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Integration of AI-driven digital twins for real-time optimization of renewable energy grids

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The increasing integration of renewable energy sources, such as solar photovoltaics, wind turbines, hydropower, and energy storage systems, introduces substantial variability and complexity into modern power grids. This variability challenges grid stability, supply-demand balancing, and operational resilience. Digital twin (DT) technology, which provides a dynamic, real-time virtual representation of physical assets and systems, has emerged as a transformative tool for monitoring, analyzing, and optimizing energy grids. The incorporation of artificial intelligence (AI) into digital twins further enhances their capabilities, enabling predictive analytics, adaptive control, fault detection, and real-time decision-making for grid-specific objectives such as voltage/frequency regulation, congestion management, DER coordination, curtailment reduction, and resilience under fast renewable ramps. Machine learning, deep learning, and reinforcement learning techniques facilitate accurate forecasting of energy generation and demand, intelligent dispatch of distributed energy resources, and predictive maintenance, while hybrid models combining physics-based simulations with AI improve prediction accuracy in data-sparse or high-uncertainty environments. Despite these advancements, challenges persist, including data quality and availability, computational scalability, cybersecurity risks, and interoperability issues. This review synthesizes current research on AI-driven digital twins in renewable energy grids, highlights methodological and technological gaps, and identifies future research directions for developing resilient, scalable, and adaptive energy systems. The findings underscore the potential of AI-integrated digital twins to accelerate the transition toward intelligent, sustainable, and climate-resilient energy infrastructures. In addition, this review incorporates sustainability-oriented intelligent-system methodologies such as energy-aware edge–cloud cyber-physical architectures and digital-twin-enabled lifecycle sustainability frameworks to align DT optimization with contemporary sustainability practice better.

KEYWORDS

AI-driven digital twins, hybrid modeling, predictive maintenance, real-time optimization, renewable energy grids

1 Introduction

Renewable energy grids, integrating solar photovoltaics (PV), wind turbines, hydropower, and energy storage technologies, are central to global decarbonization efforts and the transition toward sustainable electricity generation (Nekahi et al., 2025). Unlike conventional centralized systems, renewable energy generation is inherently intermittent and variable, as solar and wind outputs fluctuate in response to weather dynamics, diurnal cycles, and environmental conditions. Such variability complicates grid management tasks, including balancing supply and demand, maintaining voltage and frequency stability, and ensuring resilience against extreme weather events and growing energy consumption (Addo et al., 2025). As a result, renewable energy systems are evolving into complex, distributed networks that require advanced approaches for real-time monitoring and optimization. Within this evolving landscape, the concept of Digital Twins (DTs) has emerged as a transformative innovation in energy systems. A DT is a dynamic, virtual representation of a physical asset, system, or process that is continuously updated with real-time data to simulate, analyze, and predict system behavior under diverse conditions (Jafari et al., 2023). In the power sector, DTs can model assets such as solar farms, wind turbines, microgrids, and transmission networks. Supported by high-fidelity sensors, Internet of Things (IoT) infrastructures, and advanced simulation platforms, DTs enable predictive maintenance, anomaly detection, performance optimization, and "what-if" scenario testing, all of which enhance operational efficiency and reduce risks (Bhatia and Malik, 2025).

The integration of Artificial Intelligence (AI) into digital twin frameworks significantly extends their capabilities, facilitating real-time optimization of renewable energy grids (Fan and Li, 2023). AI techniques, including machine learning, deep learning, reinforcement learning, and swarm intelligence, enable predictive analytics, adaptive control, and intelligent decision-making based on large volumes of heterogeneous data from grid operations, demand patterns, and weather forecasts (Yalla et al., 2025). For instance, AI-enhanced DTs can provide accurate forecasting of renewable generation and load demand, optimize the adaptive dispatch of distributed resources, regulate voltage and frequency, and perform early fault detection with predictive maintenance strategies (Addo et al., 2025). The convergence of AI and DTs shifts energy system operations from static, rule-based approaches to dynamic, data-driven optimization strategies. In inverter-dominated renewable grids, DT + AI must respect domain constraints that generic AI descriptions often omit: (i) AC power-flow physics and network limits (thermal loading, voltage bounds), (ii) grid-code requirements (ride-through and inverter control modes), (iii) protection coordination and safety margins, and (iv) multi-timescale operation (sub-second frequency response vs. hourly scheduling). Therefore, "model performance" should be reported using grid-relevant outcomes (voltage/frequency violations, curtailment, losses, congestion hours, and restoration time), not accuracy metrics alone. Despite substantial progress, notable research gaps persist. Current studies on AI-driven DTs often emphasize isolated applications such as predictive maintenance, short-term forecasting, or localized microgrid optimization, while comprehensive frameworks for system-wide resilience, scalability, and uncertainty management under extreme conditions remain underdeveloped. Furthermore, challenges related to computational costs, interoperability of diverse platforms, and cyber-physical security risks are insufficiently addressed in real-world deployments. From a technical sustainability perspective, recent intelligent-system research increasingly frames AI and digital twins not only as performance tools (accuracy/cost) but also as mechanisms for "sustainability-by-design," where optimization explicitly considers energy efficiency, lifecycle impacts, and the computational footprint of continuous analytics. For example, Cicceri et al. (2023) introduce an energy-aware, deep-learning-driven distributed cyber-physical architecture for renewable energy communities that integrates sustainability constraints (e.g., energy consumption) into edge-cloud design decisions, an approach directly relevant to real-time DT deployments in renewable grids. In parallel, He and Bai (2021) review digital-twin-based sustainable intelligent manufacturing and show how DTs support sustainability improvements through closed-loop, lifecycle-oriented monitoring and decision-making; these principles transfer to renewable grids by enabling DT-driven evaluation of operational policies that trade short-term performance against long-term asset health, resource efficiency, and system resilience. Additionally, "Green AI" emphasizes reporting and minimizing the energy/carbon cost of model development and deployment, an increasingly important consideration for always-on DT analytics at grid scale. This review contributes to the literature in the following ways:

a. It synthesizes AI techniques (ML, DL, RL, and hybrid physics-informed approaches) used within renewable-grid digital twins and maps them to operational objectives (forecasting, dispatch, stability control, and maintenance).
b. It consolidates digital twin architectures and deployment patterns (cloud/edge, IoT pipelines, and simulation toolchains), highlighting practical considerations for real-time grid optimization.
c. It identifies cross-cutting implementation challenges data quality, scalability/latency, interoperability, and cybersecurity and links them to mitigation strategies reported in the literature.
d. It highlights methodological and technological gaps (system-wide resilience, uncertainty-aware optimization, and extreme-event operation) and proposes future research directions toward scalable, adaptive, and secure AI-driven grid twins.

