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Review

Digital twins for smart asset management in the energy industry: State-of-the-art

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ABSTRACT

With the most recent developments in the Internet of Things (IoT), Machine Learning, and Big Data, digital twins (DTs) are gaining popularity across several sectors. Since digital twin (DT) could be viewed as a cyber-physical system, many DT applications have been successfully implemented for the Industrial Internet of Things (IIoT). Following DT's success with Industry 4.0, DT is increasingly receiving the attention of academia and industry for smart asset management (SAM) in Energy 4.0. Nevertheless, there has been a notable absence of research papers specifically dedicated to reviewing the applications of DTs in the context of the SAM domain within the Energy 4.0 paradigm. Hence, this paper addresses this gap by thoroughly examining the latest advancements in DT research on SAM in Energy 4.0. It comprehensively explores the fundamental aspects of DTs, provides insights into their current progress within the Energy 4.0 framework, and elucidates the various applications of DTs within the SAM domain. Furthermore, the paper highlights the existing challenges and presents potential directions for future research endeavors in this field. This review will assist industry experts in implementing DT in SAM applications and provide new research directions for researchers.

1. Introduction

Smart asset management (SAM), which utilizes advanced digital technologies, real-time data analytics, and AI-driven decision-making to optimize the utilization and lifespan of assets, is a crucial focus area shared by major asset-intensive industries (AII) (Rajora et al., 2024). These industries require large capital investments in physical infrastructure, equipment, and facilities such as manufacturing, transportation, water and power utilities, and energy. These industries rely heavily on long-term asset management, maintenance, and optimization to ensure operational efficiency, profitability, and sustainability (Sivapalan and Bowen, 2020; Sigalas). SAM in AII goes beyond traditional asset management (AM) by including prominent initiatives like Energy 4.0 and the Industrial Internet of Things (IIoT) (Hairuddin et al., 2024; Serrano, 2023). In the realm of AM, which relies on fixed schedules and manual processes, the utilization of sensors and data transmission technologies has witnessed a significant rise in recent years due to technological advancements. These technologies enable data collection across various stages of AM, encompassing investment planning, life cycle performance, environmental requirements, operation, and maintenance (O&M) planning, as well as asset condition and performance evaluation. The application of big data analytics plays a pivotal role in harnessing the collected data for fault detection and diagnostics, real-time monitoring, predictive maintenance, and overall enhancement of asset performance within the framework of SAM (El and Bounjimi, 2021; Lee et al., 2017). However, one of the key challenges faced by SAM revolves around establishing a seamless connection between the physical and virtual domains. Fortunately, advancements in artificial intelligence (AI), cloud computing, big data processing approaches, and simulation models have opened new avenues for enhanced interactions between physical and virtual spaces (Rathore et al., 2021).

A concept garnering increasing attention from researchers and energy industry leaders is the digital twin (DT), which is a virtual replica of a physical system that simulates its behavior and performance (Choi et al., 2024; De Kooning et al., 2021). By combining the physical and digital realms, digital twins (DTs) serve as digital replicas of physical assets, facilitating cyber-physical integration (Mchirgui et al., 2024). DT enables real-time monitoring, analysis, and optimization of system

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performance with real-time data synchronization from the physical system (dos Santos et al., 2023). With this feature, it plays a crucial role in enhancing monitoring, control, and predictive capabilities, ultimately improving the reliability and efficiency of physical systems. DTs, alongside big data technology and advanced analytics, serve as complementary tools in the development of a digital ecosystem for SAM (Mousavi et al., 2024). They seamlessly integrate real-time and virtual data throughout the SAM process, resulting in abundant asset data in various formats. This seamless integration of DTs and big data analytics allows for real-time synchronization between physical and virtual environments, enabling predictive asset management and operational efficiency. Big data platforms aggregate vast amounts of sensor-generated information, including temperature fluctuations, mechanical stress levels, and power output metrics, from energy assets such as wind turbines, solar power plants, and substations (Kandemir et al., 2024; Alao et al., 2024; Qian et al., 2023).

DTs leverage this continuous data influx to update virtual models dynamically, simulate potential failure conditions, and optimize operational strategies. Advanced analytics algorithms, including machine learning (ML) and deep learning models, process historical and real-time data, improving failure prediction accuracy and maintenance scheduling (Alexopoulos et al., 2020). For instance, AI-driven anomaly detection systems within DTs identify irregular equipment behavior and trigger preventive maintenance alerts before system failures occur. Additionally, cloud-based big data infrastructures enable DTs to process, store, and analyze energy asset data at scale, ensuring scalability and remote accessibility. The integration of edge computing technology further reduces latency, allowing DTs to make real-time adjustments to asset performance without relying on centralized data processing centers (Lee et al., 2017).

The combination of DTs, big data, and AI-driven analytics creates a self-learning digital ecosystem that continuously enhances predictive maintenance accuracy, optimizes asset performance, and reduces operational costs in the energy industry. Advanced predictive analytics tools are employed to process this data, enabling the prediction of physical asset conditions and performance (Macchi et al., 2018; Cosmo et al., 2022). This paper aims to comprehensively review the current state-of-the-art regarding the implementation of DTs within the asset-intensive energy industry. DTs have experienced widespread application across various industries, as evident from the surge in patents, publications, and adoption by industry leaders over the past decade (Fuller et al., 2020; Mylonas et al., 2021; Bazmohammadi, 2022). DTs offer AII the ability to proactively detect and address anomalies, thereby enabling informed decision-making to enhance asset performance while minimizing costs and risks. By providing real-time information on the operating status and conditions of physical assets, DTs contribute to the intelligence of cyber-physical SAM systems. This information empowers predictive analytics to optimize asset operations and performance, positioning DTs as a crucial driver within the SAM paradigm. Furthermore, DTs represent the next frontier in simulation, where they have evolved from multi-level, multidisciplinary model-based systems engineering to become an integral part of operational data-driven systems. This development presents an exciting real-time simulation opportunity throughout the asset life cycle (El and Bounjimi, 2021; Bazmohammadi, 2022).

While Digital Twin (DT) technology has gained significant traction and commercialization in industries such as manufacturing and aviation, its application in the energy industry for SAM has only recently been explored. The concept of DTs for Asset Management (AM) in the energy sector was introduced in 2015 (Lee et al., 2017) and has since attracted growing attention from AII and academia. Most of the existing reviews in the literature (Attaran et al., 2023; Murgod et al., 2023; Ismail et al., 2024) have focused on DT applications in manufacturing and Industry 4.0. Recent review studies on Energy 4.0 primarily focused on the implementation of DTs in overall building/energy system management (Akerele et al., 2023; Doellner et al., 2023) asset lifecycle (Choi et al., 2024) and renewables investment decisions (Cao et al., 2024). Thus, there has been a lack of comprehensive studies specifically examining DT applications for SAM within the Energy 4.0 paradigm. This study bridges this gap by capturing DT applications in Energy 4.0 and discusses its revolution, development, opportunities, challenges, and future research endeavors in the energy sector. Different from existing literature, this review systematically categorizes DT applications across wind farms, solar power plants, and transformers, providing a comparative analysis of real-world implementations. This study offers valuable insights into the role of DTs in enhancing predictive maintenance, performance optimization, and fault detection for key energy assets, thereby contributing to the broader discourse on Energy 4.0 and digital transformation in asset management. (See Table 1).

Table 1
Key terms and abbreviations.

Abbreviation	Full-Term
ABB	Asea Brown Boveri, a robotic and electrical equipment company
AII	Asset Intensive-Industries
AI	Artificial Intelligence
AM	Asset Management
APM	Asset Performance Management
AVR	Automatic Voltage Regulation
BIM	Building Information System
CBM	Condition-Based Monitoring
CPS	Cyber-Physical Systems
CAD	Computer-Aided Design
DT	Digital Twin
FOWTs	Floating Offshore Wind Turbines
FEA	Finite Element Analysis
FL	Federated Learning
DERs	Distributed Energy Resources
GE	General Electric
GIS	Global Information System
GMPP	Global Maximum Power Point
GDPR	General Data Protection Regulation
HPS	High-Performance Computing
HFPT	High-Frequency Power Transformer
IoT	Internet of Things
ISO	International Organization for Standardization
IIoT	Industrial Internet of Things
IEEE	Institute of Electrical and Electronics Engineers
IEC	International Electrotechnical Commission
KPI	Key Performance Indicator
ML	Machine Learning
MFA	Multi-Factor Authentication
MPPT	Maximum Power Point Tracking
NASA	National Aeronautics and Space Administration
O&M	Operations and Maintenance
OSWTs	Offshore Wind Turbines
PPAs	Power Purchase Agreements
PV	Photovoltaic
RUL	Remaining Useful Life
ROI	Return on Investment
ROM	Reduced Order Modeling
RESs	Renewable Energy Sources
SAM	Smart Asset Management
SCADA	Supervisory Control and Data Acquisition
SPPs	Solar Power Plants
WFs	Wind Farms
XAI	Explainable AI

1.1. Methodology

This review paper aims to compile relevant publications, patents, and practices of leading companies within the SAM domain. To ensure a structured and comprehensive review, a systematic literature review approach was employed for selecting relevant studies. The literature was sourced from multiple academic databases, including IEEE Xplore, ScienceDirect, Google Scholar, MDPI, Engineering Village, Wiley Online Library, SpringerLink, and the ACM Digital Library. The selection criteria focused on peer-reviewed journal articles, conference papers,

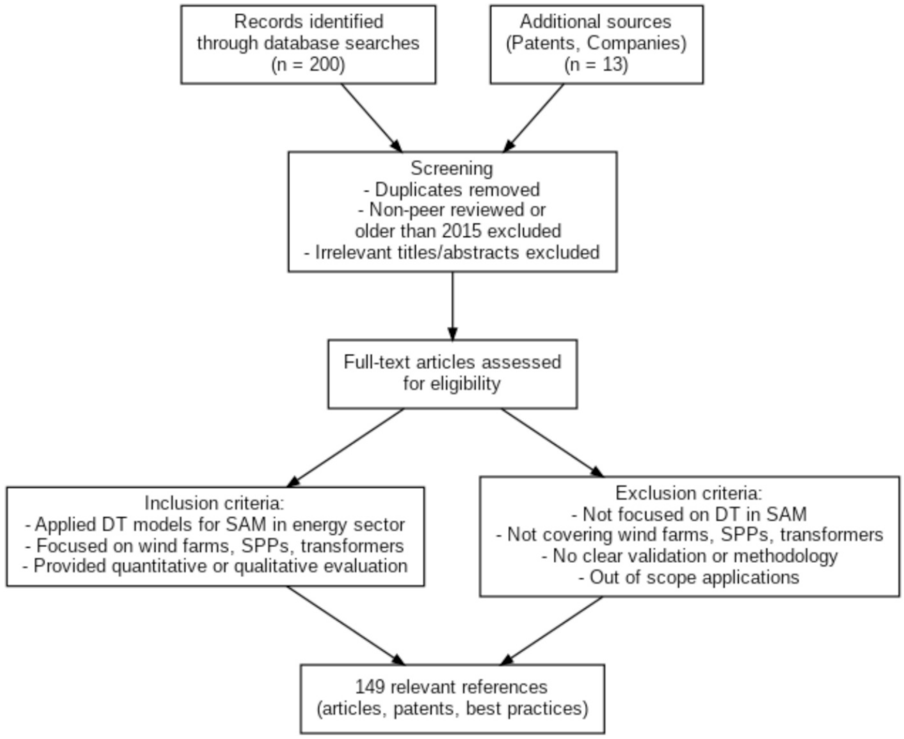

Fig. 1. Diagrammatic representation of the inclusion and exclusion criteria of studies.

and reputable industry reports published in the last 10 years (2015–2025) to capture recent advancements in DT technologies for the energy sector. Given the scope of this study, we specifically targeted research that developed DT models for SAM in the energy industry, with a focus on three key assets: wind farms (WFs), solar power plants (SPPs), and transformers. The selection of these assets as a focus of this study is driven by their critical role in modern energy infrastructure, their widespread use, and the substantial body of initial research that has been dedicated to the development and application of DT in these areas. The primary application areas considered were predictive maintenance, optimizing performance, fault detection and diagnosis, and performance prediction.

The search strategy involved using a combination of keywords such as "digital twin in energy industry,“ ”smart asset management and digital twins,“ ”digital twins for wind farms, solar power plants and transformers,“ ”transformer health monitoring,“ and ”predictive maintenance in energy systems.“ Studies were included if they developed or applied DT models for SAM in the energy sector, focused on key assets such as wind farms, solar power plants, and transformers, and provided quantitative or qualitative evaluations of DT performance. Studies were excluded if they did not explicitly address DT applications in SAM, lacked methodological details or validation, or were duplicate or non-peer-reviewed sources. Each selected study was analyzed based on the DT modeling approach (e.g., physics-based, AI-driven, hybrid models), Application area (e.g., predictive maintenance, performance optimization, fault detection), and validation method (e.g., simulation, experimental case studies, real-world deployment). Additionally, to incorporate industry advancements, we reviewed patents from Google Patents, Espacenet (European Patent Office), the United States Patent and Trademark Office (USPTO), and the World Intellectual Property Organization (WIPO), selecting those focused-on DT frameworks for predictive maintenance, asset health monitoring, and energy system optimization. Through this search, best practices from nine leading companies and four patents in the SAM field were identified. Further, more than 200 publications were initially found, but 135 research articles were selected after carefully evaluating their relevance to the research topic. Articles lacking substantial discussion on DT applications for these selected assets or those outside the defined scope were excluded. The diagrammatic representation of the inclusion and exclusion criteria of studies is shown in Fig. 1.

This comprehensive review endeavors to address the following research questions.

RQ1: What is the significance of DTs for the Energy Industry revolution?

RQ2: What is the current development of DTs in the context of Energy 4.0?

RQ3 How is the concept of DT applied to the SAM domain, and what are the key areas of application identified thus far?

RQ4: What are the challenges associated with implementing DTs in the SAM domain, and what are the potential future directions for addressing these challenges?

The subsequent sections will systematically address each research question, as shown in Fig. 2, which depicts the flow chart of the structure of the review paper.

1.2. Research landscape synthesis

To provide a structured overview of the scholarly landscape surrounding DTs, we conducted a keyword-based thematic *meta*-analysis of the 149 references included in this review. This synthesis aims to clarify dominant research directions, identify gaps, and visually cluster literature around shared themes. Fig. 3 presents a keyword clustering heatmap that categorizes these references across three primary clusters: Foundations, Applications, and Modelling, cross-referenced with ten prominent keywords in DT literature.

As shown in Fig. 3, several dominant research trends emerge:

- Application-focused research dominates the field, particularly in energy systems (18 references), real-time monitoring (12 references), and smart asset management (11 references). This indicates strong industrial and domain-specific interest, especially in wind farms, transformers, and power grid applications.

