibration, surface damage, icing effects, or structural weakness that may affect turbine output and safety. Recent work on floating offshore wind turbines also shows that real-time digital twins can support blade and platform monitoring where physical inspection is difficult (Pastor-Sanchez et al., 2025).

The gearbox and drivetrain are other important areas of application. These components transfer mechanical energy from the rotor to the generator and are subject to vibration, wear, misalignment, bearing faults, and lubrication problems. Because gearbox failure can cause long downtime and high repair cost, digital twins are increasingly being used to track gearbox health and estimate remaining useful life. Xu et al. (2025) integrated a fault-diagnosis algorithm into a digital twin monitoring system for wind-turbine gearboxes, demonstrating how intelligent models can be used for early diagnosis and maintenance support.

Digital twins can also support wind-farm operation and performance optimization. A single wind turbine does not operate in isolation; turbines in a wind farm interact through wake effects, wind direction, turbine spacing, and control strategies. A digital twin can help operators understand these interactions and adjust turbine operation to improve total energy production. It can also support forecasting, yaw control, load reduction, and decision-making under changing wind conditions. This is important because optimizing a wind farm requires understanding both individual turbine behaviour and the collective behaviour of the whole plant (Leon-Medina et al., 2025).

Digital twin implementation in wind energy still faces several challenges. Wind turbines operate under highly uncertain environmental conditions, and their mechanical behaviour can be difficult to model accurately. In addition, digital twins require reliable sensors, high-quality data, validated models, strong communication systems, and skilled operators. Offshore wind systems add further challenges because of harsh marine conditions, high inspection cost, and limited accessibility. Therefore, while digital twins offer strong potential for condition monitoring, predictive maintenance, structural health monitoring, and performance optimization, their practical value depends on how well they can be validated and deployed under real operating conditions.

3.5 Digital Twin Applications in Battery Storage, Hybrid Renewable Systems, and Microgrids

Battery energy storage systems are central to renewable energy deployment because they help reduce the mismatch between variable generation and electricity demand. Solar and wind resources are intermittent, so storage is needed to improve supply reliability, smooth power fluctuations, support backup operation, and strengthen grid stability. In this context, digital twins are increasingly being used to monitor battery behaviour, estimate internal states, and support safer operation. A battery digital twin can combine measured data, electrochemical models, thermal models, and intelligent algorithms to represent how the physical battery performs under different charging, discharging, ageing, and temperature conditions (Bendaouia et al., 2026).

One of the most important uses of digital twins in battery systems is state estimation. Battery state of charge, state of health, remaining useful life, internal resistance, and thermal condition are not always directly measurable, yet they strongly determine battery performance and safety. A digital twin can estimate these hidden states by comparing real-time battery data with virtual models. Zhao et al. (2025) introduced a digital twin-supported battery state estimation method, showing how digital twins can improve battery monitoring by linking operational data with model-based state prediction.

Digital twins are also valuable for battery health prognosis. Renewable energy systems often depend on batteries for long-term storage, but battery ageing can reduce capacity, increase internal resistance, and shorten system lifetime. If battery degradation is not properly monitored, the entire renewable energy system may become unreliable. Wang et al. (2025) reviewed digital twins for lithium-ion battery health prognosis and emphasized their importance in predicting state of health, remaining useful life, and fault conditions. This makes digital twins useful not only for present-time monitoring but also for planning battery replacement and maintenance.

Beyond individual battery units, digital twins are becoming useful in hybrid renewable energy systems where PV, wind, diesel backup, storage, converters, and loads may operate together. Hybrid systems are more complex than single-source systems because energy must be coordinated across different sources with different operating characteristics. A digital twin can support this coordination by simulating energy flows, predicting renewable generation, monitoring storage availability, and recommending control actions. Testasecca et al. (2025) demonstrated this direction in a microgrid context by using a digital twin for real-time and predictive optimization of electric-vehicle charging in renewable-integrated microgrids.