This mini-review also has limitations that should be considered when interpreting its findings:

a. It is limited to English-language studies published between 2010 and 2025, which may exclude relevant non-English or very recent contributions.
b. Evidence is heterogeneous in datasets, evaluation metrics, and validation settings, restricting direct quantitative comparability across studies.
c. Real-world utility deployments are sometimes underreported or proprietary; therefore, reported performance may be biased toward simulation-based or positive results.
d. Some rapidly evolving pre-print and industrial materials may not be comprehensively captured despite snowballing and selective grey-literature inclusion.

This review aims to synthesize existing knowledge on the integration of AI-driven digital twins for real-time optimization of renewable energy grids, identify methodological and technological gaps, and propose future research directions for building resilient, scalable, and adaptive energy systems. This analysis advances the discourse on digital twin applications by moving beyond experimental prototypes to consider practical, system-wide solutions for integrating renewable energy.

2 Methodology

2.1 Review type

This mini-review employs a systematic-narrative literature review methodology designed to provide both rigorous retrieval of relevant evidence and interpretive synthesis of interdisciplinary advances in AI-driven digital twins for renewable energy grids. The approach combines systematic search and selection procedures (to ensure reproducibility and coverage) with narrative synthesis (to integrate methodological, technological, and policy insights across engineering, computer science, and energy systems literature).

2.2 Search strategy and keywords

A structured search was performed across the following bibliographic databases and platforms: Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, PubMed, and Google Scholar. Searches targeted literature published between 2010 and 2025 to capture foundational work and recent developments in AI, digital twins, and renewable energy applications. Search queries combined controlled vocabulary and free-text terms, using Boolean operators to improve precision and recall. Representative search strings included permutations of the following terms:

> "digital twin" OR "digital twins" AND "renewable energy" OR "power grid" OR "microgrid"

> "digital twin" AND "artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "reinforcement learning"

> "digital twin" AND "predictive maintenance" OR "fault detection" OR "real-time optimization"

> "hybrid model" OR "physics-informed" OR "PINN" AND "digital twin"

> "distributed energy resources" OR "DER" AND "digital twin" OR "AI"

> "edge computing" OR "cloud computing" AND "digital twin" AND "scalability"

> "cybersecurity" AND "digital twin" AND "energy grid"

Search terms were adapted to the indexing and query syntax of each database; snowballing (forward and backward citation tracking) and hand-searching of key journals and conference proceedings (e.g., IEEE Transactions, Renewable Energy, Applied Energy, ACM/IEEE conference proceedings) supplemented database queries. Grey literature (technical reports, standards, and relevant white papers from utilities, grid operators, and international organisations) were sought selectively to inform practical deployment and policy discussions.

2.3 Inclusion and exclusion criteria

Studies were eligible for inclusion if they met all of the following criteria: (i) peer-reviewed articles, high-quality conference papers, or authoritative technical reports; (ii) focused on digital twin applications in power systems, renewable energy integration, microgrids, or DER orchestration where AI/ML methods are applied or discussed; (iii) presented empirical results, simulation experiments, methodological developments (e.g., hybrid modelling, PINNs), system architectures (cloud/edge implementations), or security/interoperability analyses relevant to real-time grid operation; and (iv) published in English between 2010 and 2025.

Exclusion criteria were: (i) articles solely concerned with digital twins outside the energy domain (unless offering transferable methods); (ii) opinion pieces lacking technical or methodological substance; (iii) non-English publications; (iv) undergraduate student theses and non-peer-reviewed blog posts except where they represented standards or vendor technical specifications cited for context; and (v) studies with insufficient methodological detail to assess performance claims (e.g., missing evaluation metrics or reproducible experimental setup).

2.4 Study selection, data extraction, and synthesis

Search results were de-duplicated and screened in two stages: title/abstract screening followed by full-text review. Two reviewers independently screened records and resolved disagreements by consensus; a third reviewer adjudicated unresolved conflicts. From each included study we extracted: bibliographic details, system domain (wind, solar, microgrid, hybrid), digital twin architecture (physical model, data pipelines, cloud/edge topology), AI methods used (ML, DL, RL, hybrid PINNs), datasets and experimental setup, evaluation metrics (forecast accuracy, time-to-detect faults, computational latency), demonstrated applications (forecasting, dispatch, predictive maintenance), scalability and deployment notes, and identified limitations (data quality, cybersecurity, interoperability). Extracted data were organised in evidence tables and synthesised narratively to identify common methods, performance benchmarks, gaps, and research opportunities. Where quantitative results were comparable (e.g., forecasting RMSE), they were tabulated to illustrate typical performance ranges.

2.5 Quality appraisal and bias assessment

Included studies were appraised for methodological rigour using a domain-adapted checklist assessing (i) clarity of objectives; (ii) adequacy of data description and preprocessing; (iii) completeness of methodological detail (model architectures, hyperparameters, training/validation procedure); (iv) appropriateness of evaluation metrics and baselines; and (v) disclosure of limitations and reproducibility artifacts (code, datasets). Risk of bias was noted where studies reported only favourable results without comparative baselines, used small or non-representative datasets, or lacked real-world validation. These assessments informed the weight accorded to individual findings during synthesis.

2.6 Limitations of the review

The review is limited by language (English-only) and by the practical difficulty of exhaustively capturing rapidly evolving pre-print and industrial literature; while major pre-prints and industry reports were considered when methodological detail was sufficient, some proprietary deployments and commercial platforms remain opaque. Publication bias toward positive results and heterogeneous evaluation metrics across studies constrained quantitative aggregation. These limitations are acknowledged in the interpretation of evidence and in recommended future research directions.

3 Digital twin technology in energy systems

3.1 Definition and core components

Digital twin technology is a virtual representation of a physical asset, system, or process that enables real-time monitoring, analysis, and decision-making (Fuller et al., 2020). In the context of energy systems, digital twins integrate data from sensors, communication networks, and computational models to provide a dynamic replica of grid operations. The core components typically include the physical system (e.g., solar panels, wind turbines, or grid infrastructure), a digital model that mirrors its behavior, and a communication layer that ensures continuous data exchange between the two (Imam, 2025). This integration allows operators to track asset performance and predict future states under varying conditions.