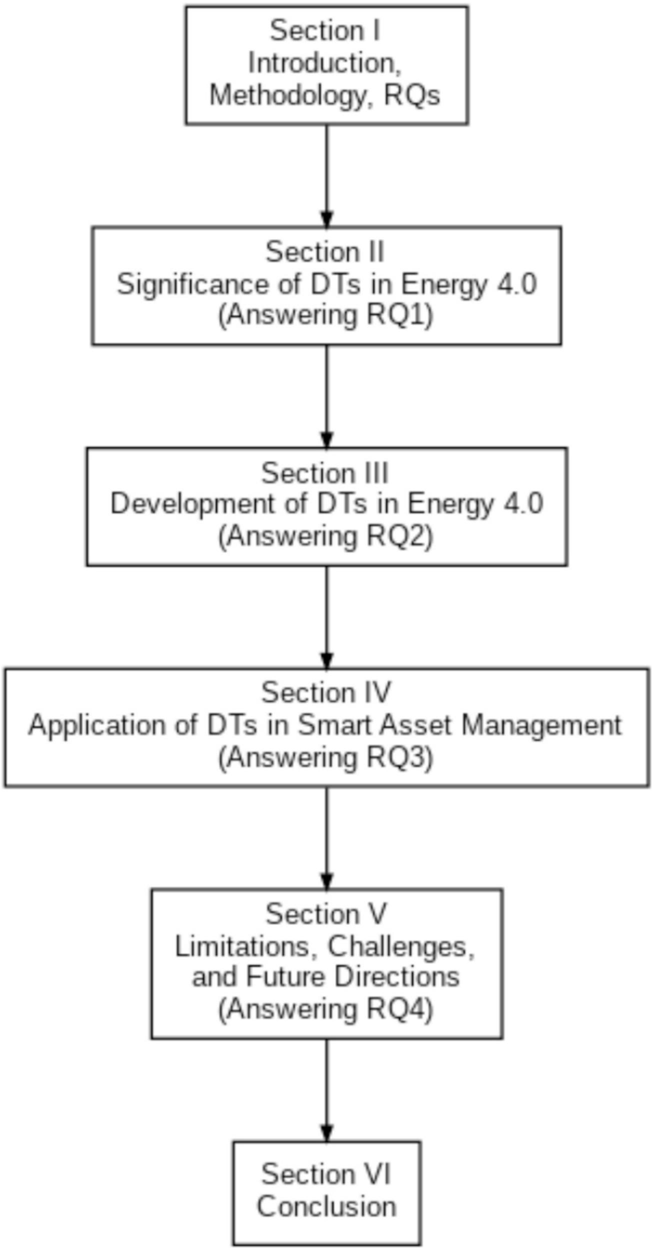

Fig. 2. The flowchart of the structure of the review paper.

- AI integration is an equally active research area, with notable contributions across both application (6 references) and modelling (14 references) clusters. This reflects growing reliance on machine learning for predictive analytics, anomaly detection, and operational decision-making in DTs.
- Hybrid modelling, which blends physics-based and data-driven approaches, shows a balanced presence in both application (4 references) and modelling (13 references) clusters. However, literature on hybrid DTs remains somewhat scattered, suggesting opportunities for more unified frameworks and standardized methodologies.

In terms of thematic clustering:

- The Foundations cluster is well populated in Digital Twin (12 references) and Simulation Models (3 references), yet has lower representation in advanced concepts like AI, Hybrid, or Predictive Maintenance, highlighting a need for foundational exploration of these evolving areas.
- The Applications cluster reveals strong focus on Energy Systems (18 references), Real-Time Monitoring (12 references), and Smart Asset Management (11 references), indicating high practical engagement. However, fewer foundational or modelling studies support these implementations, revealing a gap between use and theory.
- The Modelling cluster is rich in AI Integration (14 references), Hybrid Models (13 references), and Simulation Models (11 references), yet areas like Predictive Maintenance (3 references) and Data-Driven Models (9 references) remain underexplored. This indicates the need for methodological innovation in underrepresented modelling areas.

1) ***Literature Gaps and Emerging Directions:***

- Despite the breadth of literature, key future-facing areas such as Federated Learning, DTs in the Metaverse, and System-of-Systems (SoS) architectures are largely absent, offering clear avenues for novel research.
- There is a lack of comprehensive end-to-end DT frameworks that bridge foundational concepts, modelling techniques, and full-scale SoS-level integration. Our review addresses this by systematically categorizing DT maturity levels and asset-specific implementations.

2) ***Contribution and Novelty:***

This thematic *meta*-analysis enhances the originality and value of our review by:

- Providing a visual synthesis that spans foundational concepts, applied domains, and modelling approaches in DT literature.
- Highlighting fragmentation in hybrid and multi-scale DT studies, highlighting the need for integrative frameworks..
- Situating our work within the evolving landscape of Energy 4.0, offering relevance and insight to academic researchers and industrial practitioners.

The remaining sections of this paper are structured as follows: Section II highlights the significance of DTs in visualizing and implementing the energy industry revolution. Section III provides an overview of the current development of DTs within the Energy 4.0 framework. Section IV focuses on highlighting the specific applications of DTs in SAM within the energy industry. Section V outlines the limitations, DT development challenges, and major avenues for future research based on the comprehensive review of the state-of-the-art. Finally, Section VI concludes the review paper.

2. Significance of digital twins in energy 4.0

To address RQ1, regarding the significance of DTs in the energy industry, this section will explore their evolution and key technological advancements. During the 18th-century Industrial Revolution, the industrial environment experienced significant transformations, as illustrated in Fig. 4. This depiction highlights the accelerating pace of the ongoing transition.

Notably, the shift from the 1st to the 2nd Industrial Revolution spanned around a century, whereas the progression from the 3rd to the 4th Revolution transpired in a mere few decades. Additionally, this ongoing transition involves the seamless integration of advanced technologies across diverse fields. The inception of James Watt's steam engine marked the commencement of mechanized manufacturing and transportation. To generate substantial quantities of high-temperature steam, coal served as the primary energy source during that era (Energy, 2016). The inaugural Industrial Revolution, also referred to as Industry 1.0, established the groundwork for industrial automation and mass production. In the mid-19th century, the second industrial revolution (Industry 2.0) emerged, marked by the development of oilfields and the utilization of petroleum as the principal energy source (Energy, 2020). This transition led to the establishment of vast production facilities and the manufacture of enormous quantities of products.

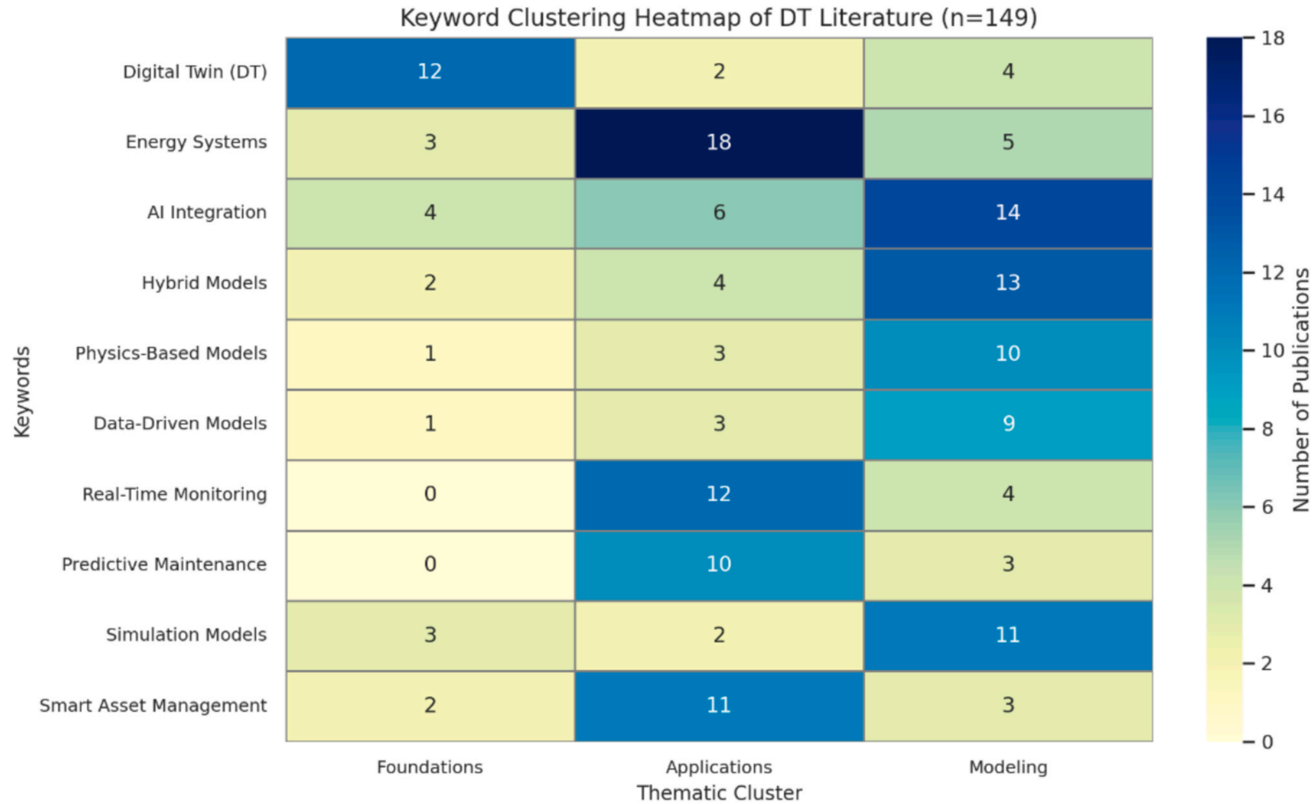

Fig. 3. Literature heatmap of DT research clusters.

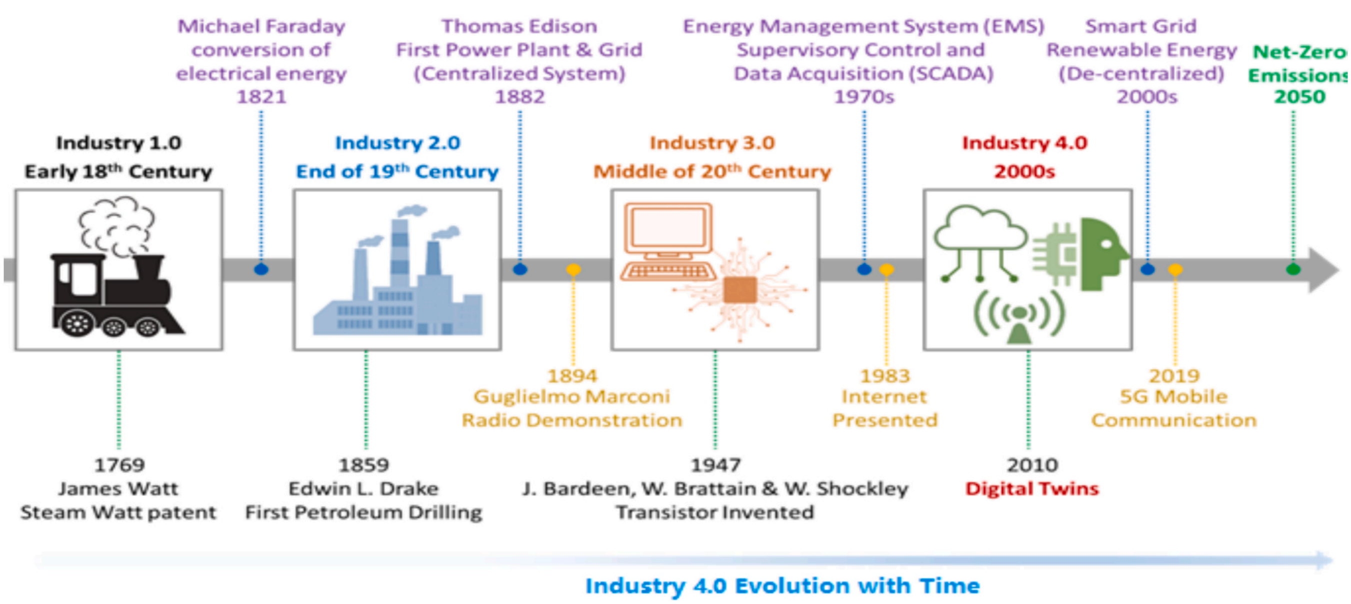

Fig. 4. Industry evolution and milestones.

Throughout this period, the global economy experienced remarkable expansion, with several nations taking the lead in both the oil and manufacturing industries. The worldwide gross domestic product growth rate surged from 1.82 % in 1913 to 4.9 % in the 1970 s (D. GL., 2021). The onset of the third industrial revolution (Industry 3.0) was triggered by the advent of the transistor in 1947 (QBurst, 2021), ushering in the era of digital civilization.

Technological advancements still relied on natural resources such as oil and gas, and certain countries that nurtured digital devices, computers, and semiconductor development and manufacturing industries achieved noteworthy economic growth (Community, 2016). Ever since Guglielmo Marconi introduced the first instance of wireless communication in 1896 (ABB, 2018), the field of communication engineering has progressed over numerous decades. The Internet was built upon a standardized protocol that became commercially viable in 1983 (Energy, 2020), and as data mobile transmission technology advances swiftly through the present fifth-generation and prospective sixth-generation mobile systems (Apollo – Performance Intelligence Health

Analytics accelerator, 2021), a convergence is occurring between the tangible physical world and the network-centric virtual world.

The primary utilization of energy lies in the electric supply and transportation sectors. In Australia, 25.3 % of the energy was allocated to electricity generation, while 24.6 % was utilized as fuel for transportation, including internal combustion engine vehicles (INSECTEC). The demand for electric vehicles has been steadily rising since the mid-2010 s, and it is projected that electric vehicles will comprise over 20 % of all passenger cars by 2030 (J. S., 2020). Despite not emitting exhaust gases, the adoption of electric vehicles will lead to an increased demand for electricity, necessitating the expansion of charging infrastructure. In the early 19th century, Michael Faraday discovered the generation of electricity through mechanical movement, while Thomas Edison established the first centralized power network decades later (I. TEC, 2020). Synchronizing with the second industrial revolution, global electricity consumption has experienced exponential growth since the 1950 s. In 2021, approximately 77 % of total electric power was derived from fossil fuels (Energy, Anylogic). Given the rapid escalation in power demand, efficient management and control of the power system became imperative. Consequently, an energy management system, equipped with supervisory control and a data acquisition system, was implemented in the 1970 s (Siemens, 2021). The establishment of such a system was facilitated by the integration of communication technology, capable of monitoring and controlling remote devices, and computer technology, which facilitated optimal energy management following the advent of Industry 3.0.

