IEEE Access
Multidisciplinary ⁝ Rapid Review ⁝ Open Access Journal

Received 21 October 2024, accepted 19 November 2024, date of publication 26 November 2024, date of current version 4 December 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3506660

SURVEY

Digital Twins for IoT-Driven Energy Systems: A Survey

MD RAFIUL KABIR[1], DIPAL HALDER[2], (Graduate Student Member, IEEE), AND SANDIP RAY[2], (Senior Member, IEEE)
[1]School of Engineering and Technology, Central Michigan University, Mount Pleasant, MI 48859, USA
[2]Department of Electrical and Computer Engineering, University of Florida, Gainesville, FL 32611, USA

Corresponding author: Md Rafiul Kabir (kabir2m@cmich.edu)

ABSTRACT As energy systems become more complex, the need for innovative technologies to manage and optimize their performance is critical. The integration of Digital Twin (DT) technology into Internet of Things (IoT)-based energy systems offers a novel approach to improving resource management, sustainability, and operational efficiency. While existing studies have explored various aspects of DTs in energy systems, this paper focuses on the specific convergence of DTs and IoT infrastructure in emerging smart energy systems, emphasizing their role in optimizing energy efficiency, production, consumption, and storage. Through a comprehensive review of recent literature, we analyze the distinctive applications of DTs in areas such as real-time energy monitoring, predictive maintenance, and enhanced grid management. Additionally, this paper distinguishes itself by examining the current research trends, key technological advancements, and the unique challenges associated with deploying DTs in IoT-driven energy ecosystems. Our review provides a thorough understanding of how DT technology can transform smart energy systems and offers insights into future research directions.

INDEX TERMS Digital twin, Internet of Things, energy, smart grid.

I. INTRODUCTION

The global energy sector has been moving toward a more digitalized and interconnected future in recent times because of the advancement of technologies like the Internet of Things, cloud computing, and machine learning/artificial intelligence [1]. In the evolving landscape of energy systems, digital twin technology has emerged as a pivotal innovation, enabling optimization, efficiency, and resilience. Digital Twins are defined as virtual prototypes that simulate, emulate, mirror, or ''twin'' the life of a physical entity, which can be an object or process [2]. The adoption of this technology in smart energy systems has been driven by its capacity to address complex challenges such as demand forecasting, asset management, and the integration of renewable energy sources, ultimately contributing to the sustainability and reliability of energy infrastructures [3]. Significantly, the implementation of digital twins has been identified as a catalyst for enhancing operational performance, extending asset lifespans, and ensuring compliance with stringent environmental standards. These virtual models serve not only to validate and monitor real-time functions but also to simulate and optimize processes before physical implementation, thereby reducing the need for costly prototypes and expediting development cycles.

The rapid growth in digital twins, with an expected market increase of 42.7% between 2021 and 2028, highlights their key role in transitioning energy systems to be more agile, resilient, and sustainable [4]. To achieve this transformation, IoT technology is crucial for making energy infrastructures smarter and more automated. IoT facilitates real-time monitoring and control of energy resources, enabling the dynamic optimization of energy production, distribution, and consumption. By embedding sensors and smart devices throughout the energy network, IoT allows for the seamless collection of data on energy usage patterns, system performance, and environmental conditions. This data-driven intelligence supports the development of smart grids that

The associate editor coordinating the review of this manuscript and approving it for publication was Alessandro Pozzebon.

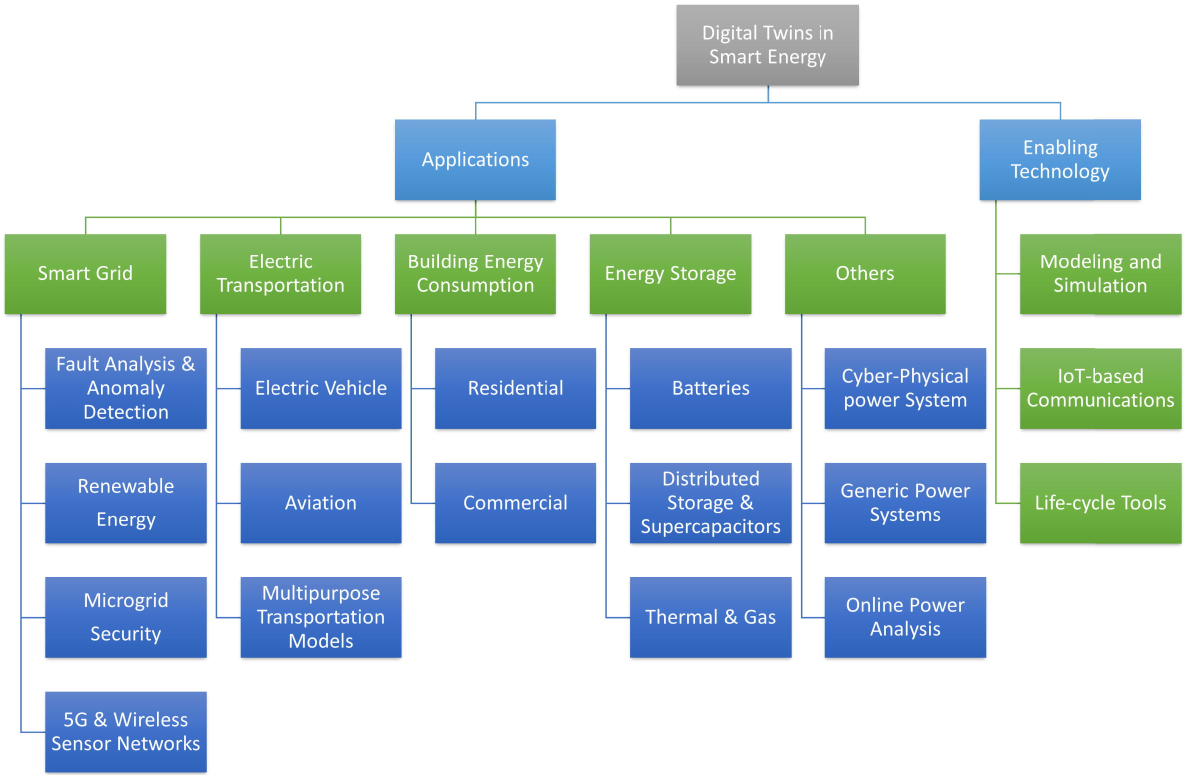

FIGURE 1. **A taxonomy of digital twins in smart energy systems.**

can automatically balance supply and demand, integrate renewable energy sources more effectively, and enhance the reliability and resilience of energy systems. Furthermore, IoT applications empower consumers with detailed insights into their energy consumption, fostering energy-saving behaviors and contributing to the overall reduction of carbon footprints.

In the framework of IoT-driven energy systems, this paper provides a thorough analysis of digital twin technology, evaluating its impact, challenges, and prospects for advancement. Several studies have focused on generic energy systems or specific sections of the energy infrastructure. However, our study specifically focused on the applications of DTs solely within the energy infrastructure that is enhanced with IoT technology. We will explore the practical applications of digital twins in this specialized field by reviewing a variety of studies, with a particular emphasis on innovative approaches and advanced tools that are shaping the future of sustainability and energy optimization. Since this is primarily a survey, we do not delve deeply into the technical architectures, models, or optimization tools of specific DTs. Given the breadth of research in this area, covering all technical models in detail would be challenging. We showcase the creative approaches and fixes that IoT-driven systems provide to improve energy conservation and management through this particular lens. Figure 1 presents a taxonomy of digital twins in smart energy systems discussed in this paper. While it does not directly address specific energy generation sources, it is important to note that digital twins can be employed across a variety of energy sources — renewable and non-renewable — to enhance system efficiency, reliability, and integration into the energy mix. Their role in balancing and optimizing the energy mix is critical, particularly in facilitating the transition to a more sustainable energy landscape by improving the performance of both renewable energy sources and conventional power generation. While the diagrams throughout the paper share a common theme, i.e., demonstrating how digital twins can be applied across various domains — the aim is to highlight the diversity of applications enabled by it. The recurring theme across the diagrams emphasizes that, despite the varied applications, the technology consistently enhances system performance across different fields.

The rest of the paper is organized as follows. In, Section II, we discuss the conceptual background including various concepts and classifications of digital twins. Section III discusses various applications of digital twin methods in the IoT-based energy industry. Section IV presents an overview of enabling technology for DTs for the energy sector. In Section IV, we discuss the current trends of DT usage, publications, challenges, and future roadmap. We conclude in Section VI.

II. BACKGROUND

A. DIGITAL TWIN DEFINITIONS

Digital Twin technology was originally conceptualized as the Mirrored Space Model by Grieves and Vickers [5] and later specified by NASA in 2011 [6] for spacecraft health maintenance. It is defined as a virtual model that mirrors a physical entity, utilizing data to replicate and predict the physical entity's behavior within its real environment. This technology has seen widespread application beyond aerospace, extending into manufacturing, design, production process optimization, and smart cities, thanks to the advent of industrial IoT [7]. DTs can be seen from three different perspectives: the first sees it as a virtual mirror of a physical object or process, omitting automated data or simulation aspects. The second views it primarily as a simulation, focusing on automated data and predictive models, where data flow from the physical to the virtual is one-way [8]. The third definition integrates both the physical object and its virtual counterpart, constantly adapting based on their interaction.

Several studies have coined the term "Energy Digital Twin" (EDT) [9], [10] — defined as a digital representation that mimics the behavior and performance of physical energy systems. Therefore, in the context of energy systems, an EDT can represent a range from a single wind turbine to an entire power grid, incorporating renewable energy sources, power plants, transmission lines, and distribution networks.

B. DIGITAL TWIN CLASSIFICATIONS

Digital Twin technology represents a complex, integrated simulation approach that mirrors multi-physical, multi-scale, probabilistic aspects of product systems. This classification highlights the multifaceted, multidisciplinary nature of DTs, emphasizing their role across different stages and applications tailored to specific needs. Within this framework, several researchers have classified DTs based on their functionality, i.e., as tools for simulation, facilitating virtual-real connectivity, building models, and processing data. Notably, Kritzinger et al. [11] made a distinction between digital models, digital shadows, and digital twins, each representing different levels of interaction between the physical and digital states. Digital models operate independently of their physical counterparts, digital shadows reflect changes in the physical object without affecting it, and digital twins offer a bidirectional interaction, where changes in one domain directly impact the other. This classification underscores the versatility of DTs in modeling and simulation, enhancing our expertise in managing complex systems across various domains.

DTs can be classified into several types based on their application and complexity. These classifications include Product Twins, which simulate products to predict performance; Process Twins, focused on optimizing manufacturing or operational processes; and System Twins, which model entire ecosystems or infrastructures [12]. Each type serves a distinct purpose, from improving product design and testing to enhancing system-wide operations and decision-making processes. This stratification allows for tailored solutions addressing specific challenges within various industries, from manufacturing to smart cities, enhancing efficiency, reliability, and innovation.

C. IoT-DRIVEN ENERGY

The term "IoT-driven energy system" refers to the integration of the Internet of Things technology into the management and operation of energy systems. IoT enables a network of interconnected devices to collect, exchange, and process data without the need for human-to-computer or human-to-human interaction. When applied to energy systems, IoT technology facilitates the monitoring, control, and optimization of energy production, distribution, and consumption in a more efficient, reliable, and sustainable manner. Here is a discussion of its meaning and implications:

- Monitoring and Data Collection: IoT devices, such as smart meters and sensors, collect data on energy usage, environmental conditions, and system performance in real-time [13]. This data is crucial for understanding patterns, identifying inefficiencies, and making informed decisions.
- Control and Automation: Through IoT, energy systems can automatically adjust based on the data received. For instance, temperature settings on smart thermostats can be changed in response to occupancy and the climate, and smart grids can balance supply and demand across the network.
- Optimization: IoT-driven energy systems can analyze data from various sources to optimize energy consumption and reduce waste. For instance, by predicting peak demand times, an IoT-enabled system can store energy during off-peak times and release it during peak times, thereby enhancing energy efficiency.
- Integration of Renewable Energy: IoT is essential in more efficiently incorporating renewable energy sources, like solar and wind, into the current power grid. It allows for real-time monitoring and control of energy production, enabling a more seamless shift towards cleaner energy solutions. [14].
- Enhanced Reliability and Maintenance: With IoT, energy systems can predict and identify potential issues before they cause system failures. Predictive maintenance minimizes downtime and extends the lifespan of equipment by scheduling maintenance based on actual needs rather than fixed intervals.
- User Engagement and Demand Response: IoT-driven systems can engage consumers by providing them with detailed energy usage data, enabling them to make more informed decisions about their consumption. Additionally, demand response programs can be implemented more effectively, where consumers are motivated to reduce or shift their energy use during peak times [15].

In summary, IoT is revolutionizing existing energy systems, transforming them into smarter, more secure infrastructures. This transformation has inspired us to concentrate exclusively on the DTs of smart energy systems, analyzing both their current applications and future research directions, as well as their potential impacts.

D. RELATED SURVEYS AND REVIEWS

Numerous reviews discuss the application of DTs across various energy systems, ranging from comprehensive overviews to those concentrating on specific aspects of energy, such as smart grids and energy storage. However, there are no existing reviews or survey papers exclusively focusing on IoT-driven systems. It is important to note that this section is not designed to comprehensively review all existing literature in the field but instead aims to provide an overview of prior research and perspectives on the topic, guiding the development of the research protocol. Consequently, some keywords that might be synonymous with the terms adopted were not considered during this exploratory phase. The absence of IoT-driven smart systems motivated our exploration in this paper. We summarize these papers in Table 1.