3.2 Modeling and simulation approaches

Modeling and simulation lie at the heart of digital twin development. Physics-based models, such as finite element or thermodynamic simulations, are widely used to capture the operational dynamics of energy components (Tao et al., 2024). These models can be combined with data-driven approaches, including machine learning algorithms, to enhance accuracy and adaptability in complex renewable energy environments. Hybrid models, which integrate physical laws with real-time sensor data, are particularly effective for predicting system failures, optimizing load management, and improving grid stability.

3.2.1 Physics-based models

Physics-based models employ well-established scientific and engineering principles to replicate the behavior of energy system components. Finite element models (FEM) allow detailed structural analysis of wind turbine blades, computational fluid dynamics (CFD) provides insights into aerodynamic performance, and thermodynamic models assess solar thermal and hydropower system efficiency. These models deliver high-fidelity simulations that respect the physical laws governing energy systems, offering reliable performance evaluation, scenario testing, and design optimization. Their adherence to fundamental constraints improves interpretability and enables operators to trace cause-and-effect relationships in system behavior (Tao et al., 2024; Liu et al., 2021).

3.2.2 Data-driven approaches

Data-driven modeling leverages historical and real-time operational datasets to identify patterns, correlations, and anomalies that may be challenging to capture with purely physics-based approaches. Machine learning (ML) algorithms, including regression models, support vector machines, and ensemble techniques, are frequently applied to forecast energy production, load demand, and equipment degradation. Deep learning architectures such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) enable advanced processing of temporal and spatial data streams obtained from distributed grid sensors. These models excel at handling nonlinearities, uncertainties, and stochastic behaviors inherent in renewable energy systems (Sun et al., 2020; Zhang et al., 2019).

3.2.3 Hybrid modeling approach

Hybrid models integrate physics-based and data-driven techniques to achieve enhanced predictive accuracy and adaptability in digital twins. Physics-informed neural networks (PINNs) incorporate physical laws as constraints within neural network training, ensuring predictions remain consistent with known system dynamics while capturing unmodeled or stochastic behaviors. Such hybrid frameworks improve load management, fault prediction, and voltage and frequency stability in renewable grids. They also support real-time decision-making, enabling simulation of "what-if" scenarios, optimal energy dispatch, and dynamic response to fluctuations in supply and demand (Figure 1) (Morstyn and McCulloch, 2018; Xu et al., 2023).

3.2.4 Simulation platforms and tools

Advanced digital twin platforms combine physics-based solvers, machine learning modules, and real-time IoT data streams. Cloud and edge computing architectures allow scalable simulations with near real-time updates of system states, facilitating rapid responses to operational anomalies. Commonly used tools include MATLAB/Simulink, ANSYS, OpenDSS, and Python-based ML libraries, which collectively support predictive maintenance, energy optimization, and reliability assessment (Czekster, 2020).

3.2.5 Implications for renewable energy grids

The integration of high-fidelity physics-based models with adaptive AI algorithms enhances operational efficiency and resilience in renewable energy grids (Cavus, 2025; Abdul Rasheed et al., 2025). Hybrid digital twins anticipate failures,

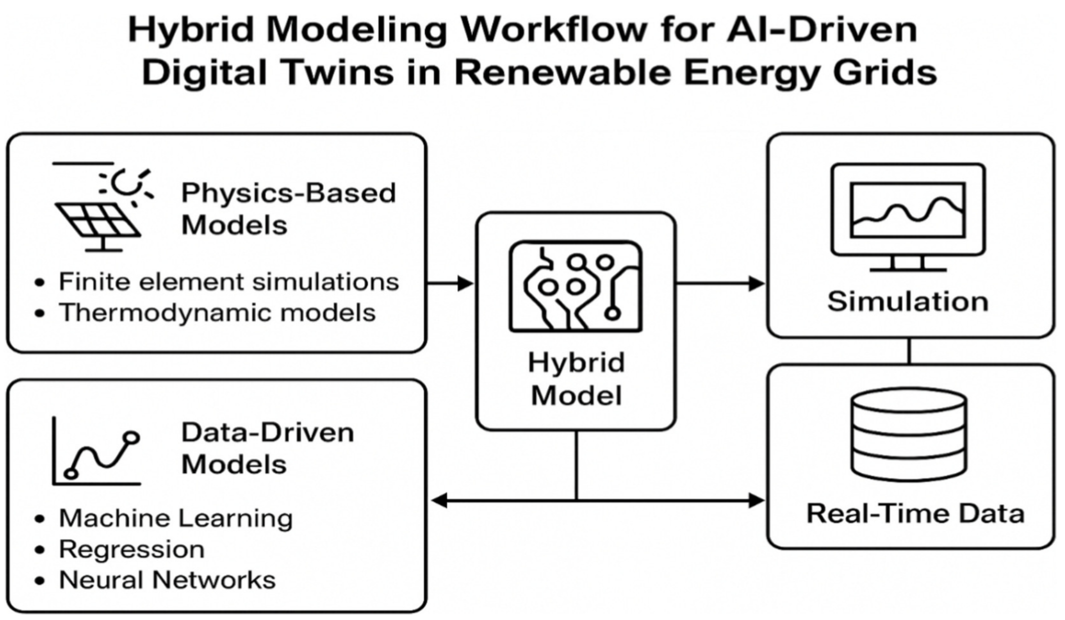

FIGURE 1
Hybrid modeling workflow for AI-driven digital twins in Renewable energy grids.

reduce downtime, optimize energy flow, and enable smooth integration of intermittent energy sources. The scalability and flexibility of these models provide a robust framework for managing the growing complexity of modern energy systems, ensuring grid stability, efficiency, and reliability amid variable renewable energy outputs (Cavus, 2025).

3.3 Applications in renewable energy grids

The deployment of digital twins has expanded rapidly within renewable energy grids. In wind energy, digital twins facilitate predictive maintenance by analyzing turbine blade stress and performance degradation (Liu et al., 2021). For solar power, they enable forecasting of photovoltaic output based on weather conditions and operational parameters (Chen et al., 2024). In microgrids and hybrid systems, digital twins optimize energy dispatch, balance supply-demand fluctuations, and integrate storage solutions to improve reliability (Lai et al., 2024). Collectively, these applications demonstrate how digital twins enhance resilience, reduce operational costs, and accelerate the transition to intelligent renewable energy systems. Table 1 and Figure 2 summarizes the major applications, mechanisms, and impacts.

