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Digital twins in renewable energy systems: A comprehensive review of concepts, applications, and future directions

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ABSTRACT

Digital Twin (DT) technologies are rapidly transforming the design, operation, and lifecycle management of renewable energy systems. This systematic review investigates DT applications across four major renewable energy domains—solar, wind, hydro, and hybrid systems—encompassing all lifecycle phases from initial design and simulation to maintenance and end-of-life (EoL) optimization. Using a PRISMA-guided methodology and keyword-driven thematic classification, the study analyzes over 150 peer-reviewed and industry-sourced publications from 2014 to 2024. A novel taxonomy is introduced to categorize DT applications by energy type and lifecycle phase, offering a structured and comprehensive perspective on current practices and research directions. The review synthesizes enabling technologies within a layered DT architecture, highlighting the roles of Artificial Intelligence (AI), Internet of Things (IoT), cloud/edge computing, and big data in realizing scalable, intelligent, and autonomous systems. Real-world deployments—such as GE's Digital Wind Farm and Huawei's DT-enhanced solar inverters—demonstrate tangible benefits, including up to a 25 % reduction in downtime and 10–20 % improvements in energy yield. Key challenges are critically examined, including model fidelity, data heterogeneity, standardization, and cybersecurity. In response, the study outlines a forward-looking agenda aligned with global sustainability frameworks such as the UN Sustainable Development Goals (SDGs) and the EU Green Deal. By integrating fragmented literature into a coherent, application-driven framework, this work advances academic understanding, supports industrial innovation, and informs policy development for the next generation of intelligent renewable energy systems.

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Table of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
CPS	Cyber-Physical Systems
DT	Digital Twin
EoL	End-of-Life
GE	General Electric
IoT	Internet of Things
MTTR	Mean Time to Repair
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PV	Photovoltaic
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
SDGs	Sustainable Development Goals
SOC	State of Charge
US DOE	United States Department of Energy

1. Introduction

1.1. Background and motivation

According to a recent white paper by the **International Renewable Energy Agency (IRENA, 2022)**, digital technologies—including Digital Twins (DTs)—are central to enabling renewable energy scalability, flexibility, and real-time operational intelligence. The report underscores the need for harmonizing digital innovation with policy, infrastructure, and regulation, emphasizing the importance of DTs in bridging physical infrastructure with digital capabilities across solar, wind, and hybrid systems. This digital transition is framed as a foundational enabler for achieving the targets of the Paris Agreement and UN SDGs. In the last few decades, the energy sector has undergone a major transformation. This is because there is a necessity to address climate change, decrease reliance on fossil fuels, and protect the environment [1] discussed climate-related energy policies [2], focused on fossil fuel dependency, and [3] emphasized environmental sustainability. The goals of sustainability, structural resilience, and low-carbon emissions have brought the development of renewable energy technologies to the forefront of domestic and global policy frameworks. This shift is also a result of growing awareness about the risks posed by greenhouse gas emissions, the finite reserves of fossil fuels, the degradation of energy security due to geopolitical turmoil, and tensions in the fossil fuel-driven economy [4] noted geopolitical influences on energy security, while [5] elaborated on fossil fuel-driven economic tensions. In reaction, governments, industries, and research organizations worldwide have stepped up their activities to harness renewable energy sources and integrate them into the current and future power infrastructure. Solar photovoltaic (PV) and wind energy, as well as hydroelectric power, biomass, and geothermal energy, are now recognized as critical components for achieving global decarbonization targets. These clean and sustainable energy sources provide environmental protection by mitigating carbon emissions and pollution while also enhancing economic prosperity through long-term energy cost savings, diversification, and new employment opportunities. According to the International Energy Agency (IEA), by the end of this decade, renewables are projected to have over 90 % share in new installations of power capacity, making it the most predominant energy sector [6]. This growth also increases the importance of renewable sources in fulfilling global electricity requirements as well as fulfilling climate targets such as the ones put forward in the Paris Agreement.

Even with their promise, renewable energy systems are deep rooted complicated and provide many operational and technological difficulties. One of the more important issues is their strong dependency on environmental factors which are highly unpredictable and dynamic. The amplitude of solar irradiance, wind speed, ambient temperature, and humidity levels fluctuate remarkably over time and space which directly impact the energy output, achieving system performance stability and optimization becomes very difficult [7,8]. This variability brings a high level of risk, increasing the needs of sophisticated prediction, monitoring, control mechanisms, and reliability for ensuring grid stability. In addition, the growing decentralization and interconnection of renewable energy infrastructures through smart grids and distributed energy resources (DERs) adds new elements of complexity to system management [9]. Oftentimes, traditional control and supervisory approaches are inadequate to address the changes within operational timeframes and fail to adequately represent the nonlinear interactions between the different components of the system. Therefore, advanced digital technologies are needed that would increase system observability, renewables controllability, adaptability, and responsiveness to changing conditions [10]. Hence, digitalization stands as a primary driver, providing an array of tools and methods that can change how energy systems are imagined, designed, operated, and maintained. Among these technologies, DT appears as a particularly promising innovation. A DT is defined as a real-time digital counterpart of a tangible system that perpetually replicates its state, behavior, and performance [11]. In combination with data analytics, AI, and real-time sensors, DTs offer unrivaled visibility and insight into the operations of renewable energy assets [12]. The use of DT technologies in the renewable energy industry signifies a paradigm shift in how stakeholders manage uncertainty, failure prediction, and performance optimization. The ability of DTs to simulate operational environments, predict system deterioration, determine maintenance schedules, and respond to shifting parameters is unmatched. DTs enable the real-time application of intelligence and predictive controls with high precision and adaptability, resulting in enhanced system reliability, operational efficiency, and reduced costs [13]. With the continuing digital transformation of the worldwide energy sector, incorporating DTs into renewable energy systems will be crucial in building a resilient, intelligent, and sustainable energy future.

1.2. Definition and concept of DT

A Digital Twin (DT) is a recent technological innovation that enables real-time monitoring, analysis, and control of physical systems. It is a virtual representation of a physical asset, process, or system, continuously updated based on live data from the physical counterpart. Unlike static simulations, DTs dynamically evolve with changes in system behavior, environmental conditions, and operational parameters [14]. This bi-directional, real-time integration enhances responsiveness across the asset's lifecycle. DTs aggregate diverse data streams—including sensor readings, control signals, logs, and physics- or data-driven models—to closely replicate system performance [15]. This allows the DT to simulate scenarios, evaluate performance, diagnose faults, and support decision-making in near real-time [16]. The architecture typically comprises three layers: the physical system, digital model, and a data stream layer linking the two [17]. This framework applies to systems such as solar PV arrays, wind turbines, and hydroelectric generators. The digital layer incorporates design models, algorithms, and simulations, while the data stream layer ensures real-time feedback between the physical and virtual entities. Advanced DTs increasingly integrate AI, machine learning, and cloud or edge computing to enhance adaptability and intelligence [18]. AI supports anomaly detection and predictive maintenance, cloud computing manages large-scale data, and edge computing enables low-latency control. Collectively, these features make DTs core components of cyber-physical systems (CPS) for real-time optimization and autonomous control [19,20]. In renewable energy, DTs simulate solar panel performance under varying irradiance, temperature, and shading conditions [21,22], and model wind turbine dynamics using real wind data and vibration profiles [23]. Hydropower DTs can emulate water flow and sediment accumulation to optimize output and maintenance. As renewable systems grow in complexity and data intensity, DTs are increasingly essential for enhancing efficiency, reducing downtime, and enabling flexible, intelligent control [24,25]. Fig. 1 illustrates the layered architecture of a Digital Twin system for renewable energy, bridging physical and digital components. The framework captures how sensor-acquired data flows through the communication interface, gets modeled in a virtual environment, and enables intelligent decision-making for monitoring, fault detection, and control.

1.3. Relevance of DTs in renewable energy contexts

The increasing complexity of renewable energy systems as well as their penetration into modern power grids makes the application of DT technology timely and crucial. In contrast with traditional power generation assets, renewable energy installations are often situated in remote and environmentally challenging locations [26]. Examples of these include urban rooftop installations, solar farms in arid deserts, offshore wind turbines in harsh marine conditions, and small-scale hydro or hydro microgrids in remote rural regions. Such operational environments are often associated with logistical challenges, problems related to accessibility, and increased maintenance costs because of weather or infrastructural difficulties. Adopting renewable energy sources contributes to the green and blue aspects of the Ecological Footprint, balancing with corresponding carbon expenditures, while maximizing the efficiency of existing resources [27]. To ensure service system and user satisfaction, as well as operational interfaces, the most modern technologies such as AI, machine learning, data analysis, and deep learning models can and should be used. DTs, along with the Internet of Things (IoT), constitute one of the most powerful technologies in the contemporary world, particularly in relation to asset performance monitoring and maintenance. The key benefit of using DTs in wind turbine and renewable energy captures is the technological foresight and remote operational capabilities modern AI provides [28,29].

DTs help to alleviate these issues by allowing for remote and constant monitoring of renewable energy systems. With the integration of advanced modeling techniques and real-time sensor data, DTs permit virtual inspection of important components, thus minimizing physical interactions. Maintenance-based on conditions where DTs enable shifts in maintenance strategies from traditional time intervals to advanced, predictive, and data-driven approaches [30]. This change not only helps to avoid operational disruptions and unplanned outages, but also enhances asset lifespans while constraining operational expenditures. For operators of energy systems as well as asset managers, the ability to foresee performance issues, degradation trends, or even component failures facilitate a significant improvement in reliability and cost-effectiveness. Beyond upkeep, DTs are critical for refining the operational efficiency, flexibility, and robustness of renewable energy systems. With respect to solar PV systems, DTs can be utilized for estimating irradiance levels, monitoring partial shading, assessing the temperature impact on module efficiency, as well as projecting long-term degradation patterns [31]. With these abilities, energy output forecasting becomes more precise, and system operation can be adjusted dynamically. In DT models of wind energy systems, DTs can also simulate the aerodynamics of turbine blade of changing wind speeds, supervision of gearbox vibrations and mechanical components wear, and rendering performance forecasts [32]. Because DGs are based on inputs from the environment, they provide valuable guidance for sustaining operation even under adverse and rapidly changing conditions.

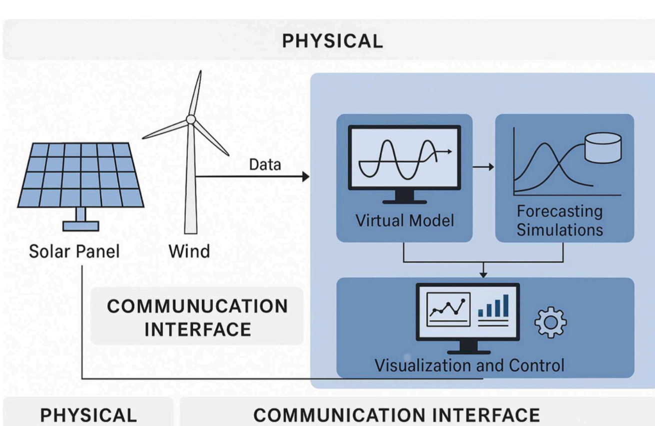

Fig. 1. Physical and digital architecture of a digital Twin system for renewable energy.

In hybrid systems and microgrids comprising of diverse energy generation, storage units, and even load demands, DTs facilitate intelligent energy orchestration and management. Considering the real-time energy availability, load profiles, and meteorological forecasts, DTs can analyze and identify the most efficient balance in dispatch strategy, provide automated optimization of battery charging and discharging cycles, and even balance supply-demand dynamics autonomously [33,34]. This leads to a more reliable, self-regulating system to work efficiently regardless of whether it is in grid-connected or islanded mode. Furthermore, DTs help considerably with the initial phases of system development. In the design and pre-deployment stage, a DT allows engineers and planners to model different scenarios with simulated components which can be placed in different environments. This allows the evaluation of control system tuning, risk assessment, and control system tuning within a virtual setting, which is leaps ahead in reducing the uncertainties which comes hand in hand with the physical prototype. With the option of validating the configuration digitally before any digitized implementation takes place means acceleration of both system reliability as well as development timelines resulting in the mitigation of overall investment and system capital.

As the technology develops, the integrating of AI and machine learning into the DT framework enhances the performance of the twin multitudes. A DT which is enhanced with AI has the potential to become a self learning system which improves it assistive powers of predictive model by evaluating data that has already been collected in real time [35]. In addition, evaluating past data in real time translates to outperforming earlier set standards in the detection of system permanent faults, being able to startlingly forecast energy expenditure, and being able to assess dynamic system behaviors shocking to the operator. Eventually, the intelligent DT can guarantee the autonomous systems decision making while using renewable energy systems which will allow them to react to any urging internal and external changes. The implementation of DT technologies across the renewable energy domain marks a notable progression towards the development of CPS, which integrate digital infrastructure and intelligence. DTs of energy assets amplify their intelligence and autonomy by making energy operations more automated and resilient, owing to the close coupling of the physical energy assets with their real-time virtual counterparts. This transformation is not simply a digital upgrade; it serves as a powerful accelerator of the strategic goals set for energy system changes. It strengthens the scalability of decentralized generation, facilitates grid stability in variable renewable energy-dominated systems, and is in sync with the internationally agreed goal of achieving net-zero carbon emissions. In this perspective, DTs are configured not just as facilitators of operational efficiency, but as fundamental pillars of the intelligent and adaptive synergetic systems of sustainable energy of the forthcoming days.