III. DT APPLICATION FOR SMART ENERGY SYSTEMS

We explore a range of digital applications within smart energy systems, focusing on the enhancement of smart grids, energy consumption, and storage, as well as the advancement of electric transportation and other related energy systems. This categorization facilitates a targeted analysis of each application's unique contributions to energy efficiency and sustainability, thereby streamlining the development of effective DT solutions. Indeed, some areas naturally intersect. For example, Vehicle-to-Grid (V2G) technology can be part of both smart grids and electric transportation, while energy storage can span across smart grids and building management. While we have categorized these areas separately for clarity, some overlap is inevitable due to the integrated nature of modern energy systems. Our structure aims to reflect the key aspects of each area while recognizing these interdependencies.

A. SMART GRIDS

The evolution of smart grids marks a significant leap in the utility industry's adoption of advanced technologies to enhance efficiency, reliability, security, and service quality. By leveraging innovations such as cloud computing, reinforcement learning, and big data analytics, smart grids are transforming energy networks through improved communication, automation, and connectivity [27], [28]. These grids are not only integrating both non-renewable and renewable energy sources to meet growing energy demands but also focusing on minimizing environmental impacts and promoting sustainability [29]. The drive towards smarter energy solutions underscores the critical role of communication and information technology in overcoming challenges brought on by the growing size and complexity of power management, environmental concerns, and the quest for energy independence and superior service quality [30]. This transformation represents a pivotal shift towards utilizing emerging technologies e.g., digital twins, to foster a more efficient, secure, and sustainable energy future.

TABLE 1. Summary of related surveys and reviews on DTs in energy.

Topic	Keywords	Reference
Comprehensive review	Digital twin, energy systems, Planning and operations, Literature review, Decision-making, Renewable energy, Digitalization, Energy supply, Iot, Energy demand, Energy forecasting, Energy storage, Energy optimization	Do Amaral *et al.* [10], Ghenai *et al.* [16]
Smart manufacturing and energy management	Digital Twin, Smart grid, Smart energy application, Low carbon city, Industry 4.0, Electrified transportation, Energy storage system, Barriers, Modelling, Real-time analyses, Sustainable energy, Energy engineering, Process systems engineering	Wang *et al.* [17], Lamagna *et al.* [18], Yu *et al.* [9]
Energy storage	Digital twin, Energy storage, Batteries, Optimization, Electric vehicle, Cyber-physical systems	Semeraro *et al.* [19], Vandana *et al.* [20]
Power Electronics-based energy conversion Systems	Not specified	Chen *et al.* [21]
Smart grid, smart city, and transportation	Transportation system, Digital twin, Microgrid, Machine learning, Security Physical twin, Power system	Jafari *et al.* [22]
Electric vehicle	Digital twin, IoT, Vehicle health monitoring, Battery management system, Sustainable transportation, Smart electric vehicles, Intelligent charging, Power converter	Bhatti *et al.* [23]
Power system research and development	Digital twin, Internet of things, Cyber-physical systems, Communication channel, Machine learning	Yassin *et al.* [24]
Electric grid	Not specified	Sifat *et al.* [25]
Building energy consumption	Operation, Maintenance, Digital twin, IoT system, Building Information, Modeling (BIM), Energy efficiency, Energy modeling,	Cespedes-Cubides *et al.* [26]

Smart grids exemplify the best representation of IoT-based energy applications, and to better understand their scope, we categorize these applications based on the use of digital twins. This division helps in exploring the diverse functionalities and efficiencies these systems bring to energy management and distribution. Fig. 2 provides an overview

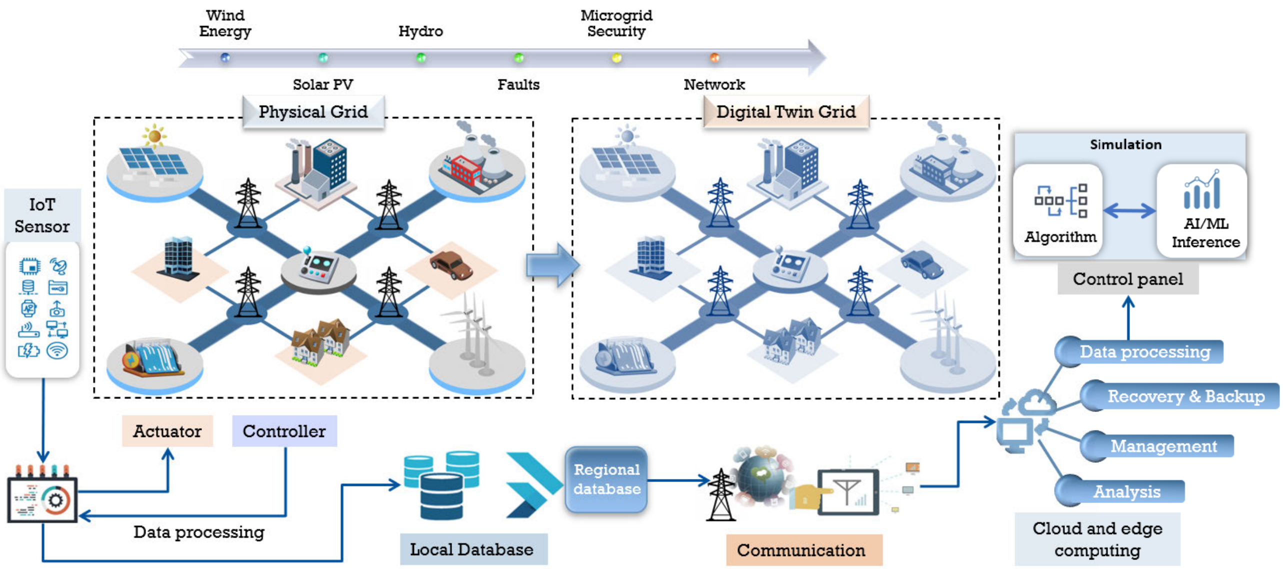

FIGURE 2. An overview of digital twin for smart grid.

of a DT for a smart grid, comprising a grid with all IoT components, and detailing energy distribution and consumption.

1) FAULT ANALYSIS AND ANOMALY DETECTION

Digital twin technology is increasingly used for fault analysis and anomaly detection in smart grids, offering a practical solution to improve grid reliability and efficiency through virtual replicas that simulate and analyze grid operations in real-time. Tzanid et al. [31] addresses the increased complexity in managing and operating power networks due to the widespread integration of high-speed power electronics and Distributed Energy Resources (DER), especially at the distribution grid edge. It introduces a CPS model for a distribution subsystem, enhanced by a low latency Industrial Internet of Things (IIoT) network and edge computing resources, including a DT represented by a hybrid model that combines a data-driven machine learning approach with a discrete-time model-based transient state estimator. Another work [32] proposes a deep learning convolutional neural network (CNN) approach within the DT environment for detecting and classifying physical faults in power systems. Highlighting the critical nature of the power grid and its evolution into a complex CPS, the method leverages high-fidelity measurement data from IEEE benchmark power systems to ensure reliability and protect infrastructure by accurately identifying fault locations. Olatunji et al. [33] highlighted the significance of DT technology for fault diagnosis and condition monitoring in wind turbines, presenting an overview of its application in identifying and managing mechanical component failures. The benefits, challenges, and necessary steps to fully harness the potential of DTs in the wind energy industry are discussed, emphasizing the need for enhanced accessibility, visibility, and availability.

In the photovoltaic domain, Jain et al. [34] developed a DT for real-time fault diagnosis in PV energy conversion units, incorporating a source-level power converter and demonstrating the detection and identification of various faults with high sensitivity. Their experimental validation showed the ability to identify faults in the power converter and sensors under 290 microseconds and faults in PV panels in less than 80 milliseconds, outperforming existing methods. Furthermore, several works [32], [35], [36] have made significant contributions to anomaly detection in the power grid using deep learning and supervised learning models.

2) RENEWABLE ENERGY

Recent applications of renewable energy in smart grids have significantly transformed the energy landscape, making power systems more sustainable, efficient, and resilient. Integrating renewable energy sources (e.g., solar and wind) into smart grids has enabled dynamic management of both supply and demand, using advanced technologies for real-time monitoring, energy storage, and predictive analytics [37]. This integration facilitates not only the optimization of renewable energy distribution based on consumption patterns but also enhances grid stability and reduces carbon emissions. Moreover, the advent of smart meters and IoT devices within these grids allows for more informed consumer choices, promoting energy savings and fostering a more environmentally friendly consumption model.

Baboli et al. [38] looks into identifying the time-varying load dynamics within the distribution grid, a complexity arising from the integration of distributed energy resources (DERs) and influenced by climate change, new consumer load patterns (e.g., electric vehicles), and renewable energy sources. Employing a combination of nonlinear numerical optimizations and system identification techniques and utilizing artificial neural networks to relate model parameters to measurement data, the study provides a novel approach to recognizing similar load dynamics without the need for extensive numerical optimization. In the case of solar PV, Jain et al. [34] introduces a DT approach for distributed PV system fault diagnostics in buildings and rooftops, focusing on real-time estimation of PV energy conversion unit outputs for detecting and identifying faults with high sensitivity. Experimental validation shows the approach's capability to detect and identify various faults in PV components swiftly, outperforming existing methods in fault sensitivity and diagnostic speed.

Fahim et al. [39] proposed a model that enhances wind farm management by using a 5G-assisted cloud-based DT framework for real-time monitoring and predictive analysis of wind speeds and power generation, showing superior performance over classical models through deep learning and K-Nearest Neighbors (K-NN) regression, based on experiments with onshore wind turbine data. Li et al. [40] introduces a DT-driven sensing methodology to address the inaccuracies and failures of wind speed sensors in wind turbines, utilizing virtual sensor arrays for fault identification and data reconstruction based on a spatiotemporal network. The methodology significantly improves sensor reliability and turbine operation safety, as demonstrated by a comprehensive analysis showing a root mean square error of 0.45 and an uncertainty of ± 0.009, outperforming baseline models in engineering applications. Demonstrated on IEEE 33-node and real-world networks, Yin et al. [41] introduced a DT framework for real-time fault identification in distribution networks with integrated distributed wind power, utilizing fully electromagnetic transient calculations and skip-connected dilated causal convolution for multi-time-scale data analysis. The framework achieves ultra-real-time, high-precision fault identification, and simulation, significantly enhancing traditional post-fault analysis by accelerating it to microsecond-level situation awareness.

In the domain of hydropower, Moussa et al. [42] developed a DT of a large hydro generator using finite element simulation to design, monitor, and conduct tests, including analysis under normal operations and at the limits of its capability curve. This case study examined a three-phase synchronous machine generator rated at 310 MVA, with 56 poles and 13.8 kV. The model was verified in accordance with IEEE Standard 115, and the damper bar currents and air gap magnetic flux density distribution in both under- and over-excitation modes were analyzed. Ebrahim et al. [43] highlighted the critical importance of digital twin (DT) technology in ensuring the optimal design and reliable operation of large generators for future renewable energy systems, while also pointing out the lack of a real strategy and thorough investigation on this concept. They explored the need for and challenges associated with DT models for large-scale renewable energy producers and developed a comprehensive modeling proposal to create a multi-domain live simulation platform for hydropower and wind farms.

3) MICROGRID SECURITY

Cai et al. [44] proposed a comprehensive energy management framework for renewable hybrid AC-DC microgrids, incorporating various renewable resources, energy storage, and PHEVs, optimized with a bat optimization algorithm to reduce operating costs for both island and grid-connected operations. It also integrates an intrusion detection system using sequential hypothesis testing to protect wireless metering infrastructures against cyber-attacks, with the framework's reliability and efficiency validated on an IEEE 33-bus hybrid microgrid model. Danilczyk et al. [32], [45] introduced a new DT framework named *ANGEL*, aimed at enhancing the security and durability of microgrids. This framework not only enables real-time data visualization of both cyber and physical layers of the microgrid but also provides capabilities for diagnosing and healing the system, thereby mitigating component failures and the impacts of cyber attacks, with its effectiveness demonstrated through a simulation on the IEEE 39-bus benchmark. Another study [46] developed an IoT-based DT that addresses a wider spectrum of attack resiliency, such as denial of service (DoS), fault injection, etc., in order to prevent microgrid cyberattacks.

A perspective article [47] explored DT applications across various stages of microgrid development, from design to operation and maintenance, highlighting four key applications, one of which is microgrid protection. They talked about the unique problems that the microgrid protection system must consider and how DTs can offer practical solutions to these problems. Atalay et al. [48] proposed a DT-based methodology to support cybersecurity in smart grids, an essential component of industrial control systems (ICS), which face increased risks from the rapid expansion of IoT. The goal of this approach is to provide a standardized framework for extensive and ongoing penetration testing across the smart grid's lifecycle, effectively modeling its physical operations to prevent disruptions during security evaluations.