4 AI techniques for digital twin optimization

4.1 Machine learning algorithms for predictive analytics

Machine learning (ML) has increasingly become a fundamental component in the development of digital twins for energy systems, providing advanced capabilities for predictive analytics, real-time optimization, and decision support. ML algorithms leverage both historical datasets and real-time sensor data to uncover complex, non-linear relationships within energy system operations, enabling accurate forecasting of energy demand, renewable generation variability, and potential equipment failures (Sun et al., 2020; Tao et al. (2019)). Supervised learning techniques, including regression models, support vector machines (SVMs), and artificial neural networks (ANNs), have demonstrated high efficacy in load forecasting and performance prediction of energy assets. For example, ANNs can model highly non-linear behavior of wind turbines under variable wind conditions, while regression-based approaches can provide short-term and long-term electricity demand forecasts, critical for grid stability and energy market operations (Zhou et al., 2021). Similarly, SVMs are particularly effective in handling high-dimensional datasets for predicting anomalies in energy equipment performance, thus reducing the likelihood of unplanned outages (Di Persio et al., 2024).

Unsupervised learning methods, such as k-means clustering, hierarchical clustering, and principal component analysis (PCA), are widely employed for anomaly detection and fault diagnosis within digital twin frameworks (Ding Q. et al., 2025). These algorithms can identify deviations from normal operational patterns, classify unknown fault types, and optimize maintenance schedules without requiring labeled datasets, which is particularly advantageous for complex energy systems with limited failure records (Afridi et al., 2022). In addition, ensemble learning approaches such as random forests and gradient boosting have been utilized to improve predictive accuracy by combining multiple models, thereby reducing the risk of over-fitting and enhancing robustness under varying operational conditions. Recent advances in deep learning have further augmented the predictive capabilities of digital twins. Convolutional neural networks (CNNs) and

TABLE 1 Applications of digital twins in renewable energy grids: Mechanisms and operational impacts.

Energy domain	Digital twin application	Mechanism/Function	Operational impact	Representative studies
Wind energy	Predictive maintenance and performance optimization	Simulation of turbine blade stress, rotor dynamics, and mechanical wear; real-time monitoring via IoT sensors	Reduces unplanned downtime, extends turbine lifespan, enhances energy output efficiency	Liu et al., 2021; Tao et al. (2019)
	Fault detection and early warning	Machine learning models detect abnormal vibration, temperature, or load patterns	Minimizes maintenance costs and prevents catastrophic failures	Morstyn et al. (2019)
Solar energy	Output forecasting and efficiency analysis	Integration of weather data, irradiance models, and PV performance parameters using hybrid ML-physics approaches	Improves energy yield prediction and optimizes grid integration	Zhang et al. (2019)
	Panel degradation assessment	Physics-based and data-driven models track degradation trends and hotspot formation	Enables timely maintenance and replacement, ensuring consistent performance	Sun et al. (2020)
Microgrids/Hybrid systems	Energy dispatch and load balancing	Real-time simulations of energy flow between generation, storage, and load; predictive algorithms for demand response	Maintains supply-demand equilibrium, enhances grid stability, and reduces energy wastage	Xu et al. (2023)
	Integration of energy storage systems	Models optimize charge/discharge cycles of batteries and other storage technologies	Increases reliability and supports high penetration of intermittent renewables	Morstyn et al. (2019)
Hydropower and thermal systems	Operational optimization	Simulation of water flow, reservoir levels, and turbine efficiency	Enhances energy efficiency and supports scheduling under variable demand	Tao et al. (2019)
	Risk management and scenario analysis	Predictive models simulate extreme weather or demand fluctuations	Improves preparedness and reduces risk of grid instability	Liu et al. (2021)

recurrent neural networks (RNNs), including long short-term memory (LSTM) networks, can process temporal and spatial data from energy systems to detect subtle trends and patterns that traditional ML models may overlook. For instance, LSTMs are particularly effective in forecasting time-series energy consumption and generation profiles, accounting for seasonality, weather fluctuations, and system interdependencies (Waheed et al., 2024). In renewable grids, the most predictive inputs are typically SCADA/EMS/DER telemetry and grid measurements rather than generic time series alone: wind turbine pitch/rotor speed and gearbox temperature; PV inverter DC-link voltage, irradiance and module temperature; battery SoC/SoH and temperature; feeder voltage profiles; and where available, PMU synchrophasors (voltage/current phasors, frequency, RoCoF). Feature engineering that captures grid behavior net-load ramp rates, variability indices, curtailment flags, inverter operating modes (Volt/VAR, Volt/Watt), and event markers (switching/reclosing) often improves generalization because it encodes operational actions unique to renewable grids.

The integration of ML with digital twin technology enables the creation of hybrid predictive frameworks, where physics-based models are augmented with data-driven insights (Gebreab et al., 2024). This synergy allows for real-time monitoring of system health, predictive maintenance scheduling, and optimization of energy production and consumption. As a result, ML-enhanced digital twins not only reduce operational costs and system downtime but also improve reliability, resilience, and efficiency of renewable energy systems (Wang et al., 2022). From a comparative perspective, classical ML models (e.g., SVMs, Random Forests, Gradient Boosting) often outperform deep networks when datasets are relatively small, feature-engineered, and noise-limited because they impose stronger inductive biases and require fewer samples to generalize. In contrast, deep learning models (e.g., CNNs/LSTMs) typically outperform classical ML in high-dimensional sensor settings (high-frequency PMU synchrophasors and feeder-level SCADA/AMI streams, images/thermal maps) and when sufficient data are available, because they learn hierarchical representations and capture complex nonlinearities without extensive manual feature design. However, deep models introduce higher computational cost, risk of overfitting in data-scarce regimes, and reduced interpretability, making them less suitable for latency-constrained or safety-critical operations unless paired with explainability or hybrid physics constraints. Therefore, the choice of ML approach should be guided by data volume/quality,