Microgrids also benefit from digital twin technology because they require continuous balancing of generation, storage, and demand. In off-grid and grid-connected microgrids, the digital twin can act as a decision-support platform for energy management, load balancing, demand response, fault detection, and dispatch optimization. This is particularly useful when renewable penetration is high and the system must respond quickly to changing weather, load variations, or grid disturbances. Sifat et al. (2026) reviewed digital twin-based microgrid control and energy management, showing that digital twins can improve microgrid resilience by supporting real-time modelling, control, and operational planning.

In practical terms, digital twins can help hybrid renewable microgrids decide when to charge or discharge batteries, when to use grid power, when to curtail excess renewable generation, and how to maintain voltage and frequency stability. This is important because poor energy management can lead to battery overuse, reduced battery lifetime, unstable supply, or unnecessary reliance on backup generation. Recent studies on IoT-enabled DC microgrids show that digital twin frameworks can integrate solar PV, wind generation, battery storage, and load control into a more coordinated energy-management system (Zhang et al., 2026).

Battery and microgrid digital twins still face several limitations. Battery behaviour is highly nonlinear, and accurate modelling becomes difficult under changing temperature, irregular cycling, ageing, and different operating conditions. Hybrid systems and microgrids also require reliable communication, synchronized data, accurate forecasting, and compatible

control platforms. Where these conditions are weak, the digital twin may not provide dependable decisions. Therefore, while digital twins have strong potential for improving battery monitoring, energy management, and microgrid reliability, their effectiveness depends on accurate models, high-quality data, cybersecurity protection, and practical field validation.

3.6 Digital Twin Technology for Smart Grids and Renewable Energy Integration

The integration of renewable energy into modern power grids has created new operational challenges because solar and wind generation are variable, decentralized, and strongly influenced by weather conditions. Unlike conventional power plants, renewable energy sources can change rapidly within short time intervals, making grid operation more complex. Digital twin technology is useful in this context because it can create a virtual representation of the grid and its connected renewable assets, allowing operators to monitor system behaviour, test operational scenarios, and support real-time decision-making (Al-Shetwi et al., 2025).

One important application of digital twins in smart grids is real-time grid monitoring. A smart grid contains different components such as transmission lines, distribution feeders, transformers, substations, smart meters, distributed generators, storage systems, and controllable loads. A digital twin can bring data from these components into a virtual environment where the grid condition can be continuously observed. This makes it easier to detect abnormal operating conditions such as overloads, voltage deviation, equipment stress, and network congestion before they develop into wider reliability problems (Mchirgui et al., 2024).

Digital twins also support renewable energy forecasting and dispatch planning. Since renewable output depends on solar irradiance, wind speed, temperature, and weather variability, accurate forecasting is needed to balance generation and demand. A grid digital twin can combine weather data, historical generation patterns, load profiles, and power-flow models to estimate future operating conditions. This helps system operators decide how much renewable energy can be absorbed, when storage should be charged or discharged, and when backup supply or demand-response actions may be required (Ugwu et al., 2026).

Another key area is voltage and frequency stability. High penetration of inverter-based renewable energy can reduce system inertia and make the grid more sensitive to disturbances. Digital twins can help operators simulate how the grid responds to sudden changes in generation, load demand, or fault conditions. This is useful for planning control strategies such as reactive power compensation, inverter control, battery dispatch, and load adjustment. For large grid-connected PV plants, digital twin-driven voltage and reactive power optimization has been proposed as a way to improve dynamic voltage regulation and reduce operational risk (Shi et al., 2026).

Digital twins are also relevant for fault detection, restoration, and resilience planning. In renewable-rich grids, faults may be more difficult to manage because power can flow from several distributed energy resources instead of one central source. A digital twin can support fault location, isolation, service restoration, and contingency analysis by testing different

network responses in the virtual environment before applying decisions to the physical grid. This is particularly valuable for distribution networks where rooftop PV, battery storage, electric vehicles, and flexible loads are increasingly connected (Thwe et al., 2025).

In addition, digital twins can support distributed energy resource management. As more consumers become “prosumers” by generating and storing electricity locally, grid operators need better tools to coordinate many small energy resources. Digital twins can help manage the interaction between rooftop PV systems, batteries, electric vehicles, smart buildings, and the main grid. This can improve load balancing, reduce curtailment, support demand response, and improve the use of locally generated renewable energy (Malik et al., 2026).