4) 5G AND WIRELESS SENSOR NETWORKS

While there has been rapid advancement in the development of DTs for different aspects of the smart grid, their use in 5G and 6G networks is still relatively new [49]. However, there is no denying that DTs have a huge potential to aid in the creation and implementation of the complex 5G ecosystem. Zhou et al. [50] proposed a secure and latency-aware resource allocation approach with DT assistance, along with a federated learning-based DT framework for 5G networks, focusing on accuracy, latency, and security. It optimizes DT performance, showing superior results in reducing iteration delays and, energy consumption while ensuring secure and prioritized access. Lopez et al. [51] examined the role of AI and DTs in enhancing B5G communication networks within power grids, focusing on managing dynamic data and evolving authorization policies. Their analysis emphasizes the potential for DTss to advance fault detection and cybersecurity, aiming for autonomous, self-learning systems in smart grids. Another work by Xu et al. [52] took a different approach by integrating 5G, UAVs, Beidou Positioning, artificial intelligence, and DTs to enhance the transmission grid's efficiency and safety through intelligent inspection and monitoring. Their research demonstrates how this combination enables remote centralized controls, intelligent fault diagnosis, autonomous problem tracking, and immersive monitoring operations, significantly improving the efficiency of transmission line inspections and the overall economic performance of power grid operations.

The contribution of DTs is also noteworthy in the field of energy management for wireless sensor networks. Fu et al. [53] proposed a cascaded sensor dynamic activation and information fusion algorithm that optimizes both energy efficiency and sensing performance in wireless sensor networks. By using a combined state ranking activation and event-driven mechanism approach and improved distributed Kalman information fusion, the algorithm reduces energy consumption, minimizes sensing errors, and demonstrates superior performance with nearly zero dead nodes and a 62.1% reduction in average error in simulations. Another work by Sakhri et al. [54] proposed a DT-based energy-efficient Wireless Multimedia Sensor Network (WMSN) monitoring system for wetlands, which optimizes energy use by combining local audio identification, image compression, and real-time feedback. The integration of DT technology enhances system performance by enabling dynamic adjustments, real-time decision-making, and superior energy efficiency compared to conventional WMSN systems, as validated through real-world experiments.

B. ELECTRIC TRANSPORTATION

The transportation industry's rapid growth is leading to an ongoing energy crisis, resulting in a growing supply-demand gap. To solve this, DTs emerged by transforming electric transportation, including electric vehicles (EVs), aviation, and railways, by optimizing energy efficiency and system reliability (see Fig. 3 for an overview of DTs in electric transportation).

1) ELECTRIC VEHICLE

The integration of IoT with EVs has become the hallmark of the transportation sector, enhancing vehicle efficiency, performance, and connectivity. IoT-equipped EVs utilize real-time data analytics to optimize energy consumption and battery management, significantly extending their range and reliability. The applications of DTs in electric vehicles range from Li-ion batteries to motors and propulsion systems. We discuss energy storage devices e.g., Li-ion batteries or ultra-capacitors in Section III-D, while here we focus on other aspects of DT applications on EVs.

The growing popularity of electric vehicles and their integration into V2G-CPSs enhances flexibility and reliability

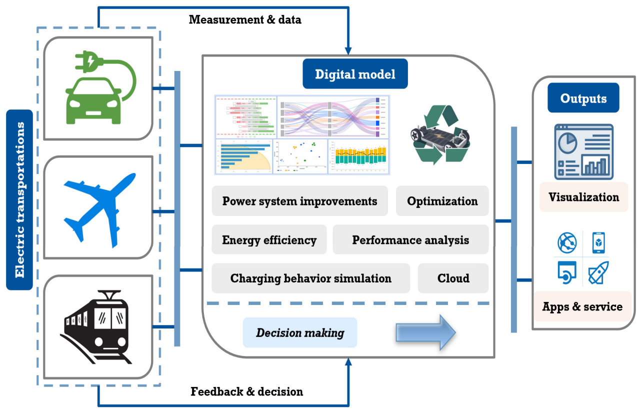

FIGURE 3. Digital twins in electric transportation.

but also raises vulnerability to cyber-physical threats, particularly coordinated cyber attacks (CCAs). To address this, Ali et al. [55] proposes a resilient framework utilizing DT technologies and LSTM-based deep reinforcement learning for effective CCA detection and mitigation, demonstrating its efficacy through case studies on an IEEE 30 bus system-based V2G-CPS with rapid response times. Another work by Rassolkin et al. [56] aims to outline the development of an unsupervised prognosis and control platform for optimizing the energy systems of autonomous electric vehicles, emphasizing the creation of DTs that integrate physical entities, their virtual counterparts, and interconnected data for comprehensive performance estimation. Zhang et al. [57] took a different approach by presenting a DT of real-world electric vehicles (EVs), simulating their mobility and charging behaviors to evaluate charging algorithms and pile arrangement policies. This simulation aids in assessing the impact of dynamic traffic patterns on charging infrastructure efficiency, guiding the optimization of charging pile deployment and utilization. Ahmadi et al. [58] introduced an approach to implement the DT concept at both the equipment and system levels of Electric Railway Power Systems (ERPSs), highlighting DT's ability to accurately represent current and future states of ERPS operations. This implementation ensures reliable and secure operations by playing a crucial role in the monitoring and control functions of the complex electric railway networks.

2) AVIATION

In aviation energy management, the advent of digital twins marks a groundbreaking shift, enabling optimization of fuel efficiency, emissions reduction, and overall sustainability through detailed virtual modeling and live data analysis. Xu et al. [59] discussed a DT-driven optimization method for 2-stroke heavy fuel aircraft engines, enabling efficient virtual simulation and optimization of manufacturing and performance. The method improved power and gas exchange performance by 4%, integrating virtual and real-world system development. A seminal work by Keller et al. [60] introduced an advanced program: "Aircraft Electrical Power

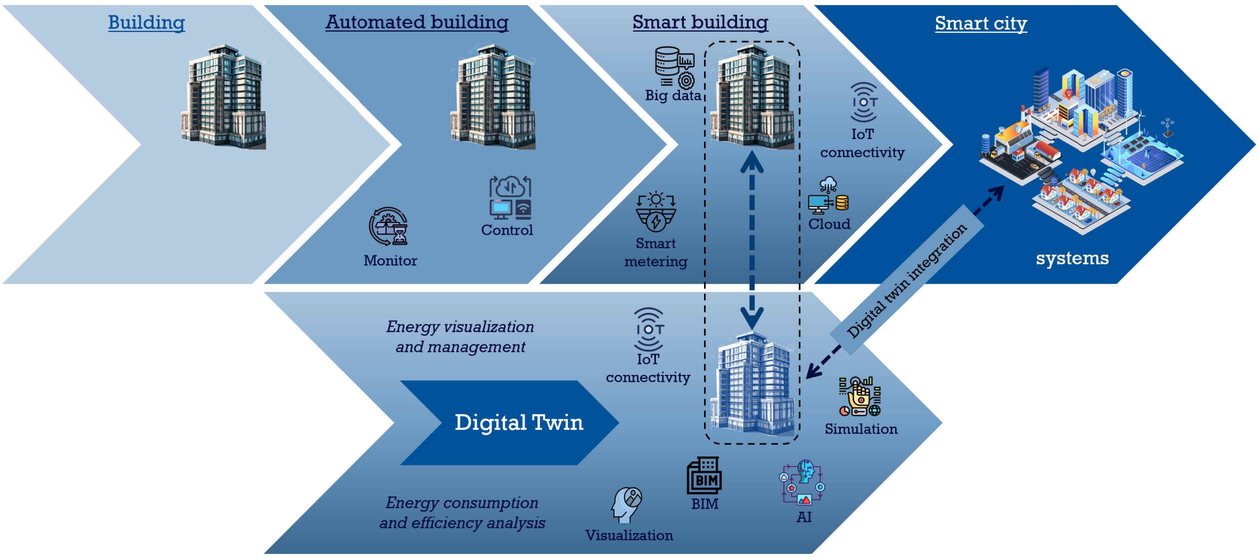

FIGURE 4. **Digital twin in building energy management.**

Systems Prognostics and Health Management (AEPHM)'', developed by Boeing, Air Force Research Laboratories, and Smiths Aerospace, focusing on diagnostics, prognostics, and decision aids for critical vehicle systems. The program, advancing through phases, leverages data from digital controllers for system health monitoring, aiming to enhance mission reliability and reduce lifecycle costs.

3) MULTIPURPOSE TRANSPORTATION MODELS

DTs play key roles by providing multi-purpose, generic models that enable real-time simulation, analysis, and optimization of various transport systems, from urban mobility solutions to global logistics networks. González et al. [61] discussed the development and application of a DT for a vertical transportation system, utilizing object-oriented modeling for adaptability to various monitoring scenarios. The study demonstrated the DT's effectiveness in estimating installation parameters and simulating corrective actions through reduced models and scaled test bench measurements. Liu et al. [62] developed a maritime transportation model using DTs and IoT technologies that enhance safety performance through relay cooperation, where interference information plays a crucial role in securing data and allowing the model to harvest energy for improved communication. This energy-efficient approach not only boosts the system's transmission and security capabilities but also demonstrates optimal performance and lower outage probability through simulation, offering a promising foundation for future intelligent and secure maritime transportation.

C. BUILDING ENERGY CONSUMPTION

Digital Twin significantly enhances the bottom line of smart building energy management by optimizing energy efficiency. Through real-time simulation and analysis of energy consumption patterns, DT identifies inefficiencies and proposes actionable insights for optimization [63]. This not only enhances the operation of individual buildings but also plays a crucial role in the transition from isolated smart buildings to interconnected smart cities. We discuss building energy management in terms of residential and commercial settings. Fig. 4 shows an overview of DT in building energy management.

1) RESIDENTIAL

Zhou et al. [64] have come up with a cutting-edge building digital twin (BDT) framework by merging computer vision with Building Information Modeling (BIM), enabling real-time synchronization between physical buildings and their digital counterparts. It focuses on dynamic object detection and positioning through video feeds, improving the accuracy and interaction between the physical and digital realms. This method shows promise in significantly reducing location errors and enhancing building model management through real-world applications.

Khajavi et al. [65] demonstrated a methodology for creating a DT of building facades using environmental sensor networks, focusing on optimizing sensor configurations for accurate real-time modeling. It emphasizes the integration of sensors to measure parameters like light, temperature, and humidity, detailing technical challenges and solutions for establishing effective DTs. The study showcases the potential benefits of DTs in building management, energy efficiency, and architectural design, illustrating its application through a case study and discussing future research directions for indoor and larger-scale implementations.

Hadjidemetriou et al. [66] introduced a DT architecture designed for smart buildings to simulate and analyze energy efficiency, occupant comfort, and air quality in real-time and through high-granularity offline analysis. It incorporates ordinary differential equations for real-time simulation and computational fluid dynamics for detailed offline analysis. Validated through real-world experiments, this framework facilitates accurate building operation simulations, enabling effective energy management and operational optimization by integrating with a user-friendly software platform for comprehensive building analysis and control.

Song et al. [67] showcased an advanced control strategy for a solar photovoltaic (PV) system integrated with energy storage, aiming to optimize self-consumption and reduce grid dependency in residential buildings. It introduces a novel algorithm that dynamically adjusts the energy flow between the PV system, battery storage, and the grid based on real-time data and forecasts. This approach significantly enhances energy efficiency, ensures a more sustainable energy profile for homes, and demonstrates potential cost savings on electricity bills. In the case of smart homes, Huang et al. [68] presented an artificial neural network-based hour-ahead demand response (DR) algorithm for energy management that forecasts steady costs to manage price uncertainty. The algorithm's effectiveness is validated through simulations with different types of household devices, showing significant reductions in energy costs and consumer discomfort compared to systems without DR.

2) COMMERCIAL

Clausen et al. [69] presented a DT framework designed to enhance energy efficiency and occupant comfort in public and commercial buildings by integrating Model Predictive Control (MPC) with building automation systems. This framework utilizes weather forecasts, occupancy predictions, and current state data to optimize building operations for comfort and efficiency. Francisco et al. [70] utilized smart meter data to develop daily, temporally segmented building energy benchmarks, revealing periods of over- or underperformance that are masked by traditional annual benchmarks. These insights pave the way for DT–enabled urban energy management platforms, allowing for the identification of specific retrofit strategies and the achievement of near real-time efficiency improvements. Jafari et al. [71] presented a comprehensive overview of DT Technology in the realm of building operations and maintenance, emphasizing the integration of predictive modeling and control for enhanced O&M planning. It highlights the pivotal role of DTs in achieving operational efficiency, reducing maintenance costs, and improving building life-cycle management through real-time data analysis and simulation.

D. ENERGY STORAGE

A revolutionary trend toward the integration of advanced digital technology in battery energy storage systems and wider energy applications is seen in recent studies [10], [16], [19], [72] on the use of DTs in energy management. These studies demonstrate new approaches and trends as well as the vital role that DTs play in resolving industrial issues, maintaining cybersecurity, and opening the door for further developments in the energy storage system.