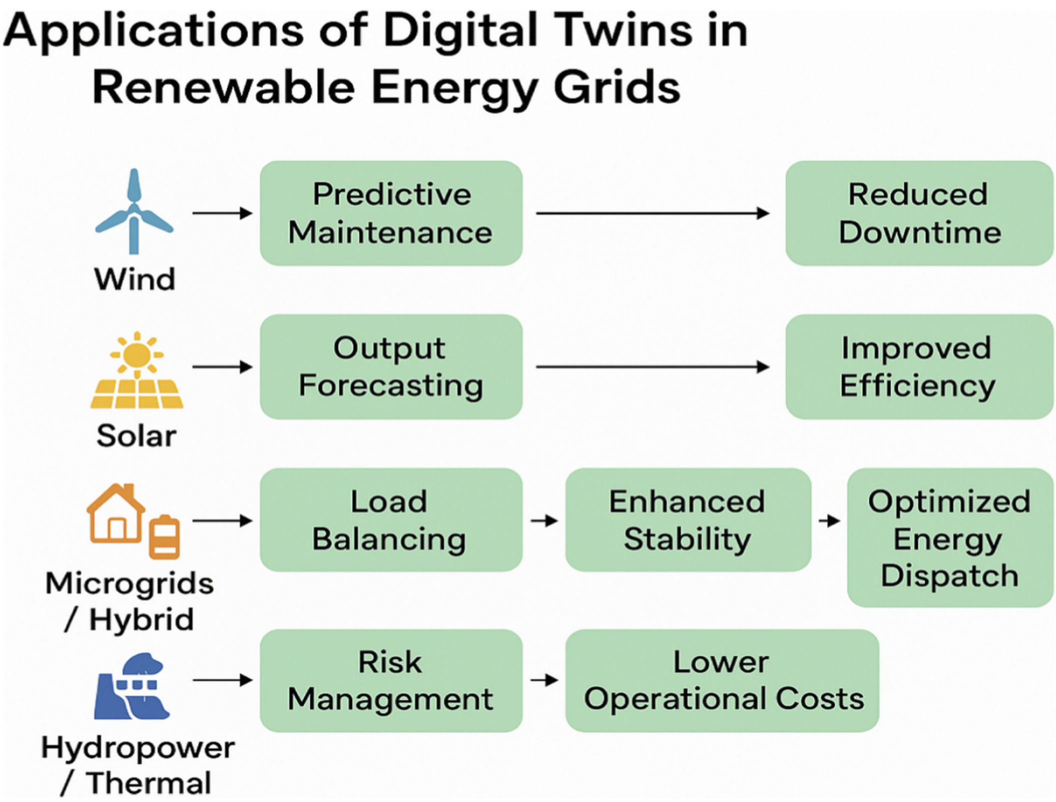

FIGURE 2
Applications of digital twins in renewable energy grids.

feature dimensionality, and deployment constraints (latency, compute budget, and interpretability requirements), not only predictive accuracy (Vanderhorst et al., 2024).

4.2 Deep learning and reinforcement learning for control

Deep learning (DL) has emerged as a transformative approach within digital twin frameworks, extending predictive and diagnostic capabilities beyond conventional machine learning by effectively capturing highly nonlinear relationships and temporal dependencies in renewable energy systems (Rahmani-Sane et al., 2025). Advanced neural network architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are particularly suited to process the high-dimensional, time-series data generated by modern smart grids. CNNs excel in extracting spatial correlations from distributed sensor arrays, enabling the identification of localized anomalies in equipment such as photovoltaic arrays or wind turbine components, while RNNs, including long short-term memory (LSTM) networks, model temporal dependencies in energy production and load demand, improving forecasting accuracy under variable environmental and operational conditions (Chouksey, 2025). Beyond fault detection and forecasting, deep learning facilitates real-time system optimization. For instance, hybrid DL models combining CNNs and LSTMs can simultaneously capture spatial and temporal patterns, enabling predictive maintenance scheduling, energy loss minimization, and adaptive load balancing. These models are particularly advantageous in renewable energy grids where intermittent generation, such as solar irradiance or wind speed variability, introduces significant uncertainty and operational complexity (Ahmed et al., 2024).

Reinforcement learning (RL) complements DL by providing adaptive control capabilities for complex and dynamic energy systems. Within digital twin simulations, RL agents iteratively interact with the modeled environment, receiving feedback in the form of rewards or penalties, and progressively learning optimal control policies for energy dispatch, voltage regulation, and demand response management (Zhang et al., 2019). In renewable grids, RL/DRL policies must map to concrete actuation: inverter set-points (Volt/VAR, Volt/Watt), battery charge/discharge and reserve scheduling, dispatch of flexible loads, and microgrid islanding/reconnection logic. Unlike generic RL tasks, these actions are bounded by grid codes and network constraints; thus, DT-trained RL should include constraint handling (safe RL, penalties, or constrained optimization layers) to prevent voltage violations, frequency excursions, feeder overloads, and protection miscoordination. Hierarchical control is often required because fast inverter control (milliseconds–seconds) interacts with slower storage and demand-response decisions (minutes–hours). This trial-and-error learning process allows RL agents to handle uncertainties arising from fluctuating renewable outputs, varying load demands, and contingencies such as equipment failures or grid faults. Notably, deep reinforcement learning (DRL), which integrates deep neural networks with RL, further enhances decision-making by enabling high-dimensional state and action space management, allowing for sophisticated grid control strategies that traditional rule-based methods cannot achieve. While RL/DRL can outperform rule-based control in highly dynamic environments (high renewable penetration, frequent contingencies) because policies adapt through interaction, RL performance depends strongly on reward design, state observability, and simulation fidelity of the digital twin. Poorly specified rewards can yield unsafe or unstable behavior, and "reality gaps" between simulation and the physical grid can degrade performance after deployment. Moreover, RL commonly requires many training episodes and can be computationally intensive, which limits rapid deployment unless pre-training, transfer learning, or constrained/safe RL is used. In comparison, model predictive control (MPC) or optimization-based dispatch can provide stronger stability guarantees but may struggle with nonlinear uncertainty or scaling. Hence, RL is most beneficial when the DT environment is accurate enough for training, operational objectives change over time, and adaptive control is needed, whereas MPC/optimization may be preferred when formal constraints, explainability, and safety guarantees are paramount. (Massaoudi et al., 2023).

The combination of DL and RL within digital twin frameworks offers a robust paradigm for autonomous and intelligent energy system management. DL models provide precise forecasting and fault diagnosis, while RL agents leverage these insights to make adaptive, real-time control decisions. This integrated approach not only enhances operational efficiency and system reliability but also supports higher penetration of renewable energy sources, mitigating the risks of instability associated with variable generation and ensuring grid resilience in smart energy networks (Li et al., 2025).

4.3 Data-driven decision-making in real-time operations

The integration of machine learning (ML), deep learning (DL), and reinforcement learning (RL) within digital twins establishes a synergistic framework that significantly advances data-driven decision-making in renewable energy systems. Leveraging the complementary strengths of these computational paradigms allows digital twins to evolve from predictive models into intelligent platforms capable of real-time monitoring, control, and optimization (Tao et al., 2019; Khan et al., 2022). ML algorithms form the foundational predictive layer, enabling accurate forecasting of load demand, renewable generation variability, and equipment degradation. DL architectures, including CNNs and LSTMs, extend predictive capabilities, handling complex, high-dimensional sensor datasets and capturing both spatial and temporal patterns across distributed energy resources. RL introduces an adaptive control layer, enabling the digital twin to autonomously learn optimal operational strategies through interactions with simulated environments, enhancing decision-making under uncertain and dynamic conditions (Zhang et al., 2019).