The urgency of climate change and resource depletion has brought global attention to the necessity of transitioning from conventional energy sources to renewables. Several major emitting nations have set targets to reduce emissions by 45 % by 2030 and achieve net-zero emissions by 2050, aligning with the goals of the Paris Agreement in 2015 (Custeau, 2017; QBurst, 2021). Consequently, the energy sector has rapidly shifted toward renewable energy sources (RESs) since the 2010 s (A. M. L. e. al., 2018). This transition introduces complexities beyond the traditional centralized energy model due to the integration of renewable and innovative energy sources. As these RESs, both established and newly engineered, are integrated, the energy sector's structure becomes more intricate. Customers can become sellers by owning RESs (Lund, et al., 2016), enabling bidirectional power flow between the grid owner and the customer (Lund, 2018). Furthermore, the inclusion of power electronic devices like inverters and converters is necessary to connect RESs to the existing power network (Ghand, 2019). Concurrently, real-time monitoring systems for power equipment (Haghshenas et al., 2023), dynamic energy management for intricate energy sources (Tao et al., 2018), and optimization of renewables with varying outputs (Moghadam, 2021) are essential components of the power energy industry.

As outlined earlier, the current energy sector necessitates a system capable of processing vast amounts of data acquired from diverse sensors, whether local or remote, in real time. This system must accurately assess and predict system reliability and economic viability. Achieving this demands the convergence of various technologies such as computing, communication networks, power engineering, data processing, and fields like economics. This convergence can be realized through Industry 4.0, which spearheads the ongoing technological revolution. The fourth industrial revolution primarily hinges on the Internet of Things (IoT) and mass digitization (Moghadam and Nejad, 2022). The IoT and digitalization employ AI for data analysis, processes, and decision-making. These technologies are already in use within the energy sector (Zhao and Chen, 2022; Sivalingam et al., 2018; Oñederra et al., 2019; Pimenta et al., 2020). Additionally, the full implementation of Industry 4.0 facilitates the realization of cyber-physical systems, including DTs that replicate actual energy system facilities within virtual environments (Botz, 2019). The energy industry's technological advancements have progressed in tandem with industrial revolutions, and the energy sector is now entering the fourth stage of innovation (Energy 4.0).

3. Development of digital twins in energy 4.0

To address RQ2, which explores the current development of DTs in the energy industry, this section provides an overview of their technological evolution, key advancements, and integration within Energy 4.0. We examine the foundational models of DTs, their progression from static digital replicas to AI-driven predictive systems, and their increasing role in optimizing energy infrastructure. This discussion sets the stage for understanding how DTs are shaping the future of SAM.

The concept of DTs was initially introduced in 2010 by the N (NASA) in their roadmap explanation (Nuñez-Montoya et al., 2022). NASA defined DTs as hyper-realistic systems that amalgamate physical models, sensor data, and historical information by incorporating multiscale National Aeronautics and Space Administration and stochastic simulations. Indeed, in 2016, General Electric (GE) showcased a tangible DT model of generator steam turbines, using it to assess integrity status, remaining lifespan, and projected costs (Xiangjun et al., 2020). This demonstration underscored the practical applicability of DTs in contemporary energy sectors. This highlighted how DTs can enhance predictive maintenance and asset optimization in the energy industry. DTs have evolved from NASA's initial concept to real-world implementations by GE, Siemens, and ABB, demonstrating their critical role in real-time monitoring, performance optimization, and decision-making in energy asset management (Energy, 2020; ABB, 2018; Energy).

3.1. Classification of digital twin models

DTs are categorized based on their technological maturity and application approach. DTs' three primary modeling approaches include physics-based, data-driven, and hybrid DTs. Each of these models defines how a DT simulates and interacts with its physical counterpart, impacting its ability to adapt, predict failures, and optimize performance. Some DTs operate purely on physics-based models, relying on first-principle equations and computational simulations to predict asset behavior under varying operational conditions. These are commonly used in energy flow modeling and structural analysis, where performance is dictated by well-established physical laws. However, such models, while highly accurate, require significant computational resources and are limited in their ability to adapt dynamically to real-time operational changes (El and Bounjimi, 2021; De Kooning et al., 2021).

In contrast, data-driven DTs leverage artificial intelligence and machine learning techniques, integrating vast amounts of real-time sensor

Table 2
Comparative analysis of digital twin models in energy systems.

DT Model Type	Key Features	Strengths	Limitations	Example Use Cases
Physics-Based DTs	Uses computational physics, deterministic models	High accuracy for structural analysis and energy flow modeling	Requires high computational power, lacks adaptability	Power grid simulations, transformer aging prediction
Data-Driven DTs	AI and ML-based, rely on real-time sensor data	Adapts dynamically, effective for predictive maintenance	Requires large datasets, vulnerable to data noise	Wind farm fault detection, PV panel efficiency monitoring
Hybrid DTs	Integrates AI-driven adaptability with physics-based modeling	Balances accuracy and adaptability, real-time decision-making	Computationally intensive, complex implementation	Wind turbine performance optimization, battery storage, predictive analytics

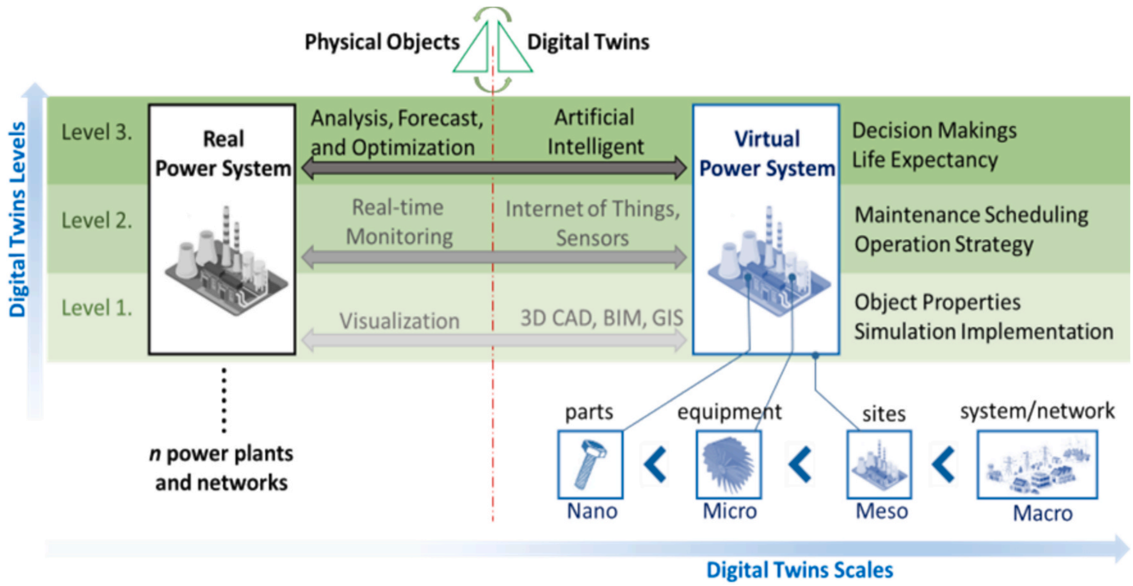

Fig. 5. Digital twins model example in power system asset management.

data to enable predictive maintenance, anomaly detection, and operational optimization (Perno et al., 2023). These models are particularly advantageous in complex environments like wind farms and solar power plants, where continuous monitoring and automated decision-making enhance asset efficiency (Ismail et al., 2024). However, data-driven approaches are inherently dependent on the quality and consistency of incoming data, making them susceptible to inaccuracies caused by sensor noise, missing data, or biased datasets (Sinsel et al., 2020).

To bridge the gap between these two approaches, hybrid DTs have emerged, combining physics-based simulations with AI-driven adaptability to refine predictions dynamically and improve decision-making in real-world scenarios. For instance, a hybrid DT for a wind turbine may incorporate airflow simulations for structural analysis while simultaneously using machine learning models to predict component failures based on historical performance data. This integrated approach enhances accuracy, adaptability, and resilience in asset management applications (De Kooning et al., 2021). The comparative Table 2 below summarizes the key distinctions between the three types of DT models, which highlights their strengths, limitations, and application areas.

The practical effectiveness of hybrid DTs has been demonstrated in real-world deployments. For instance, General Electric's WindSCADA system and Siemens' Basslink DT show how the integration of physics-based modeling with AI-driven analytics leads to significant performance gains such as enhanced failure prediction accuracy, extended asset life, and reduced maintenance costs (Energy, 2020; Energy). In wind energy applications, hybrid DTs use airflow simulations alongside real-time telemetry to dynamically adjust maintenance schedules, while in transformer monitoring, thermal stress simulations are complemented with live sensor input for improved asset health predictions. These industrial implementations highlight how hybrid DTs translate theoretical benefits into tangible performance improvements across various energy assets. Further technical and implementation details of these systems are discussed in Section IV, supporting the hybrid model's relevance across energy sectors.

However, the implementation of hybrid DTs at a large scale, particularly in grid-level energy systems, introduces significant computational and hardware challenges. These systems require intensive resources to perform real-time data acquisition, AI-based inference, and physics-based simulation concurrently. The synchronization of multi-modal data streams, along with the need for rapid decision-making, demands high-performance computing environments and optimized network infrastructures. Moreover, latency-sensitive applications such as fault detection and grid reconfiguration can be bottlenecked by delays in data transmission and model updates. The integration of edge computing, GPU-accelerated processing, and scalable data pipelines becomes critical to mitigate these limitations. Without adequate computational resources and infrastructure, the scalability and real-time responsiveness of hybrid DTs remain constrained, particularly in complex, distributed energy networks (Rathore et al., 2021; Fuller et al., 2020; Kober et al., 2024).

3.2. Maturity levels and technology integration

DTs can also be classified into three primary levels of maturity based on their technological evolution and application, as illustrated in Fig. 5. At the first level, the physical model is visualized using techniques such as three-dimensional (3D) computer-aided design (CAD), scanning, and printing (Iosifidis, et al., 2021; Walker et al., 2021), alongside Building Information Modeling (BIM) (Sørensen et al., 2022) and Geographic Information System (GIS) (Fahim et al., 2022). This level furnishes users or operators with spatial data by mapping tangible structures and drawings, facilitating the simulation of diverse scenarios with precision. Currently, this level finds practical use in power systems. For instance, a 110/20 kV, 40 MVA power transformer has been 3D modeled using laser scanning for quality control and diagnostics (Li et al., 2023), while 11 kV distribution lines are mapped through GIS to analyze insulation conditions, with the system alerting operators remotely (Yuan et al., 2022). Furthermore, power networks encompassing different energy sources and grid connections are designed and simulated based on GIS (Huang et al., 2022; Natgunanathan et al., 2023). As the initial stage of DT involves visualizing real-world components, ensuring the accuracy and currency of model parameters or properties is of paramount importance. Therefore, first-level DTs provide enhanced visualization and spatial analysis capabilities that enable engineers to simulate asset conditions and optimize infrastructure planning.

At the second level of DTs, real-time condition monitoring and system diagnosis are achievable by harnessing the capabilities of IoT (Wang et al., 2022). To establish a comprehensive IoT platform, equipping sensors on each equipment unit and facilitating communication over a high-speed network, such as a 5G network, is crucial (Jain et al., 2020). Consequently, the reliability of online diagnostics can be enhanced through extended processing of a diverse range of measurement data, leading to comprehensive condition-based maintenance and scheduling configurations (Livera, et al., 2022; Hong and Pula, 2023). IoT-based real-time monitoring systems are extensively employed for diagnosing the condition of major components and preemptively identifying wind turbine anomalies (Chen et al., 2022). Furthermore, energy utilities can deliver superior services to consumers using interactive monitoring of energy utilities, enabling the identification of additional cost factors and their sources (Gui, 2023). Effectively utilizing IoT, various devices within isolated renewable grids containing fuel cells, photovoltaic (PV) arrays, and battery storage, including pipe valves and protective systems, can be accurately sensed (Zhang and Wang, 2021). The robust groundwork established by the DT model across the first and second levels facilitates optimization and predictive capabilities within the energy sector. This effectiveness can be gauged through the calculation or formulation of objective metrics, including the remaining lifespan, optimal maintenance schedules, performance projections, and estimated costs. Therefore, second-level DTs integrate IoT and real-time monitoring to enable automatic fault detection, predictive maintenance, and enhanced energy efficiency in smart grids.

At the third level, AI-driven Digital Twins leverage machine learning algorithms to process vast amounts of real-time sensor data, optimize performance, and predict failures before they occur (Lopez-Lorente et al., 2022; Yang, et al., 2019; Kolesnikov et al., 2020). The sheer volume of data generated in energy systems necessitates high-speed processing and advanced analytics, making cloud-based and edge-computing solutions essential for large-scale DT implementations. Notably, DT systems play a pivotal role in aiding system operators or designers in making optimal decisions within contemporary energy systems, encompassing multiple networks and diverse power sources, even amidst uncertain conditions (Wang et al., 2023; Zhang et al., 2020). Third-level DTs integrate AI and predictive analytics to enable real-time decision-making, optimize asset maintenance, and enhance operational efficiency in the energy sector.

In (Xiong et al., 2021; Ahmed et al., 2014), the scale of DTs is categorized into three stages: unit, system, and system of systems (SoS). Similarly, as depicted in Fig. 5, this scale can be further subdivided into four classes: nano, micro, meso, and macro sizes. At the nanoscale, individual components or segments can be embodied as physical models. By assembling these components, fully-fledged equipment, or units, like generator turbines, transformers, and other devices, can be constructed at the microscale. Subsequently, multiple units can be configured into sites, such as power plants, substations, or factories, at the mesoscale. Lastly, a digitized system within the energy domain can be realized at the macroscale, where each site is interconnected within a network, such as a power grid or energy network. Moreover, the concept of a 3D virtual universe, known as the Metaverse, can ultimately be materialized through DTs (Wang et al., 2022; Yang et al., 2022). This development enables comprehensive consideration of environmental variables beyond the energy sector, encompassing aspects like traffic, consumption patterns, economic conditions, and weather conditions (Moutis and Alizadeh-Mousavi, 2021). The scalability of DTs from individual asset monitoring to full energy system simulations demonstrates their transformative potential in optimizing global power infrastructure and smart city planning.

Over the past decade, DT technology has progressed from basic 3D modeling to fully integrated AI-driven systems for real-time monitoring and predictive maintenance in the energy sector. The advancements in sensor technologies, big data analytics, and AI-powered simulation models have enabled DTs to become essential components of smart energy management systems (Rathore et al., 2021). The transition from static digital models to dynamic, self-learning twins has revolutionized power grid management, wind farm optimization, and industrial energy systems. Recent implementations by GE, Siemens, and ABB demonstrate the real-world applicability of DTs in reducing operational costs, improving energy efficiency, and enhancing asset reliability (Energy, 2020; , Energy; ABB, 2018). Despite these advancements, challenges remain in data standardization, cybersecurity, and large-scale scalability (Mousavi et al., 2024). Addressing these limitations will be crucial for the next phase of DT adoption in Energy 4.0. Moving forward, the integration of edge computing, federated learning, and cybersecurity frameworks will be crucial in expanding DT capabilities while ensuring data integrity and system resilience (Fuller et al., 2020).