1) BATTERIES

Batteries are the most common form of chemical energy storage and serve as the primary energy storage systems in vehicular applications. They efficiently convert chemical energy into electrical energy to power various vehicle components, ensuring reliable performance. For electric vehicle energy storage systems, Vandana et al. [20] present a multidimensional DT that includes phases for research and development, production, operation, and recycling. This integrated strategy demonstrates an inventive breakthrough in battery lifecycle management by utilizing IoT, AI, and cloud computing to improve battery performance, cybersecurity, and longevity while addressing material shortages through recycling techniques. A DT model for Battery Energy Storage Systems (BESS) is presented by Kharlamova et al. [73] with the goal of improving frequency regulation capabilities. This approach considerably increases the accuracy of SOC (State of Charge) predictions by utilizing artificial intelligence. Their case study highlights the potential of this technique to guarantee the steady and effective operation of BESS inside contemporary energy systems and shows how effective it is in real-world scenarios. To aid in the cyber-security investigation, Shitole et al. [74] present a reasonably priced Real-Time Digital Twin (RTDT) for Residential Energy Storage Systems (RESS). Through the use of a single board computer and Simulink Desktop Real-Time, the RTDT provides an adaptable and affordable method of simulating micro-grid test beds or Cyber-Physical Systems. Through an experimental case study, this paper validates the RTDT's performance, demonstrating its potential for commercial RESS and Cloud-based Energy Management Systems (CEMS), beyond theoretical applications.

Li et al. [75] developed a cloud-based battery management system using cloud computing and IoT to diagnose batteries, specifically focusing on SoC and SoH estimation for lithium-ion and lead-acid types. By using Particle Swarm Optimization for SoH and an Adaptive Extended H-infinity Filter for SoC prediction, the system shows enhanced battery management using DTs. Validation results affirm the system's accuracy and reliability in SoC and SoH estimations, enhancing management for stationary and mobile uses. Tang et al. [76] designed a DT-based battery management system (BMS) focusing on the accurate estimation of SoC using a novel joint HIF-PF (Hybrid Information Filter-Particle Filter) algorithm. This system addresses the limitations of traditional BMS in terms of data sharing, processing capability, and storage capacity, significantly enhancing SoC estimation accuracy. Fig. 5 shows DT structure in energy storage for battery management systems.

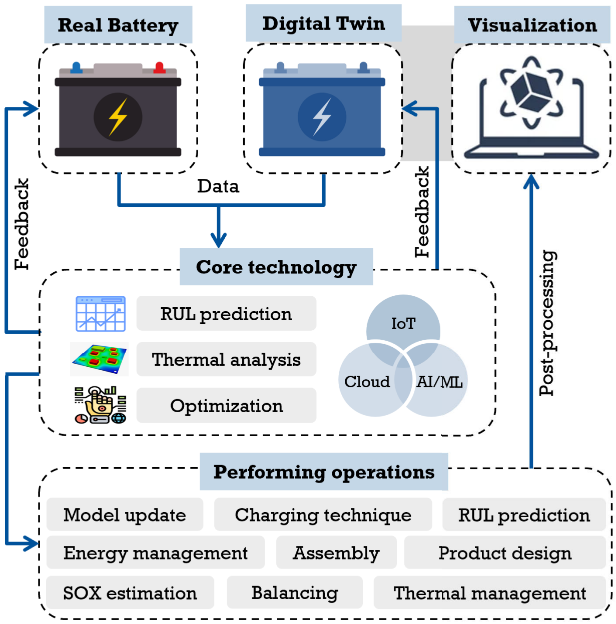

FIGURE 5. A digital twin structure in energy storage for battery management.

2) DISTRIBUTED STORAGE AND SUPERCAPACITORS

Apart from batteries, several other energy storage systems (ESS) are being integrated with the Internet of Things (IoT) to enhance their efficiency, reliability, and smart management. Gao et al. [77] introduces a novel distributed energy management strategy for microgrids with high penetration of renewable energy sources and stochastic loads, addressing power system challenges by decomposing the optimization problem into two levels and considering loads as stochastic variables. Utilizing the moth flame optimization algorithm and integrating various renewable sources and batteries, the developed distributed EMS demonstrates efficiency and applicability in practical simulations. Furthermore, several papers [78], [79] developed DTs to provide estimations and control of the charge of a supercapacitor for enhanced energy storage. This becomes especially critical given that all data on the supercapacitor are collected and transmitted to the cloud via IoT, leading to the creation of a DT model for the supercapacitor management system. These DT models can utilize real-time data within the data interaction network to assess the operational status of the supercapacitor. O'Dwyer et al. [80] introduced an energy management tool leveraging IoT-based DT technologies for optimal control, scheduling, forecasting, and coordination of energy assets, including energy storage, across urban districts to meet environmental, economic, and resilience goals. This tool, which is adaptable across various energy sectors, enables local governments to manage assets like low-carbon heating and electric vehicle charging in a coordinated manner, as demonstrated in case studies from Greenwich, London. Zhang et al. [81] enhanced photovoltaic power prediction with a DT-based framework that ensures accurate data transmission and mapping from physical to digital realms. The approach uses a Generative Adversarial Network (GAN) for restoring historical data, improving DT quality, and introducing a new prediction technique combining a digital-physical model with a CNN-BiLSTM network.

3) THERMAL AND GAS

The integration of IoT technology into thermal systems has transformed the way energy storage and heating systems operate, making them more efficient and easier to control. IoT-based frameworks are now being used in a wide range of applications, from heat storage systems in smart buildings to solar thermal power plants, helping optimize energy management [82]. Deng et al. [83] proposed a Metaverse-driven system for energy storage, including technologies like digital twins and AI for real-time monitoring, fault detection, and remote management. It uses a GA-BP neural network for accurate power load prediction, which applies to various storage types, including thermal storage, enhancing efficiency, and reducing costs. Shen et al. [84] focused on the thermal management of cell-to-pack (CTP) battery systems for electric vehicles. It develops a detailed thermal model using a liquid cooling plate structure to optimize temperature control during charging and cooling processes. The study offers insights for improving CTP battery thermal management design, applicable to various storage systems, including thermal storage.

Kang et al. [85] developed a DT model for a plant-scale solid oxide fuel cell (SOFC) system using hydrogen as the primary fuel source. It focuses on scaling the model from a 1 kW pilot plant to a 25 kW commercial plant, optimizing temperature and fuel flow rates to ensure efficient hydrogen conversion and power generation. Zhao et al. [86] came up with a DT model for high-temperature membrane electrolyzers with proton exchange using hydrogen generation. It combined multiphysics simulations and system identification to predict dynamic behaviors like power consumption, temperature, and hydrogen output, optimizing control strategies for improved system stability and efficiency. Meraghni et al. [87] introduced a data-driven DT prognostics method for proton exchange membrane fuel cells (PEMFCs) to predict their remaining useful life (RUL). The approach integrates a stacked autoencoder model with transfer learning, allowing the system to adapt to operational changes and limited data, thereby improving accuracy in hydrogen-based energy systems. Wang et al. [88] proposed a multi-physics DT for proton exchange membrane fuel cells (PEMFCs), combining 3D modeling and machine learning to predict temperature, gas, and humidity fields accurately. It enhances hydrogen-based PEMFC efficiency and real-time monitoring.

E. OTHERS

Beyond the literature reviews categorized in various subsections discussed above, there are several other noteworthy works that we will explore here i.e., cyber-physical power systems, generic power systems, and online power analysis tools.

1) CYBER-PHYSICAL POWER SYSTEMS

IoT-based energy systems and cyber-physical energy systems (CPES) share similarities but are not exactly the same thing [89], [90]. They differ primarily in scope and focus, though they overlap in certain areas. CPES refers to a broader, more integrated system where physical components (e.g., power plants, grids, energy storage systems) are tightly coupled with computational models and algorithms. CPES emphasizes the integration of physical and cyber layers — the energy infrastructure and digital control systems — to create feedback loops for monitoring, automation, and optimization. Due to the strong similarity with generic IoT-based systems, we highlight a few notable research works in this field.

When focusing specifically on electrical energy systems, the term Cyber-Physical Power Systems (CPPS) is also prominent. Several notable surveys have explored various aspects of CPPS, including modeling methods for future energy systems [91], smart grids [92], and applications in cybersecurity [93]. CPPS modeling is closely related to DT, as both involve the integration of physical and digital components for real-time monitoring, control, and optimization. In CPPS, modeling is used to simulate the interactions between physical power systems and their cyber layers, such as control algorithms and communication networks. DTs take this concept further by creating dynamic, real-time replicas of the physical system, continuously updated with live data. In other words, DTs appear as an advanced form of CPPS modeling that provides a more detailed and responsive representation of power systems. For instance, Yohanandhan et al. [93] discussed CPPS modeling as three primary categories: interconnection, interdependent, and interaction modeling [see Fig. 6]. Interconnection modeling focuses on the distinct roles of the physical and cyber systems, treating them separately. Interaction modeling, on the other hand, examines the influence each system has on the other. Interdependent modeling evaluates the extent to which the two systems rely on one another. Although these categories may seem similar, each offers a unique perspective on CPPS. Interconnection modeling typically targets individual components, while interdependent modeling takes a broader, system-level approach.

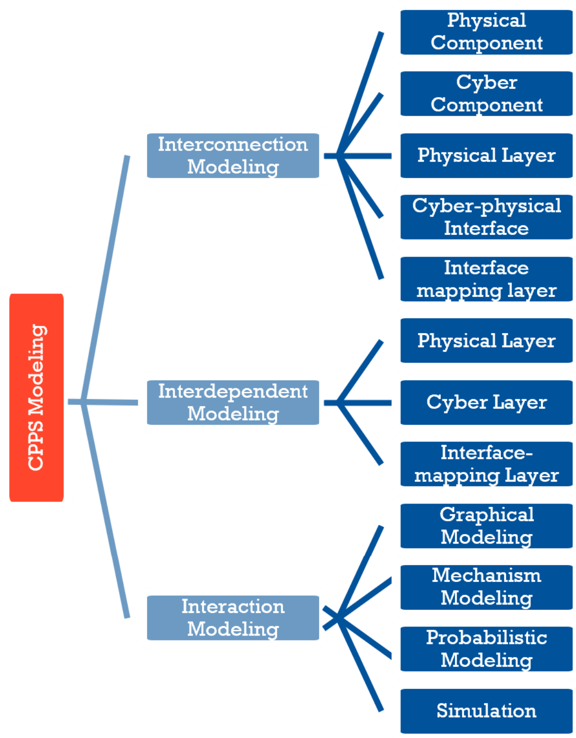

FIGURE 6. CPPS modeling categories [93].

2) GENERIC POWER SYSTEMS

Several DT applications emphasize the development of architectural and comprehensive frameworks designed for the broad spectrum of generic power systems. Vargas et al. [94] designed a modular framework for implementing Power System Digital Twins (PSDTs), offering a flexible, reliable, and affordable approach. It highlights the significance of PSDTs in enhancing network operation, planning, and monitoring across the power industry. By adopting a modular design, the framework enables expansion beyond specific power system components, which in turn makes it easier to integrate various services and users. The implementation of this framework is demonstrated through a real-time model of the Australian National Electricity Market, showcasing its application in renewable energy integration and prospective scenario analysis. Kummerow et al. [95] structured a DT framework for enhancing the cybersecurity and operational reliability of power systems, focusing on the integration of DTs at both control center and substation levels. It discusses the benefits of DTs in improving dynamic observability, anomaly detection, and counteraction against cyber-physical threats through real-time simulations and data analysis. Additionally, the paper presents a holistic approach to secure communication and data management, showcasing a test bench for validating DT-based services in power systems. Kulikov et al. [96] developed a DT model for electricity systems to manage emergencies and operational decisions in electric power systems, using a mathematical model that merges virtual and real components for real-time simulation and response. It introduces a method to resolve system contradictions and ensure controllable, non-contradictory models, facilitating efficient emergency recovery and system functionality restoration. This approach enhances the predictability and operational efficiency of electric power systems, aligning with Industry 4.0 and digital economy transitions.

Tang et al. [97] outlined the development of multi-timescale DT models for regional multiple energy systems (RMES) on the CloudPSS platform, aimed at improving energy utilization and system optimization. It discusses constructing DTs with power flow and electromagnetic transient models to cater to varied analysis needs. Validated through the IEEE-13 and a photovoltaic test system, the models demonstrate effective system parameter verification, abnormal device detection, and optimized operation, showcasing the practicality of DTs in ensuring the safety and stability of RMES. Dufour et al. [98] designed a Hardware-In-the-Loop (HIL) testing of modern onboard power systems using DTs, focusing on their application in navy ships. It emphasizes the importance of HIL simulation in safely and effectively integrating, testing, and verifying complex power systems, reducing risks and costs associated with direct subsystem interconnection. By employing a Model-Based Design approach, the paper highlights how real-time simulators facilitate the development and integration of these systems, enabling detailed testing across various control hierarchy levels, ultimately improving system reliability and performance. Another work [99] introduces a DT that merges multi-disciplinary and multi-scale simulation processes using physical models and sensors to map the entire lifecycle of entities in a virtual space, analyzing existing DT models, their applications, and implementation methods in various fields. This technology, when applied to the power system, facilitates the optimization design of power grids, simulation of faults, management of virtual power plants, and monitoring of intelligent equipment, with the key technologies of PSDT illustrated through the Cai-Lun Station example.