Data fusion techniques play a pivotal role in this convergence, integrating heterogeneous datasets from weather predictions, market signals, smart meters, and IoT-enabled sensors. This integration generates a comprehensive view of the grid's operational state, allowing the digital twin to anticipate fluctuations in generation and demand, detect emerging faults, and recommend corrective actions before system performance is compromised (Khan et al., 2022). Fused data also supports multi-objective optimization, with decision-making algorithms minimizing operational costs, enhancing reliability, and reducing environmental impact simultaneously. Intelligent orchestration enables digital twins to perform real-time power flow optimization, dynamic load balancing, and predictive maintenance scheduling. RL-based control policies adjust dispatch strategies to maximize renewable utilization while maintaining grid stability, and ML-driven anomaly detection triggers maintenance interventions to prevent equipment failure. DL-based forecasting of renewable output enhances coordination of distributed energy resources, mitigating intermittency challenges that often hinder large-scale integration (Li et al., 2022). The convergence of these technologies enhances grid resilience, reduces operational inefficiencies, and supports the transition toward highly flexible and sustainable energy systems. This integrated approach forms the foundation for next-generation smart grids capable of self-optimization, accommodating increasing penetration of renewables while ensuring economic and environmental sustainability. As digital twins continue to evolve, the synergy of ML, DL, and RL remains essential for achieving autonomous, predictive, and adaptive energy management at scale. Critically, "better forecasting accuracy" does not always translate into "better grid outcomes." For example, marginal improvements in RMSE may provide limited operational benefit if dispatch decisions are constrained by network limits, ramping constraints, or market rules. Conversely, slightly less accurate forecasts paired with uncertainty quantification (prediction intervals) can outperform point forecasts in operational value by enabling risk-aware reserve sizing and robust dispatch. Similarly, multi-objective optimization introduces explicit trade-offs between cost, reliability, emissions/curtailment, and asset degradation; selecting a solution requires stakeholders to prioritize objectives (e.g., minimizing curtailment may increase cycling of batteries and accelerate degradation). Therefore, comparative evaluation should include not only predictive metrics (RMSE/MAE) but also decision metrics (curtailment reduction, stability violations, outage risk, and asset lifetime impacts), ideally assessed within the DT loop.

5 Real-time grid optimization applications

5.1 Load balancing in renewable energy grids

Load balancing constitutes a cornerstone for the reliable operation of modern renewable energy grids, particularly given the inherent intermittency and variability of solar and wind generation. Digital twins, integrated with artificial intelligence (AI) techniques, facilitate dynamic load forecasting and adaptive demand response strategies that synchronize energy consumption with available generation capacity (He et al., 2021). These systems exploit historical consumption patterns, weather forecasts, and real-time sensor data to create predictive models capable of anticipating fluctuations in both supply and demand. Optimized allocation of distributed energy resources (DERs), including photovoltaic systems, wind turbines, and energy storage units, is achieved through simulations within the digital twin environment. Such predictive orchestration ensures system equilibrium, prevents overloads, and maintains voltage and frequency stability across the grid. Incorporating AI-driven load balancing enables near-real-time adjustments to energy dispatch, allowing renewable generation to be fully utilized while reducing reliance on conventional, fossil-fuel-based backup sources (Zhou et al., 2021). In load balancing, supervised learning (e.g., LSTM-based load forecasting) is strong for anticipatory scheduling because it leverages historical temporal patterns; however, it can underperform during regime shifts (new consumption behaviors, extreme events) unless retrained and monitored for drift. RL-based demand response and dispatch can outperform static heuristics by adapting control actions to real-time conditions, but it requires carefully designed reward functions to avoid undesirable outcomes (e.g., excessive load shifting that violates comfort or industrial constraints). Hybrid approaches, forecasting and constrained optimization/MPC often provide the best trade-off in practice: forecasts provide look-ahead, while optimization enforces grid constraints and safety margins, improving reliability compared with purely data-driven control.

Demand response mechanisms represent an essential component of this framework, allowing flexible consumers such as industrial facilities or smart homes to adjust consumption in response to grid conditions. Digital twin simulations evaluate the impact of these interventions on overall system performance, optimizing participation schedules to flatten peak demand periods and enhance grid flexibility. Machine learning models can predict consumer behavior and energy usage trends, while reinforcement learning algorithms determine optimal control policies that maximize renewable utilization and minimize operational costs (Li et al., 2022). Furthermore, digital twins enable scenario analysis for extreme or unanticipated conditions, such as sudden drops in wind generation or spikes in demand. These simulations support proactive strategies, including energy storage dispatch, load shedding, or temporary curtailment of non-critical loads, ensuring continuous grid stability. The integration of AI-driven load balancing with digital twin technology, therefore, not only enhances operational efficiency but also supports large-scale integration of renewables, facilitates consumer engagement, and strengthens overall system resilience. In practice, operators often prefer "forecast + constrained optimization/MPC" because it provides look-ahead while enforcing feeder limits and voltage constraints an important requirement in weak grids with high PV penetration and reverse power flows.

5.2 Integration of intermittent renewable sources

The intermittency of renewable energy sources such as solar photovoltaics and wind turbines remains a significant challenge to grid stability. AI-enhanced digital twins mitigate this challenge through advanced forecasting, adaptive dispatch strategies, and energy storage optimization (Morstyn et al., 2019). Neural networks and reinforcement learning algorithms embedded within digital twin models improve short-term and long-term predictions of renewable generation, enabling grid operators to proactively manage variability. Hybrid optimization techniques also allow digital twins to coordinate renewable sources with battery systems, thus reducing curtailment rates and improving grid reliability under high renewable penetration scenarios (Xu et al., 2023).