3.3. Role of real-time data and simulation models in optimizing asset performance with DTs

Real-time data and simulation models are fundamental to DT technology, enabling predictive maintenance, operational efficiency, and fault detection in the energy sector. As outlined above, DTs have evolved from static digital models to AI-driven, self-learning systems that continuously synchronize with real-world assets to improve performance. The integration of IoT-based real-time monitoring in second-level DTs allows for continuous condition assessment of energy assets, such as wind turbines, transformers, and grid infrastructure, enabling early fault detection and proactive maintenance scheduling. For example, GE's Digital Power Plant for Steam utilizes real-time sensor data to assess integrity status, predict remaining lifespan, and optimize maintenance strategies, reducing unplanned downtime and extending asset longevity (Electric, 2016).

Similarly, DNV's WindGEMINI DT platform has been validated using operational datasets from over 6,000 wind turbines globally. The experimental conditions involve high-resolution SCADA data, meteorological inputs (e.g., wind speed, direction, and turbulence intensity), and mechanical loading metrics from turbine nacelle sensors (Digital, 2023; Custeau, 2017). Calibration was performed by comparing DT-derived fatigue predictions with actual inspection records and supervisory system alerts. Evaluation metrics included Mean Absolute Percentage Error (MAPE) for damage estimation and precision-recall curves for failure classification (Xue et al., 2024; Ma et al., 2023). In selected turbine types, WindGEMINI demonstrated lead times of up to 30 days for fault prediction and accuracy levels exceeding 85 % (D. GL., 2021). This comprehensive experimental framework highlights the reliability and scalability of hybrid DTs in predictive maintenance for distributed wind assets.

Simulation models, combined with big data analytics and AI-driven optimization, further enhance asset performance by predicting system behaviour under different operational conditions. Physics-based DTs use computational models to simulate energy flow, thermal stress, and mechanical wear, ensuring structural stability and efficiency. In contrast, data-driven DTs, powered by machine learning algorithms, process vast amounts of historical and real-time sensor data to identify performance trends, detect anomalies, and recommend operational adjustments. The hybrid DT approach, as seen in wind farm and power grid applications, combines real-time telemetry with AI-driven simulations to refine predictions and dynamically optimize energy generation and distribution (De Kooning et al., 2021).

Traditional asset management in the energy sector has largely relied on reactive maintenance or static, time-based schedules that lack context awareness and adaptability. For example, wind turbines were previously maintained at fixed intervals, regardless of component stress levels or environmental wear. In contrast, DT-driven platforms such as GE's WindSCADA (Energy, 2020) and Siemens' Basslink (Energy) dynamically integrate real-time telemetry with simulation outputs to adjust maintenance cycles based on real asset condition, significantly reducing downtime and extending operational life. DNV's WindGEMINI (D. GL., 2021) further exemplifies this shift by combining structural health models with real-time sensor analytics to provide a probabilistic risk index and personalized maintenance predictions. These examples demonstrate that DTs are not incremental improvements but rather represent a paradigm shift from passive monitoring to active, predictive, and adaptive asset management. This technological transformation enables granular fault diagnostics, scenario-based what-if simulations, and cross-domain system optimization capabilities that were not feasible under legacy SCADA or static monitoring systems.

Table 3
Digital twin & smart asset management relationship.

DT Functionality	Impact on SAM
Real-Time Monitoring	Enables continuous asset performance tracking and early fault detection.
Predictive Maintenance	Uses AI-driven diagnostics to forecast failures before they occur.
Data-Driven Decision Making	Helps operators optimize energy distribution and maintenance schedules based on live analytics.
Simulation & Scenario Testing	Allows engineers to test asset performance under different conditions before real-world deployment.
Lifecycle Optimization	Extends asset lifespan by preventing excessive wear through condition-based maintenance strategies.
Remote Operations	Allows operators to monitor and control assets in remote or hazardous locations.
Cost Reduction	Reduces unnecessary maintenance costs and minimizes unplanned downtime.
Performance Benchmarking	Provides comparative analytics to assess asset efficiency and identify areas for improvement.
Integration with AI & IoT	Leverages big data analytics and IoT connectivity for automated asset insights.

Beyond individual assets, macro-scale DT models are transforming energy systems by enhancing grid reliability and balancing distributed energy resources (DERs). By incorporating real-time data from smart meters, substations, and renewable energy sources, simulation models enable real-time load forecasting, energy storage optimization, and adaptive grid management (Mchirgui et al., 2024). Siemens' single digital grid model for Finland is a prime example, where DT technology automates grid simulations, enhances grid resilience, and optimizes resource allocation to minimize energy losses and improve operational efficiency (Ismail et al., 2024). Furthermore, in smart cities and industrial energy systems, DT-enabled predictive analytics optimize heating, cooling, and power distribution strategies to reduce energy waste and carbon emissions (Mylonas et al., 2021). Advanced DT implementations in solar power plants, microgrids, and industrial automation have demonstrated significant improvements in energy efficiency, cost reduction, and sustainability by leveraging real-time data fusion, cloud computing, and AI-powered decision-making (Mylonas et al., 2021). As DT technology continues to advance, the integration of high-speed data processing, federated learning, and cybersecurity frameworks will be crucial for further enhancing the scalability, accuracy, and reliability of real-time digital twins. The synergy between real-time data acquisition and AI-driven simulations is shaping the future of Energy 4.0, enabling smarter, more resilient, and more sustainable energy infrastructures (Ismail et al., 2024).

4. Applications of digital twins in smart asset management

To answer RQ3, which investigates the concept of DTs applied in the SAM domain and the applications of DTs in this domain within the energy industry, this section explores various real-world implementations of DTs across key energy assets. By analyzing case studies, industry best practices, patents, and existing literature, we highlight how DT technology enhances predictive maintenance, fault detection, and performance optimization in asset-intensive energy systems. Given the scope of this study, we specifically targeted research that developed DT models for SAM in the energy industry, with a focus on three key assets: wind farms (WFs), solar power plants (SPPs), and transformers. The selection of these assets as a focus of this study is driven by their critical role in modern energy infrastructure, their widespread use, the maturity of DT adoption, and a substantial portion of leading asset-intensive companies' practices, patents, and publications that revolve around the smart management of these assets.

DTs play a crucial role in modern SAM by enabling real-time monitoring, predictive maintenance, and performance optimization across energy assets. The following Table 3 illustrates the key functionalities of DTs and their direct impact on SAM.

4.1. DT applications by industry leaders

This subsection provides an overview of the endeavors undertaken by major global leading companies that have developed and implemented DTs in the domain of SAM, specifically focusing on WFs, SPPs, and transformers.

1) ***Real-world case studies for DTs for wind farms***
- General Electric— Predix and WindSCADA

GE's DT interface streamlines wind turbine management (Energy, 2016). It offers a graphical representation of wind farms, with real-time turbine status and optimization controls. Additionally, GE provides advanced solutions via Predix, a cloud-based software platform (Energy, 2020). GE's platform streamlines data collection, enabling real-time data analysis from wind turbines (WTs). This data fuels a powerful predictive model for wind energy, enhanced by specialized applications like WindSCADA and cybersecurity services. This digital solution has already delivered a 16 % production increase in a U.S. project and saved 9.0 man-hours, with a 33 % reduction in megawatt-hour losses in Brazilian onshore wind farms. It empowers operators to optimize maintenance and boost reliability and availability.

Traditional wind farm management typically relies on scheduled maintenance, SCADA-based monitoring, and reactive fault detection. Operators conduct manual inspections and respond to alarms when system thresholds are breached. However, these conventional methods lack real-time intelligence, often leading to unnecessary maintenance cycles, undetected early-stage faults, and operational inefficiencies (Ullah, 2024).

In contrast, DT-based systems like GE's WindSCADA and Predix eliminate the limitations of rule-based monitoring. DTs continuously collect real-time turbine data and apply machine learning-driven predictive models to anticipate failures before they occur. This approach enables condition-based maintenance, optimizing operational scheduling, and reducing downtime. Additionally, DTs provide turbine operators with virtual simulations, allowing for scenario testing and predictive energy production modeling capabilities that traditional systems cannot offer (Digital, 2023).

- ***DNV WindGEMINI DT***

DNV's WindGEMINI DT is a comprehensive solution for optimizing wind turbine performance (D. GL., 2021), providing data-driven insights for cost reduction and production maximization. It efficiently identifies issues like pitch control errors, incorrect systems, and blade cracks, leading to significant performance improvements and preventing revenue losses. For instance, it rectified a 30 % underperformance, saving $10,000 per month and avoiding revenue loss exceeding $8,500. The WindGEMINI DT was validated in both controlled laboratory simulations and real-world operational deployments. Initially, it was tested in a simulated environment using historical failure data to train predictive maintenance algorithms under controlled conditions. After this lab phase, WindGEMINI was implemented in live wind farms across the UK and North America, where it processed real-time sensor data from turbine components, including gearbox temperature, blade stress, and power output fluctuations. The field deployment allowed WindGEMINI to adapt to real-world environmental factors such as varying wind speeds, turbine loads, and operational anomalies, ensuring its practical effectiveness beyond theoretical modeling. By validating WindGEMINI in both simulated and operational environments, DNV ensured its predictive analytics and fault detection capabilities were optimized for real-world wind farm operations to reinforce its role as a critical tool for performance optimization and cost savings (D. GL., 2021).

While DT-driven predictive maintenance and optimization have demonstrated substantial benefits, the practical deployment of DT technology in wind farms still faces significant challenges. One major issue is data synchronization, as real-time sensor data must be continuously integrated into DT models with minimal latency. Given that wind turbines operate in highly dynamic environments, inconsistencies in data transmission from different components (blades, gearboxes, generators, and SCADA systems) can cause misalignment in predictive analytics, leading to inaccurate diagnostics or delayed maintenance actions (De Kooning et al., 2021).

Another critical limitation is model updating and adaptation. Many existing DT implementations rely on static physics-based models, which may struggle to adapt to operational variability over time. For example, changes in wind patterns, aging turbine components, and software updates in control systems require continuous recalibration of DT algorithms (Sinsel et al., 2020). However, current industry implementations still face difficulties in automating DT model updates without manual intervention. These challenges highlight the need for more advanced data processing frameworks and self-learning AI techniques, which are further discussed in Section V.

- ***SAP Fedem Arctic Wind Project***

SAP Fedem Technology offered Arctic Wind a cloud-based solution for digital inspections of industrial assets, replacing physical inspections with real-time sensor data (Community, 2016). This DT has enabled efficient management of the northernmost wind turbine, reducing the need for inspections in harsh conditions. Ensuring turbine uptime is critical for power generation, revenue, and profitability due to the impact of unscheduled downtime on the levelized cost of energy. Likewise, ABB offers ABB Ability™ remote support services for wind farm operators, boosting turbine uptime and reducing operational costs (ABB, 2018). ABB focuses on digitizing the electrical drivetrain, collecting real-time data from the converter, generator, and transformer, which is processed using intelligent algorithms and analytics. These analytics provide visibility into key components, forming the basis for ABB's remote support services. One prominent asset owner has already successfully implemented ABB Ability™ condition monitoring with data visualization.

- ***QBurst DT for Wind Turbine Monitoring***

QBurst offers a cloud-based IoT solution for comprehensive wind turbine monitoring, leveraging cutting-edge technologies like Apache Kafka, Spark, and MongoDB (QBurst, 2021). It consolidates data through an analytical engine and presents insights via a centralized dashboard. The solution allows monitoring of crucial turbine parameters and enables underperformance detection and asset performance tracking. Implementing this IoT-based solution enhances return on investment (ROI) by proactively identifying deviations and reducing manual monitoring costs, leading to increased operational efficiency and cost savings in wind farm management. Wind parks in remote or offshore locations require digital remote support due to challenging access. Maintaining remote wind farms under extreme weather conditions is crucial, as turbine structural integrity is paramount to preventing catastrophic damages, financial losses, and fatalities at such heights and blade weights.

2) Real-world case studies DTs for solar power plants

To ensure the profitability of SPPs, amidst the rapidly decreasing prices of power purchase agreements, it is essential to reduce maintenance costs and maximize power production. Achieving optimal efficiency requires effective monitoring and maintenance strategies, ensuring sustainable ROI while mitigating operational risks. A key challenge in SPP asset management is accurately assessing whether assets operate at peak efficiency and determining the most effective methods for predictive maintenance and performance optimization.

- *GE and Pratiti Technologies DT for Solar Power Plants*

GE has developed an SPPs power monitoring solution that integrates digital analytics for real-time performance tracking (Energy, 2020). This digital solution offers seamless integration with monitoring software, ensuring data availability and providing comprehensive asset health visualization. Actionable recommendations based on real-time insights prevent component failures and enable proactive maintenance. Additionally, GE's system employs signature detection algorithms to quantify production losses, ensuring precise KPI tracking. This approach has resulted in a 40 % reduction in production losses, a 30 % increase in plant productivity, and a 20 % decrease in O&M expenses. Likewise, the leading company, Prati Technologies, introduces Apollo, a solar energy analytics solution driven by patented DT technology (Apollo – Performance Intelligence & Health Analytics accelerator). Apollo optimizes PV power plants with features like a plant configurator, performance insights, and event discovery.

3) Real-world case studies for DTs for transformers

- *NESC TEC, Siemens and AnyLogic DT for Transformer*

INESC TEC institute, along with four research organizations, pioneered the "Transformer 4.0-Digital Revolution of Power Transformers platform" based on the DT concept (INSECTEC; Jones, 2020; I. TEC, 2020). This platform employs operational research, AI, and information management to acquire and manage knowledge throughout a power transformer's lifecycle. Siemens implemented a trial DT system at the Basslink transmission line in Australia (Energy), enabling operators to simulate thermal stress for performance optimization. AnyLogic DT technology replicated power transformer core production processes, efficiently managing production line movements and avoiding bottlenecks, leading to better production planning and cost savings (Anylogic). Notable features include seamless data integration between physical and digital systems and the software's ability to interface with machine learning technologies, enhancing analysis and decision-making for improved operational efficiency and performance.