3) ONLINE POWER ANALYSIS

With an emphasis on real-time analysis systems to manage the complexity of contemporary power grids, Zhou et al. [100] presented a DT framework for power grid online analysis. The system uses machine learning-based security assessment, complex event processing, high-performance parallel computing, and in-memory computing to create an Online Analysis DT (OADT) that can imitate a power grid in real-time with delays of less than a second. This approach has been tested on a large-scale network model and deployed in a provincial dispatching center in China, showcasing its ability to enhance the efficiency and security of power grid operations. Liu et al. [101] explored the implementation of DT technology for online status evaluation of key power transmission and transformation equipment. It highlights the technology's capacity for enhancing real-time data accuracy, equipment status modeling, and fault prediction by integrating big data analysis and IoT. The framework consists of a layered architecture including data, platform, application, and display layers, facilitating comprehensive monitoring, diagnosis, and predictive analysis. Guan et al. [102] introduced a DT-based online tool for electric power communication system training, focusing on enhancing training and daily operations for staff and communication commissioners through a virtual-real interactive, comprehensive system. It covers the design, modeling, control principles, data collection, and visual display of DT tools, validated through a case study on optical fiber damage recovery in communication malfunctions.

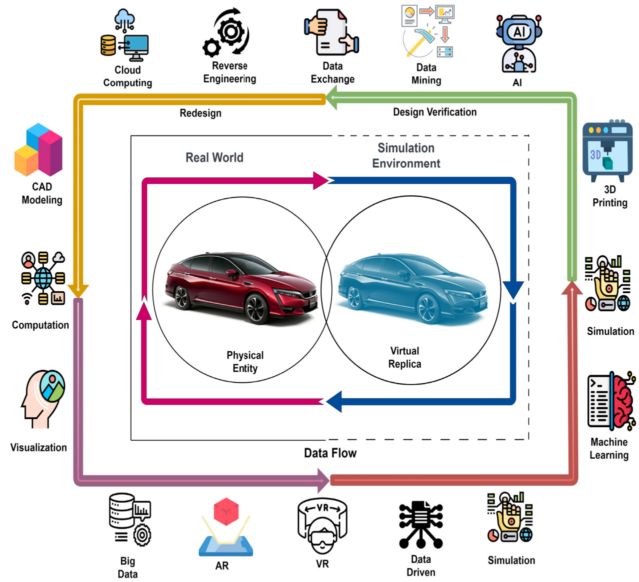

FIGURE 7. Digital twin related technologies.

IV. ENABLING TECHNOLOGY

Numerous foundational technologies play a pivotal role in constructing an intelligent DT of a physical energy system, ensuring an ongoing bidirectional feedback mechanism between the virtual and physical entities. In this section, we discuss key technologies that have been instrumental in the development of DTs for the energy sector, highlighting their application in various virtualization frameworks tailored to specific requirements. An overview of digital twin-related technologies outlined in various studies i.e., [103] and [104] is shown in Fig. 7.

A. MODELING AND SIMULATION

Numerous research efforts have explored energy systems, both with and without IoT integrations, employing a diverse array of simulation and modeling methodologies. These approaches range from differential equation-based frameworks to sophisticated mathematical modeling techniques, including the Finite Element Method (FEM), Computational Fluid Dynamics (CFD), Electromagnetic Simulation, and both Linear and Non-linear modeling strategies [10], [105]. Generic numerical techniques have been used the most to model the cyber backbone of DTs.

There are some key distinctions between a DTs and traditional modeling approaches that can be highlighted in the following areas:

- Static vs. Dynamic: A simulation model doesn't change until new components are manually added by the designer; otherwise, it stays static. On the other hand, a digital twin, while at first resembling a simulation model, gains dynamic properties by including real-time data, which allows it to adjust and change over time [104]. This continuous data input allows the digital

twin to grow and refine throughout the product lifecycle, offering insights beyond what a static simulation can achieve [106].
- Present vs. Predictive: Simulations provide a way to predict potential outcomes based on preset conditions, helping to assess possible future scenarios. Digital twins, however, offer real-time insights, allowing for a deeper understanding of not only future possibilities but also current conditions as they unfold [107].
- Scope of Application: While simulations are primarily focused on product design and allow for the testing of various scenarios against predefined parameters, digital twins have a much broader application. They are not confined to specific workflows but can be utilized across the entire product lifecycle, encompassing design, development, and operational stages.

Several studies [84], [108], [109] employed the usage of CFD simulation models for energy grids and energy storage systems. For building energy management, using a Geographic Information System (GIS) has been instrumental in some studies [110], [111]. Building Energy Models (BEM) and Building Information Models (BIM) were also commonly used for both residential and industrial building design [71], [112], [113]. Another useful approach found in several emerging works is metamodeling, an advanced modeling technique that involves creating a model of a model [114]. It refers to the process of developing simplified, abstract representations (metamodels) that capture the essential features and behaviors of more complex models within a specific domain. These metamodels are designed to be computationally less intensive, enabling quicker and more efficient analysis, simulation, and optimization tasks. Some DT applications using metamodelling in energy systems include model-based development of power systems [115] and enabling digital services for battery systems [116].

Another important activity is model migration which involves repurposing high-accuracy DT models across different scenarios within the same domain or linking them across various domains, facilitating new model development with insights gained from existing models [17]. This approach streamlines model building, reduces complexity, accelerates development timelines, and enhances model applicability across diverse operational conditions. Several studies have employed data-driven approaches, utilizing system data to develop machine learning models including techniques like extreme gradient boost (XGBoost) and extended kalman filter (EKF) [117], [118], neural networks [32], [119], support vector machines [120], dynamic equivalent model (DEM) [121] and k-nearest neighbor (KNN) [39].

B. IoT-BASED COMMUNICATIONS

A critical element of a digital twin is the communication framework, which enables the integration and coexistence of physical and virtual entities. Moreover, the interaction between computational processes within a DT is vital for the functionality of the cyber-physical system as a whole. For effective data and information exchange, these processes within the prototyping framework must engage in seamless communication. This communication method among processes is referred to as inter-process communication (IPC) [122]. Numerous IoT technologies play a crucial role, as IoT stands at the forefront of the fourth industrial revolution. It integrates homes, vehicles, and various devices through sensors and connectivity, allowing them to collect and exchange data over the internet [10]. In order to connect the DT with the physical system data, several studies [123], [124] employed core concepts of IoT technologies. Furthermore, several papers proposed DT infrastructures that incorporate key IoT components, e.g., cloud technology [75], [125], [126], [127].

C. LIFE-CYCLE TOOLS

The use of various life cycle tools for DTs emerges as a promising future direction, with recent advancements highlighting their potential. The integration of human-computer interaction and data visualization stands out as critical in optimizing FLC management within DT frameworks [17]. These technologies empower operators to make informed corrections and control decisions throughout the lifecycle stages, enhancing operational efficiency. Moreover, data visualization offers a compelling means for the intuitive monitoring of DT models, enabling stakeholders to track changes and discern trends in the data seamlessly. Huang et al. [128] proposed a system that combines cold energy recovery with heating, cooling, and power to efficiently utilize liquified natural gas (LNG) with a focus on improving sustainability through life cycle operational optimization using a DT approach. This approach, enhanced by a cascade forward neural network (CFNN) and a parameter-free intelligent algorithm, significantly improves the primary energy saving rate by optimizing operation parameters in real-time, particularly effective during system degradation and efficiency loss. In applications related to monitoring, the DT serves to assess systems continuously, aiding in decision-making throughout their lifecycle, including identifying malfunctions and predicting behaviors e.g., observing wind turbine functionalities [39].

V. DISCUSSIONS

A. CURRENT TRENDS IN DTs IN RESEARCH

We have analyzed the trend of notable research works published focusing on the usage of DTs in IoT-driven energy systems within the last few years. Fig. 8 illustrates a clear upward trend in the number of documents published from 2017 through 2023. The starting point in 2017 shows a relatively low number of documents, which suggests that the topic might have been in its nascent stages within the scholarly or industry community at that time. There is a consistent increase in publications year-over-year, indicating growing interest and possibly advancements in the field. This

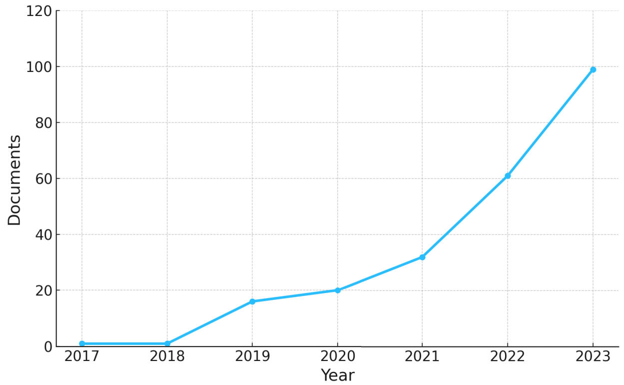

FIGURE 8. Publications by year.

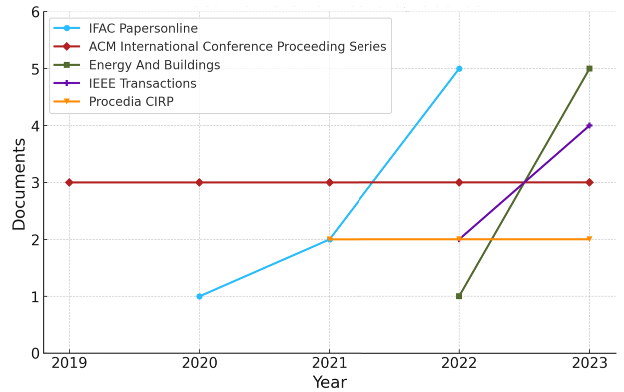

FIGURE 9. Publications by source.

is due to an increase in the technology's capabilities, wider adoption of IoT in energy systems, and more research funding being allocated to this area. A notable surge occurs between 2021 and 2023 which points to a breakthrough in the field and a realization of the practical applications of digital twins in energy systems, leading to more research and publications.

The topic is covered across various sources, indicating multidisciplinary interest and applications. Fig. 9 shows the number of documents categorized by the source of publication from 2019 to 2023. Most sources show an increasing trend in publications over the years, with IFAC PapersOnline and Procedia CIRP showing the most significant growth, reflecting their respective communities' increasing focus on this area. The ACM series shows a possible decline in 2023, due to various factors, including shifts in research focus and the specific themes of conferences for that year. IEEE Transactions has maintained a stable interest over the years, reflecting a continuous but niche focus on the topic within the engineering and technical community. The increase in energy and building sources is attributed to the rising relevance of DTs in building energy management systems and the growing need for energy efficiency in buildings.

B. CHALLENGES IN QUANTIFYING DT CONTRIBUTIONS

It is difficult to develop quantitative metrics to evaluate DT's contributions to energy systems due to the complexity and dynamic nature of both the systems and the DTs themselves. Energy systems involve numerous interconnected components and variables, and DTs continuously evolve by integrating real-time data, making it hard to define fixed metrics. Additionally, the varied applications of DTs across different scales — from microgrids to large power plants — complicate the creation of standardized metrics that apply universally. Data uncertainties, the interdisciplinary nature of energy optimization, and the lack of standardized frameworks further hinder the development of reliable and comprehensive quantitative metrics. Nevertheless, some studies [129], [130] have developed their own specific quantitative metrics to measure their contributions.

TABLE 2. DT application in various IEEE bus systems.

IEEE bus systems	Reference
9-bus	[32]
14-bus	[132], [133]
30-bus	[31], [55]
33-bus	[41], [44], [134], [135], [136], [137]
34-bus	[138]
39-bus	[32], [45], [121]
118-bus	[55], [121]

C. IEEE BUS SYSTEMS

The IEEE bus systems are standard models used for testing and benchmarking in power system studies, including DT applications. The adoption of DTs across various IEEE bus systems — ranging from the simpler 9-bus, 14-bus, 33-bus, and 34-bus models to the more complex 30-bus, 39-bus, and 118-bus systems — demonstrates their versatility and efficacy in simulating diverse electrical networks. These bus systems, each with unique configurations and challenges, serve as standardized benchmarks for testing and refining various DT technologies. Much of the literature has utilized bus systems as either validation testbeds or benchmarks for implementation studies. Test benchmarks serve to meet diverse research requirements and enhancements, categorized into small-scale and large-scale test cases, facilitating targeted analysis and development [131]. Table 2 outlines an overview of the different DT applications across various IEEE bus systems, highlighting their versatility in adapting to different scales and requirements in power system management.

In order to achieve a level of development where EDTs can be virtually indistinguishable from their physical counterparts necessitates addressing a multitude of challenges, such as:

D. CHALLENGES AND FUTURE DIRECTIONS

- Data Synchronization: Ensuring real-time, seamless synchronization between the DT and its physical

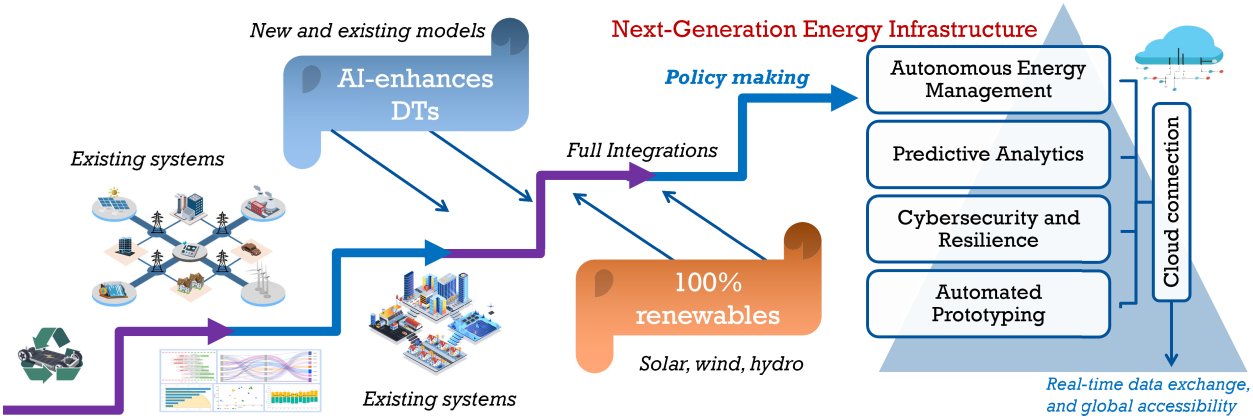

FIGURE 10. **Future roadmap for DT applications in energy.**

counterpart to reflect the current state of the energy system accurately.