The use of digital twins for smart grids and renewable energy integration still faces important limitations. Power grids are large, interconnected, and highly dynamic, so developing accurate and scalable digital twins is technically demanding. The system requires high-quality data, secure communication, interoperability between devices, fast computation, and reliable cybersecurity protection. Without these, the digital twin may become too slow, inaccurate, or vulnerable for real grid operation. Therefore, while digital twin technology offers strong potential for renewable energy integration, its practical success depends on field validation, standardization, data governance, and affordable deployment frameworks.

3.7 Reported Benefits, Limitations, and Research Gaps in Existing Studies

Existing studies generally present digital twin technology as a promising tool for improving the design, operation, monitoring, and lifecycle management of renewable energy systems. Its main benefit is that it allows the behaviour of a physical energy system to be represented virtually and updated with operational data. This makes it useful for detecting abnormal conditions, comparing expected and actual performance, and supporting better technical decisions. In renewable energy systems, this is important because solar, wind, storage, and hybrid systems operate under variable environmental and electrical conditions, making static design assumptions insufficient for long-term performance management (Semeraro et al., 2025).

Another reported benefit is improved maintenance planning. Instead of relying only on scheduled or corrective maintenance, digital twins can support predictive maintenance by identifying early signs of performance decline or component stress. This can reduce downtime, prevent unexpected failures, and improve the availability of renewable energy assets. A recent study on digital twin-enabled predictive maintenance emphasized its relevance for wind, solar, hydro, and geothermal systems, particularly where continuous monitoring and early fault identification are needed to improve reliability.

Digital twins also provide benefits for energy management and grid operation. By combining real-time monitoring, simulation, forecasting, and optimization, they can support renewable energy dispatch, storage coordination, demand response, and grid stability. This is especially important as modern power systems move from centralized generation to decentralized and renewable-rich networks. Recent work on digital twins for IoT-driven energy systems shows that they can support real-time energy monitoring, predictive maintenance, and enhanced grid

management, while also exposing deployment challenges in data-intensive energy environments (Kabir et al., 2024).

Despite these benefits, the literature also shows that digital twin technology is not yet fully mature for many renewable energy applications. One major limitation is data quality. A digital twin depends heavily on accurate, continuous, and reliable data from sensors, meters, controllers, weather stations, and communication platforms. If the data are incomplete, noisy, delayed, or poorly synchronized, the virtual model may not correctly represent the physical system. This means that a digital twin can only be as reliable as the data infrastructure supporting it.

Another limitation is interoperability. Renewable energy systems often involve equipment from different manufacturers, communication protocols, software platforms, databases, and control systems. If these components cannot communicate properly, it becomes difficult to build a unified digital twin. Acharya et al. (2024) identified interoperability as a major challenge in cyber-physical digital twins, especially where different data formats, platforms, and system layers must be integrated into one functional architecture.

Cybersecurity and privacy are also important concerns. Digital twins rely on continuous data exchange between physical assets and virtual platforms, which can expose energy systems to cyberattacks, unauthorized access, data manipulation, and operational disruption. This issue becomes more serious in smart grids and distributed renewable energy systems where many devices are connected through IoT and cloud platforms. Therefore, digital twin deployment must include secure communication, access control, data governance, and resilience against cyber threats rather than treating cybersecurity as an afterthought.

Cost and technical complexity remain additional barriers. Developing a useful digital twin may require sensors, communication networks, data storage systems, cloud or edge computing platforms, modelling tools, AI algorithms, and skilled personnel. These requirements can be difficult for small renewable energy operators or developing countries where digital infrastructure is limited. This creates a research gap because many studies demonstrate digital twin models under controlled or simulated conditions, but fewer studies show how the same technology can be implemented affordably in real renewable energy systems.

The existing literature also shows a gap between conceptual frameworks and field validation. Many digital twin studies propose architectures, models, or algorithms, but fewer provide long-term testing with real renewable energy assets under changing environmental and operational conditions. This weakens confidence in how well digital twins perform outside laboratory or simulation environments. Reviews on digital twins in renewable energy systems therefore emphasize the need for more practical studies covering design, operation, maintenance, and end-of-life management across different renewable energy domains (Mbasso et al., 2025).