5.3 Fault detection and predictive maintenance

Operational reliability of renewable energy grids depends on early detection of equipment faults and efficient maintenance scheduling. AI-driven digital twins provide advanced fault detection capabilities by continuously monitoring system states, identifying anomalies, and simulating potential failure scenarios in real time (Rasheed et al., 2025). Machine learning classifiers, trained on labeled fault datasets, enable rapid diagnosis of common issues in turbines, inverters, and storage systems. Predictive maintenance strategies supported by digital twin analytics extend equipment lifetimes, minimize downtime, and reduce maintenance costs. Such approaches also enhance safety and resilience by preventing cascading failures within interconnected grid components. For fault detection, supervised classifiers generally outperform unsupervised anomaly detection when labeled fault data are representative because they learn fault-specific signatures and yield clearer diagnostic categories. However, labeled fault data are often scarce and biased toward common failures, making supervised models brittle to novel or evolving faults. In such cases, unsupervised and self-supervised methods (e.g., autoencoder reconstruction error, clustering of embeddings) can outperform supervised models for early warning by detecting "unknown unknowns," although they may produce more false alarms and require human-in-the-loop validation. A pragmatic DT strategy is staged detection: unsupervised anomaly screening for early warning, followed by supervised diagnosis where labels exist, and physics-informed/hybrid checks to reduce false positives and improve trust. Fault modes in renewable grids are often inverter- and power-electronics-driven (DC-link capacitor aging, IGBT thermal stress, controller instability, harmonics/THD, islanding), which differ from conventional synchronous-generation faults. DT-enabled PdM should therefore combine electrical indicators (harmonics, voltage flicker, reactive power oscillations) with thermal/operational signals from inverters and storage, since purely mechanical or purely electrical monitoring can miss cross-domain precursors in inverter-dominated systems.

6 Challenges and limitations

6.1 Data availability and quality

Reliable data streams are essential for training artificial intelligence models and sustaining accurate digital twin representations of renewable energy systems. In many regions, particularly within developing energy infrastructures, access to high-resolution, real-time datasets remains limited (Ding S. L. et al., 2025). Missing, noisy, or inconsistent data undermine the performance of forecasting algorithms, compromise anomaly detection accuracy, and reduce the fidelity of simulations. The heterogeneity of data sources, including

TABLE 2 Major challenges and limitations of AI-Enhanced digital twins in renewable energy grids.

Challenge	Description	Implications	Potential solutions/Mitigation
Data availability and quality	Reliable, high-resolution, real-time datasets are often limited, especially in developing energy infrastructures. Heterogeneous data sources (weather sensors, smart meters, DERs) vary in granularity, format, and communication protocols	Poor forecasting accuracy, reduced anomaly detection reliability, and lower fidelity of digital twin simulations	Develop robust data preprocessing pipelines, improve sensor networks, leverage data augmentation, and integrate standardized data collection protocols (Ding S. L. et al., 2025; Khan et al., 2022)
Scalability and computational requirements	High computational capacity is needed for processing large volumes of sensor data, running simulations, and executing optimization models in real time	Increased latency, high memory and processing demands, barriers to adoption in resource-constrained settings	Utilize cloud and edge computing, lightweight modeling, distributed AI, and federated learning frameworks to reduce computational overhead (Fuller et al., 2020; Liu et al., 2023)
Cybersecurity and system integration issues	Interconnected IoT devices, communication networks, and cloud infrastructures introduce vulnerabilities such as data breaches, model poisoning, and denial-of-service attacks. Interoperability challenges arise with diverse hardware/software systems	Compromised grid stability, fragmented systems, increased cyber-physical risk	Implement secure, standardized protocols for data exchange, adopt robust encryption and authentication, and establish trustworthy AI governance frameworks (Aheleroff et al., 2021)

weather sensors, smart meters, and distributed energy resources, further complicates integration due to variations in granularity, formats, and communication protocols (Khan et al., 2022). Addressing data scarcity and ensuring robust data preprocessing pipelines are therefore critical for enabling effective AI-driven optimization (Table 2).

6.2 Scalability and computational requirements

Digital twins in renewable energy grids demand high computational capacity to process vast volumes of sensor data, run complex simulations, and execute optimization models in real time. While cloud computing and edge computing architectures provide scalable solutions, challenges arise in balancing latency, cost, and energy efficiency (Fuller et al., 2020). As the number of interconnected renewable energy assets grows, so does the complexity of maintaining synchronized digital twin environments. High-fidelity models require significant memory and processing power, raising barriers to widespread adoption in resource-constrained contexts. Research into lightweight modeling approaches, distributed AI, and federated learning frameworks is ongoing, but large-scale deployments remain computationally intensive (Liu et al., 2023).

6.3 Cybersecurity and system integration issues

Integration of AI-enhanced digital twins within renewable energy grids introduces new cybersecurity risks due to the reliance on interconnected IoT devices, communication networks, and cloud-based infrastructures. Vulnerabilities such as data breaches, model poisoning, and denial-of-service attacks can compromise both the physical grid and its digital counterpart (Aheleroff et al., 2021). Furthermore, interoperability challenges emerge when combining diverse hardware and software systems across different vendors and energy markets. Ensuring secure, standardized protocols for data exchange and system integration is essential to prevent fragmentation and reduce risks associated with cyber-physical attacks. Trustworthy AI governance frameworks, coupled with robust encryption and authentication mechanisms, are necessary to safeguard the reliability of AI-driven digital twins in critical energy infrastructures. Overall, the dominant trade-off across AI-driven DT approaches is between adaptability and assurance: deep models and RL offer higher flexibility under uncertainty, but increase compute burden and reduce interpretability, whereas physics-based and optimization-driven methods provide stronger constraints and transparency but may underperform when dynamics are poorly modeled or highly stochastic. Hybrid DTs aim to balance these trade-offs by combining physical constraints with data-driven learning.

7 Future perspectives and research opportunities in AI-driven digital twins

7.1 Next-generation AI-driven digital twins

Advancements in AI are expanding digital-twin capabilities specifically for renewable energy grid optimization. In this context, generative AI is most relevant when it directly improves DT operation and decision-making under grid constraints. Key grid-facing opportunities include: (i) synthetic data generation to augment scarce fault and extreme-event records (e.g., rare inverter instabilities, feeder overvoltage episodes, black-start/islanding events); (ii) scenario generation for stress-testing renewable ramps, congestion, and contingency events inside the DT; (iii) surrogate modeling to accelerate AC power-flow and time-domain

TABLE 3 Policy, industrial adoption, and sustainability implications of AI-Driven digital twins.

Aspect	Description	Major considerations/Examples
Policy	The deployment of AI-driven digital twins requires comprehensive regulatory frameworks that address data privacy, standardization, and ethical considerations	Collaborative efforts between governments, regulatory authorities, and industry stakeholders are necessary to establish responsible and effective guidelines Khan et al. (2022); Tao et al. (2019)
Industrial adoption	Digital twins offer industries the potential to enhance operational efficiency, predictive maintenance, and optimal resource utilization	Implementation challenges include high upfront costs, integration of heterogeneous data sources, and the need for trained personnel to manage and interpret digital twin outputs (Fuller et al., 2020; Li et al., 2022)
Sustainability	AI-enabled digital twins support environmental monitoring, energy consumption optimization, and sustainable infrastructure design	Cities such as Singapore and Amsterdam utilize urban digital twins to mitigate flooding, air pollution, and urban heat islands, promoting climate resilience, sustainable urban development, and energy-aware edge-cloud CPS designs plus lifecycle DT frameworks that embed sustainability constraints into DT/AI architectures (Batty et al., 2012)

simulations for near-real-time decision support; and (iv) operator-facing "DT copilots" that translate DT outputs into recommended actions (e.g., inverter set-point adjustments, storage dispatch, curtailment choices) while preserving auditable constraint logic.