4) DT platform for assets management for businesses

Facilities and businesses rely heavily on complex and expensive equipment, which can jeopardize their success if not function optimally. Companies are turning to advanced AM platforms tailored to their specific needs to mitigate these risks and ensure business continuity. Siemens has developed a cloud-based AM platform that acts as a central hub for consolidating asset health and maintenance data. Using cloud-based algorithms (Siemens, 2021), this data is analyzed to inform decision-making, resulting in significant benefits such as 30 % maintenance savings and a 45 % reduction in downtime. Likewise, Schneider Electric has introduced an Asset Performance Management (APM) platform, APM 4.0, leveraging Industry 4.0 and IIoT principles (Custeau, 2017). It integrates predictive analytics, augmented reality, and cloud solutions to enhance operational insights. Advanced analytics enable predictive maintenance, using pattern recognition and machine learning to preemptively identify equipment issues, resulting in a 30 % improvement in asset utilization, a 25 % decrease in unplanned downtime, a 20 % increase in asset availability, and over $17 million in savings. QBurst has developed the SeeMyMachines-One platform, tailored for renewable energy firms (QBurst, 2021). Leveraging DT technology, it offers advanced analytics customizable for AM, operations, and business optimization. The developed IoT software continuously monitors equipment health, ensuring reliability and maintaining a comprehensive machine-related information repository.

5) Economic implications of adopting DTs for asset management in the energy industry

The adoption of Digital Twin (DT) technology in asset management has led to significant economic benefits by improving operational efficiency, reducing maintenance costs, and maximizing asset lifespan. This section explores the financial advantages of DT implementation in wind farms, solar power plants, transformers, and business asset management.

- ***Economic Implications in Wind Farm Management***

The adoption of DT technology in wind farms has led to substantial economic benefits by improving operational efficiency, reducing maintenance costs, and maximizing energy production. Traditional wind farm management relies on scheduled maintenance and reactive fault detection, often leading to unnecessary servicing and costly unplanned failures (Ullah, 2024). In contrast, DT-driven predictive maintenance optimizes service schedules and prevents unexpected breakdowns, significantly reducing repair expenses and revenue losses. For instance, GE's WindSCADA and Predix solutions helped achieve a 16 % production increase in the U.S. and a 33 % reduction in megawatt-hour losses in Brazil, demonstrating the financial advantages of real-time monitoring and AI-driven analytics (Digital, 2023). Similarly, DNV WindGEMINI corrected a 30 % underperformance issue, saving $10,000 per month and preventing additional revenue losses exceeding $8,500 per month (D. GL., 2021).

Beyond cost savings, DTs enhance asset lifespan and lower operational expenses by enabling real-time condition monitoring and virtual simulations. The SAP Fedem Arctic Wind Project reduced reliance on manual inspections in extreme weather conditions, cutting logistical costs while ensuring turbine reliability (Community, 2016). Likewise, ABB Ability™'s remote monitoring capabilities helped digitize drivetrain health assessments, further minimizing maintenance expenses (ABB, 2018). Additionally, DT solutions such as QBurst's cloud-based IoT monitoring system improve return on investment (ROI) by detecting underperformance early, reducing manual intervention costs, and optimizing energy generation (QBurst, 2021). By continuously analyzing turbine performance and making real-time adjustments, DTs ensure that wind farms operate at peak efficiency, providing long-term financial returns. The success of these implementations by GE, DNV, SAP, ABB, and QBurst highlights the strong economic incentives for adopting DTs in wind energy management. Shifting from reactive to predictive asset management enables energy companies to minimize operational costs, enhance revenue generation, and ensure long-term profitability in the renewable energy sector.

- ***Economic Implications of Adopting DTs in Solar Power Plants***

The adoption of DT technology in solar power plants has led to significant economic advantages by enhancing performance monitoring, reducing operational costs, and optimizing energy production. Traditional solar asset management often relies on periodic inspections and reactive maintenance, which can result in inefficiencies, unexpected failures, and revenue losses (Ullah, 2024). In contrast, DT-based solutions enable real-time performance tracking, predictive maintenance, and data-driven decision-making, leading to substantial cost savings. For instance, GE's solar power monitoring system integrates digital analytics to provide actionable insights, preventing component failures and optimizing maintenance schedules. This approach has led to a 40 % reduction in production losses, a 30 % increase in plant productivity, and a 20 % decrease in operation and maintenance (O&M) expenses, demonstrating the financial benefits of real-time data integration (Energy, 2020).

Similarly, Pratiti Technologies' Apollo DT solution leverages advanced analytics to optimize photovoltaic (PV) power plant performance, offering features such as automated fault detection, performance benchmarking, and predictive maintenance scheduling ("Apollo – Performance Intelligence Health Analytics accelerator." https://www.pratititech.com/industries/energy/ (accessed 7/12/, 2021). By enabling early identification of underperformance and ensuring optimal asset utilization, DTs minimize downtime, extend equipment lifespan, and enhance return on investment (ROI) for solar energy operators. Additionally, the ability to accurately quantify production losses through signature detection algorithms allows for better financial planning and resource allocation. These advancements illustrate that integrating DT technology into solar power plants not only enhances energy generation efficiency but also provides a highly cost-effective strategy for long-term sustainability and profitability in the renewable energy sector.

- ***Economic Implications of Adopting DTs in Transformers***

The implementation of DT technology in power transformers has yielded significant economic benefits by enhancing operational efficiency, optimizing maintenance, and reducing overall costs. Traditional transformer management relies on scheduled maintenance and reactive fault detection, often leading to unnecessary servicing, unexpected failures, and costly downtime (Ullah, 2024). In contrast, DT-driven solutions provide real-time monitoring, predictive analytics, and lifecycle management, ensuring that transformers operate at peak efficiency while minimizing operational disruptions. For instance, INESC TEC's Transformer 4.0 platform integrates operational research, AI, and information management to optimize transformer performance, reducing maintenance costs and extending asset lifespan.

Similarly, Siemens' DT system for the Basslink transmission line in Australia enables operators to simulate thermal stress conditions, allowing for better performance optimization and preventing costly transformer failures (INSECTEC). Additionally, AnyLogic's DT technology for transformer core production has improved manufacturing efficiency by optimizing production line movements, eliminating bottlenecks, and enhancing resource allocation, resulting in cost savings and better production planning (Anylogic). The integration of DTs into transformer management enhances data-driven decision-making, reduces operational risks, and lowers capital expenditures associated with unexpected failures and inefficient maintenance. By providing real-time insights, seamless data integration, and advanced analytics, DT technology significantly improves the economic viability of power transformer operations, ensuring long-term financial sustainability and optimized asset utilization for energy providers.

- ***Economic Implications in Business Asset Management***

The adoption of DT platforms for AM in businesses has generated substantial economic benefits by reducing maintenance costs, minimizing downtime, and optimizing asset utilization. Traditional asset management approaches often rely on fixed maintenance schedules and reactive repairs, leading to inefficiencies, unexpected failures, and financial losses (Ullah, 2024). However, cloud-based DT solutions offer real-time monitoring, predictive analytics, and data-driven decision-making, significantly improving operational efficiency and cost savings. For example, Siemens' cloud-based AM platform consolidates asset health and maintenance data, enabling companies to achieve 30 % savings in maintenance costs and a 45 % reduction in downtime, directly impacting profitability (Siemens, 2021).

Similarly, Schneider Electric's APM 4.0 platform, which integrates predictive analytics, augmented reality, and IIoT, has demonstrated a 30 % improvement in asset utilization, a 25 % decrease in unplanned downtime, and a 20 % increase in asset availability, resulting in over $17 million in savings (Custeau, 2017). These figures highlight the strong return on investment (ROI) that businesses can achieve through AI-driven maintenance and automated asset monitoring. Moreover, QBurst's SeeMyMachines-One platform, specifically designed for renewable energy firms, enhances equipment reliability and operational efficiency by leveraging IoT-based continuous monitoring (QBurst, 2021). The ability to preemptively identify failures, optimize operational performance, and ensure data-driven maintenance scheduling not only reduces operational expenses but also extends asset lifespan, maximizing financial returns. By replacing traditional AM methods with DT-powered predictive maintenance and cloud-based analytics, businesses can significantly lower capital expenditures, improve resource allocation, and ensure sustainable long-term cost efficiency, making DT platforms an essential tool for modern industrial and energy sectors.

4.2. DT-related patents

GE holds ownership of three patents directly related to DTs in the context of WFs. Their research and development have substantiated the transformative potential of DTs, profoundly impacting the development, operation, and maintenance of WFs (A. M. L. e. al., 2018). When compared to the traditional paradigm without DTs, this new approach has demonstrated a remarkable 20 % increase in operational efficiency. Furthermore, GE has made significant strides in creating the necessary hardware and software components to establish DTs for OSWFs. In one instance (Lund, et al., 2016), GE invented a DT specifically for WFs, incorporating two distinct communication networks. The first network establishes connectivity between the WTs' control systems within a wind farm, while the second network connects the cloud-based digital models of the WTs. Moreover, GE has introduced a digital platform for managing WFs featuring multiple WTs electrically connected to a power grid (Lund, 2018). The system encompasses several components: a farm-based communication network that establishes communication with one or more WTs, a cloud-based communication network that encompasses multiple DTs representing the digital infrastructure, and an industrial gateway coupling both communication networks.

In a separate instance, Pratiti Technologies possesses a patent specifically related to an electrical DT for SPPs (Ghand, 2019). They have developed an automated system and method that implements an electrical DT, facilitating efficient operation, maintenance, and AM of SPPs. The system incorporates weather sensors to collect real-time or on-demand time-stamped operational data specific to the geographical location of the SPP. Additionally, it includes: 1) a plant-build module to configure the as-built and as-operated characteristics of the SPP; 2) a component module to manage device-specific data provided by original equipment manufacturers; 3) an electrical DT engine to predict performance and losses using weather data and plant configuration data; and 4) a remote server for storing, executing, and delivering prediction data to end consumers.

4.3. DT-related publications

DT technology is gaining increasing attention due to its significant potential and substantial impact within the energy industry, particularly in the realm of SAM. This subsection presents a compilation of publications within the SAM domain, specifically focusing on WFs, SPPs, and transformers.

1) DTs in the wind farms

DTs offer a valuable application for predictive maintenance within WFs, leading to heightened safety and decreased operational and maintenance costs. The following papers are pertinent to this domain:

Haghshenas et al. introduce the concept of a predictive DT for wind farm operations and the predictive maintenance of bearings. Their developed digital platform is proficient in offering predictive insights concerning potential failures in wind turbine components (Haghshenas et al., 2023; Xue et al., 2024). In (Tao et al., 2018; Ma et al., 2023; Wadhwani et al., 2022; Raja, et al., 2023), DT models of a wind turbine are presented to enhance gearbox prognosis accuracy and failure forecasting, respectively. Moghadam et al. put forth a DT model for predictive maintenance of gearboxes in drivetrains within floating offshore wind turbines (FOWTs) (Moghadam et al., 2021). Other studies (Moghadam and Nejad, 2022; Pujana et al., 2023) established computationally efficient DT models for drivetrain systems, enabling the monitoring of remaining useful life in components. Zhao et al. devise an acoustic emission-based structural damage localization method for the structural DT of wind turbine blades. Simulation results endorse the method's efficiency and robustness, proving its utility in establishing wind turbine blade structural DT (Zhao and Chen, 2022). Just as with bearings, gearboxes, and blades, power converters endure high thermal stress. Addressing this concern, a DT framework is developed in (Sivalingam et al., 2018) to predict the remaining useful life of offshore wind turbine (OSWT) power converters, facilitating predictive maintenance. Onederra et al. present a DT model for a medium-voltage cable prototype within a wind farm. This model simulates cable behavior, extending its lifespan to enable preventive maintenance (Oñederra et al., 2019).

The development of a reliable wind turbine numerical model where results can be validated with experimental data is a key challenge toward DT adoption. Pimenta et al. developed a reliable offshore wind turbine numerical model using monitoring data from the WindFarmsSHM project. Wind farm owners can leverage this established DT tool for ongoing fatigue damage assessment and exploration of alternative operational strategies (Pimenta et al., 2020). In (Botz et al., 2019), the authors collected and applied crucial data from specific points on hybrid WTs to devise a reliable DT framework aimed at optimizing operating parameters and maintenance. Similarly, Nuñez-Montoya et al. fashioned a DT for a wind turbine, utilizing SCADA data from an actual wind turbine (Nuñez-Montoya et al., 2022). In (Haghshenas et al., 2023; Abdullahi et al., 2025; Li et al., 2021; Abdullahi et al., 2024) SCADA systems have been improved by developing cloud computing and OPC unified architecture-based platforms to deploy the DTs for predictive maintenance of WTs.

Furthermore, as part of reliable model development, Xiangjun et al. propose a novel approach to detecting wind turbine gearbox anomalies using DT technology. This endeavor involves comparing actual wind turbine SCADA data with virtual simulation model results to enhance anomaly detection reliability (Xiangjun et al., 2020). Likewise in (Zhou et al., 2024) vibration-based damage monitoring DT is proposed to enable the online intelligent evaluation of WT gearboxes. The model takes the input data from the SCADA system to estimate the real-time fatigue-damaging monitoring of key components in the WT gearbox. In (Iosifidis, et al., 2021), a DT framework is created for assessing the reliability of power electronics converters in WTs. This study integrates an electrothermal model into a turbine model to monitor changes in wind speed. Real-world, 1-second wind speed data is employed to track semiconductor device fatigue caused by abrupt wind fluctuations. Simulation outcomes demonstrate that the proposed DT framework more precisely estimates fatigue compared to conventional methods. Walker et al. focused on developing a DT of the most critical component of FOWTs, which is the Mooring Lines, to unlock the widespread adoption of FOWT technology. The developed DT is capable of accurately predicting the health and behavior of the system, allowing for a comparison with the actual behavior. The authors utilized data from the Hywind Pilot Park project, the world's first commercial FOWTs, to demonstrate the effectiveness of their DT (Walker et al., 2021).

The literature primarily concentrates on WTs, specifically on predictive maintenance, neglecting the wind environment's role in predicting wind energy and real-time monitoring. Sørensen et al. developed a prototype DT for wind power using game engines. This study selected two types of WTs (Vestas V164-8 and Enercon E-126 7.580) and one location (Esbjerg, Denmark) due to data availability. Unreal Engine 5.0 was employed to model the landscape and surrounding water and to investigate the wind turbine model. The results indicated that the developed DT effectively monitors the environment and predicts energy production from OSWT (Sørensen et al., 2022). Similarly, in (Fahim et al., 2022), a cloud-based DT framework assisted by 5G next-generation radio access networks was designed to remotely monitor WFs and estimate power generation in advance. Given the significant fluctuations in wind speed in ultra-short and short-term time scales, accurately predicting wind speed for wind energy prediction remains a challenging task. Addressing this challenge, Li et al. developed a multi-turbine spatiotemporal correlation prediction model assisted by DT and IoT technologies. The proposed framework incorporates wind speed correlations among WTs that vary with time on an ultra-short-term scale to enhance the accuracy of the correlation model (Li et al., 2023). In future work, the proposed framework can be explored further for accurate wind power prediction. Yi Liu et al. (Liu et al., 2025) proposed a monitoring and analysis framework of floating wind turbines considering the ocean environment. This study, by integrating digital models and ocean environmental data, supports informed decision-making.