1.4. Scope and objectives of the review

Although the application of DT technology started with Aerospace Engineering, and later migrated to manufacturing and industrial automation, its use within the context of renewable energy is a new venture [36]. Historically, traditional sectors have realized the value DTs provide in predictive maintenance, lifecycle optimization, and advanced process control. However, there is still some way to go in the full-scale implementation of renewable energy systems, although, with the growing focus on sustainable energy generation, there is great interest in utilizing DTs to overcome fundamental barriers towards effective management of generation and control. With the accelerated pace of digital transformation in the global energy industry, there is a stronger motivation to incorporate DTs into renewable infrastructures [37]. The use of advanced analytics, virtual modeling, and real-time decision making unlocks new potential in the design, monitoring, and control of renewables – but much of the existing literature remains scattered. There is much work to be done regarding studies that focus on practical implementation rather than theoretical frameworks. Comprehensive reviews are lacking that map out the full-scale application of DTs across all technologies and stages of the asset lifecycle, as well as the underlying enabling digital architecture.

This review focuses on providing a deep analysis of DT technologies in renewable energy systems for literature that has been previously neglected. We start with explaining and positioning renewable energy operations within the industry and studying the impact of DTs on the operation and management of the wide variety of renewable sources such as solar PV, wind, hydroelectric, and hybrid systems. Covering the entire lifecycle of a renewable energy asset, from design and configuration to DTs-enhanced operation, condition monitoring, predictive, maintenance inter-maintenance, and dismantling showcases the sophistication of these systems and their potential for optimizing performance and reliability during various stages. A central focus of this review is examining the digital frameworks and technology accelerators that are critical for the development of contemporary DT architectures. Special attention is paid to AI, IoT, cloud and edge computing, and data science. These technologies enable the construction of agile and sophisticated DTs, and, at the same time, are essential for the smart CPS of the future energy systems. The DT's relationship dynamics with these technologies is fundamental in understanding their disruptive capability in the energy systems.

Alongside the theoretical framework, the review includes a number of practical case studies from testbed facilities, industry innovations, and other non-scientific research activities that showcase the practical application of DTs in the context of renewable energy. These illustrations capture the extremes of benefits, challenges, and consequences of adopting dual technologies, forming comprehensive knowledge for educational and industrial purposes. DTs hold incredible potential but their widespread adoption is impeded by numerous technical and operational issues. This review systematically evaluates the most prominent barriers, including model fidelity and heterogeneity, absence of uniform guidelines, complexities of cyber-physical integration, and computational scalability. Besides being technical obstacles, these challenges are often institutional, financial, and legal in nature which makes harnessing the full value of DTs in energy systems incredibly difficult.

The concluding section of the review suggests innovative pathways for subsequent work aimed at fulfilling the articulated challenges, including the creation of agile and resilient frameworks that can effectively respond to the specific demands posed by renewable energy systems. Furthermore, these frameworks need to go beyond traditional disciplinary boundaries with regard to standardization of frameworks, development of comprehensive ecosystems, and the integration of DTs for large-scale implementation. This paper attempts to merge the gaps between the existing theoretical work on DT technology and its practical implementation within the renewable energy industry by accomplishing the stated goals. Advanced Theory emphasizes the considerable and balancing consideration of the digitization and the automation modern energy systems. We aspire to advance the awareness of the role DTs play in expediting the shift to a more intelligent, flexible, and cleaner energy system by conducting this review.

These research questions help to methodically organize the review and guarantee congruence with its declared goals.

- Applied to renewable energy systems, what are the fundamental ideas, building blocks, and architectural forms of DT technologies?
- From design to operation, maintenance, and end-of-life (EoL), how have DTs been practically applied across the lifetimes of several renewable energy systems including solar, wind, hydro, and hybrid infrastructures?
- Which enabling technologies—such as artificial intelligence, IoT, edge/cloud computing, and big data—are essential for the development and operation of DTs in renewable energy environments, and how are they synergistically combined?
- In real-world renewable energy environments, what main technological, operational, and institutional obstacles restrict the scalability, integrity, and dependability of DT deployment?
- What research gaps exist, and what road map might be suggested to direct next developments in DT frameworks for intelligent, adaptable, and sustainable energy systems?

These guiding questions form the structural backbone of the evaluation and are discussed in great length in Section 2 through Section 7 of this work.

1.5. What previous reviews have not covered?

Although earlier studies on DT technology across several industries—including manufacturing, aerospace, and power systems—including manufacturing, aerospace, and power systems have examined parts of DTs within renewable energy systems remain poorly unexplored. Most current publications have addressed DTs via either a general-purpose technology lens or via fractured case studies with limited scope limited to a single type of energy source such wind or solar. These studies may ignore hybrid energy systems, lack a thorough lifecycle viewpoint, and do not methodically address enabling technologies as AI, IoT, and edge/cloud computing in concert with DT implementations. Unlike these disjointed approaches, the present review provides a complete, multi-dimensional taxonomy classifying DT applications across four renewable energy domains (solar, wind, hydro, hybrid) and throughout four lifetime stages (design, operation, maintenance, EoL). Moreover, current evaluations usually underrepresent actual case studies or limit them to high-level summaries devoid of critical assessment of their impact, problems, or scalability. By combining academic and industrial case studies together with empirical performance gains, cost savings, and operational improvements directly attributable to DT deployment, this work closes that void. Furthermore, absent from previous studies is a clear road map for future research organized around short-, mid-, and long-term goals based on technological and operational deficiencies including model integrity, computational overhead, data heterogeneity, and cybersecurity. This evaluation is especially important for academic and industrial stakeholders since it not only shows these obstacles with quantitative assessment (e.g., via Fig. 5 and Table 4) but also connects them to practical research initiatives. Finally, although other publications note enabling technologies like AI or IoT in passing, this analysis offers a layered integration framework (e.g., Fig. 5 and Table 3) that contextualizes how these technologies interact inside a functional DT architecture customized for renewable systems. Most earlier studies lack this degree of cross-technology synergy.

DTs first found use in the aerospace and manufacturing industries, setting the foundation for their later adaptation to energy systems. Offering a commonly referenced formalization of the DT idea [38], framed it as a fundamental component of Product Lifecycle Management. Reliability-driven applications were made possible by NASA's work [39], which also greatly helped to employ digital replicas for structural integrity monitoring during missions [40]. presented a layered architecture for DTs in production systems combining data, models, and service apps in smart manufacturing. Early industrial adopters including GE's Predix, Siemens' MindSphere, and Bosch's CPS platforms—which leveraged DTs for predictive diagnostics, dynamic control, and virtual commissioning—operationalized these theoretical contributions. These initiatives together show the fundamental function of DTs in industrial environments and offer the methodological framework for their migration to the renewable energy sphere. Drawing on these industrial predecessors, the present review extends their applicability to dispersed, sensor-rich, and mission-critical energy contexts.

1.6. Gap analysis and target audience

Despite growing interest in DT applications across various energy domains, a comprehensive and lifecycle-spanning review tailored to renewable energy remains lacking. Table 1 below summarizes key prior reviews and highlights their thematic limitations in scope, technology integration, or sectoral coverage.

This review advances beyond prior work by offering a **unified taxonomy**, **multi-technology integration**, and **sector-specific case studies**, positioning it as a unique reference for practitioners and scholars alike.

This review is intended to serve a diverse but interconnected audience.

- **Academic Researchers**: It offers a coherent synthesis of DT architectures and enablers, empirical metrics from real-world deployments, and a structured roadmap for future investigations.
- **Utility and System Engineers**: It provides actionable insights into predictive maintenance, system-level optimization, and integration strategies for AI-enabled DTs.
- **Policy Makers and Planners**: The review highlights technology readiness levels, deployment barriers, and alignment with global decarbonization goals (e.g., SDGs, EU Green Deal, Inflation Reduction Act), enabling better policy formulation.
- **Technology Developers**: By presenting real-world case studies and deployment challenges, this work serves as a decision-support tool for prototyping, testing, and commercializing scalable DT solutions in renewable systems.

In sum, this review fills a crucial knowledge void and enables multi-stakeholder decision-making through a balanced integration of theory, application, and strategic foresight.

1.7. Contribution and Novelty of this review

The fast-changing interaction between DT technologies and renewable energy systems is synthesised in this timely and thorough overview. By means of a disciplined, cross-domain study spanning technical, operational, and strategic dimensions, its contribution is both novel and multidimensional, providing major scholarly and pragmatic value. This work provides a comprehensive investigation of DT applications across solar, wind, hydro, and hybrid systems, encompassing the whole asset lifetime: from design and simulation to real-time operation, predictive maintenance, and EoL optimization, while past reviews have typically focused narrowly—either on a specific renewable technology such as PV, or on isolated stages like monitoring. The inclusion of a fresh classification taxonomy—which methodically groups DT implementations by energy type, lifetime stage, and functional role—makes this study among the most unique. This taxonomy, shown in Fig. 5 and Table 3, gives a field sometimes marked by scattered and isolated insights structural clarity. It helps academics and professionals to spot areas of concentration for DT applications, areas of weakness, and how different subsystems link across both physical and digital spheres. This review's layered integration of enabling technologies—including AI, the Internet of Things (IoT), cloud and edge computing, and big data analytics—adds still another special quality. The review shows—through architectural mappings (e.g., Fig. 4 and Table 3)—how various technologies combine to construct intelligent, autonomous, and scalable DT ecosystems, therefore transcending their status as auxiliary components. By stressing the cooperative roles of these technologies in improving real-time decision-making, defect detection, asset optimization, and distributed energy coordination, this study expands the scholarly debate.

Unlike many conceptual or theoretical studies available in the literature, this work is based on actual uses and empirical case studies. Inspired by both academic research and industrial installations like DT-enhanced wind farms, solar inverters, hydroelectric systems, and microgrid pilots These case studies provide objective data—such as a 10–20 % improvement in energy yield and up to 25 % decrease in maintenance downtime—that supports the useful influence of DTs in operational contexts. Engineers, developers, and energy system designers especially should find the review very pertinent. Beyond only technical contributions, the paper presents a forward-looking research roadmap identifying and contextualizing major obstacles confronting the field: including model authenticity, data heterogeneity, lack of standardizing, cybersecurity concerns, and computational scalability. These problems are localized to the practical and institutional reality of renewable energy systems rather than being addressed generally. The roadmap is thus divided into short-, medium-, and long-term priorities, thereby offering strategic guidance for industry as well as for academia. The multidisciplinary character of this evaluation adds even more its uniqueness. Combining ideas from CPS, computer science, and energy systems engineering, it shows how DTs are enablers of intelligent, flexible, and resilient infrastructues rather than isolated digital tools. Supporting autonomous system control, performance optimization, and sustainable energy transitions, the study places DTs as basic for the digital transformation of the energy industry.

In summary, this review fills in a major hole in the literature with a disciplined, practical, and future-oriented framework. It not only arranges a scattered body of knowledge into a logical totality but also presents innovative approaches, taxonomies, and integration models. For researchers, system designers, legislators, and technologists at the nexus of renewable energy and digital change, its observations provide authoritative direction.

1.8. Structure of the paper

This review has been purposefully arranged to lead the reader through a logical sequence reflecting the tiered method applied in the process of literature screening, selection, and synthesis. From basic ideas to enabling technologies, practical applications, new challenges, and finally a forward-looking research program, the aim is to progress from This tiered structure guarantees that the study delivers a coherent narrative that catches the changing function of DTs in renewable energy

Table 1
Comparison of prior review articles on DTs in renewable energy contexts.

Author(s) & Year	Energy Focus	Lifecycle Coverage	Tech Integration (AI, IoT, Edge)	Gap Identified
[41]	Wind only	Operation phase only	Limited to IoT	No multi-energy comparison
[42]	PV systems	Monitoring only	AI-focused	No discussion on hybrid systems or EoL strategies
[43]	General DTs	Broad but non-renewable	Not discussed	No RE context or taxonomy
This Review	Solar, Wind, Hydro, Hybrid	Full lifecycle: Design → EoL	AI, IoT, Edge, Cloud	Comprehensive lifecycle and system taxonomy, practical roadmap

systems, not only aggregates past work. Section 2 describes the review approach, including the search strategy, inclusion criteria, period span (2014–2024), databases consulted, and thematic sorting techniques guiding the later structure. This methodological openness guarantees a repeatability and a systematic approach to the review. Section 3 opens with the theoretical underpinnings and core ideas of DT technology. Through tracking the development of DTs from aerospace and manufacturing sectors into the energy sector, it offers historical background. It then addresses important architectural components like the physical asset, virtual model, and data interface and explores their interactions inside a real-time, cyber-physical loop. The conceptual basis required to grasp the relevance of DTs to contemporary energy infrastructures is established in this part. Section 4 shows the enabling digital technologies enabling intelligent and functional DT systems. Emphasizing AI, the IoT, cloud-edge computing, and big data analytics. These systems are investigated in respect to their functions in autonomous control, fault detection, predictive diagnostics, and system optimization. Their combined value is positioned as indispensable for the evolution of scalable, adaptable, and robust energy systems. Section 5 presents a thorough taxonomy and classification system for DT uses in renewable energy. It arranges current research in line with lifetime stage—design, operation, maintenance, and EoL as well as energy type—solar PV, wind, hydroelectric, and hybrid systems. This part summarizes industrial methods and scholarly achievements, so stressing the flexibility of DTs in many fields and system phases. Section 6 provides an evidence-based summary of actual implementations. Using industry reports, case studies, and peer-reviewed literature, it looks at how DTs have been used in operating environments. The section evaluates the results, scalability, and efficiency of these implementations, therefore offering objective analysis of how theory is being put into use. Section 7 points up ongoing difficulties and research limitations that now restrict the complete adoption of DTs in the renewable energy industry. These cover problems such model accuracy, data heterogeneity, lack of standardizing, cybersecurity flaws, and heavy computing load. Understanding these constraints prepares one for focused research projects and significant invention. Building on the earlier study, Section 8 offers a strategic road map for next investigations and development. The road map calls for the integration of DTs in energy storage management, climate adaption modeling, and decentralized grid control among short-, medium-, and long-term priorities. This forward-looking part matches technical needs with world policy frameworks including the Paris Agreement, the Sustainable Development Goals (SDGs), the EU Green Deal, and the U.S. Inflation Reduction Act. The last section, Section 9, summarizes the main conclusions of the review and emphasizes the transforming power DTs can have in the worldwide change toward a decarbonized, intelligent, and inclusive energy future. The ending further supports the dual significance of this assessment as a scholarly source and a useful manual for those involved in digital energy transitions.