Another research gap concerns sustainability and lifecycle assessment. Although digital twins are often promoted as tools for improving efficiency and reducing waste, fewer studies examine their own environmental and economic implications. The sensors, data centers,

communication systems, and computing resources used to support digital twins also consume energy and materials. Future studies should therefore assess whether the operational benefits of digital twins outweigh their cost, energy demand, and environmental burden.

4. Discussion of Key Findings

The reviewed studies show that digital twin technology is becoming an important pathway for improving the intelligence, reliability, and operational performance of renewable energy systems. Across solar PV systems, wind turbines, battery storage, hybrid microgrids, and smart grids, one clear insight is that renewable energy systems are no longer just electrical or mechanical systems; they are gradually becoming data-driven cyber-physical systems. This means that their performance can no longer be fully understood through physical design alone. Real-time data, predictive models, intelligent algorithms, and decision-support platforms are now becoming essential for managing renewable energy assets under changing operating conditions.

A major point that emerges from the reviewed literature is that digital twin technology provides a bridge between physical renewable energy assets and intelligent system management. In solar PV systems, the digital twin can help identify performance losses caused by dust, shading, degradation, inverter faults, and environmental variation. In wind energy systems, it can support structural health monitoring, blade assessment, gearbox fault diagnosis, and predictive maintenance. In battery energy storage systems, it can improve state of charge estimation, state of health monitoring, thermal tracking, and remaining useful life prediction. In hybrid systems and microgrids, it can assist in energy dispatch, load balancing, storage coordination, and demand-side management. These applications show that the digital twin is not restricted to one renewable energy technology; rather, it is a flexible framework that can be adapted to different renewable energy assets depending on the data available, the model used, and the decision required.

However, the reviewed works also suggest that digital twin technology should not be treated as a simple extension of simulation. This distinction is very important. A simulation may predict how a renewable energy system should behave under assumed conditions, but a digital twin is expected to update itself with real operating data and support decisions based on the actual condition of the physical system. Therefore, the real value of a digital twin lies in its ability to connect modelling with operation. Without real-time or near-real-time data exchange, many so-called digital twins remain closer to digital models or digital shadows. This means that future research must be careful in how it uses the term “digital twin,” especially in renewable energy studies where many works still remain at the modelling or prototype level.

Another insight from the reviewed studies is that the benefits of digital twins are strongest in systems where uncertainty, variability, and maintenance complexity are high. Renewable energy systems naturally fall into this category. Solar and wind generation vary with weather conditions, while batteries degrade with cycling, temperature, and ageing. Microgrids and smart grids also face continuous changes in load demand, distributed generation, and network conditions. Digital twins are therefore useful because they provide a way to monitor these changes, predict future behaviour, and support better control decisions. This makes the

technology especially relevant for renewable-rich grids, where operators must manage uncertainty while maintaining voltage stability, frequency stability, reliability, and energy quality.

The reviewed works also show that predictive maintenance is one of the most practical and convincing applications of digital twin technology. Renewable energy assets often suffer losses not only from major failures but also from gradual performance decline. In PV systems, unnoticed soiling or module degradation can reduce energy yield. In wind turbines, blade damage, bearing defects, or gearbox faults can become expensive if not detected early. In battery systems, poor monitoring of degradation can lead to reduced capacity, safety risk, and premature replacement. Digital twins can reduce these problems by identifying abnormal behaviour before it becomes severe. This moves renewable energy maintenance away from reactive repair toward condition-based and predictive maintenance.

At the same time, the discussion shows that digital twin implementation is highly dependent on data quality. A digital twin cannot be better than the data feeding it. If sensors are inaccurate, communication is delayed, weather data are incomplete, or operational data are poorly synchronized, the digital twin may produce unreliable results. This is a major concern because renewable energy systems are often installed in harsh, remote, or resource-limited environments. For example, a digital twin for an offshore wind turbine may require high-quality vibration, strain, weather, and structural data, while a digital twin for a rural microgrid may depend on low-cost sensors and limited communication infrastructure. Therefore, the quality and availability of data remain one of the most important factors determining whether a digital twin will succeed in practice.