2) DTs in solar power plants

Researchers have utilized DT technology for various applications related to photovoltaic (PV) electrical characteristics and power prediction, including optimizing output power, diagnosing faults, and controlling voltage in PV systems. The following papers pertain to this area:

Jiang et al. (Yuan et al., 2022) developed a DT model to predict the electrical characteristics of bifacial solar panels using a dynamic parameter estimation process. The proposed model was simulated and experimentally verified across three different environmental scenarios. The results obtained demonstrate that the proposed model can accurately predict the electrical characteristics of solar panels compared to traditional static models. In (Huang et al., 2022; Walters and Venayagamoorthy, 2024; Yonce et al., 2023, Asheville, 2023; Institute of Electrical and Electronics Engineers Inc., 2023), authors proposed a power prediction model for distributed PVs within a DT system, employing a genetic algorithm backpropagation, Elman recurrent, and multilayer perception neural networks, respectively. Other studies (Al-Isawi et al., 2023; Minhas et al., 2023; Zhang et al., 2022) developed data-driven DTs of SPPs for accurate forecasting of PV power prediction by employing recurrent neural networks. Simulation results indicate that the proposed method, in comparison to two other traditional methods, achieves higher accuracy with minimal time consumption. In (Natgunanathan et al., 2023), an AI-powered DT for the Deakin University solar farm was developed to predict power generation in microgrids. The proposed model was tested using real-time on-site weather station sensor data, and the results show that the developed algorithm effectively predicts the power generation of the microgrid. Wang et al. introduced a DT- based maximum power point tracking (MPPT) technique aimed at estimating the global maximum power point (GMPP). Comparative to conventional methods, the proposed technique accurately estimates the GMPP (Wang et al., 2022).

In (Jain et al., 2020) a DT is developed for fault diagnosis in distributed photovoltaic systems. The proposed technique estimates the measurable output characteristics of each PV energy conversion unit (PVECU) in real time for fault diagnosis. The experimental results demonstrate the effectiveness of the proposed approach in detecting and identifying various faults in PVECU, outperforming conventional approaches. Abdelrahman et al. (Abdelrahman et al., 2024) developed a dimensional DT platform as an integrated solution to detect and classify faults in the PV system arrays. They utilized correlation coefficient R^2 to evaluate the accuracy and detect different events in the PV arrays. An intelligent cloud-based platform incorporating a control DT is proposed in (Livera, et al., 2022) to monitor and control MW-scale PV power plants. The DT's performance was validated using a test-bench PV system in Cyprus and verified with a utility-scale PV system in the Netherlands, demonstrating high accuracy in fault diagnosis. Hong et al. combined DT and AI techniques to develop a novel approach for detecting and classifying PV faults (Hong and Pula, 2023). Experimental results illustrate that fault detection and classification are successfully achieved in minimal time compared to other techniques. Jian et al (Chen et al., 2022) introduced an intelligent DT-based coordinated control strategy for large-scale distributed photovoltaic systems, aiming to address voltage instability issues and predict PV output. The results demonstrate that the proposed technique effectively manages and adjusts the system's operational state promptly compared to other techniques. In (Gui, 2023), a three-layered architecture is proposed for voltage regulation of PV inverters in low-voltage (LV) distribution grids. Alongside the automatic voltage regulation (AVR) application, this work employs a DT of the cyber-physical system to ensure the control system's appropriate operation. For simulation, real-time data is collected from the LV distribution feeder located in Denmark. The results illustrate that the proposed method enhances voltage quality and increases the grid's hosting capacity.

Zhang et al. (Zhang and Wang, 2021) presented a DT modeling approach for PV panels using a hybrid neural network to control PV power-voltage characteristics under different lighting conditions. The well-trained DT model is capable of predicting the power-voltage characteristics of PV panels amidst varying environmental factors such as uneven lighting conditions, temperature, and humidity. In (Livera, et al., 2022), two DT approaches (model-free and model-based) were developed for a PV-based nanogrid situated at the University of Cyprus, and their performances were analyzed. These models were created to estimate voltage levels with high PV penetrations under diverse meteorological conditions. The proposed DT-based approach reduces the voltage state estimation operating time from 15 s to 1 s, in contrast to non-DT-based approaches. Comparing the two approaches reveals their high fidelity in voltage estimation; the choice between the models depends on the availability of information and data used for their development. Xi Zaho et al. (Zhao, 2024) proposed a novel DT model based on a domain-matched transformer using a convolutional neural network. The developed DT model can accurately predict the PV system performance.

3) DTs in the transformers

In the literature, DT technology has found applications in transformer state evaluation, fault diagnostics, monitoring operating status, predictive maintenance, and predicting remaining useful life. The following papers pertain to this area:

An approach for the state evaluation of a 110 kV power transformer based on DT technology is presented in (Yang, et al., 2019). The accuracy and reliability of the results support the implementation of a DT system to ensure the safe and reliable operation of the power system. Similarly, in (Chen et al., 2022), a simplified simulation model that emulates the DT of a power transformer in the LabVIEW environment is developed. This work proposes the utilization of a DT-based method for digitally diagnosing power transformers. In (Zhang et al., 2020), an architecture based on DT is developed utilizing advanced AI technologies. The proposed architecture, in comparison to traditional approaches, can enhance the performance of distribution transformers by enabling fault detection, predictive maintenance, and life assessment capabilities. An intelligent monitoring and maintenance model of the transformer based on DT technology and multi-model language is developed in (Zhang et al., 2024). The proposed model can achieve real-time monitoring of the transformer's operational status. In (Xiong et al., 2021), a novel field-programmable gate array- DT is introduced for monitoring and diagnosing power electronic transformers. The performance of the proposed method is assessed across four distinct scenarios. The results illustrate that the developed technique can assess each scenario in real-time, monitor the operational state, and diagnose the power electronic transformer's functioning. Yoon et al. (Yoon et al., 2024) developed a method to prevent the malfunction of differential protection of power transformers by estimating the second harmonic content using DT.

The thermal performance of a 10 kHz power electronic high-frequency power transformer (HFPT) based on the DT model is presented in (Wang et al., 2022). The simulation results demonstrate that the proposed method can accurately estimate the HFPT's thermal performance and the thermal stress affecting the insulation. This model can be employed for lifetime prediction, condition monitoring, and fault diagnostics of HFPTs. Chu et al. (Chu et al., 2024) presented a comprehensive DT platform for dynamically monitoring the temperature rise across a dry-type power transformer. Conversely, in (Yang et al., 2022), a DT for the operation system of oil-immersed power transformers is constructed using the resource-oriented Petri net system engineering modeling method. The proposed approach can accurately predict the transformer's operational state, as well as aid in fault prediction and diagnosis. Luo et al (Luo et al., 2023) developed DT for the transformer using a virtual-real sensing approach to estimate the temperature and moisture distribution of the Transformer. Results indicate a

3.5 % error in temperature distribution compared to monitoring data with the traditional approach. In (Ren et al., 2024), a DT technology based on an extreme machine learning-based algorithm in the neural network is designed to predict transformer hot-spot temperature. Likewise, in (Yonce et al., 2023); a DT-based residual life prediction model for a power grid transformer is designed to predict the hot spot temperature under different load rates. The results demonstrate the 99.97 % accuracy of the developed DT model. In (Dongxue, 2024), a 1000 kV oil-immersed power transformer DT is built to analyze the thermal life loss of the transformer.

Liang et al. (Wang et al., 2023) constructed a DT-based reduced-order model for the transformer's coupling temperature field. This model addresses the time-consuming nature of traditional methods for calculating the temperature rise in transformers. The results demonstrate that the reduced-order model reduces the calculation time by 192 times compared to the traditional Galerkin full-order finite element approach.

Panayiotis et al (Moutis and Alizadeh-Mousavi, 2021) developed a DT for the medium-voltage side of a distribution transformer, enabling real-time monitoring of voltage and current. The simulation results of the DT method aligned with field data from an actual medium-voltage distribution transformer, demonstrating the effectiveness of the proposed approach. Similarly, in (Minhas et al., 2023), a DT for voltage transformers is proposed to monitor the online state of voltage transformers. Experimental results reveal that the proposed method outperforms traditional techniques, achieving 90 % accuracy in state monitoring performance. Ruoyu et al utilized a convolutional neural network and a multilayer perceptron network technique to construct a digital model of an oil-immersed power transformer (Wu et al., 2023). The developed model, when compared to other models, exhibits superior fault generalization ability and is capable of real-time monitoring and diagnosis of transformer faults with 98 % accuracy. Similarly, in (Abdelrahman et al., 2024); the DT of transformers based on neural network algorithms is designed for transformer condition monitoring to detect and diagnose faults, predict failures, and optimize maintenance schedules. Aiqing et al (Aiqing et al., 2024) developed the DT based on the Eagle Search algorithm for inter-turn fault identification of the transformer. The results indicate that the fault identification accuracy increased by 7.85 % compared to conventional approaches. Zhou et al (Zhou et al., 2023) combined the digital twinning system and actual monitoring hardware for transformer running state detection and early fault diagnostic.

In (Huang, et al., 2022), a DT model of a 220 kV oil-immersed power transformer winding is presented to analyze the heat distribution characteristics of the transformer based on winding losses. The proposed model accurately identifies the winding's hot spot by analyzing the internal heat dissipation within the transformer winding. Likewise, in (Chu et al., 2024), the DT of an oil-immersed transformer is built based on an optimized kernel extreme learning machine. The developed model achieves intelligent diagnosis and health monitoring. In (Liu et al., 2022), an attempt is made to locate transformer winding faults using DT technology. This work constructs a DT of the transformer winding based on a double ladder network to identify variations in disk space faults. Verifying the proposed model on an actual transformer demonstrates its potential in fault location. Yongteng et al. (Jing et al., 2022) constructed the neural network-based DT for the transformer to diagnose the failure signal of winding. The diagnostic test is carried out on an experimental prototype of a transformer with 110 kV, and results show that the method can diagnose the problems that occur in transformer winding with high accuracy. In (Zhang et al., 2025), a framework based on deep vision and DT is developed to achieve real-time monitoring and intelligent maintenance of transformers. The results indicate that the model surpasses the advanced deep-learning-based models in fault detection tasks.

In (Zhang et al., 2021), the authors investigate the feasibility of employing DT to identify partial discharge (PD) signals in transformer bushings. A virtual DT-based simulation model of a 330 kV high-voltage transformer bushing is developed to study the propagation characteristics of PD signals. The simulation results showcase the DT-based model's capability to identify various types of PD signals in transformer bushings. An approach to developing a new protective relay for power transformers using DT technology is introduced in (Hamidi, 2022). The developed method enhances sensitivity and selectivity in transformer protection compared to other techniques. Yongteng et al. (Jing et al., 2021) developed a DT for predicting the remaining life of a transformer. The results demonstrate that a DT technology-based transformer can effectively predict the remaining operational life with an accuracy rate of 95 %.

4) Shared digital twin methodologies across energy sectors

Across various energy sectors, DTs real-time data acquisition, AI-driven fault detection, predictive maintenance, and optimization algorithms to enhance asset performance. These common methodologies enable:

- Real-time Monitoring & Data Analytics: Continuous tracking of operational parameters to detect anomalies early (Moutis and Alizadeh-Mousavi, 2021; Zhang et al., 2024).
- AI-based Predictive Maintenance: Machine learning models forecast equipment failures, allowing proactive interventions (Zhang et al., 2020; Abdullahi et al., 2025).
- Optimization of Energy Efficiency: DTs optimize asset operations to reduce energy consumption and carbon footprints (Energy; Custeau, 2017).

These foundational methodologies are customized for specific applications. For instance, the effectiveness of DTs for predictive maintenance can be measured with various performance indicators as described in the subsections below.

5) Performance indicators to evaluate the effectiveness of DTs for predictive maintenance

In the above literature, predictive maintenance has been discussed in various applications of DTs. To quantitatively assess the effectiveness of DTs for predictive maintenance, different performance indicators are used. These indicators help evaluate how well DT-driven predictive maintenance strategies optimize asset performance, reduce failures, and improve cost efficiency. The following metrics provide a comprehensive framework for analyzing DT effectiveness for predictive maintenance.

- **Remaining Useful Life (RUL):** This metric predicts how long an asset or component will function before requiring maintenance or replacement. DTs leverage AI-driven models and real-time sensor data to estimate RUL, enabling proactive maintenance scheduling and minimizing unexpected failures (Sivalingam et al., 2018).
- **Failure Detection Rate (FDR):** This measures the accuracy of DT-based predictive models in identifying faults before they occur. A higher FDR indicates better failure prediction, reducing downtime and repair costs (Wang et al., 2022).
- **Mean Time Between Failures (MTBF):** This metric assesses asset reliability by measuring the average operational time between failures. DTs improve MTBF by enabling real-time condition monitoring and predictive diagnostics (Liu et al., 2025// 2025:).
- **Downtime Reduction (%):** This quantifies the impact of DT-driven predictive maintenance in minimizing unplanned outages. Studies show that DT-enabled maintenance can reduce downtime by up to 40 %, significantly improving asset availability (Siemens. , 2021).
- **Maintenance Cost Reduction (%):** By preventing failures before they occur, DTs reduce maintenance expenses. Real-world implementations have shown a 20–30 % decrease in maintenance costs using DT-driven predictive analytics (Energy, 2020).
- **Prediction Accuracy (%):** This measures how precisely DTs forecast failures based on historical and real-time data. AI-enhanced DT

models have demonstrated prediction accuracies of over 90 %, improving fault detection reliability (Al-Isawi et al., 2023).

- **Energy Efficiency Gains (%):** DTs optimize asset operations, leading to better energy efficiency. Research indicates that AI-powered DTs can improve energy utilization by 15–25 %, reducing carbon footprints and operational costs (Zhang and Wang, 2021; Ren et al., 2024).

4.4. Enhancing sustainability and efficiency with DTs

DT technology is revolutionizing energy production, distribution, and consumption by improving efficiency, optimizing resource utilization, and enhancing sustainability. DTs enable real-time monitoring, predictive maintenance, and operational optimization, significantly reducing energy waste and minimizing carbon footprints (Sharma et al., 2024). In wind farms, DT-based platforms such as GE's WindSCADA and Predix have achieved a 16 % production increase and a 33 % reduction in megawatt-hour losses, leading to improved energy efficiency and reduced operational costs (Energy, 2020). Similarly, in solar power plants, GE's digital analytics system and Pratiti Technologies' Apollo DT have enhanced energy yield, resulting in a 40 % reduction in production losses, a 30 % increase in plant productivity, and a 20 % decrease in operation and maintenance expenses (Energy, 2020; Apollo – Performance Intelligence & Health Analytics accelerator). In power transmission and distribution, Siemens' DT system for the Basslink transmission line has optimized thermal stress management in transformers, reducing failures, extending asset lifespan, and improving grid resilience (Energy).