The structure of the study thus shows a well-chosen analytical sequence, starting with basic knowledge and moving toward implementation, criticism, and future vision. It reflects the methodological logic of the review, which categorized the literature along three axes: (i) theoretical and architectural foundations, (ii) enabling technologies, and (iii) application domains defined by energy type and lifecycle phase. This intentional architecture guarantees that every part logically builds on the one before it helps to provide a consistent knowledge of how DTs are changing renewable energy systems. Driven by policy, technological developments, and industrial impetus, the assessment addresses an important worldwide need—driven by which scattered ideas should be consolidated and steer the next wave of invention in sustainable digital energy infrastructure.

2. Methodology of the review

This section outlines the systematic methodology used to conduct the review. It follows PRISMA guidelines, detailing the search strategy, inclusion/exclusion criteria, and classification approach. The aim is to ensure transparency, reproducibility, and thematic coherence in the literature selection and synthesis process. Having ensured scholarly depth, complete coverage, and relevance to context, this review employs a particular strategy and style. The methodology aims to collect, analyze, and integrate the most important advancements concerning the intersection of DT technologies and renewable energy systems from academic and industrial sources. The objective is to provide an overview that is both comprehensive in detail and accurate regarding the current progression of the field while recognizing the notable trends, challenges, and opportunities that exist. The literature reviewed in this work incorporates a broad range of scholarly and industry publications published between **2014 and 2024**. This ten-year span was selected to capture both foundational and cutting-edge developments in DT applications relevant to renewable energy systems. Special focus was given to journal articles published in peer-reviewed journals that have gained significant attention and prestige for their quality and impact. These are journals that can be accessed via IEEE Xplore, ScienceDirect, SpringerLink, and Web of Science. The review also captures non-journal material, including quality conference proceedings, technical reports, and industry white papers authored by prominent energy companies, technology firms, and standardization organizations. The addition of these documents enriches the theoretical perspective and practical framework applicable to DT technologies in the energy industry. To ensure methodological transparency and reproducibility, a systematic literature search strategy was adopted. Major scientific databases—**IEEE Xplore**, **ScienceDirect**, **SpringerLink**, and **Web of Science**—were queried between **January 2024 and April 2024**. The search focused on journal articles, conference proceedings, technical reports, and white papers published between **2014 and 2024**, covering both academic and industrial contributions.

The following keyword combinations were used with Boolean operators to refine the search.

- ("Digital Twin" OR "DT") AND ("Renewable Energy" OR "Solar PV" OR "Wind Turbine" OR "Hydropower" OR "Hybrid Systems")
- ("Smart Grid" OR "CPS") AND ("Monitoring" OR "Predictive Maintenance")
- ("AI" OR "Machine Learning") AND ("Digital Twin" AND "Energy Systems")

Titles, abstracts, and keywords were screened to eliminate duplicates and off-topic records. Articles were then sorted based on **thematic alignment**, **technical depth**, and **publication quality** (peer-reviewed, high-impact journals prioritized). Further screening involved a **second-level evaluation** of full texts, assessing **relevance, methodological soundness**, and **practical or theoretical contribution** to DTs in renewable energy. Studies were **excluded** if they were purely conceptual without energy system relevance, lacked analytical depth, or were outdated in terms of DT integration.

This process resulted in a curated set of **156 peer-reviewed sources**, including studies with substantial simulation, experimental validation, and real-world deployment of DT solutions across solar, wind, hydro, and hybrid systems. To enhance transparency and reproducibility, the methodology follows the PRISMA 2020 framework. Fig. 1 presents the PRISMA flow diagram illustrating the number of records identified, screened, excluded, and included at each stage of the review. The following selection criteria were applied.

- **Time Range:** Publications from January 2014 to April 2024
- **Inclusion Criteria:** Peer-reviewed journal articles, industry case studies, and technical white papers reporting on DT applications in solar, wind, hydro, or hybrid renewable energy systems, with a clear technical or operational contribution

- **Exclusion Criteria:** Articles not directly related to DTs or renewable energy, studies lacking technical depth or methodological transparency, duplicates, and review articles without novel synthesis

After applying these filters, a curated set of 156 publications was finalized for inclusion in this review. Fig. 2 presents the revised PRISMA 2020-compliant flow diagram, which clearly delineates each stage of the systematic review process—identification, screening, eligibility, and inclusion—along with exclusion reasons and source types, thereby enhancing clarity and reproducibility.

A second level assessment was done in order to assess published works with regard to their thematic relevance, relevance impact, technical level profundity, innovativeness, and value add to the discipline. In this regard, only those works which had substantial analytical depth, methodical scrutiny, or practical understanding were put through selected scrutiny. Each of the selected works was categorized in accordance with pre-established key parameters: the focus of the renewable energy technology was categorized as solar, wind, hydro or hybrid systems; the functions and lifecycle of the DT were system design, operation, monitoring and maintenance, and the last parameter was the types of enabling digital technologies used which include, but are not limited to, AI, IoT or edge/cloud computing. Such categorization enabled systematic evaluation of the energy-specific implementations of DTs. Where relevant, the review adds comparative assessment of several frameworks, architectures, or models of DTs examining their effectiveness, flexibility, and extent of scalability concerning different operational environments. This further includes study analysis, simulation analysis, and experimental validation analyses which shed light on the benefits and drawbacks of particular DT implementations. The chosen methodology makes certain that the review is not only academically sound, but also practically relevant. It provides a uniform and neutral approach which allows for identifying trends, defining focal points, and developing innovative research hypotheses. Furthermore, it nurtures the clarity and coherence of the synthesis aimed at informing researchers, practitioners, and policymakers by dividing the methodology-guided parts of the review using these structural principles with the underlying goal of enabling effective engagement with DT solutions in renewable energy development. A second-level relevance assessment was undertaken following the first keyword-guided screening. Studies were ranked according to their conceptual fit with DT applications in renewable energy, their analytical depth—that is, inclusion of simulation, modeling, or experimental validation—their degree of technical innovation, and their practical usefulness or industrial significance. Retained were only studies offering significant value for the knowledge, growth, or application of DTs within solar, wind, hydro, or hybrid energy systems. This strategy guaranteed the selected literature corpus's methodological soundness and practical relevance.

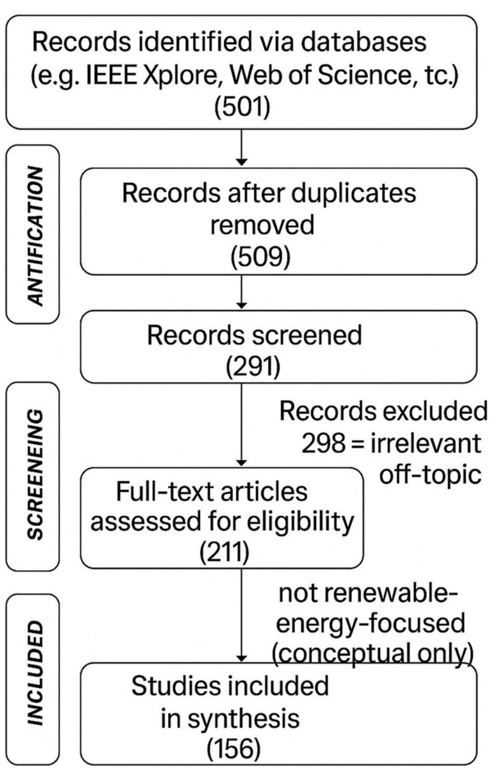

Fig. 2. PRISMA-style flow diagram.

In line with the objective of this systematic review, the following Research Question guides our investigation:

What is the current state, emerging trends, and technological readiness level of Digital Twin (DT) frameworks and their enabling technologies in the context of renewable energy systems?

This RQ serves as the foundation for our literature selection criteria, review methodology, and synthesis structure, focusing on both theoretical contributions and real-world deployment evidence.

3. Fundamentals of DT technology

This section introduces the foundational principles of DT technology. It covers its evolution, core components, and architectural structure. The aim is to establish a conceptual basis for understanding how DTs are applied in renewable energy systems.

3.1. Historical development and evolution of DTs

DT technology's beginnings dates back to the early 2000s, together with its foundation emerging from the aerospace industry [44]. This specific field integrates complex and mission-critical systems that perform in inaccessible or dangerous locations. One of DT's earliest documented application was during NASA's space exploration programs. Engineers with NASA created high-fidelity virtual replicas of spacecraft subsystems and monitored their performance in real-time is simulation environments during space missions. With these virtual models, mission control was able to monitor a spacecraft's state millions of kilometers away from earth and predict future system failures, assess, and provide anomaly detection. The immense practical necessity of ensuring system reliability in unfathomable remote locations leads to the concept of a DT: a model that continuously evolves to capture the essence of system's behavior in accurate real-time scenarios [45]. With early models showing the importance of digital replicas in managing intricate physical systems, the term "DT" was later defined. The application of the concept advanced to manufacturing during the fourth industrial revolution. Enabling the production of virtual real time models of factory floors, machines, robotic arms, and production lines are the DTs in the manufacturing sector. The advent of sensors, simulation, and control systems provided unprecedented insight into operational processes, which in turn allowed for real time optimization, predictive maintenance, reduced downtimes, and improved equipment and systems life cycle management.

The implementation of DTs within the manufacturing sector was a novel step since industrial operations shifted from reactive problem-solving business models to proactive, data-driven decision-making frameworks. This change was fueled by peripheral growth of supporting new technologies such as CPS, IoT, and AI. CPS provided a mechanism to merge physical and digital realms, IoT facilitated data collection from numerous sensors and devices to be captured in real-time, and AI enhanced self-learning models with advanced intelligent decision-making capabilities [46–48]. This evolution transformed DTs from obsolete representations into dynamic, adaptive systems with the ability to reason, forecast, and execute autonomously. After maturing in aerospace and industrial sectors, DT technology began gaining traction in other vital areas. In the healthcare sector, DTs have been used for modeling pupils' specific anatomic and physiologic features for optimal treatment planning and monitoring. Virtual reproduction of urban infrastructures as part of smart city initiatives have been carried out to control the management of traffic, energy consumption, emergency response, and other services. Vehicle dynamics and fleet operations have also been managed through real-time digital monitoring. The variety of applications illustrates the unique scalability of DT technology whose impacts can be felt in multiple industries.

The renewable energy sector has recently emerged as one of the most promising and recent frontiers for the use of DTs. It is logical, as well as timely, to expect that the DT technology transition to renewable energy systems will occur. The increasing penetration of distributed energy resources together with the volatility and intermittency of solar and wind renewables add new challenges to energy generation, forecasting, and grid integration [49]. Renewables systems are frequently located in isolated, climatically volatile, and physically harsh regions where routine maintenance is hard, and operational uncertainty is high. Such conditions mirror those, which in the first place motivated the development of DTs in aerospace and, thus, emphasizes the significance of DTs in the context of renewable energy. In renewable applications, DTs provide the same transformational benefits that other industries adopted. They enhance system monitoring through data collection, improve system dependability through fault, and predictive diagnostics, as well as assist decision-making using simulation and virtual testing. Furthermore, with the progressing modularity and intelligence of renewable systems from the storage units, power electronics, and smart inverters, DTs become the unifying control hardware, software, environment inputs, and systems [50]. Therefore, the development history of DT technology, starting from the space's DT and now including sustainable energy systems, signifies the digital fusion and automation evolution. This exemplifies the advances of DTs in coping with ever-increasing newer challenges in modern infrastructure systems, which are complex, fragmented, data-rich, and eco-sensitive. With increasing pace of global energy transformation, growing needs for robust renewable energy systems, DTs will serve as crucial components for optimal, dependable, and smart management of renewable energy systems.