The reviewed literature also points to a tension between model accuracy and practical deployment. Highly detailed models may provide better representation of the physical system, but they may also require more data, more computing power, and more technical expertise. On the other hand, simpler models may be easier to implement but may not capture complex system behaviour accurately. This creates a design trade-off. For large wind farms, smart grids, or utility-scale PV plants, advanced hybrid models combining physics-based modelling and machine learning may be suitable. For smaller renewable energy systems, especially in developing regions, simpler and cheaper digital twin frameworks may be more practical. This means that there is no single digital twin architecture that fits every renewable energy system. The architecture must be designed according to the system size, purpose, available data, required accuracy, and economic capacity of the operator.

Another important issue is the role of artificial intelligence in digital twin systems. AI and machine learning improve the ability of digital twins to detect faults, forecast energy output, classify abnormal conditions, estimate battery states, and optimize system operation. However, overdependence on AI can also create challenges. Many AI models operate as black boxes, making it difficult for engineers and operators to understand why a particular decision or prediction was made. In critical energy systems, this lack of transparency can reduce trust. Therefore, future digital twin systems should not only be accurate but also interpretable. Explainable AI may become important in renewable energy digital twins because operators need to understand the basis of decisions affecting maintenance, dispatch, safety, and grid stability.

The reviewed studies further reveal that digital twins can support renewable energy integration into smart grids, but only if interoperability issues are addressed. Modern power systems contain devices from different manufacturers, different communication protocols, different data formats, and different software platforms. For a digital twin to function properly, these systems must exchange information smoothly. Without interoperability, the digital twin may become fragmented, representing only part of the system rather than the entire energy network. This is especially important for smart grids, where PV systems, wind farms, storage units, electric vehicles, smart meters, substations, and loads must be coordinated in real time.

Cybersecurity is another major concern. Since digital twins depend on continuous communication between physical and virtual systems, they increase the digital exposure of renewable energy infrastructure. If attackers manipulate sensor data, control signals, or model outputs, the digital twin may support wrong decisions that affect system performance or safety. This issue is particularly serious for smart grids and microgrids, where digital control is linked directly to power flow, protection systems, and energy dispatch. Therefore, cybersecurity should not be treated as an external add-on. It should be built into the design of digital twin systems from the beginning through secure communication, authentication, data validation, access control, and resilience planning.

The reviewed works also show that most digital twin applications are still stronger in concept than in widespread field deployment. Many studies propose frameworks, models, and algorithms, but fewer demonstrate long-term operation in real renewable energy environments. This gap is important because renewable energy systems are affected by unpredictable weather, equipment ageing, sensor failure, communication problems, and user behaviour. A model that performs well in simulation may not always perform well under real field conditions. Therefore, future studies should place more emphasis on field validation, long-term performance testing, and comparison between digital twin predictions and actual system outcomes.

From a developing-country perspective, digital twin technology presents both an opportunity and a challenge. On one hand, it can improve renewable energy reliability, reduce maintenance problems, support microgrid operation, and improve energy access. This is valuable in regions where grid supply is unreliable and renewable energy systems are increasingly used for backup or off-grid electricity. On the other hand, the cost of sensors, communication infrastructure, computing platforms, software, and skilled personnel may limit adoption. This means that digital twin research should not focus only on high-end applications in advanced energy markets. There is a need for low-cost, scalable, and locally adaptable digital twin solutions that can support renewable energy systems in developing economies.

Sustainability is another area that needs stronger attention. Digital twins are often presented as tools for improving efficiency, reducing downtime, and extending equipment life. These benefits can indirectly reduce waste and improve resource use. However, the digital twin itself also requires physical and digital infrastructure, including sensors, communication devices, servers, cloud platforms, and computing resources. These have their own energy demand, material footprint, and environmental burden. Therefore, future research should

evaluate not only the technical performance of digital twins but also their economic and environmental justification. A digital twin should be considered truly beneficial only when its operational benefits outweigh its cost, complexity, energy use, and lifecycle burden.