Academic research further highlights the importance of DTs in enabling microgrid and smart grid resilience, enhancing load forecasting, real-time grid balancing, and distributed energy resource management. DTs have enabled utilities to create digital replicas of power grids in power distribution and transmission, allowing for efficient load balancing, outage prediction, and grid optimization. Siemens' single digital grid model for Finland has enhanced safety, reliability, and resource efficiency by automating grid simulations. Additionally, DT-driven microgrids support real-time forecasting, demand-side management, and seamless integration of distributed energy resources (DERs), further improving grid stability and energy efficiency. In urban energy management, DTs are deployed in smart buildings for energy optimization and climate resilience, ensuring optimal heating, cooling, and ventilation strategies while minimizing energy waste. As energy systems shift towards sustainability, DTs serve as a key enabler for low-carbon transitions, helping utilities, industries, and urban planners design more resilient and energy-efficient infrastructures while meeting global sustainability goals (Sharma et al., 2024; Cali, et al., 2023). These advancements underscore the critical role of DTs in supporting the transition to a low-carbon, energy-efficient future, aligning with global sustainability goals while driving economic and operational benefits for the energy sector.

4.5. Standardization and frameworks for DTs in the energy sector

The successful deployment of DTs in the energy industry depends on standardized frameworks to ensure interoperability, security, and scalability. International organizations have established guidelines and standards to facilitate DT integration across energy infrastructure. The ISO 23247 framework provides a structured approach for implementing DTs in manufacturing, offering a foundational model applicable to energy asset management (Iso, 2021). Additionally, the IEEE P2806 standard defines a DT reference architecture for smart grids, enabling seamless interaction between virtual models and physical energy systems (EEE Standards Association, 2023).

Cybersecurity remains a critical concern in DT adoption, particularly given the large-scale deployment of IoT-enabled sensors and cloud-based platforms. The IEC 62443 standard for industrial cybersecurity offers a robust framework for protecting DT-enabled energy systems from cyber threats, particularly in critical infrastructure like power grids and renewable energy plants (International Electrotechnical Commission (IEC), 2022). Similarly, the ISO/IEC 27,001 standard ensures the integrity and security of DT data by outlining best practices for information security management systems (Iso, iec., 2022). The NIST Cybersecurity Framework further provides a risk-based approach to securing DT applications in energy asset management, offering guidelines for identifying, protecting, detecting, responding to, and recovering from cyber incidents (NIST., 2023).

Interoperability challenges in DT implementation are also being addressed through the Digital Twin Consortium (DTC), which aims to establish common standards and best practices for cross-industry DT applications, including energy systems (Digital Twin Consortium (DTC), 2023). Moreover, industry-specific initiatives such as Siemens' Digital Enterprise Framework and General Electric's Predix Platform have developed proprietary DT frameworks that align with international standards to facilitate integration across different energy assets (Digital, 2023).

By leveraging these standards and frameworks, DT solutions in the energy sector can achieve greater scalability, enhanced security, and improved decision-making capabilities. However, future research should focus on harmonizing these standards to support seamless data exchange and model synchronization across diverse DT platforms.

5. Limitations, challenges, and future work directions for DTs in SAM

In response to RQ4, this section synthesizes the key insights derived from the review in response to RQs 1–3 and outlines study limitations, challenges, and areas for future exploration. The study's limitations and challenges associated with the wider implementation of DT technology in SAM, including data integration issues, cybersecurity risks, and the need for scalable and interoperable solutions, are discussed. Further, the major avenues for future research are discussed based on the review of published work aimed at overcoming these barriers, emphasizing the importance of adaptive learning models, standardized frameworks, and enhanced data security measures for the successful deployment of DTs in the energy sector.

5.1. Limitations

While this review provides a comprehensive analysis of DT applications for SAM in the energy industry, certain limitations must be acknowledged. Firstly, most existing studies focus on DT implementations for wind farms, solar power plants, and transformers, leaving gaps in exploring their applications for other critical energy assets such as energy storage systems and microgrids. Secondly, the scalability and interoperability of DT solutions remain challenging, as most case studies are limited to specific proprietary frameworks without standardized integration across diverse energy infrastructures (Ismail et al., 2024).

A significant limitation in current DT implementations is data quality and reliability. The effectiveness of a DT depends on the accuracy, completeness, and consistency of real-time sensor data. However, sensor malfunctions, data transmission errors, and missing data points often lead to inaccurate predictive insights and suboptimal asset management decisions. Furthermore, heterogeneous data sources, including legacy monitoring systems and modern IoT sensors, can result in inconsistencies in data format, frequency, and reliability, making real-time synchronization with the DT model challenging. Addressing these issues requires robust data validation mechanisms, redundancy strategies, and AI-driven data cleaning techniques to ensure DTs maintain high data integrity (Rathore et al., 2021; Murgod et al., 2023).

Another limitation is the computational complexity and scalability of DT models. As DTs integrate real-time data from thousands of distributed assets across power grids, wind farms, and substations, their computational workload increases exponentially. Many existing DT models operate effectively at a small scale or within controlled experimental environments but struggle when extended to large-scale, multi-asset industrial applications. High-performance computing (HPC), distributed cloud architectures, and edge computing solutions are essential to enhance the scalability and responsiveness of DTs in large-scale energy systems (Rajora et al., 2024; Sinsel et al., 2020).

Furthermore, real-time data processing and cybersecurity concerns continue to pose significant barriers to large-scale DT deployment. By addressing these limitations, prospective researchers can drive further advancements in the field and contribute to the seamless integration of DTs in energy systems. It can be achieved by exploring the development of universally compatible DT models, enhanced data security measures, and the application of emerging technologies such as federated learning and blockchain to ensure robust and resilient DT implementations (Liu et al., 2024).

5.2. DT deployment challenges for asset management in the energy industry

While DT technology has demonstrated its potential for predictive maintenance, asset monitoring, and optimization, its practical implementation in real-world energy applications presents several technical and operational challenges that must be addressed for widespread adoption.

1) Data latency and real-time processing issues

One of the major challenges in DT implementation is the issue of data latency, which affects the real-time responsiveness of DT-driven asset management systems. Since DTs rely on massive volumes of real-time sensor data, any network delays or processing bottlenecks can hinder their ability to instantly predict faults and optimize operations. In large-scale renewable energy farms or smart grid applications, latency can reduce the effectiveness of automated control systems and delay critical maintenance decisions (Mchirgui et al., 2024).

To mitigate data latency, energy industries are exploring the integration of edge computing and 5G networks with DT infrastructure. Edge computing enables real-time data processing at the source (i.e., wind farms, substations, or power plants) rather than relying on centralized cloud servers, significantly reducing latency issues. Additionally, 5 G-enabled DT models provide ultra-low latency and high-speed data transfer to ensure that AI-driven fault detection and decision-making occur in real-time (Mertes et al., 2022).

2) Challenges in DT model updating and adaptability

Another significant limitation of DT technology is the difficulty in updating DT models dynamically to reflect the real-world changes in asset conditions, environmental factors, and operational parameters. Many existing DTs are developed based on static historical data models, making it difficult for them to adapt to evolving system behaviors, new equipment installations, and software upgrades. A key element of a complete DT framework is the integration of real-time feedback loops that allow continuous synchronization between physical assets and their virtual counterparts. These feedback loops enable DTs to self-correct deviations, refine predictive models, and optimize decision-making based on changing operational conditions. Without a structured mechanism for continuous updates, a DT risks becoming obsolete, reducing its effectiveness in long-term asset optimization (Rathore et al., 2021; Murgod et al., 2023).

The adoption of adaptive learning frameworks using federated learning (FL) and self-learning AI models can significantly enhance DT adaptability. Federated learning allows DT models to train collaboratively across multiple distributed energy assets without requiring centralized data aggregation, preserving data privacy while enabling continuous learning. Unlike traditional centralized AI models, FL ensures that local DT instances on wind turbines, transformers, or solar panels refine their predictive capabilities independently while periodically sharing updates with a global model (Liu et al., 2024). This decentralized approach minimizes data transfer bottlenecks, enhances cybersecurity by keeping sensitive operational data on-premises, and improves adaptability to localized environmental conditions (Alcaraz and Lopez, 2022).

Additionally, decentralized DT architectures, such as blockchain-integrated DTs and fog computing-based DT infrastructures, are emerging as solutions for secure, real-time model updates. Fog computing facilitates real-time processing at the edge, allowing DTs deployed at wind farms, substations, or power plants to preprocess sensor data locally before transmitting insights to centralized or cloud-based systems. This reduces network latency, improves resilience, and enhances fault detection efficiency in geographically dispersed energy assets. Furthermore, the use of blockchain-enabled DT architectures ensures tamper-proof, decentralized record-keeping, securing asset condition updates, maintenance logs, and operational decisions from cyber threats or data manipulation (Abdullahi et al., 2025; Liu et al., 2024).

However, a major challenge in DT model updating is ensuring data quality. Inconsistent, incomplete, or outdated sensor data can lead to inaccurate model predictions, reducing the reliability of DT-driven decisions. Many DT implementations still struggle with integrating diverse data sources, such as IoT sensor data, historical maintenance logs, and external weather forecasts, into a unified, high-quality dataset. Without robust data validation and preprocessing mechanisms, DTs may propagate errors across digital models, leading to incorrect asset performance assessments and suboptimal maintenance decisions (Mousavi et al., 2024; Fuller et al., 2020). Future research should explore advanced data cleaning, anomaly detection techniques, and AI-driven data fusion approaches to improve DT data reliability.

Another scalability issue arises when deploying DTs across large-scale energy infrastructures. Traditional DT models, designed for single assets or localized systems, often fail to scale efficiently when applied to entire smart grids, offshore wind farms, or multi-plant operations. One approach to addressing this challenge is the adoption of modular DT architectures. These architectures decompose a DT into smaller, interoperable modules that can be individually updated, trained, and optimized. For example, a modular DT for a wind farm can feature separate models for turbine efficiency, gearbox performance, and meteorological forecasting, each of which can be updated independently. This allows energy operators to scale DT implementations efficiently while minimizing computational overhead (Ismail et al., 2024; Ullah, 2024).

Furthermore, cloud-based and decentralized DT architectures are crucial for handling large-scale deployments. Traditional DTs rely on centralized cloud processing, which introduces latency issues when handling large-scale industrial energy assets. Decentralized DTs, integrated with edge computing and blockchain, enable localized data processing at substations, wind farms, and distributed power plants, significantly reducing computational burden and improving scalability (Rathore et al., 2021; Ullah, 2024; Liu et al., 2024).

Incorporating reinforcement learning techniques within DTs can further improve decision-making by continuously learning from asset performance metrics, user interventions, and failure occurrences. This approach allows DTs to autonomously optimize operational parameters, maintenance schedules, and energy consumption patterns. Moreover, hybrid DT architectures that combine physics-based simulations with AI-driven real-time analytics offer greater flexibility in updating asset performance predictions dynamically (De Kooning et al., 2021; Liu et al., 2024).

An optimized DT must also incorporate decision automation mechanisms that provide real-time recommendations to system operators. Decision optimization techniques such as multi-objective optimization and Bayesian decision models can enhance DT-driven decision-making by balancing trade-offs between cost, risk, and efficiency. These models improve the DT's ability to make proactive decisions, ensuring that the virtual model remains aligned with the physical asset's evolving behavior. By integrating these advancements, DTs can transition from being passive digital replicas to actively supporting strategic asset management and predictive control (De Kooning et al., 2021; Es-haghi et al., 2024).

3) Interoperability and standardization issues

The lack of uniform DT standards across different industries and energy sectors creates difficulties in integrating DT solutions from multiple vendors. This limits cross-platform compatibility and prevents seamless data exchange between different energy management systems. Efforts are being made to develop global DT interoperability standards, such as ISO 23247 (Digital Twin Framework for Manufacturing) (Iso, 2021) and IEEE P2806 (DT Standardization for Smart Grids) (EEE Standards Association, 2023). The adoption of open-source DT architectures and blockchain-based data-sharing protocols can further enhance interoperability, allowing DT models from different vendors to communicate seamlessly (Liu et al., 2024). However, the absence of unified protocols for data storage, processing, and communication between DTs remains a challenge, particularly when scaling DTs across multiple infrastructures.

4) Organizational and stakeholder integration challenges

Despite the clear advantages, certain utilities and grid operators have not yet adopted a DT model for AM and the improvement of businesses and operations. A DT should be capable of precisely capturing physical characteristics and mimicking behaviors of both basic and complex objects, as well as their relationships. Implementation becomes more challenging as it involves contributions from multiple stakeholders, including facility managers, design engineers, electrical engineers, equipment vendors, and others. Obtaining asset data from suppliers can be arduous, as it necessitates close coordination across various supply chain stages. Additionally, maintaining seamless connectivity within the supply chain to access asset data can be a challenge (Kober et al., 2024).

5) Complexity in digital twin model development

Another difficulty arises from the intricacy of duplicating the actual object. For instance, processes like customer relationship management or service delivery funnels are relatively easier to replicate as they involve a flow of situations, ideas, and software inputs without complex physical components. Developing a DT also requires comprehensive blueprints of previous systems, equipment failures, and mathematical systems. To predict failures, the DT needs information on equipment failure mechanisms. Complexity increases when changes occur in equipment configuration, assets, or operating status, as the digital model and algorithms need corresponding adjustments. Inaccurate modeling may lead to errors, particularly when representing situations such as new component installations or operational modifications (Fuller et al., 2020).

6) Financial and infrastructure investment barriers

Adopting DTs requires significant financial investment, collaboration, and continuous support from energy operators. Establishing the necessary technological infrastructure, such as reliable IoT installations, high-speed network connectivity, and scalable simulation platforms, is crucial for maintaining DT performance. Additionally, integrating data sources across various departments and IoT-based monitoring systems is an ongoing challenge that prevents many power sector stakeholders from fully implementing DT models (Attaran and Celik, 2023).

7) Policy and standardization needs for DT adoption

Several fundamental issues need to be addressed to fully leverage DT systems in the future. Encouraging early digital adoption by utilities and power system operators is crucial, considering the complexity, upfront costs, and uncertainties associated with DT implementation. Financial incentives and digital technology standards could be employed by governments and regulators to incentivize the electricity industry's transition to digital technology. Stakeholders, including businesses, governments, and universities, should enhance their research and development capabilities in digital energy technology to expedite the implementation of DT technologies. By producing compelling evidence that increases market participants' trust in digital outcomes while mitigating deployment risks, the adoption of DT technologies can be further facilitated (Mousavi et al., 2024; Fuller et al., 2020; Attaran and Celik, 2023).