- Interoperability: Ensuring compatibility among diverse systems and technologies within the IoT ecosystem to enable comprehensive integration and communication between the DT and other systems.
- Cybersecurity: Given the DT's reliance on data and connectivity in the smart grid, safeguarding it from cyber attacks is essential to maintaining the integrity and confidentiality of sensitive information [139].
- Accuracy and Reliability: Enhancing the precision of simulations and energy consumption predictions made by the DT to ensure they are reliable and can be trusted for critical decision-making [39].
- Cost and Resource Efficiency: Addressing the high costs and substantial computational resources required to develop and maintain highly sophisticated DTs.
- User Training and Adoption: Ensuring that stakeholders are adequately trained to use and interpret the data and insights generated by the DT, which is essential for its effective adoption and use.
- Long-term Maintenance and Updating: Establishing processes for the ongoing maintenance and updating of DTs to ensure they remain accurate over the lifecycle of their physical counterparts.

After properly dealing with various challenges we can build the future beginning with this statement: *"AI-enhanced digital twins will enable autonomous energy management, integrating 100% renewable sources into smart grids, optimizing systems in real-time, and boosting sustainability through predictive maintenance, automated prototyping, and resilient cybersecurity frameworks"*. We believe that artificial intelligence and 100% renewable energy resources can pave the way to the future of energy systems. By anticipating inefficiencies and possible system breakdowns, AI-powered DTs improve energy efficiency and minimize downtime, enabling optimum operations in renewable energy sources. AI is used in energy trading to process real-time data and understand intricate market trends, allowing companies to make profitable and well-informed trading decisions. To achieve this we showcase a brief roadmap (see Fig. 10) as follows:

1) POLICY MAKING

With the integration of 100% renewable energy through digital twin technology, the development of robust and adaptive policies becomes essential. These policies must address regulatory frameworks, grid management strategies, and sustainability goals to ensure a smooth transition. Policymakers need to consider the dynamic nature of energy markets, the rapid pace of technological advancements, and the necessity for resilient infrastructure to support renewable integration.

2) AUTONOMOUS ENERGY MANAGEMENT

AI-driven autonomous systems allow for self-optimization of energy production and consumption. These systems make real-time decisions to maximize efficiency, reduce human intervention, and adapt dynamically to changing energy demands and renewable energy availability. This reduces the need for continuous involvement of individuals, as the systems are autonomous and handle operations efficiently. While some may argue that this could lead to a reduction in employment, we contend that engineers and designers will still be crucial in overseeing and managing the integration of DT and AI technologies, ensuring their proper function and continuous improvement.

3) PREDICTIVE ANALYTICS

By using AI and data from DTs, predictive analytics can forecast potential system failures or inefficiencies before they happen. This allows for proactive maintenance and optimization of energy flows, increasing reliability and reducing downtime in renewable energy systems.

4) CYBERSECURITY AND RESILIENCE

As previously mentioned, cybersecurity remains one of the most critical challenges in the development of smart energy systems. As these systems become increasingly interconnected and intelligent, the risk of cyberattacks becomes more imminent. AI-enhanced DTs play a vital role in strengthening the cybersecurity and resilience of energy systems by detecting and mitigating potential threats in real-time. With renewable energy sources integrated and DTs overseeing system performance, resilient solutions can be developed to proactively defend against vulnerabilities, ensuring stability and security across the energy grid.

5) AUTOMATED PROTOTYPING

DTs, when paired with AI, revolutionize the future of energy by enabling rapid, automated prototyping through virtual simulations. This allows engineers to experiment with designs, test various scenarios, and optimize systems without the time, cost, or risk of real-world trials. Automated prototyping not only accelerates innovation but also enhances precision, as AI can sift through countless variables and configurations to find the most efficient solutions. It empowers energy companies to adapt swiftly to changes, integrate renewable sources more seamlessly, and develop solutions that are both innovative and resilient — transforming ideas into reality faster than ever before. For industry practitioners, this leads to faster deployment of new technologies, minimizing time-to-market, and offering a safer environment for testing disruptive innovations without risking existing infrastructure.

6) CLOUD CONNECTION

The cloud unlocks real-time data exchange, acting as the backbone of scalability and global connectivity for energy systems. It delivers the immense computational power needed to process vast streams of data, enabling predictive analytics, real-time monitoring, and flawless communication across distributed energy sources. By seamlessly linking renewable power systems and smart grids worldwide, the cloud paves the way for smarter, faster, and more efficient energy management, transforming how we harness and distribute energy on a global scale.

E. ECONOMIC INTEGRATION

DTs integrate economic considerations into energy systems by optimizing performance, reducing costs, and improving overall operational efficiency. Through real-time monitoring, predictive maintenance, and fault detection, DTs minimize downtime, prevent equipment failures, and extend the lifespan of energy assets, leading to significant cost reductions. They also optimize energy efficiency by identifying and addressing inefficiencies in smart grids, building energy management, and energy storage systems, ultimately lowering energy consumption and operational expenses. For instance, Xu et al. [140] demonstrated the cost-effective impact of a DT on a 320 MW coal-fired thermal power plant, highlighting substantial improvements in operating economics through its digital model.

Additionally, DTs help evaluate the integration of renewable energy sources, balancing sustainability with cost-effectiveness. By simulating various energy mixes, DTs allow decision-makers to optimize the economic and environmental impact of energy systems. They also support lifecycle cost analysis, ensuring informed decisions that consider long-term costs such as maintenance and upgrades. In energy trading and demand-response markets, DTs improve profitability by simulating market trends and optimizing participation strategies. Furthermore, DTs can assist in investment decision-making, enabling stakeholders to explore different infrastructure and energy technology investments for maximum financial returns.

VI. CONCLUSION

The emergence of the Internet of Things has catalyzed an interdisciplinary fusion, integrating artificial intelligence, computing system design, and smart industrial infrastructure, paving the way for the evolution of virtual prototyping solutions such as digital twins. These innovations, integral to IoT applications, have profoundly influenced the development and optimization of IoT-driven smart energy systems. Digital twins, by mirroring the complexities of these systems, offer useful platforms for simulation, analysis, and real-time decision-making, thereby enhancing operational efficiency, resilience, and sustainability. In this paper, we narrowed our focus to the application of digital twins in emerging smart energy systems powered by IoT infrastructure for several compelling reasons. To begin with, the combination of IoT technology and DTs offers a novel way to improve the sustainability, dependability, and efficiency of smart energy systems. DTs can facilitate more informed decision-making and proactive maintenance strategies by utilizing real-time data from IoT devices to generate detailed simulations and predictive analytics. Furthermore, as the demand for cleaner and more efficient energy solutions grows, the need for sophisticated management and optimization tools becomes increasingly critical.

In order to address these issues, DTs provide a strong platform that makes it possible to dynamically model and optimize the production, distribution, and consumption of energy. Finally, by concentrating on this intersection, we can investigate novel solutions to challenging energy issues, advancing the energy sector's transition to more resilient and sustainable infrastructure.

ACRONYMS

DT	Digital Twin.
IoT	Internet-of-Things.
EDT	Energy Digital Twin.
V2G	Vehicle-to-Grid.
DER	Distributed Energy Resources.
CPS	Cyber-Physical System.
IIoT	Industrial Internet of Things.
AC	Alternate Current.
DC	Direct Current.

PHEVs	Plug-In Hybrid Electric Vehicles.
B5G	Beyond 5th Generation.
PV	Photovoltaics.
CCA	Coordinated Cyber Attack.
UAV	Unmanned Aerial Vehicle.
EV	Electric Vehicle.
WMSN	Wireless Multimedia Sensor Network.
ERPS	Electric Railway Power System.
BIM	Building Information Modeling.
BEM	Building Energy Modeling.
DR	Demand Response.
RTDT	Real Time Digital Twin.
BESS	Battery Energy Storage System.
RESS	Residential Energy Storage Systems.
SOC	State of Charge.
SOH	State of health.
BMS	Battery Management System.
CEMS	Cloud-based Energy Management System.
ERPS	Electric Railway Power System.
PSDT	Power System Digital Twins.
CPPS	Cyber-Physical Power Systems.
CPES	Cyber-Physical Energy Systems.
RMES	Regional Multiple Energy System.
CloudPSS	Cloud Power System Simulator.
GDTA	Generic Digital Twin Architecture.
PBTES	Packed-Bed Thermal Energy Storage.
PEMFC	Proton Exchange Membrane Fuel Cell.
OADT	Online Analysis Digital Twin.

REFERENCES

[1] F. F. Ahmad, C. Ghenai, and M. Bettayeb, "Maximum power point tracking and photovoltaic energy harvesting for Internet of Things: A comprehensive review," *Sustain. Energy Technol. Assessments*, vol. 47, Oct. 2021, Art. no. 101430.

[2] S. Boschert and R. Rosen, "Digital twin—The simulation aspect," in *Mechatronic Futures*. Cham, Switzerland: Springer, 2016, pp. 59–74.

[3] (2023). *Digital Twins for Energy Systems*. Accessed: Feb. 2, 2024. [Online]. Available: https://innovate.ieee.org/innovation-spotlight/digital-twins-for-energy-systems/

[4] J. Tuttle. (Mar. 2022). *Digital Twin: Driving Innovation in the Energy Sector*. Accessed: Feb. 2, 2024. [Online]. Available: https://blogs.sw.siemens.com/energy-utilities/2022/03/23/digital-twin-driving-innovation-in-the-energy-sector/

[5] M. Grieves and J. Vickers, "Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems," in *Transdisciplinary Perspectives on Complex Systems*. Cham, Switzerland: Springer, 2017, pp. 85–113.

[6] E. Negri, L. Fumagalli, and M. Macchi, "A review of the roles of digital twin in CPS-based production systems," *Proc. Manuf.*, vol. 11, pp. 939–948, 2017.

[7] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, and A. Y. C. Nee, "Enabling technologies and tools for digital twin," *J. Manuf. Syst.*, vol. 58, pp. 3–21, Jan. 2021.

[8] Y. Wu, K. Zhang, and Y. Zhang, "Digital twin networks: A survey," *IEEE Internet Things J.*, vol. 8, no. 18, pp. 13789–13804, Sep. 2021.

[9] W. Yu, P. Patros, B. Young, E. Klinac, and T. G. Walmsley, "Energy digital twin technology for industrial energy management: Classification, challenges and future," *Renew. Sustain. Energy Rev.*, vol. 161, Jun. 2022, Art. no. 112407.

[10] J. V. S. do Amaral, C. H. dos Santos, J. A. B. Montevechi, and A. R. de Queiroz, "Energy digital twin applications: A review," *Renew. Sustain. Energy Rev.*, vol. 188, Dec. 2023, Art. no. 113891.

[11] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018.

[12] M. R. Kabir and S. Ray, "Virtual prototyping for modern Internet-of-Things applications: A survey," *IEEE Access*, vol. 11, pp. 31384–31398, 2023.

[13] P. Pandiyan, S. Saravanan, K. Usha, R. Kannadasan, M. H. Alsharif, and M.-K. Kim, "Technological advancements toward smart energy management in smart cities," *Energy Rep.*, vol. 10, pp. 648–677, Nov. 2023.

[14] L. Lei, Y. Tan, G. Dahlenburg, W. Xiang, and K. Zheng, "Dynamic energy dispatch based on deep reinforcement learning in IoT-driven smart isolated microgrids," *IEEE Internet Things J.*, vol. 8, no. 10, pp. 7938–7953, May 2021.

[15] C. X. Hui, G. Dan, S. Alamri, and D. Toghraie, "Greening smart cities: An investigation of the integration of urban natural resources and smart city technologies for promoting environmental sustainability," *Sustain. Cities Soc.*, vol. 99, Dec. 2023, Art. no. 104985.

[16] C. Ghenai, L. A. Husein, M. A. Nahlawi, A. K. Hamid, and M. Bettayeb, "Recent trends of digital twin technologies in the energy sector: A comprehensive review," *Sustain. Energy Technol. Assessments*, vol. 54, Dec. 2022, Art. no. 102837.

[17] Y. Wang, X. Kang, and Z. Chen, "A survey of digital twin techniques in smart manufacturing and management of energy applications," *Green Energy Intell. Transp.*, vol. 1, no. 2, Sep. 2022, Art. no. 100014.

[18] M. Lamagna, D. Groppi, M. M. Nezhad, and G. Piras, "A comprehensive review on digital twins for smart energy management system," *Int. J. Energy Prod. Manage.*, vol. 6, no. 4, pp. 323–334, 2021.