Overall, the reviewed works suggest that digital twin technology has strong potential to transform renewable energy systems from passively monitored assets into actively managed intelligent systems. Its major contributions are seen in monitoring, fault detection, forecasting, predictive maintenance, energy management, storage optimization, and grid integration. However, the technology is still limited by data quality, model validation, high cost, interoperability, cybersecurity, technical complexity, and limited real-world deployment. For digital twins to become more useful in renewable energy systems, future research should move beyond theoretical frameworks and focus on practical, secure, affordable, and field-tested solutions. The most valuable future digital twins will be those that can combine accurate modelling, reliable data, intelligent analytics, clear decision support, and real-world adaptability.

5. Conclusion

This review has shown that digital twin technology is becoming an important tool for improving the performance, reliability, and intelligent management of renewable energy systems. Unlike ordinary simulation models, digital twins provide a closer connection between physical assets and virtual models by using real-time or near-real-time data to monitor system behaviour, predict faults, support maintenance, and guide operational decisions. This makes the technology highly relevant to renewable energy systems, where performance is strongly affected by weather variation, component ageing, load changes, and grid interaction.

The reviewed studies revealed that digital twins have useful applications across different renewable energy domains. In solar photovoltaic systems, they support performance monitoring, fault diagnosis, power forecasting, energy yield optimization, and maintenance planning. In wind energy systems, they assist with turbine condition monitoring, blade and gearbox fault detection, structural health assessment, and predictive maintenance. In battery storage systems, digital twins improve state of charge estimation, state of health monitoring, thermal behaviour analysis, degradation tracking, and remaining useful life prediction. For hybrid renewable systems, microgrids, and smart grids, they provide a framework for energy management, load balancing, renewable energy integration, voltage and frequency support, and real-time decision-making.

Despite these advantages, the review also shows that digital twin technology is not yet fully mature for widespread deployment in renewable energy systems. Its effectiveness depends on reliable sensors, accurate models, high-quality data, stable communication networks, cybersecurity protection, interoperability, and skilled technical support. Many existing studies still remain at conceptual, simulation, or prototype level, with limited evidence of long-term field implementation. This creates a need for more practical studies that validate digital twin systems under real operating conditions.

In conclusion, digital twin technology has strong potential to transform renewable energy systems from passively monitored assets into intelligent, data-driven, and actively managed systems. However, future research should focus on affordability, scalability, standardization, cybersecurity, field validation, and sustainability assessment. Greater attention should also be given to developing low-cost digital twin frameworks suitable for developing countries, where renewable energy systems are increasingly needed but digital infrastructure may be limited. When properly designed and implemented, digital twins can support more reliable, efficient, and sustainable renewable energy deployment.

References

1. Acharya, S., Khan, A. A., & Päiväranta, T. (2024). Interoperability levels and challenges of digital twins in cyber-physical systems. *Journal of Industrial Information Integration*, 42, 100714.
2. Aghazadeh Ardebili, A., Zappatore, M., Ramadan, A. I. H. A., Longo, A., & Ficarella, A. (2024). Digital Twins of smart energy systems: a systematic literature review on enablers, design, management and computational challenges. *Energy Informatics*, 7(1), 94.
3. Al-Shetwi, A. Q., Atawi, I. E., El-Hameed, M. A., & Abuelrub, A. (2025). Digital Twin Technology for Renewable Energy, Smart Grids, Energy Storage and Vehicle-to-Grid Integration: Advancements, applications, key players, challenges and future perspectives in modernising sustainable grids. *IET Smart Grid*, 8(1), e70026.
4. Bendaouia, A., Wang, F., Ouifak, H., & Li, J. (2026). Digital twin for battery energy storage systems. *Renewable and Sustainable Energy Reviews*, 226, 116347.
5. Dimitrova-Angelova, D., González-González, J. F., Carmona-Fernández, D., & Jaramillo-Morán, M. A. (2025). Photovoltaic Digital Twins: Mathematical Modeling vs. Neural Networks for Energy Management in Smart Buildings. *Applied Sciences*, 15(16), 8883.
6. Elnosh, A., Calais, M., & Parlevliet, D. (2026). A systematic literature review of digital twin research for photovoltaic systems: Trends, challenges, and opportunities. *Renewable and Sustainable Energy Reviews*, 226, 116326.
7. Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE access*, 8, 108952-108971.
8. Grieves, M., & Vickers, J. (2016). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary perspectives on complex systems: New findings and approaches* (pp. 85-113). Cham: Springer International Publishing.
9. Hong, Y. Y., & Pula, R. A. (2024). Diagnosis of photovoltaic faults using digital twin and PSO-optimized shifted window transformer. *Applied Soft Computing*, 150, 111092.
10. Jiang, C., & Chen, N. Z. (2025). G-Twin: Graph neural network-based digital twin for real-time and high-fidelity structural health monitoring for offshore wind turbines. *Marine Structures*, 103, 103813.

11. Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP journal of manufacturing science and technology*, 29, 36-52.
12. Kabir, M. R., Halder, D., & Ray, S. (2024). Digital twins for IoT-driven energy systems: A survey. *IEEE Access*, 12, 177123-177143.
13. Kandemir, E., Hasan, A., Kvamsdal, T., & Abdel-Afou Alaliyat, S. (2024). Predictive digital twin for wind energy systems: a literature review. *Energy Informatics*, 7(1), 68.
14. Kazeem, O. U., Godwin, I. O., Oyubu, O. A., Ilori, E. G., Peretomode, E., & Ewere, O. E. (2026). Design and Implementation of a Voice-Activated Security Door System Using Matlab. *NIPES-Journal of Science and Technology Research*, 8(1), 315-323.
15. Khazaeli Moghadam, F., Keprate, A., & Gao, Z. (2024). Online monitoring of wind power plants using digital twin models. *Frontiers in Energy Research*, 12, 1531689.
16. Kim, M., Ghobadi, F., Tayerani Charmchi, A. S., Lee, M., & Lee, J. (2025). Digital Twins for Clean Energy Systems: A State-of-the-Art Review of Applications, Integrated Technologies, and Key Challenges. *Sustainability*, 18(1), 43.
17. Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *Ifac-Papers Online*, 51(11), 1016-1022.
18. Leon-Medina, J. X., Tibaduiza, D. A., Parés, N., & Pozo, F. (2025). Digital twin technology in wind turbine components: A review. *Intelligent Systems with Applications*, 26, 200535.
19. Malik, M. T., Obaid, H. M., & Rasool, H. F. (2026). Integrating digital twin and sensor technologies for future-ready smart grids. *Discover Electronics*, 3(1), 42.
20. Mbasso, W. F., Harrison, A., Dagal, I., Jangir, P., Khishe, M., Kotb, H., ... & Kumar, R. (2025). Digital twins in renewable energy systems: A comprehensive review of concepts, applications, and future directions. *Energy Strategy Reviews*, 61, 101814.
21. Mchirgui, N., Quadar, N., Kraiem, H., & Lakhssassi, A. (2024). The applications and challenges of digital twin technology in smart grids: A comprehensive review. *Applied Sciences*, 14(23), 10933.
22. Nasri, I., Mansouri, M., Refaat, S. S., Dhibi, K., & Skorek, A. W. (2025). Digital Twin-Based Kernel RF for Fault Detection and Diagnosis in Photovoltaic Systems. *IEEE Access*, 13, 211533-211542.
23. Nneoma Ugwu, C., Chukwudi Ogenyi, F., Nnenna Ugwu, J., Okechukwu Ugwu, P. C., & Ben Okon, M. (2026). Integration of AI-driven digital twins for real-time optimization of renewable energy grids. *Frontiers in Energy Research*, 14, 1748233.
24. Obuseh, E., EBISINE, E. E., OKIEKE, U. J., ALOAMAKA, C. A., & ANAMONYE, G. U. (2025). Sustainability of Decarbonization: A Systematic Review of Policy Integration and Regional Realities. *Nigerian Journal of Sustainability Research*, 3(2), 77-95.
25. Obuseh, E., Eyenubo, J., Alele, J., Okpare, A., & Oghogho, I. (2025). A systematic review of barriers to renewable energy integration and adoption. *Journal of Asian Energy Studies*, 9, 26-45.