The concept of DT was introduced by NASA in aerospace engineering to track and replicate spacecraft systems under highly demanding operational conditions. But DTs found great conceptual and practical relevance in the field of smart manufacturing and the more general Industry 4.0 movement. DTs were the pillar of cyber-physical production systems (CPPS) in this age since they allowed real-time coordination between digital and physical manufacturing techniques. Among the first to embrace DTs for uses including process optimization, predictive maintenance, factory automation, and dynamic product lifecycle management were leading industrial companies including Siemens, General Electric (GE), and Bosch. In these environments, DTs were used to generate high-fidelity virtual replicas of physical assets—from CNC machines and robotic arms to entire production lines—which could then be used to simulate operational scenarios, evaluate wear and failure probabilities, and optimize control parameters without so disrupting real-world operations. The viability and scope of DTs were much improved by the explosion of enabling technologies during the Industry 4.0 transition—especially the integration of IoT sensors, cloud and edge computing, AI, and big data analytics. These technologies supplied the sensory, computational, and analytical tools needed for DTs to develop from stationary design-time models into dynamic, self-adaptive, and intelligence-driven systems. DTs' success in manufacturing settings prepared the way for their cross-domain spread. Their versatility, scalability, and real-time adaptation made them perfect for use in sophisticated, dispersed, sensor-rich contexts like renewable energy systems. Within this framework, renewable energy systems—which include solar farms, wind turbines, hydroelectric plants, and hybrid micro-grids—miracle many of the traits of contemporary factories: distributed operation, component heterogeneity, the need of dependability, and growing use of automation and intelligent control. Thus, where they now support system monitoring, fault detection, predictive maintenance, and lifecycle optimization, the basic approaches and technologies established in the context of Industry 4.0 have immediately facilitated the migration of DT frameworks into the energy industry.

Early industry-led use of DTs in renewable energy systems started with businesses like Vestas and Siemens Gamesa, who created DT-enabled platforms to track wind turbine health, simulate aerodynamic fatigue, and predict component failures based on real-time telemetry data. Their implementations demonstrated how realistically DT frameworks might be used in offshore and onshore wind farms. In PV plant management, First Solar also used DT modeling methods to replicate module degradation, maximize inverter loading, and match site-specific performance with long-term yield projections. These first uses signal the change of DTs from manufacture into vital energy infrastructure. This evolutionary road is shown in Fig. 3 below together with important industrial benchmarks in the advancement of DT applications.

3.2. Core principles and architecture of DTs

The DT technology surpasses simple simulation, digital model, or even a static representation of a physical system. Static representations capture only a snapshot of the system's features, whereas DTs provide a virtual replica of systems that are autonomous, interactive, and self-adaptive [51]. Such features dynamically evolve with the asset's processes, systems, physical features, functionality, and real-time updates of operational states. The main goal of DTs is to furnish a precise representation of the asset over its entire lifecycle, including sustained design, commissioning, operational use, maintenance, and decommissioning phases. As a result, they yield improved and advanced capabilities like condition monitoring, state diagnostics, performance forecasting, optimization of processes, and even self-sufficient control. The construction of a DT and its virtualization uses a smart data management system. For the model to work properly and for its functions to be useful, a layered architecture needs to be implemented. This begins with the physical system layer that includes the actual asset like this solar panel, wind turbine, battery storage unit, or hydroelectric turbine. These hardware assets include sensors, actuators, controllers, and communication modals. These deliverances are specialized in capturing data real time. These are the primary sources of operational data. These devices provide key parameters which range from: temperature, current, voltage, pressure, wind speed, vibrance, or even irradiance. The measurements done may influence the DT operating. Therefore, measuring standards need to be accurate, granular, and consistent over time.

As with the other layers, the DT layer completes the physical layer and is responsible for the system's computation (or processing). This layer contains the models, simulations, and intelligent algorithms that reconstruct digitally the actions of the system's physical counterpart

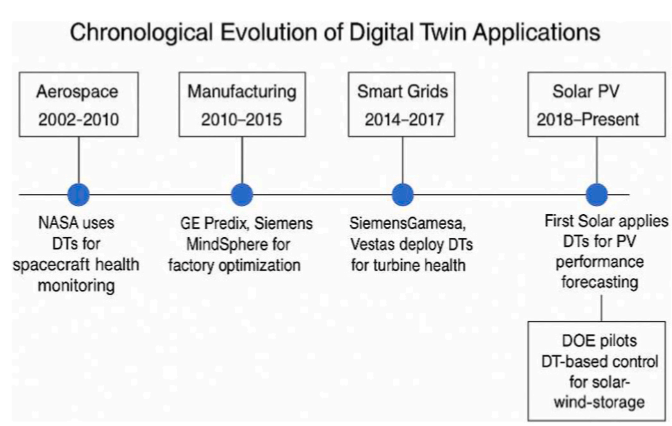

Fig. 3. Chronological evolution of dt applications.

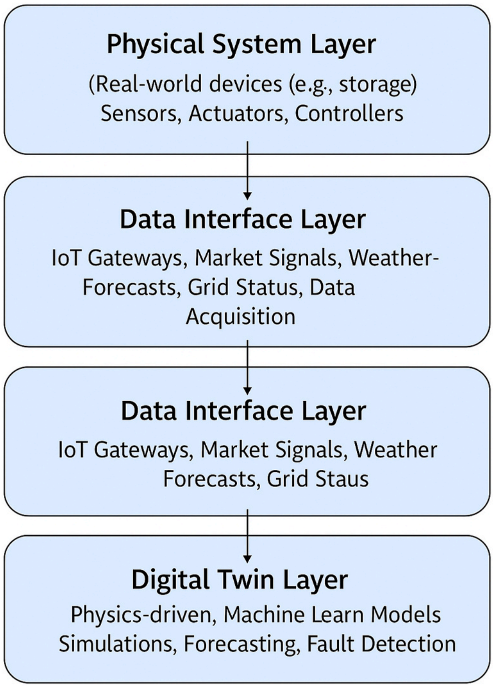

Fig. 4. Conceptual architecture of a DT in renewable energy systems.

depending on the operational scenarios being run. Such models could either be based on physics (or first principles) through governing equations or alternatively be approximations created through data using machine learning and statistical inference techniques. More often, there are hybrids, where the data-centric approaches are combined with existing physical laws for better model accuracy, generalization, and adaptability to the operating conditions. The DT not only replicates system states that can be observed, but also makes estimates about system states that cannot be directly measured, predicts future actions, and computes what-if scenarios for decision support [52,53]. The data interface layer creates the bridge into the digital world while maintaining 2-way, continuous communication with the asset's digital counterpart. This layer comprises of the hardware and software systems that build a framework for the collection, transmission, storage, and processing of large amounts of diverse data. Streams from sensors are fused with operational records logs and relevant context data such as weather, geospatial information, and grid supplied information. Hence, it becomes possible to ensure constant updating of changes to the physical asset as and when they occur, alongside the virtual model. Furthermore, it allows for the execution of control strategies where the DT, after executing prediction-based optimization algorithms, issues command or makes alerts tailored for the physical apparatus.

Integration of these three levels creates a closed-loop cyber-physical system where the DT provides feedback to refine operations, and the physical model updates in real time. Such two-way interaction alters the role of the DT, shifting it from a static analytical instrument to a dynamic participant within the system's command and control network. For instance, a DT of a solar PV array could observe deterioration of a panel's performance and automatically adjust the MPPT algorithm to optimize output. A DT of a wind turbine could, on the other hand, pre-emptively issue a maintenance warning due to anticipated gearbox failure well ahead of an expensive breakdown. Adaptability is incorporating self-learning capabilities, while monitoring data trends, and autonomy means acting on one's own judgement. Such principles are what allows this architecture enhance safety, efficiency, and reliability. In the scope of renewable energy systems, this configuration has immense importance. Because renewable energy generation is intrinsically variable and distributed, DTs offer a singular solution for constant system supervision, multi-level integration, and intelligent management. DTs are pivotal to contemporary, smart, and resilient energy systems infrastructure because they help facilitate the virtualization of physical assets alongside embedding intelligence into the operational processes of the system [54]. These tools aid energy stakeholders shift from reacting to systems to adopting proactive strategies, improving system availability, reducing costs, and expediting the transition to sustainable energy systems. Fig. 4 illustrates this layered DT architecture, where data flows continuously between the physical and virtual realms to ensure accurate synchronization. This diagram depicts the three-dimensional view of a DT system's architecture on a renewable energy asset. The Physical System Layer comprises the sensing devices and energy-generating machines. The Data Interface Layer functions as the communication channel which consolidates data streams to be delivered in real-time and provides context. The DT Layer encompasses the scanning and analytical tools responsible for simulating and anticipating the behaviors of the actual systems. Moreover, the Control and Decision Loop facilitates optimal feedback control, enabling the twin to assist passively or actively in ensuring the safety and efficient operation of the physical system.

3.3. Mathematical modeling of DT synchronization

To function effectively, a DT must accurately replicate the behavior

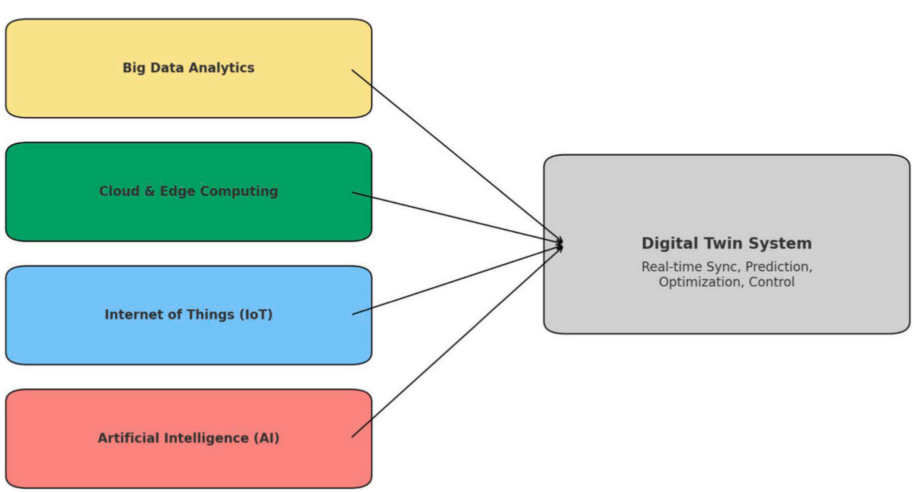

Fig. 5. Integrated architecture showing the layered interaction between key enabling technologies (AI, IoT, Cloud/Edge Computing, Big Data) and the core functions of DTs in renewable energy systems.

of its physical counterpart [55]. Let the state of the physical system be denoted as x(t), and the corresponding state of the DT as $\hat{x}$ (t). The synchronization of the twin can be mathematically expressed as per relation (1) [56]:

$$\hat{x}(t) = f(x(t), u(t), \theta(t)) + \varepsilon(t) \tag{1}$$

Where.

- x(t) represents the real-time state of the physical system,
- u(t) is the control input,
- θ(t) denotes environmental and operational parameters (e.g., solar irradiance, wind speed),
- f(·) is the behavioral model (physics-based, data-driven, or hybrid),
- ε(t) is the modeling error, ideally minimized through learning and calibration.

The objective of a high-fidelity DT is to minimize ε(t) over time using AI techniques, sensor fusion, and online recalibration mechanisms.

3.4. Real-time data integration and feedback mechanism

An aspect that sets apart DTs is their peculiarity to receive, process, and act on live data stemming from the actual system. Operational data streams like temperature, voltage, current, vibration, wind speed, and irradiance are perpetually available from the sensor networks associated with renewable energy systems [57]. These data streams are utilized by the DT for state reproduction, fault isolation, or operational scenario prediction. Considering the time function t, let the vector of incoming sensor signals be S(t) and let the twin's output action be y(t). Then, the feedback control loop can be modeled as in Equation (2) [58]:

$$y(t) = g(S(t), \hat{x}(t)) \tag{2}$$

Where g(·) may involve optimization algorithms, control laws, or rule-based logic to update system operations in real-time. This functionality allows DTs to serve not only as diagnostic tools but as intelligent agents within control architectures for renewable systems.

3.5. DT integration in renewable energy systems

The spatial distribution and high data availability of renewable energy systems makes them vastly profit from DT technologies. In solar power systems, DTs can simulate real-time degradation of components, temperature impacts, and losses in power conversion. For Wind Turbines, DTs can simulate the structural dynamics of blades, gear wear, summative optimization of orientation, and max efficiency. Hydropower plants use DTs for simulation of flow dynamics and build-up of sediment in addition to maintenance intervals of the turbines and gates. Typical DT Applications for various renewable energy technologies and their lifecycle phases are presented in Table 2 [59].

Table 2
Application of DTs in renewable energy systems.

Renewable Source	Design & Simulation	Operation & Monitoring	Maintenance & Optimization	Example Use Case/ Reference
Solar PV	Panel layout optimization	Irradiance forecasting	Degradation tracking, MPPT tuning	Huawei FusionSolar platform [21], University of Seville DT model [23]
Wind	Blade aerodynamics	Gearbox vibration analysis	Predictive maintenance	GE Digital Wind Farm [24], Vestas turbine diagnostics [59]
Hydro	Turbine flow modeling	Water level estimation	Sediment and wear diagnostics	EDF Villerest Dam [24]
Hybrid Systems	System coordination	Load balancing	Battery life extension, control	US DOE hybrid pilot [24]

4. Enabling technologies for DTs in renewable energy systems

This section explores the critical digital technologies that empower DT functionality. It highlights the roles of AI, IoT, cloud/edge computing, and big data analytics. These technologies are presented as integral to real-time control, predictive diagnostics, and system optimization. The functionalities of DTs in renewable energy includes their real-time linking and automated task handling. Their achievements are sustained by a powerful system of technology and infrastructure, which includes: AI, the IoT, cloud and edge computing systems, and big data analytics [60]. Together, these systems supply as much needed intelligence and data for the DTs to function as autonomous, self-modifying, and scalable cyber-physical frameworks. Among the many enablers of DT systems, perhaps the most disruptive one is AI. AI equips DTs with the necessary intelligence that enables them to recognize patterns, 'learn' how their systems operate, and make rational choices [61]. For renewable systems, AI is essential in predictive upkeep, calculating energy requirements, spotting faults, and optimizing operations in real-time. To illustrate, a wind turbine is subject to various fluctuations in wind speed. A DT of such a turbine can be fitted with a neural network capable of relating operational parameters such as blade rotation speed, torque, vibration, and generator temperature to a health state index. This is representable as (3):

Table 3
Roles of enabling technologies in DT functions.