To avoid "hallucinated control," generative components should be deployed as decision-support layers (scenario generation, summarization, or surrogate acceleration) that remain bounded by physical models, grid codes, and safety constraints.

7.2 Hybrid models combining physics-based and AI approaches

The integration of physics-based models with AI-driven methodologies has led to the development of hybrid digital twins. These models leverage the interpretability and reliability of physics-based simulations alongside the adaptability and learning capabilities of AI algorithms. Such hybrid approaches are particularly beneficial in scenarios where data is sparse or incomplete, as they combine the strengths of both paradigms to provide more accurate and robust predictions. For example, the use of hybrid physics-informed neural networks (PINNs) has shown promise in applications like structural health monitoring and health management, where understanding the underlying physical processes is crucial for accurate modeling and prognosis (Wu et al., 2024).

7.3 Policy, industrial adoption, and sustainability implications

The widespread adoption of AI-driven digital twins necessitates the development of supportive policy frameworks that address data privacy, standardization, and ethical considerations (Evangeline, 2025). Governments and regulatory bodies must collaborate with industry stakeholders to establish guidelines that facilitate the responsible deployment of these technologies. From an industrial perspective, the integration of digital twins can lead to significant improvements in operational efficiency, predictive maintenance, and resource optimization. However, challenges such as high implementation costs, data integration complexities, and the need for skilled personnel must be addressed to ensure successful adoption (Owen et al., 2010). In terms of sustainability and resilience for renewable grids, AI-driven DTs are most impactful when applied to grid-operator objectives such as curtailment reduction, congestion management, hosting-capacity improvement, outage prevention/restoration, and lifecycle-aware asset management for DER fleets (inverters, storage, transformers, feeders). Practical adoption therefore depends on (i) interoperability and standardized data exchange between EMS/SCADA/DERMS platforms and DT toolchains; (ii) clear governance for model risk (validation, monitoring, change control) in safety-critical settings; and (iii) regulatory alignment for how DT-informed actions are audited (e.g., why an inverter-control change or curtailment decision was made). Accordingly, the sustainability case should be evaluated using grid-relevant metrics (reduced losses and curtailment, avoided diesel backup operation, improved restoration time, reduced asset replacement via predictive maintenance) alongside the energy/carbon footprint of DT analytics ("Green AI") to ensure net benefit (Table 3).

7.4 Sustainability-oriented technical methodologies for AI-driven digital twins

Sustainability-aligned AI-driven digital twins should incorporate technical methodologies that explicitly connect real-time optimization with environmental and lifecycle outcomes. One direction is energy-aware intelligent cyber-physical deployment, where DT analytics are partitioned across edge-cloud layers to reduce latency and communication overhead while also constraining compute energy use; sustainability attributes (e.g., energy consumption of the digital pipeline) become first-class design requirements rather than afterthoughts (He and Bai 2021).

A second direction is DT-enabled lifecycle sustainability, extending DT objectives beyond operational KPIs (frequency/voltage, losses, cost) to include asset lifetime extension, reduced replacement waste, and decision-making that accounts for long-term degradation under different dispatch/control policies. Lifecycle-oriented DT practices have been formalized in sustainability-focused DT frameworks in adjacent domains and can be adapted to renewable-grid assets and DER fleets (Cicceri et al., 2023). Finally, the “Green AI” agenda motivates reporting and optimizing the computational footprint (training/inference energy, hardware intensity) of AI models embedded in DTs, especially for always-on forecasting and control. For renewable grids, this enables a clearer sustainability accounting: net benefits should consider both (i) avoided emissions via improved renewable utilization and reduced downtime, and (ii) the energy overhead of DT + AI computation.

8 Conclusion

The integration of AI-driven digital twins into renewable energy grids represents a transformative approach to addressing the complexities associated with variable and distributed energy generation. These technologies enable real-time monitoring, predictive analytics, and adaptive control, thereby enhancing grid stability, operational efficiency, and resilience under fluctuating conditions. Machine learning, deep learning, and reinforcement learning techniques embedded within digital twin frameworks facilitate accurate forecasting, optimized dispatch of distributed energy resources, fault detection, and predictive maintenance. Hybrid models that combine physics-based simulations with AI methodologies further strengthen the reliability and accuracy of digital twin predictions, particularly in data-scarce or high-uncertainty environments. Despite these advancements, challenges remain, including data availability and quality, computational scalability, cyber security risks, and interoperability issues across heterogeneous systems. Policy frameworks, standardized protocols, and robust governance mechanisms are essential to support safe and responsible deployment. Furthermore, the potential for AI-enhanced digital twins to contribute to sustainability through optimized energy consumption, integration of renewable resources, and climate-resilient infrastructure underscores their strategic relevance for future energy systems. Future research should focus on developing comprehensive, system-wide AI-driven digital twin frameworks that address scalability, uncertainty management, and real-time resilience under extreme operating conditions. Investigations into lightweight modeling, distributed AI, and federated learning can reduce computational burdens and facilitate large-scale implementation. Comparative evidence suggests no single AI technique is universally optimal; method choice should be driven by data regime (scarce vs. abundant), operational requirements (latency/safety), and whether the objective is prediction (forecasting/diagnosis) or control (dispatch/DR), with hybrid constrained designs often providing the most deployable trade-off. Collectively, the convergence of AI and digital twins provides a pathway toward intelligent, adaptive, and sustainable renewable energy grids, advancing global decarbonization efforts and supporting the transition to resilient, next-generation energy infrastructures.

Author contributions

CN: Supervision, Investigation, Writing – review and editing, Conceptualization, Writing – original draft, Funding acquisition. FC: Writing – original draft, Writing – review and editing, Supervision, Methodology, Conceptualization. JN: Methodology, Investigation, Conceptualization, Writing – review and editing, Project administration, Writing – original draft. P-CO: Writing – original draft, Supervision, Project administration, Investigation, Writing – review and editing, Conceptualization. MB: Writing – original draft, Investigation, Writing – review and editing, Project administration, Data curation.

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The author(s) declared that generative AI was not used in the creation of this manuscript.

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