5.3. Ethical considerations and cybersecurity risks in DT deployment

While DT technology offers transformative benefits for SAM in the energy industry, its implementation raises ethical concerns and cybersecurity risks that must be addressed to ensure safe, responsible, and secure deployment. The increasing reliance on real-time data, AI-driven decision-making, and cloud-based systems introduces vulnerabilities that could impact data privacy, infrastructure security, and the ethical use of DT-driven automation.

1) Ethical considerations in DT implementation

The integration of DTs with SAM in the energy sector involves the collection, processing, and analysis of vast amounts of real-time operational data, raising several ethical concerns regarding data privacy, algorithmic bias, and workforce displacement. One major issue is data privacy and ownership, as the energy industry increasingly relies on real-time sensor data, AI-driven analytics, and cloud computing (Pargmann et al., 2018). A critical question arises: Who owns the data collected by DTs? If third-party vendors manage DT infrastructures, sensitive operational data may be misused or accessed without explicit consent. Ensuring compliance with the General Data Protection Regulation (GDPR) (Karimabadi and Leal-Arcas, 2023) ISO 27001 and other data protection standards are essential for preventing unauthorized access and ensuring responsible data usage (Iso, iec., 2022).

Another ethical concern is bias and algorithmic transparency in AI-driven DT models. These models rely on historical data and machine learning algorithms, which may introduce bias in predictive maintenance and operational decision-making. If training datasets contain historical biases or incomplete data, AI-based DTs may lead to unfair prioritization of maintenance schedules, inefficient asset optimization, or imbalanced energy distribution. To prevent this, algorithmic transparency must be ensured, and AI models should undergo regular audits to maintain fairness, accountability, and reliability in decision-making (Helbing et al., 2022).

Additionally, workforce displacement poses a significant ethical challenge as automated DT-driven asset monitoring and predictive maintenance reduce reliance on manual inspections. Traditional maintenance and monitoring jobs in the energy sector may become obsolete, raising concerns about job security for skilled workers. To address this issue, energy companies should implement upskilling and reskilling programs that equip employees with the necessary expertise to manage, operate, and optimize DT-driven infrastructures. By ensuring ethical AI adoption, transparent decision-making, and responsible workforce transition strategies, the energy sector can maximize the benefits of DTs while minimizing ethical risks and workforce disruptions (Helbing et al., 2022).

2) Cybersecurity risks in DT deployment

As DTs create real-time digital replicas of critical energy infrastructure, they introduce significant cybersecurity risks that could impact operational security, data integrity, and system resilience. A compromised DT system could expose real-world assets such as power grids, wind farms, and energy storage systems to cyber threats, potentially leading to grid failures, data manipulation, or operational disruptions. Given the real-time data exchange between physical and virtual assets, DTs are particularly vulnerable to cyber-physical security threats. A malicious attack on a DT controlling a power grid could result in grid instability, blackouts, or even deliberate sabotage of energy distribution networks. To mitigate these risks, it is crucial to implement robust encryption methods, network segmentation strategies, and real-time intrusion detection mechanisms to safeguard DT infrastructures from unauthorized intrusions (Cali, et al., 2023; NIST, 2023).

Ensuring data integrity and protection against unauthorized access is another critical concern, as DT models store vast amounts of operational data. If malicious actors gain access to this data, they could alter predictive maintenance models, manipulate asset performance metrics, or inject false operational insights, leading to severe financial and operational consequences. To prevent this, organizations should implement multi-factor authentication (MFA), strict access control policies, and blockchain-based data integrity mechanisms that protect DT-generated data from unauthorized alterations (Liu et al., 2024).

Furthermore, regulatory and compliance challenges must be addressed to align DT cybersecurity measures with existing industry standards. The energy sector must ensure compliance with frameworks such as the NIST Cybersecurity Framework (for critical infrastructure protection), ISO/IEC 27,001 (for information security management) (Iso, iec., 2022), IEC 62443 (for industrial cybersecurity standards in energy applications) (International Electrotechnical Commission (IEC), 2022), and GDPR (for data privacy compliance in smart grids and SAM applications) (Karimabadi and Leal-Arcas, 2023). Establishing legal accountability and cybersecurity compliance protocols will help reduce data breach risks and cyber exploitation, ensuring that DTs operate securely and efficiently within the energy industry.

3) Strategies for ethical and secure DT implementation

To mitigate ethical risks and cybersecurity vulnerabilities in DT deployment, several key approaches should be implemented. Transparent and explainable AI models is essential to ensure that AI-driven DTs remain auditable, bias-free, and accountable in SAM applications. This involves integrating explainable AI (XAI) frameworks that provide clear reasoning for predictive maintenance and decision-making processes. Additionally, strengthening cybersecurity infrastructure is crucial to safeguarding operational data from cyber threats (Cali, et al., 2023). DTs should incorporate advanced encryption mechanisms, blockchain-based security frameworks, and real-time intrusion detection systems to prevent unauthorized access and data manipulation (Liu et al., 2024). Furthermore, ensuring ethical data governance plays a vital role in protecting sensitive asset information. Establishing clear data ownership policies, privacy safeguards, and responsible data-sharing protocols will help prevent misuse and unauthorized exploitation of operational data (Karimabadi and Leal-Arcas, 2023). Lastly, developing cyber-resilience plans is necessary to enhance the security and continuity of DT operations. Energy operators should implement redundant security measures, emergency response protocols, and backup digital models to ensure that DT systems remain functional even in the event of a cyberattack (Es-haghi et al., 2024). By adopting these measures, organizations can effectively address ethical concerns and reinforce the security of DT implementations in the energy sector.

5.4. Directions for future work

In the existing literature, researchers have primarily focused on modeling onshore WTs and their corresponding environments. However, it's important to acknowledge that the environment can differ significantly between onshore and offshore wind energy contexts. Hence, it is recommended that future research explore the offshore environment as well. Furthermore, among researchers who have engaged with OSWTs modeling, attention has been directed toward subsystems rather than the overall turbine, possibly to mitigate the complexities associated with the complete wind turbine system. In the coming years, an area of potential exploration could involve the development of a system-level DT framework that could leverage a combination of virtual-real modeling alongside real-time data updates and monitoring. Such a system-level framework could have the potential to facilitate real-time monitoring, fault analysis, and operational optimization for OSWT support structures (Wang et al., 2021).

The literature introduces the concept of a multi-level hierarchical virtual replica and a high-level DT architecture (De Kooning et al., 2021). The objective here is to construct a DT of the physical wind turbine and its energy conversion process, addressing challenges related to fidelity, reliability, and robustness. Addressing these challenges in future research would require a focus on potential modeling techniques, model fidelity, and computational load. In (Zhao et al., 2023), the author proposes a component-based reduced-order modeling (ROM) technique for creating a DT of a parameter-varying OSWT system. The ROM-based DT exhibits a smaller size and shorter prediction time while maintaining good accuracy when compared to conventional DTs based on high-fidelity finite element analysis (FEA) models. This ROM-based DT proves valuable when real-time prediction is essential, enabling operators to quickly assess the structural health of a turbine. However, it's important to note that the performance evaluation of ROM-based DTs has primarily centered on steady simulations, leaving the assessment of their performance in dynamic simulations unclear. Therefore, for the widespread adoption of ROM-based DT models, it becomes crucial to thoroughly evaluate their performance under dynamic simulations, making it an intriguing avenue for future research exploration (Chakraborty et al., 2021).

Moreover, the literature introduces the concept of fog computing as a decentralized architecture for implementing intelligent DTs to enhance the performance and AM of WTs, thereby achieving more efficient operation (Abdullahi et al., 2022). According to this proposed concept, sensor data is preprocessed at the fog nodes before being transmitted to the global DT in the cloud for deeper insights. Further studies are needed to validate the effectiveness of this concept in improving asset performance. Furthermore, the current literature presents a DT-driven sensing methodology aimed at detecting faulty sensors to enhance the safe operation of WTs (Li and Shen, 2022). In the realm of WF monitoring and analysis, most control stations rely solely on technical information obtained through sensors, neglecting business-related information. This lack of integration can lead to unjust decisions, particularly concerning certain smart asset owners, posing a significant challenge. To tackle this issue, a framework is proposed to integrate both technical and business data into a single DT, which is realized using augmented reality (Pargmann et al., 2018). The developed big data processing approach, based on cloud technologies, was applied to various WFs across different countries worldwide to demonstrate the efficacy of the proposed technique. The researchers successfully monitored and operated all WFs concurrently. To facilitate the broader adoption of the proposed framework, further research studies in this direction are necessary.

The current literature concerning SPPs primarily concentrates on employing DT technology for monitoring and controlling PV systems, with less emphasis on applying DT to large-scale distributed PV generation systems. In the coming years, research studies are needed to demonstrate the effectiveness of DT-based techniques in ensuring the stable operation of power grids with significant PV penetration within distribution systems. Additionally, many of the DT-based strategies proposed in current literature heavily rely on current and historical data, without considering potential future data changes. Hence, a promising avenue for future research involves developing DT-based strategies capable of integrating future conditions for tasks such as PV power prediction, fault diagnosis, and predictive maintenance. This approach has the potential to enhance the applicability and accuracy of DT-based methodologies.

1) Practical implementation challenges and mitigation strategies

While the benefits of DTs in SAM are substantial, several practical challenges hinder their full deployment. A primary issue is data latency, especially when high-frequency sensor data must be transmitted across distributed systems or remote assets. This latency affects the responsiveness and accuracy of real-time decision-making. Mitigation strategies include leveraging edge computing to perform localized data processing, reducing transmission delays, and enabling faster diagnostics. Another major barrier is the difficulty of updating models in real time, particularly for hybrid DTs that integrate physics-based and data-driven components. Model drift and data drift are common in dynamic energy systems, where operating conditions vary. To address this, online learning algorithms and self-updating neural architectures have been proposed to continually adapt model parameters based on streaming data (De Kooning et al., 2021; Walters and Venayagamoorthy,

Table 4
Summary of key findings and challenges in DT implementation for SAM.

Key Findings	Challenges
DTs enhance SAM in the energy industry by enabling predictive maintenance, real-time monitoring, and performance optimization.	Data latency and real-time processing issues limit the ability of DTs to provide instantaneous fault detection and optimization.
AI-driven DTs improve efficiency in wind farms, solar power plants, and transformers by integrating advanced analytics and big data processing.	Interoperability challenges arise due to the lack of standardized DT models across energy sectors.
DTs enable cost savings through reduced operational expenses, improved efficiency, and enhanced asset longevity.	Cybersecurity risks in DTs, such as data breaches and cyber-physical threats, require robust encryption and network security measures.
AI and machine learning enhance DT adaptability for dynamic operational changes.	High initial investment costs and infrastructure challenges hinder large-scale DT adoption.
DTs provide a scalable solution for managing complex energy infrastructure and optimizing grid performance.	Ethical concerns related to data privacy, AI transparency, and workforce displacement must be addressed through policy frameworks.

2024).

Additionally, cybersecurity risks arise due to the increased attack surface introduced by interconnected DT components. Implementing zero-trust architectures, secure bootstrapping, and federated learning can reduce data exposure and improve resilience. Finally, interoperability remains a challenge, especially when integrating DTs across heterogeneous platforms and legacy systems. Establishing standardized data ontologies and open APIs is critical for ensuring seamless integration, scalability, and long-term maintenance. These technical, infrastructural, and security-related challenges must be addressed to enable broader deployment of DTs across complex energy systems (Cali, et al., 2023; Liu et al., 2024).

6. Conclusion

The energy industry has witnessed a notable upsurge in the research and application of DTs for SAM. This trend is evident through the adoption of DTs by prominent asset-intensive industrial leaders operating in the SAM domain. Furthermore, a significant number of new articles and patents have been published in recent years, underscoring the growing interest in this field. In this paper, we aim to provide a comprehensive review of state-of-the-art DT research and applications by analyzing the outcomes of renowned asset-intensive industries worldwide. This review encompasses four patents and 45 previous publications, consolidating existing knowledge in the field.

The following conclusions can be drawn from the review:

1. We outlined the significance of DTs to visualize and implement the energy industry revolution. Further, we provided an overview of the current development of DTs in the context of the energy industry.
2. Our review focused on the present applications of DTs in the energy industry, specifically in the realm of SAM. Based on our analysis, we concluded that DTs are predominantly popular in asset-intensive energy sectors such as WFs, SPPs, and transformers. The fundamental element of DTs lies in their modeling capabilities, while the significant challenge lies in cyber-physical fusion.
3. We identified the deployment challenges faced in AM within the energy industry and highlighted key areas for future research in the DT-based SAM domain, drawing insights from existing literature.

Despite the substantial growth of DTs, this concept continues to evolve, necessitating the resolution of various critical issues to enhance its practical viability. One significant challenge lies in the development of a unified DT modeling method, which holds paramount importance in ensuring consistent and effective implementation. As the energy sector transitions toward digital transformation, collaborative research efforts between academia, industry, and regulatory bodies are crucial to establishing standardized DT models. Developing universally accepted DT protocols and fostering cross-industry partnerships will accelerate the deployment of scalable, interoperable DT solutions. Governments and standardization organizations, such as the IEEE and ISO, must take an active role in formulating guidelines for DT implementation, ensuring compliance with cybersecurity, data privacy, and interoperability requirements (Zhang et al., 2024).

Additionally, future DT research must prioritize the integration of adaptive learning models, parallel implementation for model predictive control, and decision optimization techniques to enhance real-time responsiveness and predictive accuracy (Abughalieh and Alawneh, 2019). Ensuring that DTs continuously evolve through structured feedback mechanisms will improve their ability to support complex asset management decisions. Industry stakeholders should work towards establishing global benchmarking metrics to evaluate DT performance, enabling data-driven comparisons and best practice recommendations. Table 4 below summarizes the key findings and challenges in DT implementation for SAM.

A concerted effort is required from policymakers, researchers, and industry leaders to facilitate the widespread adoption of DTs in the energy sector. Investing in DT education and workforce training programs will also be essential in preparing professionals for the AI-driven asset management landscape (Zhang et al., 2024). By fostering innovation, enhancing regulatory frameworks, and promoting interdisciplinary collaboration, DTs can achieve their full potential in transforming the future of SAM in Energy 4.0. Considering these challenges, our paper aims to serve as a valuable resource for researchers, guiding future directions for DT research and application in the energy industry.

CRediT authorship contribution statement

U. Amin: Conceptualization, Methodology, Writing – original draft, Supervision. **D. Kim:** Conceptualization, Writing – original draft. **F.N. Ahmed:** Writing – original draft. **G. Ahmad:** Writing – review & editing. **M.J. Hossain:** Writing – review & editing.

Declaration of competing interest

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

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