Enabling Technology	Core Role in DTs	Application Example in Renewable Energy	References
AI	Predictive analytics, optimization, fault detection	Wind turbine blade fatigue prediction	[60,61]
IoT	Real-time data acquisition and control	PV panel monitoring and MPPT adjustment	[62]
Cloud & Edge Computing	Scalable processing and low-latency responsiveness	Edge-based control of microgrid voltage levels	[63]
Big Data Analytics	Pattern discovery, forecasting, diagnostics	Energy yield prediction under changing weather	[64,65]

$$\hat{y}(t) = f(x_1(t), x_2(t), \ldots, x_n(t);\ \theta) \tag{3}$$

where x_i(t) represents real-time input features at time t, θ is the set of learned parameters from historical data, and $\hat{y}$ (t) is the predicted condition or performance metric. The DT can use this forecast to schedule maintenance, prevent catastrophic failures, and adjust operating points for efficiency.

The IoT delivers the crucial sensing and communication framework for DT systems. IoT networks encompass smart sensors, embedded systems, edge devices and protocols that facilitate the real-time data exchange between physical energy assets and their virtual counterparts [62]. IoT in solar PV applications, for example, allows for monitoring of solar irradiance, module temperature, and voltage output of every individual panel. All this information is transmitted to the DT so that the virtual model remains up to date with the actual physical state. Furthermore, IoT's bidirectional communication allows DTs not only to monitor and control remotely with commands sent in their feedback loop after an anomaly or predicted change in operating conditions is detected, but also to issue commands autonomously. The latency and processing issues associated with DT operations in real time are mitigated by cloud and edge computing technologies [63]. While the cloud offers virtually limitless resources for data storage, data access, historical analysis, AI model training, and more, edge computing offers real-time processing at the location data is collected, further reducing latency. This is critical in remote renewable energy locations, such as offshore wind farms or solar farms located in deserts, where high-speed internet connectivity is spotty. For instance, near sub-second decision-making for real-time fault isolation in wind turbines may not be possible via cloud servers. Local edge devices can ensure faster decision execution by processing data, executing safety protocols, and updating with DT local to the DT in milliseconds [64].

The analytical component of big data serves as the interpretive and diagnostic layer for the DT technology, or DT. It allows the functioning of the DTs with regard to the challenges of volume, velocity, variety, and veracity associated with data from renewable energy systems. Technique of time series analysis, regression models, unsupervised learning, and dimensionality reduction approaches enable actionable insights to be advanced from the sensor data. In hybrid systems of solar and wind energy, big data tools enable the DT to correlate the solar and wind environmental parameters with system output to optimize the configuration and quantity of system resource constituents [65–67]. This improves energy yield, reduces operational risk, and enhances smart grid integration. Table 3 summarizes how each of these enabling technologies contributes to the key functions of a DT in renewable energy systems.

Fig. 5 presents a layered visualization of how enabling technologies empower the functionality of DTs in renewable energy contexts. The diagram shows how IoT enables data acquisition, edge/cloud platforms facilitate scalable processing, AI contributes to real-time intelligence, and big data analytics support performance diagnostics and forecasting.

As provided in Fig. 4 and Table 3, these technologies do not work in isolation; rather, it is their convergence which allows the DT to move beyond classical system modeling and monitoring. For example, a solar power plant could use AI-powered forecasting to anticipate cloud cover and subsequently activate battery charging controls via edge computing. At the same time, IoT ensures monitoring of voltage levels in real time, while the cloud keeps predictive models current with historical datasets enhanced through big data. The merger of AI, IoT, cloud-edge computing, and big data analytics shifts the paradigm; rather than serving as passive replicas, DTs become active decision-making systems that propel enterprises into the future. This feature is crucially important in renewable energy, where the need for intelligent, autonomous, adaptive, and self-governing systems is required due to unpredictable environmental inputs, decentralized asset distribution, and high system complexity.

Using hybrid frameworks like the Deep Energy Method (DEM), which blends data-driven models with physical laws to improve learning accuracy and generalizability, is a developing progress in the integration of machine learning with DT systems. To train physics-informed neural networks, DEM has shown great efficiency in absorbing experimental data, real-world observations, and simulation-based knowledge, hence lowering dependency on large-scale labeled datasets. DEM powerfully closes the gap between simulations and physical systems, hence permitting strong generalization across dynamic situations, as proven by Ref. [68] in Computer Methods in Applied Mechanics and Engineering. Including such techniques into renewable energy DTs—for example, simulating turbulent wind flows or PV thermal interactions—offers a viable approach toward producing high-fidelity, data-efficient DTs with improved predictive power. This emphasizes the continuous change from typical ML pipelines to hybrid, physics-aware learning systems essential for intelligent, resilient, and self-adaptive renewable infrastructures.

In summary, the purpose of the enabling technology features has been fundamental to the adoption and implementation of DT systems in applications related to renewable energy. These technologies will require a DT with algorithms for intelligence, omnipresent sensors, processors for cloud-edge scalable computing, and sophisticated analytics to meet the performance, reliability, and efficiency standards of sustainable energy infrastructures.

5. Classification and applications of DTs in renewable energy systems

A novel taxonomy is introduced in this section to categorize DT applications across renewable energy types and lifecycle phases. This framework helps organize fragmented research and industry efforts into a coherent structure. It emphasizes how DTs are being used in design, monitoring, maintenance, and optimization. The applicability of DT technology is growing in scope across different renewable energy systems, with each system having its own operational difficulties and lifecycle requirements. For additional detail of the range of DT applications, a hierarchy based on the energy source and the lifecycle phases of the relevant assets is needed. This framework assists to understand how the function of DTs' changes from evolution through design, through conceptual framework to the optimization at the end of life, for various technologies including solar PV, wind energy systems, hydroelectric power, and hybrid renewables systems. The advances in the application of DTs are prominent in the design phase of solar PV systems. Advanced computer models of PV fields capture physical features such as the geometrical configuration of panels as well as the dynamically changing solar irradiance level, allowing for simulation of energy production for various weather scenarios [69]. Several of those simulations depend on solar irradiance G(t), module temperature T(t), and efficiency η(t), thus enabling the dynamic forecasting of power output with the help of equation (4):

$$P_{PV}(t) = G(t) \cdot A \cdot \eta(T(t)) \tag{4}$$

where A is the total surface area of the modules. This modeling aids in decision-making regarding the configuration of arrays and their capacity relative to geographic and climatic factors. DTs have a plethora of applications, but for this case, a DT of the solar farm would monitor and control the installation remotely. Real-time data on irradiance, temperature, and electric performance is ingested throughout the operation to fine-tune MPPT algorithms, troubleshoot shading losses, or thermal drifts. The DT autonomously learns to estimate degradation trends over time against historical data by non-linear declines in performance which are mostly unnoticed by traditional monitoring systems [70,71]. In the maintenance stage, these insights provide support for condition-based scheduling, inverter fault detection, and soiling anomaly detection. For the repowering, recycling, or reconfiguring the solar modules strategies toward the EoL phase, DTs help analyze the trade-offs of operational yield with replacement cost and augment decision-making sophistication.

Due to the stochastic characteristics of wind flow, the stress placed on the moving components, and the altitude of the turbines, wind energy systems present a more challenging environment for the application of DTs [72,73]. During the design phase, DTs are used to estimate aerodynamic loading, wake effects, and optimal turbine spacing with respect to the historical and site-specific wind speed distributions. Typically, these simulations employ computational fluid dynamics (CFD) for modeling interaction of blades with structures as well as aerodynamic loads. As for operations, DTs command real-time telemetry tracking with sensors located in the blades, nacelles, and towers to adjust yaw angle optimization, anomaly detection in vibration profiles, and regulation of rotor speed to maximize power generation. In this case, a representative equation for predictive fault detection is the Remaining Useful Life (RUL), often modeled as shown in Equation (5) [74]:

$$\mathrm{RUL}(t) = \frac{C_{threshold-C(t_-}}{dC(t)/dt} \tag{5}$$

where C(t) is a time-evolving condition index such as vibration amplitude, and dC(t)/dt denotes its rate of deterioration. This formulation allows the DT to trigger preventive maintenance actions in advance of potential failures. Maintenance also includes gear lubrication diagnostics, blade crack prediction using ultrasonic data, and bearing temperature monitoring. At the EoL phase, DTs offer structural reuse analysis, support repowering strategies, and assess fatigue accumulation for retrofitting decisions.

Hydroelectric systems, while often more centralized and stable, benefit significantly from DT models for flow optimization and infrastructure diagnostics. In the design phase, DTs simulate water inflow, turbine behavior, and structural load under different seasonal and hydrological conditions. These models incorporate Bernoulli's principle and head-flow relationships to estimate power generation [75]. These relationships are presented in Relation (6):

$$P_{hydro}(t) = \rho \cdot g \cdot H(t) \cdot Q(t) \cdot \eta \tag{6}$$

where ρ is water density, g is gravitational acceleration, H(t) is net head, Q(t)) is flow rate, and η\etaη is turbine efficiency. In operation, the DT synchronizes with SCADA systems to monitor real-time water levels, control gates, and turbine speed. Maintenance activities are enhanced by monitoring penstock corrosion, analyzing cavitation patterns in turbines, and predicting silt buildup. For aging hydro systems, DTs play a vital role in determining retrofit potential, extending plant lifespan, and ensuring that structural elements are still within their fatigue thresholds.

Hybrid renewable systems—those integrating two or more energy sources such as solar, wind, hydro, and battery storage—are particularly suited to DT deployment due to their inherent complexity and dynamic interactions. In the design stage, the DT helps size components, optimize load-generation matching, and simulate control strategies for energy dispatch. During operation, it functions as a centralized decision-making system that coordinates between generation sources and storage systems, ensuring energy reliability and quality. The DT manages inverter synchronization, forecasts generation under composite environmental data, and arbitrates between charging and discharging states for battery systems [76,77]. In maintenance, the twin monitors battery state of health, inverter switching behavior, and transformer performance. Toward system retirement, it supports cost-yield analysis to determine whether partial upgrades, total decommissioning, or hybrid reconfiguration would be most economically viable. To summarize these functions, Table 4 presents a structured view of DT applications across four major renewable energy sources and lifecycle phases. This table presents a detailed classification of DT applications across four major renewable energy systems (solar, wind, hydro, and hybrid) and each phase of the asset lifecycle, namely design, operational monitoring, maintenance, and EoL optimization. This table serves as a structured reference for understanding how DT implementations vary in functionality depending on both system type and lifecycle stage.

As shown in Fig. 6, this taxonomy reveals both the breadth and depth of DT deployments across renewable energy systems, and supports the strategic alignment of DT functions across the asset lifecycle. According to this figure, the application of DTs is implemented in four primary energy systems: Solar PV, Wind, Hydroelectric, and Hybrid Systems, as well as in each critical phase of the asset lifecycle which includes: Design, Operational Monitoring, Maintenance, and EoL Optimization. The combination of energy types and lifecycle phases outlined in Table 3 and Fig. 5 showcases the versatility and scalability of DTs to both centralized and decentralized energy systems. This view is illustrated previously in Fig. 5 which depicts the interrelation of role delineation in these technological domains vertically and the application layers horizontally. To summarize, the use of DTs in renewable energy signifies an asset management approach that is shifting from static and reactive, to design and operation that is driven by intelligence on the system, and is far more agile and autonomous. The operational and predictive simulations, along with optimization capabilities of DTs throughout the entire life of an asset, are crucial for not just operational optimization, but also broader sustainability objectives. This taxonomy helps industry stakeholders and policy drivers to strategically transform clean energy digitally as they evolve and adapt to shifting demands.

6. Real-world implementations and case studies of DTs in renewable energy

This section presents documented academic and industrial case studies that demonstrate DT applications in operational settings. The selected examples span solar, wind, hydro, and hybrid systems. Quantifiable outcomes such as energy yield improvements and maintenance reductions are discussed.

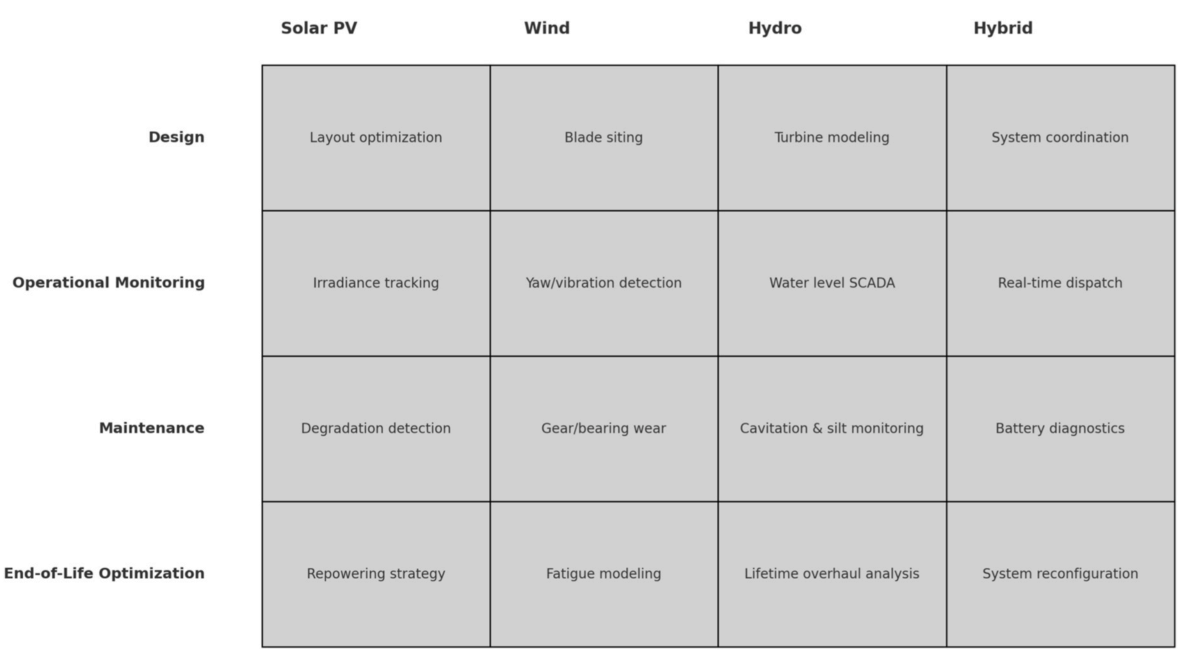

Fig. 6. Taxonomy of dt applications across renewable energy systems and lifecycle phases.