[19] C. Semeraro, A. G. Olabi, H. Aljaghoub, A. H. Alami, M. A. Radi, M. Dassisti, and M. A. Abdelkareem, "Digital twin application in energy storage: Trends and challenges," *J. Energy Storage*, vol. 58, Feb. 2023, Art. no. 106347.

[20] Vandana, A. Garg, and B. K. Panigrahi, "Multi-dimensional digital twin of energy storage system for electric vehicles: A brief review," *Energy Storage*, vol. 3, no. 6, Dec. 2021, Art. no. e242.

[21] H. Chen, Z. Zhang, P. Karamanakos, and J. Rodriguez, "Digital twin techniques for power electronics-based energy conversion systems: A survey of concepts, application scenarios, future challenges, and trends," *IEEE Ind. Electron. Mag.*, vol. 17, no. 2, pp. 2–18, Jun. 2022.

[22] M. Jafari, A. Kavousi-Fard, T. Chen, and M. Karimi, "A review on digital twin technology in smart grid, transportation system and smart city: Challenges and future," *IEEE Access*, vol. 11, pp. 17471–17484, 2023.

[23] G. Bhatti, H. Mohan, and R. R. Singh, "Towards the future of smart electric vehicles: Digital twin technology," *Renew. Sustain. Energy Rev.*, vol. 141, May 2021, Art. no. 110801.

[24] M. A. M. Yassin, A. Shrestha, and S. Rabie, "Digital twin in power system research and development: Principle, scope, and challenges," *Energy Rev.*, vol. 2, no. 3, Sep. 2023, Art. no. 100039.

[25] M. M. H. Sifat, S. M. Choudhury, S. K. Das, M. H. Ahamed, S. M. Muyeen, M. M. Hasan, M. F. Ali, Z. Tasneem, M. M. Islam, M. R. Islam, M. F. R. Badal, S. H. Abhi, S. K. Sarker, and P. Das, "Towards electric digital twin grid: Technology and framework review," *Energy AI*, vol. 11, Jan. 2023, Art. no. 100213.

[26] A. S. Cespedes-Cubides and M. Jradi, "A review of building digital twins to improve energy efficiency in the building operational stage," *Energy Informat.*, vol. 7, no. 1, p. 11, Feb. 2024.

[27] I. Priyadarshini, R. Kumar, R. Sharma, P. K. Singh, and S. C. Satapathy, "Identifying cyber insecurities in trustworthy space and energy sector for smart grids," *Comput. Electr. Eng.*, vol. 93, Jul. 2021, Art. no. 107204.

[28] L. Wei, C. Yi, and J. Yun, "Energy drive and management of smart grids with high penetration of renewable sources of wind unit and solar panel," *Int. J. Electr. Power Energy Syst.*, vol. 129, Jul. 2021, Art. no. 106846.

[29] M. I. Khalil, N. Z. Jhanjhi, M. Humayun, S. Sivanesan, M. Masud, and M. S. Hossain, "Hybrid smart grid with sustainable energy efficient resources for smart cities," *Sustain. Energy Technol. Assessments*, vol. 46, Aug. 2021, Art. no. 101211.

[30] K. Moslehi and R. Kumar, "A reliability perspective of the smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 57–64, Jun. 2010.

[31] N. Tzanis, N. Andriopoulos, A. Magklaras, E. Mylonas, M. Birbas, and A. Birbas, "A hybrid cyber physical digital twin approach for smart grid fault prediction," in *Proc. IEEE Conf. Ind. Cyberphysical Syst. (ICPS)*, vol. 1, Jun. 2020, pp. 393–397.

[32] W. Danilczyk, Y. L. Sun, and H. He, "Smart grid anomaly detection using a deep learning digital twin," in *Proc. 52nd North Amer. Power Symp. (NAPS)*, Apr. 2021, pp. 1–6.

[33] O. O. Olatunji, P. A. Adedeji, N. Madushele, and T.-C. Jen, "Overview of digital twin technology in wind turbine fault diagnosis and condition monitoring," in *Proc. IEEE 12th Int. Conf. Mech. Intell. Manuf. Technol. (ICMIMT)*, May 2021, pp. 201–207.

[34] P. Jain, J. Poon, J. P. Singh, C. Spanos, S. R. Sanders, and S. K. Panda, "A digital twin approach for fault diagnosis in distributed photovoltaic systems," *IEEE Trans. Power Electron.*, vol. 35, no. 1, pp. 940–956, Jan. 2020.

[35] A. Castellani, S. Schmitt, and S. Squartini, "Real-world anomaly detection by using digital twin systems and weakly supervised learning," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 4733–4742, Jul. 2021.

[36] T. Hossen, D. Sharma, and B. Mirafzal, "Smart inverter twin model for anomaly detection," in *Proc. IEEE 22nd Workshop Control Model. Power Electron. (COMPEL)*, Nov. 2021, pp. 1–6.

[37] I. Javid, A. Chauhan, S. Thappa, S. K. Verma, Y. Anand, A. Sawhney, V. V. Tyagi, and S. Anand, "Futuristic decentralized clean energy networks in view of inclusive-economic growth and sustainable society," *J. Cleaner Prod.*, vol. 309, Aug. 2021, Art. no. 127304.

[38] P. T. Baboli, D. Babazadeh, and D. R. Kumara Bowatte, "Measurement-based modeling of smart grid dynamics: A digital twin approach," in *Proc. 10th Smart Grid Conf. (SGC)*, Dec. 2020, pp. 1–6.

[39] M. Fahim, V. Sharma, T.-V. Cao, B. Canberk, and T. Q. Duong, "Machine learning-based digital twin for predictive modeling in wind turbines," *IEEE Access*, vol. 10, pp. 14184–14194, 2022.

[40] Y. Li and X. Shen, "A novel wind speed-sensing methodology for wind turbines based on digital twin technology," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–13, 2022.

[41] Y. Yin, H. Chen, X. Meng, and H. Xie, "Digital twin-driven identification of fault situation in distribution networks connected to distributed wind power," *Int. J. Electr. Power Energy Syst.*, vol. 155, Jan. 2024, Art. no. 109415.

[42] C. Moussa, K. Ai-Haddad, B. Kedjar, and A. Merkhouf, "Insights into digital twin based on finite element simulation of a large hydro generator," in *Proc. 44th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Oct. 2018, pp. 553–558.

[43] A. Ebrahimi, "Challenges of developing a digital twin model of renewable energy generators," in *Proc. IEEE 28th Int. Symp. Ind. Electron. (ISIE)*, Jun. 2019, pp. 1059–1066.

[44] H. Cao, D. Zhang, and S. Yi, "Real-time machine learning-based fault detection, classification, and locating in large scale solar energy-based systems: Digital twin simulation," *Sol. Energy*, vol. 251, pp. 77–85, Feb. 2023.

[45] W. Danilczyk, Y. Sun, and H. He, "ANGEL: An intelligent digital twin framework for microgrid security," in *Proc. North Amer. Power Symp. (NAPS)*, Oct. 2019, pp. 1–6.

[46] A. Saad, S. Faddel, T. Youssef, and O. A. Mohammed, "On the implementation of IoT-based digital twin for networked microgrids resiliency against cyber attacks," *IEEE Trans. Smart Grid*, vol. 11, no. 6, pp. 5138–5150, Nov. 2020.

[47] Y. Wu, J. M. Guerrero, Y. Wu, N. Bazmohammadi, J. C. Vasquez, A. J. Cabrera, and N. Lu, "Digital twins for microgrids: Opening a new dimension in the power system," *IEEE Power Energy Mag.*, vol. 22, no. 1, pp. 35–42, Jan. 2024.

[48] M. Atalay and P. Angin, "A digital twins approach to smart grid security testing and standardization," in *Proc. IEEE Int. Workshop Metrol. Ind. IoT*, Jun. 2020, pp. 435–440.

[49] H. X. Nguyen, R. Trestian, D. To, and M. Tatipamula, "Digital twin for 5G and beyond," *IEEE Commun. Mag.*, vol. 59, no. 2, pp. 10–15, Feb. 2021.

[50] Z. Zhou, Z. Jia, H. Liao, W. Lu, S. Mumtaz, M. Guizani, and M. Tariq, "Secure and latency-aware digital twin assisted resource scheduling for 5G edge computing-empowered distribution grids," *IEEE Trans. Ind. Informat.*, vol. 18, no. 7, pp. 4933–4943, Jul. 2022.

[51] J. Lopez, J. E. Rubio, and C. Alcaraz, "Digital twins for intelligent authorization in the B5G-enabled smart grid," *IEEE Wireless Commun.*, vol. 28, no. 2, pp. 48–55, Apr. 2021.

[52] M. Xu, "Research on 5G UAV smart grid inspection technology based on digital twin," in *Proc. IEEE 7th Int. Conf. Cloud Comput. Intell. Syst. (CCIS)*, Nov. 2021, pp. 367–370.

[53] J. Fu, X. Ma, H. Yu, and K. Dai, "Distributed energy-efficient wireless sensing and information fusion via event-driven and state-rank activation," *Wireless Netw.*, vol. 30, no. 4, pp. 2697–2711, May 2024.

[54] A. Sakhri, A. Ahmed, M. Maimour, M. Kherbache, E. Rondeau, and N. Doghmane, "A digital twin-based energy-efficient wireless multimedia sensor network for waterbirds monitoring," *Future Gener. Comput. Syst.*, vol. 155, pp. 146–163, Jun. 2024.

[55] M. Ali, G. Kaddoum, W.-T. Li, C. Yuen, M. Tariq, and H. V. Poor, "A smart digital twin enabled security framework for vehicle-to-grid cyber-physical systems," *IEEE Trans. Inf. Forensics Security*, vol. 18, pp. 5258–5271, 2023.

[56] A. Rassõlkin, T. Vaimann, A. Kallaste, and V. Kuts, "Digital twin for propulsion drive of autonomous electric vehicle," in *Proc. IEEE 60th Int. Sci. Conf. Power Electr. Eng. Riga Tech. Univ. (RTUCON)*, Oct. 2019, pp. 1–4.

[57] T. Zhang, X. Liu, Z. Luo, F. Dong, and Y. Jiang, "Time series behavior modeling with digital twin for Internet of Vehicles," *EURASIP J. Wireless Commun. Netw.*, vol. 2019, no. 1, pp. 1–11, Dec. 2019.

[58] M. Ahmadi, H. J. Kaleybar, M. Brenna, F. Castelli-Dezza, and M. S. Carmeli, "Adapting digital twin technology in electric railway power systems," in *Proc. 12th Power Electron., Drive Syst., Technol. Conf. (PEDSTC)*, Feb. 2021, pp. 1–6.

[59] W. Xu, J. Cui, L. Li, B. Yao, S. Tian, and Z. Zhou, "Digital twin-based industrial cloud robotics: Framework, control approach and implementation," *J. Manuf. Syst.*, vol. 58, pp. 196–209, Jan. 2021.

[60] K. Keller, K. Swearingen, J. Sheahan, M. Bailey, J. Dunsdon, K. W. Przytula, and B. Jordan, "Aircraft electrical power systems prognostics and health management," in *Proc. IEEE Aerosp. Conf.*, Mar. 2006, pp. 1–12.

[61] M. González, O. Salgado, J. Croes, B. Pluymers, and W. Desmet, "A digital twin for operational evaluation of vertical transportation systems," *IEEE Access*, vol. 8, pp. 114389–114400, 2020.

[62] J. Liu, C. Li, J. Bai, Y. Luo, H. Lv, and Z. Lv, "Security in IoT-enabled digital twins of maritime transportation systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 2, pp. 2359–2367, Feb. 2023.

[63] W. Wang, H. Guo, X. Li, S. Tang, J. Xia, and Z. Lv, "Deep learning for assessment of environmental satisfaction using BIM big data in energy efficient building digital twins," *Sustain. Energy Technol. Assessments*, vol. 50, Mar. 2022, Art. no. 101897.

[64] X. Zhou, K. Sun, J. Wang, J. Zhao, C. Feng, Y. Yang, and W. Zhou, "Computer vision enabled building digital twin using building information model," *IEEE Trans. Ind. Informat.*, vol. 19, no. 3, pp. 2684–2692, Mar. 2023.

[65] S. H. Khajavi, N. H. Motlagh, A. Jaribion, L. C. Werner, and J. Holmström, "Digital twin: Vision, benefits, boundaries, and creation for buildings," *IEEE Access*, vol. 7, pp. 147406–147419, 2019.

[66] L. Hadjidemetriou, N. Stylianidis, D. Englezos, P. Papadopoulos, D. Eliades, S. Timotheou, M. M. Polycarpou, and C. Panayiotou, "A digital twin architecture for real-time and offline high granularity analysis in smart buildings," *Sustain. Cities Soc.*, vol. 98, Nov. 2023, Art. no. 104795.

[67] Y. Song, M. Xia, Q. Chen, and F. Chen, "A data-model fusion dispatch strategy for the building energy flexibility based on the digital twin," *Appl. Energy*, vol. 332, Feb. 2023, Art. no. 120496.

[68] J. Huang, D. D. Koroteev, and M. Rynkovskaya, "Machine learning-based demand response in PV-based smart home considering energy management in digital twin," *Sol. Energy*, vol. 252, pp. 8–19, Mar. 2023.