26. Obuseh, E., Otuagoma, S., Efenedo, G. I., ANAMONYE, G., Okieke, U. J., & EYENUBO, J. (2026). Sustainability of Solar Photovoltaic Systems: A Life Cycle Assessment Review. *Nigerian Journal of Sustainability Research*, 4(1), 387-410.
27. Oghenegare, A. J., Nkemdilim, E. J., Ewere, O. E., Donald, I., & Ekene, M. C. (2024). Renewable energy in Nigeria: a comprehensive examination of the viability of solar energy in Nigeria. *Int J Innov Res Technol*, 11(5), 2433-2438.
28. Olatunji, O. O., Adedeji, P. A., Madushele, N., & Jen, T. C. (2021, May). Overview of digital twin technology in wind turbine fault diagnosis and condition monitoring. In *2021 IEEE 12th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT)* (pp. 201-207). IEEE.
29. Pastor-Sanchez, A., Garcia-Espinosa, J., Di Capua, D., Servan-Camas, B., & Berdugo-Parada, I. (2025). Real-time digital twin for structural health monitoring of floating offshore wind turbines. *Journal of Marine Science and Engineering*, 13(10), 1953.
30. Patrick, D., & Amusan, A. (2026). Digital Twin Model of a Solar Panel for Intelligent Monitoring Using Artificial Neural Network. *ABUAD Journal of Engineering Research and Development (AJERD)*, 9(1), 97-112.
31. Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE access*, 6, 3585-3593.
32. Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE access*, 8, 21980-22012.
33. Semeraro, C., Aljaghoub, H., Al-Ali, H. K. M. H., Abdelkareem, M. A., & Olabi, A. G. (2025). Harnessing the future: Exploring digital twin applications and implications in renewable energy. *Energy Nexus*, 18, 100415.
34. Semeraro, C., Lezoche, M., Panetto, H., & Dassisti, M. (2021). Digital twin paradigm: A systematic literature review. *Computers in industry*, 130, 103469.
35. Shi, Q., & Zhou, J. (2026). Digital Twin-Driven Dynamic Reactive Power and Voltage Optimization for Large Grid-Connected PV Stations. *Electronics*, 15(4), 821.
36. Sifat, M. M. H., Haque, M. E., Islam, S., Ronanki, D., & Kumar, B. K. (2026). Digital twin based microgrid control and energy management: Trends, challenges, and future directions. *Computers and Electrical Engineering*, 134, 111100.
37. Tabassum, S., Babu, A. R. V., Dheer, D. K., & Narasipuram, R. P. (2026). A Digital Twin Framework Driven Energy Management Strategy for Hybrid DC Microgrids with Integrated xEV Charging Applications. *Sustainable Computing: Informatics and Systems*, 101364.
38. Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., & Sui, F. (2018). Digital twin-driven product design, manufacturing and service with big data. *The International Journal of Advanced Manufacturing Technology*, 94(9), 3563-3576.
39. Testasecca, T., Bellesini, F., Arnone, D., & Beccali, M. (2025). A Digital Twin for Real-Time and Predictive Optimization of Electric Vehicle Charging in Microgrids Integrating Renewable Energy Sources. *Energies*, 18(21), 5605.
40. Thwe, M. M., Ştefanov, A., Rajkumar, V. S., & Palensky, P. (2025). Digital twins for power systems: Review of current practices, requirements, enabling technologies, data federation and challenges. *IEEE Access*.

41. Wang, Y., Xiao, J., Soo, Y. Y., Chen, Y., & Chen, Z. (2025). Digital twins for battery health prognosis: A comprehensive review of recent advances and challenges. *ETransportation*, 100489.
42. Zhang, Y., Sun, R., & Shang, J. (2025). Prescribed Performance Bounded- H_∞ Control for Flexible-Joint Manipulators Without Initial Condition Restriction. *Sensors*, 25(7), 2195.
43. Zhao, K., Liu, Y., Zhou, Y., Ming, W., & Wu, J. (2025). Digital twin-supported battery state estimation based on TCN-LSTM neural networks and transfer learning. *CSEE Journal of Power and Energy Systems*, 11(2), 567-579.
44. Zhao, X. (2024). A novel digital-twin approach based on transformer for photovoltaic power prediction. *Scientific Reports*, 14(1), 26661.