6.1. Solar PV systems

As the world adopts DTs to simulate engineering practices, a multitude of use cases demonstrating the practical benefits have emerged alongside their operational value and performance improvements. consider the enhancement of systems optimization, fault diagnosis, maintenance prediction, and asset lifetime extension in digitalized academic laboratories, pilot testbeds, and large-scale industrial energy projects; all of this pursuing automation [78]. Outside the technical achievements, the value of these case studies includes findings around scalability and interoperability, not to mention total return on investment. The rapid divergence of DTs for solar PV systems stems from the availability of real-time contextual data along with the configurability of PV arrays [79]. Another illustrative example of DT application on energy is developing a real-time irradiance and yield forecasting model by University of Seville researchers. Their system calibrated a digital meter of a PV array to automatically control the solar panels using weather forecasting in conjunction with I-V characteristics and temperature of the panels. The goal of estimating power output P(t) is given in terms of irradiance G(t), its real-time function, and temperature dependent efficiency η(T(t)). These pieces of the model are also illustrated in relation (4). This dual feature of the model allowed for the dynamic reconfiguration of MPPT parameters, especially during transient shading, and increased daily energy yield estimation by over 10 %. At the same time, industrial implementations have progressed significantly, with Huawei and Sungrow, for example, incorporating DT frameworks into their inverter technologies. These inverters autonomously detect performance decline, calculate the soiling ratio of the solar panels, and even remotely propose maintenance actions over communication lines. From operational data, there is an estimated 15 %–20 % decrease in mean time to repair (MTTR), and 5 %–8 % increase in overall energy yield with the use of DT-enhanced diagnostics.

6.2. Wind energy systems

The deployment of DT platforms has also been active in the wind energy sector for component health monitoring and performance optimization. A well-known example is GE Renewable Energy's "Digital Wind Farm" solution that simulates each wind turbine in real time from sensor data like nacelle position, blade strain gauges, and vibration transducers. The digital model estimates fatigue analysis of the cumulative damage done over time which follows Miner's rule of damage accumulation described in relation (7) [769]:

$$\mathrm{D(t)} = \sum_{i=1}^{n} \frac{N_i}{N_{f,i}} \tag{7}$$

where N_i is the number of stress cycles experienced and $N_{f,i}$ is the number of cycles to failure at each stress amplitude. The wind turbine's DT uses this model to predict the RUL of components and schedule preemptive repairs. By combining this with aerodynamic modeling, the DT also optimizes yaw and pitch controls in response to evolving wind conditions. These strategies have been reported to extend turbine life expectancy by up to five years and reduce unplanned maintenance by 25 %. Siemens Gamesa has similarly integrated DTs into its offshore turbine platforms, focusing on remote inspection, gearbox anomaly detection, and ice accretion modeling.

6.3. Hydroelectric systems

The role of DTs in the structural and operational management of hydroelectric systems has recently gained prominence. EDF, the Electric Company of France, has developed a DT model of Villerest Dam in France which serves as a remarkable example of industrial implementation. This model contains a simulative representation of the dam's inflow and outflow processes, gate movement algorithms, sediment transport, and structural stress behavioral feedback. The simulation is fed data from flow meters, water level sensors, and SCADA systems. The twin is aided with data from flow meters, water level sensors, and SCADA systems. Hydropower generation is modeled using the classic equation (6). Detection of early-stage cavitation, abnormal penstock pressure, and other hydraulic abnormalities has been possible with reduced incident response time and lower false alarm rates. From the Villerest case presented, DT technology has proven advantageous in flow dispatch planning resulting in twelve percent reported efficiency gains during a six-month operational cycle with variable inflow conditions.

6.4. Hybrid renewable systems

One of the most complex applications of DTs' technology must be in hybrids of renewable systems which involve the simultaneous management of solar, wind and storage. A project microgrid pilot was designed by the US Department of Energy that incorporates Solar PV, Wind Turbines, and Li-Ion Batteries along with a centralized DT that performs load forecasting, predictive dispatch, and dynamic voltage regulation [80,81]. This DT utilizes machine learning models with consumption and weather data to optimize energy balance while reducing curtailment and storage degradation. Dispatch optimization is usually described as a cost minimization problem as stated in Equation (8) [82]:

$$\mathrm{Min} \sum_{t} \left[C_{gen}(t) + C_{storage}(t) + C_{curtail}(t) \right] \tag{8}$$

subject to the constraints of power balance, inverter limits, and battery state-of-charge (SOC) trajectories. Applied validation studies demonstrated that the microgrid's operational cost was reduced by over 10 % alongside a reduction of fossil fuel reliance by 22 %, an improvement in battery longevity by 15 % with the deployment of a DT-enhanced controller [83]. DT systems have shown great potential for enabling energy supply during prolonged periods of lower resource predictability and responsiveness to demand variability in remote areas. In order to illustrate the range and focus of these implementations, Fig. 7 illustrates the quantity of documented academic and industrial case studies across four renewable energy technologies. The bar chart emphasizes that solar and wind are at the forefront of both areas because of their data abundance and modular design, while hydropower and hybrid systems, though less frequently adopted, are often accompanied by more sophisticated or system-wide DT capabilities. This forgoes the setting of the reporting and visually compares the quantitative gap of the DT use cases in literature versus those in industry for solar PV, wind, hydropower, and hybrid systems.

6.5. Comparative analysis

This is several crucial synthesizing conclusions through the use of digital twining. To begin with, DT systems always yield better results due to enhanced performance, particularly with the use of predictive analytics in anomaly detection and lifecycle planning. Integration with edge computing will always be a crucial success factor due to mitigation of latency in control loops and increased autonomy in more remote, gated areas. Flexibility of DT modules is a great domain for change since the architectures can either be fleet centered or modular systems distributed. This is important because they must align with operational objectives and complexity of the system. And lastly, there is still scope construct of proper platform for ontology standardization which comes together with interoperability and scalability. Many DT systems are created based on proprietary frameworks and asset behavior modeling ontologies are still being developed [84]. Despite the challenges, it is equally clear both in academia and industries that such challenges provide a great degree of motivation. We can expect acceleration in DT deployment over large-scale utility and remote energy projects which is

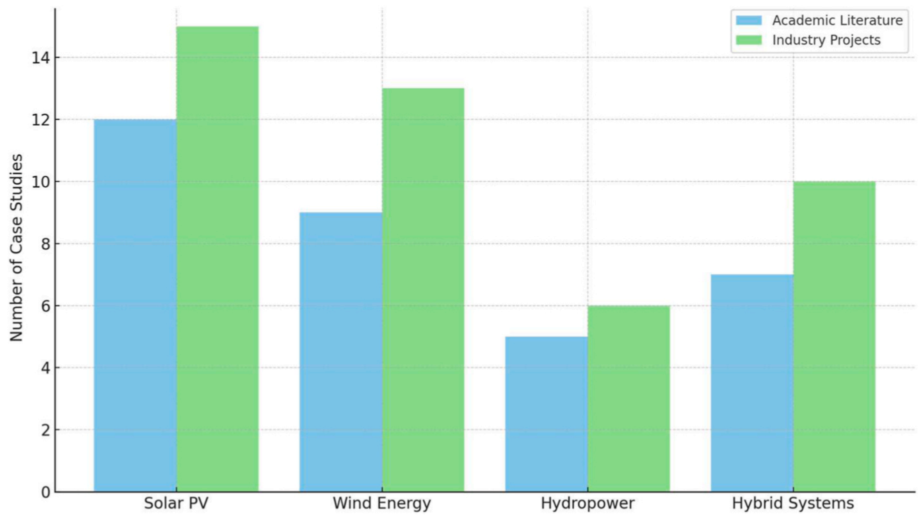

Fig. 7. Distribution of dt implementations across renewable energy sectors.

why enabling technologies and lowering cost of implementation drives such deployment. The experiences mentioned in this section is aimed to not only assist the milestones alongside the DT assumption but to aid as guiding frameworks in deployment strategical aid, future pedagogical works and research strategies [85,86].

Based on recorded case studies, Fig. 8 succinctly shows the proportional distribution of DT deployments over important renewable energy sectors: Solar PV, Wind, Hydro, and Hybrid systems. This graphic not only supports the textual debate about real-world installations but also offers a quick comparative knowledge of where DT adoption is now most concentrated. With almost 45 % of installations under Solar PV, the sector's great adaptability, sensor readiness, and integration with AI-based monitoring systems are reflected. Following with a noteworthy 30 %, wind energy shows great absorption in predictive maintenance, yaw control, and turbine performance analytics. Though it has long been a part of the world's energy supply, hydropower makes 15 % of DT use cases mostly in water level management, penstock diagnostics, and structural risk prediction. Though the lowest at 10 %, the hybrid systems segment is becoming more and more of interest as microgrids and integrated storage-control systems using synchronized digital representations are adopted. This number balances the enlarged Section 5, in which thorough case studies explore the technical depth and variety of DT applications. For example, the high percentage for Solar PV fits case studies like Huawei's and Sungrow's deployment of DT-augmented inverter systems, whereas Wind's representation fits GE's Digital Wind Farm project. With visual clarity and measurable emphasis, the figure so helps the narrative by providing an easily available summary of trends that improves reader involvement and increases the practical usefulness of the paper. By means of specialized platforms and linked software ecosystems, major industry participants have greatly sped the adoption of DTs in renewable energy systems. Using sensor telemetry coupled with cloud analytics, GE's Predix platform—one of the first industrial-grade DT solutions—allows one to replicate and control wind turbine behavior in real time. Built on Predix, GE's Digital Wind Farm system automatically adjusted turbine parameters depending on environmental data, therefore displaying a 20 % boost in wind farm efficiency. DT capability in offshore wind turbines and grid-connected PV systems has also come from Siemens' MindSphere, a cloud-based IoT operating system. By means of AI-based pattern recognition, it allows virtual commissioning, fault diagnostics, and predictive maintenance. Using AI to hone MPPT control and increase asset lifetime, Huawei's FusionSolar platform combines DT capability for PV asset monitoring, performance tuning, and remote fault detection. Sungrow's iSolarCloud also combines real-time DT visuals for inverter health with coordination of deployment. EDF's DT application at the Villerest Dam models sediment movement, hydraulic stress, and gate operations in the hydropower domain, therefore helping to reduce downtime and improve operating safety. These systems not only confirm the feasibility of DT adoption on a large scale but also provide modular designs fit for several renewable technologies. By reducing entrance barriers through standardized APIs, visual interfaces, and pre-trained diagnostic models, their impact has made DTs more available to energy utilities and system integrators. Table 5 serves as a **semi-quantitative synthesis** of real-world applications, transforming textual evidence into measurable outcomes.

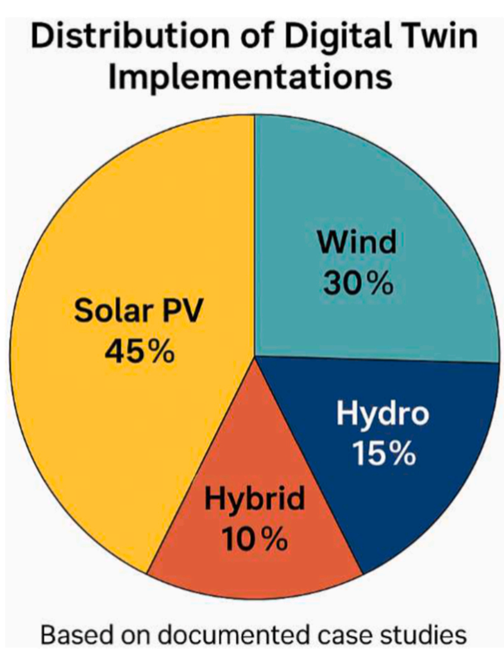

Fig. 8. Distribution of DT Implementations According to various case studies.

Several constraints limit the general scalability and economic viability of DT installations in renewable energy systems, notwithstanding the encouraging outcomes shown by several industry and academic case studies. First, many successful demonstrations—like GE's Digital Wind Farm or Huawei's DT-enhanced solar inverters—still limit themselves to highly regulated settings or big companies with significant resources for digital infrastructure. From pilot-scale DTs to full-grid or national installations, interoperability, sensor integration across legacy

Table 4
Classification of DT applications in renewable energy systems.

Energy System	Design Stage Applications	Operational Monitoring	Maintenance Strategies	EoL Optimization	Representative Studies
Solar PV	Array layout optimization, PV sizing, yield forecasting	MPPT tuning, thermal drift tracking, real-time irradiance	Inverter diagnostics, soiling detection, degradation modeling	Repowering assessment, recycling decisions	[69,70]
Wind	Blade aerodynamics, wake modeling, turbine siting	Yaw control, wind field analysis, vibration detection	Gearbox and bearing wear prediction, lubrication analysis	Fatigue life modeling, repowering or retrofitting	[71,72]
Hydroelectric	Head-flow simulation, turbine sizing, flow optimization	Gate regulation, silt detection, flow tracking	Penstock wear detection, cavitation analysis, SCADA linkage	Structural lifetime estimation, overhaul planning	[73]
Hybrid Systems	Load-source matching, control strategy simulation	Multi-source coordination, real-time dispatch	Battery diagnostics, inverter synchronization	System reconfiguration analysis, energy yield-cost forecasting	[74–77]

Table 5
Summary of key outcomes from selected DT case studies.

Case Study Source	Energy Domain	DT Functionality	Reported Outcome
Huawei & Sungrow (DT-enhanced Inverters)	Solar PV	Performance monitoring, fault detection, diagnostics	15–20 % reduction in MTTR; 5–8 % increase in energy yield
GE Digital Wind Farm	Wind	Fatigue analysis, predictive maintenance, control	Up to 5 years turbine life extension; 25 % downtime reduction
EDF Villerest Dam	Hydroelectric	Flow modeling, stress analysis, cavitation detection	12 % increase in dispatch efficiency over 6 months
US DoE Hybrid Microgrid	Hybrid (Solar + Wind)	Load forecasting, dispatch optimization	Improved voltage stability; enhanced grid autonomy
Univ. of Seville PV Forecasting System	Solar PV	Irradiance forecasting, MPPT optimization	>10 % increase in daily energy yield

assets, and real-time data infrastructure suffer. Furthermore, small and medium-sized utilities or off-grid projects in developing nations find the financial expenses of scaling DTs—from edge computing equipment to ongoing model recalibration—remain exorbitant. The return on investment (ROI) is quite context-dependent; local labor prices, dependability criteria, and legal systems all affect payback times. For example, whereas DT-based predictive maintenance shows MTTR reductions of 15–25 %, the upfront capital cost for digital instrumentation and AI model development typically surpasses the cost-savings threshold for small-scale systems. The availability and quality of training data represent still another important restriction. Accurate, time-synchronized data is what high-fidelity DT models demand, and older systems or scattered data ecosystems might not be easily accessible. The performance and generalizability of DTs across many geographical or climatic situations is degraded without consistent data schemas and interoperable protocols. These limitations highlight the requirement of adaptable and modular DT designs, regional policy support, and cost-sharing systems (e.g., utility alliances or digital infrastructure incentives) to enable more general adoption. From hypothetical or niche DT applications to a strong, scalable DT architecture across the worldwide renewable energy sector, addressing these constraints is crucial.

7. Challenges, gaps, and research opportunities in DT applications for renewable energy

Key challenges limiting the scalability and reliability of DTs in renewable energy systems are identified here. Topics include model fidelity, data heterogeneity, lack of standardization, and cybersecurity. These gaps are analyzed to set the stage for targeted future research. Although the potential advantages and growing implementation of DT technology in renewable energy systems is immense, there remain some technical, operational, and strategic hurdles. These hurdles hinder the full potential of DT capabilities harnessed but more importantly reveal crucial gaps that must be filled to ensure scalable, secured, and intelligent deployment. Addressing such constraints needs to be incorporated in the integrative frameworks for policy, standardization, and digital integration design like cybersecurity in Energy infrastructure CPS. Gaps in model accuracy for monitoring, control, and supervision of systems reflect fundamental challenges to be surmounted [87]. DTs depend on physics-based equations and data paired with a given asset's dynamic behavior to emulate it. However, deviations always occur between virtual models and real-world systems due to simplification, lack of completeness constituent parameters, or environmental ambiguity. For instance, in PV system modeling, efficiency is usually considered a linear function of temperature and irradiance. However, actual data shows non trivial impact of spectral shifts, and mismatch losses. In wind systems paired with other energy systems, accurate CFD simulation of turbulence alongside wake effects puts an elevated computational load on real-time systems dubbed as highly sophisticated. Consequently, the virtual models are not responsive or detailed enough to aid in accurate decision-making. Also, the degradation models for components such as batteries or inverters are frequently constructed from laboratory conditions and do not translate well to actual stressors in the environment [88].

Compounding the modeling challenge is the issue of **data heterogeneity and quality**. DTs depend on continuous streams of sensor data for calibration, validation, and control actuation. However, the data ingested is often noisy, asynchronous, or sampled at inconsistent rates. The integration of diverse data types—including numerical readings, categorical flags, image data, and time-series logs—poses a significant preprocessing burden. For instance, aligning SCADA data with weather station inputs and inverter telemetry requires robust temporal harmonization, interpolation, and fault handling techniques. A misalignment of even a few seconds between power output and irradiance data in a PV twin can distort MPPT analysis and hinder diagnostics. Mathematically, let $x_1(t)$, $x_2(t)$, …, $x_n(t)$ represent input variables with differing time stamps t_1, t_2 …, t_n. An effective DT model must first align them to a unified timeline as per relation (9):

$$\widehat{x_i}\ (t) = \text{Interpolate}\ \left(x_i\left(t_j\right)\right), \text{for } t_j \neq t \tag{9}$$

This alignment stage is important but still lacking refinement in several DT platforms, particularly concerning geographically distributed and multi-source data environments [89]. Another chronic problem is the absence of uniformity in the design of a DT, its communication interfaces, and data semantics. In the renewable energy sector, there are no comprehensive standards governing the architecture of DTs which leads to fragmented approaches that limit overall cooperation. While certain standards like IEC 61850 exist in support of substation automation, there is little agreement as to how cross-domain interactions in hybrid systems and AI based decision making are to be modeled by DTs [90]. Consequently, even high-fidelity DTs cannot often be reused across different projects, leading to limited scalability. Furthermore, their DT platforms are dominated by closed ecosystems and proprietary tools which curtail collaboration and transparency, resulting in little to no openness. An important issue that comes with the digitalization of energy systems is the cybersecurity aspect. Due to constant connectivity, DTs are continuously vulnerable to cyber threats. The seamless interaction between the physical and digital world creates additional intrusion possibilities such as sensor spoofing, data poisoning, and takeover, as well as control over the system. For instance, an attacker would manipulate irradiance data to controls PV twin's power output calculations and inverter command execution which would send commands that could destabilize the grid. Securing infrastructure associated with DTs necessitates applying multiple encryptions, anomaly detection, and strong authentication over the edge controls. In addition, hybrid DT systems that interface with public cloud services are required for securing APIs and encrypted channels that avert data exposure or illicit system takeover.

The last and perhaps most intimidating hurdle is the enormous computational resources needed for sustaining real-time synchronization, learning, and optimization in DTs [91]. Moreover, the execution of high-fidelity simulations, like those used for wind turbine aerodynamics or hydro flow modeling, incurs immense processing costs if required to run with sub-second ceilings. The situation is exacerbated when paired with AI-based decision engines, which use even more advanced computational resources such as GPUs or dedicated edge processors. In hybrid microgrids, for example, the DT must compute multiple differential equations and optimization problems within each time step while concurrently managing storage dispatch and demand response [92,93]. These factors form substantial obstacles to low-resource or off-grid contexts, which are particularly useful, but least implementable due to infrastructure constraints where DEs could be most beneficial. The cumulative burden of these factors is exemplified in Fig. 9, which graphs five primary limitations—model fidelity, data heterogeneity, standardization, cybersecurity, and computational demands—along with a severity scale assembled from real-world cases and expert judgment. Each of these challenges has been found to exceed an 8 out of 10 score, underscoring the importance of barriers restricting the efficiency and dependability of DTs. To blend and contrast these factors in a succinct way, Table 6 presents each limitation, its origin, its definition, and implications for operations of renewable energy categorically.

Regarding cybersecurity and data integrity concerns, it is noteworthy that the security of data flow between physical assets and their virtual counterparts becomes crucial as DTs grow essential portions of real-time renewable energy system control. Data spoofing, bogus command injection, and denial-of-service attacks—each able to compromise system operation or cause cascading failures—are among the hazards unsecured DT systems could face. In multi-site solar or wind farms, a corrupted DT might provide false control signals or deceive supervising systems. Recent studies have suggested homomorphic encryption for safe telemetry, zero-trust architectures, and blockchain-backed data provenance systems to help to counteract these dangers. First proof-of-concept solutions come from industry installations including NREL's cyber-physical threat modeling and Siemens' DT security sandboxing. Still open areas of research, nevertheless, include cost, latency overhead, and deployment difficulty of these solutions. Moreover, in the field of computational scalability and real-time processing constraints, another major obstacle to DT scalability is the great computational load needed for real-time simulation, anomaly detection, and control loop synchronization, particularly under hybrid energy systems or high-resolution meteorological databases. For large-scale wind farms, for instance, constant updating of high-fidelity fluid dynamic models and structural health diagnostics generates significant delay and memory requirements. This calls for careful architectural balancing between cloud computing for model training and historical analysis and edge computing—for low-latency judgments. To solve this trade-off, emerging paradigms including fog computing and federated learning are under investigation; nonetheless, performance criteria for renewable energy applications remain quite limited. Studies from IEEE Transactions on Industrial Informatics and Applied Energy have underlined these trade-offs and suggested event-driven data sampling, GPU acceleration, and AI model pruning as possible means to lower resource footprints.

The coordination of efforts across various domains is necessary to tackle complex problems. Data-driven and physics-informed models would benefit from more sophisticated hybrid modeling techniques. Increased edge-based data pre-processing services can improve data quality value. There is an urgent need to establish open DT standards from international consortia to unify architectures. Federated learning and blockchain-based audit trails are two emerging solutions in the cybersecurity gap. Optimization algorithms with supported hardware and lightweight simulation models are expected to alleviate the computational burden and expand the applicability of DTs to off-grid and resource-constrained areas. Moreover, while the management of renewable energy systems by DTs is unprecedentedly extensive, several critical hurdles still exist which limit their practical implementation. The roadmap for future R&D is depicted in this section. Addressing these issues will transform experimental tools into standards of the next generation of intelligent, secure, adaptive energy systems. Lack of universally accepted standardizing procedures is a major obstacle to the large-scale application of DTs in renewable energy systems. Harmonized frameworks enable consistent compatibility amongst DT platforms,

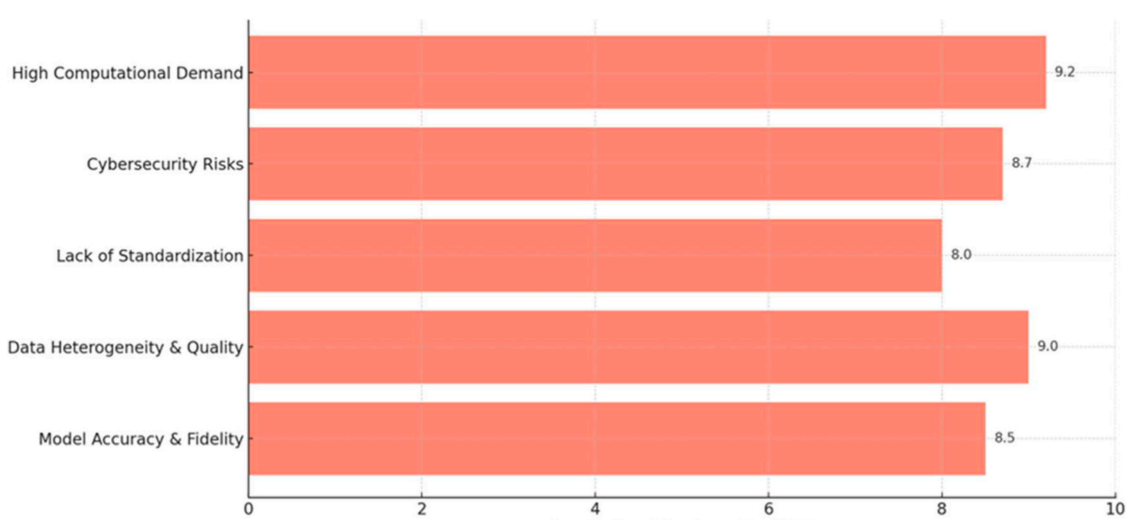

Fig. 9. Distribution of dt implementations across renewable energy sectors.

Table 6
Summary of key challenges limiting DT deployment in renewable energy.

Challenge	Technical Root	Manifestation in DT Systems	Operational Implications
Model Accuracy & Fidelity	Oversimplified assumptions, underfitted data	Poor fault prediction, inaccurate forecasts	Reduced confidence in DT outputs and false alarms
Data Heterogeneity & Quality	Multi-source asynchronous noisy data	Time lags, misalignment, and incomplete analytics	Inaccurate diagnostics and control errors
Lack of Standardization	Fragmented toolchains and vendor lock-in	Non-reusable models and poor scalability	Incompatibility across projects, high integration overhead
Cybersecurity Concerns	Increased connectivity and weak authentication	Data breaches, command spoofing, control hijacking	Grid instability, system vulnerability, legal liabilities
High Computational Demand	Real-time simulation, AI workloads, large datasets	Latency, overheating, or system inaccessibility	Infeasibility in remote or resource-constrained deployments

components, and energy management systems without which this remains uneven. Acknowledging this difficulty, various international projects have been started. Developing reference architectures and interface standards that specify how DTs should represent and interact with physical systems is the focus of the International Electrotechnical Commission (IEC) and the International Organization for Standardization (ISO). Especially ISO 23247, a series on DT frameworks for manufacturing, offers conceptual direction fit for energy systems. To assist uniform DT deployment, the DT Consortium—a group of business leaders—has also released cross-industry standards on vocabulary, trustworthiness, and interoperability. In complex, distributed renewable energy systems, seamless integration, modularity, and data interchange across disparate assets depend on these developing criteria. Scalable, safe, vendor-agnostic DT systems will depend on strengthening these standardizing efforts.

8. Strategic importance and future research directions

Building on the insights of prior sections, this section proposes a roadmap for advancing DT research and deployment. It links technological needs to global policy frameworks such as the SDGs, Paris Agreement, and EU Green Deal. Recommendations are structured across short-, mid-, and long-term priorities.

8.1. Strategic importance of DTs in renewable energy

The importance, in a strategic sense, that lies in the application of the DT technology within renewable energy stems from its ability to completely change the systems' architecture, processes, and control concepts. A DT or DT can play a fundamental role in providing solutions for some challenges related to energy systems, in its most basic principles of real-time monitoring, intelligent simulation, and control. DTs in systems analogously remove the need for a mechanical separation of energy systems which enables us to surpass non-dynamic, reactive, piecemeal approaches towards more dynamic, self-sustaining, coordinated energy systems [94,95]. At the operational level, embracing the use of DTs marks a departure from conventional monitoring and maintenance practices. For traditional energy systems, performance concerns are detected only after a failure has occurred, or during a scheduled maintenance check; both scenarios result in wasteful interventions that create asset downtime, incur high expenses, and shorten the asset's operational life. Unlike overs dependent on schedules, DTs allow maintenance to be predictive and condition-based, continuous monitoring enables the assessment of the component's health, performance deviation, and operational anomalies. Such paradigm shift adds value by optimally managing the system's assets for dependency moves ailing system reliability to embedded redundancy increases downtime sustainable cost-effective lifetime savings. Furthermore, for renewable energy assets located in difficult-to-reach remote locations, such capability adds immense relevance.

Additionally, the support DTs provide allows for progression from system management in isolation to a more sophisticated and collaborative system. The constituents of renewable energy systems are increasingly becoming distributed and diverse in nature such as solar PV panels, wind turbines, battery storage systems, and microgrids, each one possessing unique control attributes and functional restrictions. DTs allow operators to apply integrated energy management systems by providing a single digital interface for the simulation and coordination of these various parts [96]. Shifting energy management strategies this way will allow meeting the changing demand and supply, cutting back on system flexibility, curtailment, and enhancing yield, thus stabilizing the grid as well. With the aid of DTs' modern energy systems can increase their yield and stability as them facilitate autonomous system intelligence and observation control yield operational system oversight. Equally notable is the fact that dynamic monitoring technologies (DTs) help shift regulation from a static, schedule-controlled perspective to a more adaptable system management approach. Systems that harness renewable sources of energy encounter uncertainties due to changes in environmental conditions such as solar irradiance, wind speed, and temperature. These traditional control systems tend to be slow and less responsive to rapid changes. DTs, on the other hand, provide the ability to construct and update models in real time, which means energy systems can adapt to their conditions most of the time. Such anticipatory adaptations can make the system use resources more efficiently, be more resilient in operations, and better respond to the needs of the grid.

DTs technologies are emerging as key facilitators of smart, flexible, and robust renewable energy systems within the context of the ever-evolving global energy transition. With the global strive toward legal climate goals, lowering the carbon footprint, and providing balanced energy access to all citizens, renewable energy resources are expected to play a major role [97]. At the same time, place these resources are being integrated within has increasing scale and complexity, which require sophisticated digitized transparency, intelligence, and self-operating systems. DTs provide a solid base for accelerating the integration of physical energy resources into their digital counterparts, thereby closing the crucial void. DTs may significantly aid concerns regarding inclusion and energy equity. With remote monitoring, automated diagnostics, and optimized control, DTs lessens the burden of highly skilled and expensive remote technical interventions, which require onsite equipment servicing. This operational intelligence democratization enables deploying and managing renewable energy systems at scale in rural and underserved communities, where resources and expert access are limited. Thus, DTs do help augment energy accessibility while supporting equity toward clean energy technology benefits distribution.

In conclusion, DTs strategically matter not only because of their technological prowess but also for supporting the SDGs and objectives of digital transformation. With the increasing adoption of renewable energy systems and the more decentralized and digitally controlled grid infrastructure, DTs must be included to enable smart growth, ensuring resourceful, resilient, and efficient advancement. DTs' real-time situational awareness, failure prediction and prevention, system performance optimization, and autonomous operational support capabilities position DTs as foundational enabling technologies for net-zero-emission targets, improved energy security, and enduring environmental and economic sustainability.

8.2. Future research directions

These research trajectories are consistent with industry-level guidance provided in global policy documents such as the IRENA (2022) white paper [98], which advocates for investment in interoperable digital infrastructure—including DTs—as part of the pathway to resilient, intelligent, and decarbonized energy systems. For DT technologies, the rapidly emerging applications in diagnostics, fault isolation, system optimization, and lifecycle enhancement of renewable energy systems present abundant opportunities. Nevertheless, as examined in the prior sections of this paper, most achievements to date have been limited to isolated system implementations or experimental test beds. This transformation cannot happen without a concerted research and innovation effort shifting the focus of DTs from project-specific, monolithic assets to integrated, distributed, context-aware infrastructures throughout the renewable energy ecosystem value chain [99–101]. This section outlines the comprehensive roadmap needed to guide such an evolution. The roadmap consists of DT priorities for a clean energy transition and details the stepwise, tiered structure of priority execution, setting terms for short-, mid-, and long-term scheduling. In doing so, it also articulates relevant deeper scientific, technologic, and operational questions that need to be solved to enable wide-scale deployment across multiple applications. In the 1–2-year short-term window, the focus of research paradigm capture attention is the enhancement of accuracy and responsiveness while interacting with individual units of renewable energy systems. Almost all DT models, including those of PV modules, wind turbines, and energy storage units, today use overly simplified models. They, at best, replicate approximate static structures neglecting dynamic nonlinearities. This oversimplification is addressed using Hybrid modeling techniques that integrate physics-guided differential equations with machine learning algorithms. An example is the current-voltage characteristics of PV modules during partial shading represented in relation (10):

$$I = I_{ph} - I_0\left(e^{\frac{V+RI_s}{nV_t}} - 1\right) - \frac{V+RI_s}{R_{sh}} \tag{10}$$

where I represents the output current, V is the output voltage, I_{ph} is the photocurrent, I_0 is the diode reverse saturation current, R_s is the series resistance, R_{sh} is the shunt resistance, and n is the diode ideality factor. This equation, derived from the single-diode model, forms the basis for higher-fidelity DT frameworks. However, to function in real time, it must be calibrated and coupled with neural networks or adaptive filters trained on high-resolution operational data. The integration of high-frequency sensors, edge processors, and adaptive solvers will be central to overcoming the real-time simulation bottleneck in asset-level twins.

Over the **mid-term horizon (3–5 years)**, the challenge transitions from improving individual models to building scalable, interoperable, and secure DT ecosystems. Research must address the fragmentation of existing DT platforms, the lack of standardization in communication protocols, and the limited capacity for cross-domain integration. Unified ontologies for asset metadata, harmonized time-series APIs, and plug-and-play architectures will enable DT systems developed by different vendors or research groups to interoperate within shared environments. A critical milestone in this phase will be the development of modular DT libraries for hybrid systems and local grids. These libraries would allow the dynamic assembly of multi-asset twins in response to operational needs, such as demand surges or fault propagation. Moreover, edge/cloud orchestration algorithms must be optimized for renewable environments, balancing latency-sensitive decision-making with the compute-intensive needs of long-term analytics. Security will also become paramount, prompting research into lightweight encryption schemes, anomaly-based intrusion detection, and federated data governance across energy stakeholders.

The **long-term horizon (6–10 years)** envisions DTs as integral components of national and global energy intelligence platforms. In this scenario, DTs do not merely track local assets but operate at the scale of entire energy networks—interacting with markets, weather models, climate risk predictors, and policy engines. One key direction for this phase is the integration of DTs into climate-resilient grid modeling. As climate variability increasingly affects renewable generation, DTs will need to simulate probabilistic weather pathways and their effects on distributed energy flows, infrastructure stress, and storage volatility. Scenario modeling may incorporate climate variables $C_i(t)$, linked to renewable generation functions $G(t,C_i)$ that vary stochastically over time, as presented in Equation (11):

$$G_{forecast}(t) = E[G(t,C_i)] + \epsilon(t) \tag{11}$$

where E denotes the expected output and $\epsilon(t)$ accounts for residual uncertainties. These forecasts can then drive system-wide optimization models, such as mixed-integer linear programs (MILPs), that coordinate dispatch, market bidding, and resource planning at national scales.

Additionally, energy storage management represents a fertile ground for DT innovation. Advanced battery twins, capable of tracking thermal behavior, aging, and internal electrochemical dynamics, will be essential for supporting demand-response strategies, electric vehicle integration, and peak shaving in urban areas [102,103]. These models must incorporate multi-layer equations representing charge/discharge kinetics, electrolyte behavior, and diffusion effects, transforming DTs from energy flow models into full electrochemical co-simulators. To illustrate this staged approach, Fig. 10 presents a strategic roadmap linking DT R&D priorities from 2025 through 2035 with international energy policy targets. Each temporal phase emphasizes the progressive alignment between DT technological capabilities and global sustainability mandates.

A strong future roadmap for DT acceptance must not only solve technological issues and innovation shortages but also fit worldwide climate and energy policy frameworks. Driven by obligations under the Paris Agreement to limit global warming below 1.5 °C as well as the UN SDGs (SDG 7, 9, and 13) that urge clean, resilient, and smart energy infrastructure, the next decade marks a vital opportunity for action. Legislative tools like the European Union's Green Deal and the Inflation Reduction Act (IRA) in the United States directly incentivize the digitalization of energy assets, funding and regulatory support for DT deployment in grid modernization, efficiency enhancement, and low-carbon infrastructure in the Global North. Including DT development into these policy objectives guarantees congruence between technical advancement and legal requirements. Fig. 6 now links short-, mid-, and long-term DT development priorities to matching policy aims, therefore including policy alignment. This paradigm guarantees that innovation in DTs moves in line with digital equality concepts, global decarbonizing

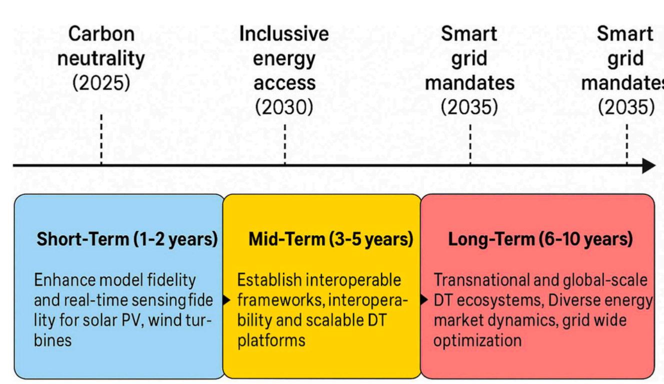

Fig. 10. Strategic research roadmap for dt development in renewable energy systems.

initiatives, and resilient infrastructure goals.

In conclusion, the future of DTs in renewable energy is poised for exponential growth, but only if key research frontiers are systematically addressed. These include hybrid modeling frameworks, standardized DT protocols, secure and scalable computing infrastructure, and advanced integration with environmental and market models. By adhering to a clearly defined roadmap and aligning multi-disciplinary research efforts, DTs can evolve into the backbone of a resilient, intelligent, and decarbonized global energy system.

9. Conclusion

This review presents a thorough and multifaceted viewpoint of the transforming power of Digital Twin (DT) technologies in systems of renewable energy. The paper proposes a layered and scalable framework for understanding and applying DTs across solar, wind, hydro, and hybrid systems by grouping scattered material into a cohesive taxonomy and merging enabling technologies including AI, IoT, cloud/edge computing, and big data analytics. such academic and industrial case examples help to highlight the useful nature of DTs by exposing real benefits such 10–25 % increases in energy efficiency and notable decreases in unexpected maintenance downtime. Beyond their practical use, the article emphasizes how strategically important DTs are in allowing durable, intelligent, autonomous CPS. Managing the growing complexity, decentralization, and volatility inherent in renewable energy ecosystems calls for these qualities. Significantly, the road map suggested in this review charts unresolved technical challenges—such as data heterogeneity, model integrity, real-time integration, and cybersecurity—to phased research priorities matched with global policy frameworks including the SDGs, the EU Green Deal, and national decarbonization mandates. The results imply that DTs are fundamental enablers of next-generation energy systems—where data-driven intelligence, predictive skills, and system adaptability constitute the cornerstone of smart, decarbonized infrastructure—not only optimization tools. Standardizing platforms, expanding interoperability protocols, tying policy with technological readiness levels, and building domain-specific benchmarking frameworks top priorities for future work. Such efforts will guarantee that the development of DTs stays anchored in actual needs and follows the course of world energy transformation.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Declaration of competing interest

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Data availability

Data will be made available on request.

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