[69] A. Clausen, K. Arendt, A. Johansen, F. C. Sangogboye, M. B. Kjærgaard, C. T. Veje, and B. N. Jørgensen, "A digital twin framework for improving energy efficiency and occupant comfort in public and commercial buildings," *Energy Informat.*, vol. 4, no. S2, p. 40, Sep. 2021.

[70] A. Francisco, N. Mohammadi, and J. E. Taylor, ''Smart city digital twin—Enabled energy management: Toward real-time urban building energy benchmarking,'' *J. Manage. Eng.*, vol. 36, no. 2, Mar. 2020, Art. no. 04019045.

[71] M. A. Jafari, E. Zaidan, A. Ghofrani, K. Mahani, and F. Farzan, ''Improving building energy footprint and asset performance using digital twin technology,'' *IFAC-PapersOnLine*, vol. 53, no. 3, pp. 386–391, 2020.

[72] C. Semeraro, H. Aljaghoub, M. A. Abdelkareem, A. H. Alami, and A. G. Olabi, ''Digital twin in battery energy storage systems: Trends and gaps detection through association rule mining,'' *Energy*, vol. 273, Jun. 2023, Art. no. 127086.

[73] N. Kharlamova, C. Træholt, and S. Hashemi, ''A digital twin of battery energy storage systems providing frequency regulation,'' in *Proc. IEEE Int. Syst. Conf. (SysCon)*, Apr. 2022, pp. 1–7. [Online]. Available: https://ieeexplore.ieee.org/document/9773919/

[74] A. B. Shitole, N. K. Kandasamy, L. S. Liew, L. Sim, and A. K. Bui, ''Real-time digital twin of residential energy storage system for cyber-security study,'' in *Proc. IEEE 2nd Int. Conf. Smart Technol. Power, Energy Control (STPEC)*, Dec. 2021, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/document/9718616/

[75] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, ''Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation,'' *J. Energy Storage*, vol. 30, Aug. 2020, Art. no. 101557.

[76] H. Tang, Y. Wu, Y. Cai, F. Wang, Z. Lin, and Y. Pei, ''Design of power lithium battery management system based on digital twin,'' *J. Energy Storage*, vol. 47, Mar. 2022, Art. no. 103679.

[77] J. Gao and H. Huang, ''Stochastic optimization for energy economics and renewable sources management: A case study of solar energy in digital twin,'' *Sol. Energy*, vol. 262, Sep. 2023, Art. no. 111865.

[78] O. Savenko, V. Martynyuk, M. Fedula, L. Koretska, and D. Makaryshkin, ''Automated control method for charging supercapacitors based on relaxation characteristics,'' in *Proc. 11th IEEE Int. Conf. Intell. Data Acquisition Adv. Comput. Systems: Technol. Appl. (IDAACS)*, vol. 1, Sep. 2021, pp. 377–382.

[79] Y. Yang, Q. Zhao, D. Gao, J. Rong, Y. Fan, H. Li, and J. Peng, ''Supercapacitor digital twin management system based on cloud environment,'' in *Proc. IEEE 23rd Int. Conf. High Perform. Comput. Commun.; 7th Int. Conf. Data Sci. Syst.; 19th Int. Conf. Smart City; 7th Int. Conf. Dependability Sensor, Cloud Big Data Syst. Appl. (HPCC/DSS/SmartCity/DependSys)*, Dec. 2021, pp. 1014–1021.

[80] E. O'Dwyer, I. Pan, R. Charlesworth, S. Butler, and N. Shah, ''Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems,'' *Sustain. Cities Soc.*, vol. 62, Nov. 2020, Art. no. 102412.

[81] X. Zhang, Y. Li, T. Li, Y. Gui, Q. Sun, and D. W. Gao, ''Digital twin empowered PV power prediction,'' *J. Modern Power Syst. Clean Energy*, vol. 12, no. 5, pp. 1472–1483, 2024.

[82] F. Tian, ''Internet of Things temperature control of indirect dual tank heat storage system in solar photo-thermal power plant,'' *Thermal Sci.*, vol. 28, no. 2, pp. 1477–1484, 2024.

[83] Y. Deng, Z. Weng, and T. Zhang, ''Metaverse-driven remote management solution for scene-based energy storage power stations,'' *Evol. Intell.*, vol. 16, no. 5, pp. 1521–1532, Oct. 2023.

[84] K. Shen, J. Sun, Y. Zheng, C. Xu, H. Wang, S. Wang, S. Chen, and X. Feng, ''A comprehensive analysis and experimental investigation for the thermal management of cell-to-pack battery system,'' *Appl. Thermal Eng.*, vol. 211, Jul. 2022, Art. no. 118422.

[85] J.-L. Kang, C.-C. Wang, D. S.-H. Wong, S.-S. Jang, and C.-H. Wang, ''Digital twin model and dynamic operation for a plant-scale solid oxide fuel cell system,'' *J. Taiwan Inst. Chem. Engineers*, vol. 118, pp. 60–67, Jan. 2021.

[86] D. Zhao, Q. He, J. Yu, M. Guo, J. Fu, X. Li, and M. Ni, ''A data-driven digital-twin model and control of high temperature proton exchange membrane electrolyzer cells,'' *Int. J. Hydrogen Energy*, vol. 47, no. 14, pp. 8687–8699, Feb. 2022.

[87] S. Meraghni, L. S. Terrissa, M. Yue, J. Ma, S. Jemei, and N. Zerhouni, ''A data-driven digital-twin prognostics method for proton exchange membrane fuel cell remaining useful life prediction,'' *Int. J. Hydrogen Energy*, vol. 46, no. 2, pp. 2555–2564, Jan. 2021.

[88] B. Wang, G. Zhang, H. Wang, J. Xuan, and K. Jiao, ''Multi-physics-resolved digital twin of proton exchange membrane fuel cells with a data-driven surrogate model,'' *Energy AI*, vol. 1, Aug. 2020, Art. no. 100004.

[89] Vanderbilt Univ. School Eng., Nashville, TN, USA. (2023). *What is the Difference Between CPS and IoT?*. Accessed: Oct. 6, 2024. [Online]. Available: https://blog.engineering.vanderbilt.edu/what-is-the-difference-between-cps-and-iot

[90] C. Virmani and A. Pillai, ''Internet of Things and cyber physical systems: An insight,'' in *Recent Advances in Intelligent Systems and Smart Applications*. Cham, Switzerland: Springer, 2021, pp. 379–401.

[91] M. Abdelmalak, V. Venkataramanan, and R. Macwan, ''A survey of cyber-physical power system modeling methods for future energy systems,'' *IEEE Access*, vol. 10, pp. 99875–99896, 2022.

[92] C. A. Macana, N. Quijano, and E. Mojica-Nava, ''A survey on cyber physical energy systems and their applications on smart grids,'' in *Proc. IEEE PES Conf. Innov. SMART GRID Technol. LATIN Amer. (ISGT LA)*, Oct. 2011, pp. 1–7.

[93] R. V. Yohanandhan, R. M. Elavarasan, P. Manoharan, and L. Mihet-Popa, ''Cyber-physical power system (CPPS): A review on modeling, simulation, and analysis with cyber security applications,'' *IEEE Access*, vol. 8, pp. 151019–151064, 2020.

[94] F. Arraño-Vargas and G. Konstantinou, ''Modular design and real-time simulators toward power system digital twins implementation,'' *IEEE Trans. Ind. Informat.*, vol. 19, no. 1, pp. 52–61, Jan. 2023.

[95] A. Kummerow, S. Nicolai, C. Brosinsky, D. Westermann, A. Naumann, and M. Richter, ''Digital-twin based services for advanced monitoring and control of future power systems,'' in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Aug. 2020, pp. 1–5.

[96] G. Kulikov, V. Antonov, L. Rodionova, A. Suleymanova, and A. Abdulnagimov, ''A digital twin model for electricity systems,'' in *Proc. Int. Conf. Electrotechnical Complexes Syst. (ICOECS)*, Nov. 2021, pp. 239–244.

[97] X. Tang, P. Ai, Q. Li, Y. Song, Q. Zhao, Y. Chen, and X. He, ''Creating multi-timescale digital twin models for regional multiple energy systems on CloudPSS,'' in *Proc. IEEE Sustain. Power Energy Conf. (iSPEC)*, Nov. 2020, pp. 1412–1418.

[98] C. Dufour, Z. Soghomonian, and W. Li, ''Hardware-in-the-loop testing of modern on-board power systems using digital twins,'' in *Proc. Int. Symp. Power Electron., Electr. Drives, Autom. Motion (SPEEDAM)*, Jun. 2018, pp. 118–123.

[99] H. Pan, Z. Dou, Y. Cai, W. Li, X. Lei, and D. Han, ''Digital twin and its application in power system,'' in *Proc. 5th Int. Conf. Power Renew. Energy (ICPRE)*, Sep. 2020, pp. 21–26.

[100] M. Zhou, J. Yan, and D. Feng, ''Digital twin framework and its application to power grid online analysis,'' *CSEE J. Power Energy Syst.*, vol. 5, no. 3, pp. 391–398, Sep. 2019.

[101] J. Liu, S. Wang, X. Lu, and T. Li, ''Research on online status evaluation technology for main equipment of power transmission and transformation based on digital twin,'' in *Proc. IEEE 5th Conf. Energy Internet Energy Syst. Integr. (EI2)*, Oct. 2021, pp. 3368–3373.

[102] S. Guan, W. Hu, Z. Lei, and H. Zhou, ''Digital twin-based online tools for electric power communication system training: Online digital twin power communication system,'' *IET Gener., Transmiss. Distrib.*, vol. 17, no. 1, pp. 146–160, Jan. 2023.

[103] C. K. Lo, C. H. Chen, and R. Y. Zhong, ''A review of digital twin in product design and development,'' *Adv. Eng. Informat.*, vol. 48, Apr. 2021, Art. no. 101297.

[104] F. Tao, F. Sui, A. Liu, Q. Qi, M. Zhang, B. Song, Z. Guo, S. C.-Y. Lu, and A. Y. C. Nee, ''Digital twin-driven product design framework,'' *Int. J. Prod. Res.*, vol. 57, no. 12, pp. 3935–3953, 2019.

[105] J. V. S. do Amaral, J. A. B. Montevechi, R. D. C. Miranda, and W. T. D. S. Junior, ''Metamodel-based simulation optimization: A systematic literature review,'' *Simul. Model. Pract. Theory*, vol. 114, Jan. 2022, Art. no. 102403.

[106] L. Wright and S. Davidson, ''How to tell the difference between a model and a digital twin,'' *Adv. Model. Simul. Eng. Sci.*, vol. 7, no. 1, pp. 1–13, Dec. 2020.

[107] V. Raghunathan. (May 2019). *Digital Twins vs Simulation: Three Key Differences*. [Online]. Available: https://www.entrepreneur.com/en-au/technology/digital-twins-vs-simulation-three-key-differences/333645

[108] T. I. Zohdi, ''An adaptive digital framework for energy management of complex multi-device systems,'' *Comput. Mech.*, vol. 70, no. 4, pp. 867–878, Oct. 2022.

[109] G. P. Lydon, S. Caranovic, I. Hischier, and A. Schlueter, "Coupled simulation of thermally active building systems to support a digital twin," *Energy Buildings*, vol. 202, Nov. 2019, Art. no. 109298.

[110] S. Hosseinihaghighi, P. M. Á. de Uribarri, R. Padsala, and U. Eicker, "Characterizing and structuring urban GIS data for housing stock energy modelling and retrofitting," *Energy Buildings*, vol. 256, Feb. 2022, Art. no. 111706.

[111] R. S. Srinivasan, B. Manohar, and R. R. A. Issa, "Urban building energy CPS (UBE-CPS): Real-time demand response using digital twin," in *Cyber-Physical Systems in the Built Environment*. Cham, Switzerland: Springer, 2020, pp. 309–322.

[112] G. Deena, K. Gulati, R. Jha, U. R. Bajjuri, M. Sahithullah, and M. Singh, "Artificial intelligence and a digital twin are effecting building energy management," in *Proc. Int. Conf. Innov. Comput., Intell. Commun. Smart Electr. Syst. (ICSES)*, Jul. 2022, pp. 1–8.

[113] F. A. Machado, C. G. Dezotti, and R. C. Ruschel, "The interface layer of a BIM-IoT prototype for energy consumption monitoring," in *Proc. 35th Conf., IT Design, Construct., Manage.* Cham, Switzerland: Springer, 2019, pp. 685–693.

[114] J. V. S. do Amaral, R. de Carvalho Miranda, J. A. B. Montevechi, C. H. dos Santos, and A. F. da Silva, "Data envelopment analysis for algorithm efficiency assessment in metamodel-based simulation optimization," *Int. J. Adv. Manuf. Technol.*, vol. 121, nos. 11–12, pp. 7493–7507, Aug. 2022.

[115] S. P. Kovalyov, "Design and development of a power system digital twin: A model-based approach," in *Proc. 3rd Int. Conf. Control Syst., Math. Model., Autom. Energy Efficiency (SUMMA)*, Nov. 2021, pp. 843–848.

[116] L. Merkle, A. S. Segura, J. Torben Grummel, and M. Lienkamp, "Architecture of a digital twin for enabling digital services for battery systems," in *Proc. IEEE Int. Conf. Ind. Cyber Phys. Syst. (ICPS)*, May 2019, pp. 155–160.

[117] S. Jafari and Y.-C. Byun, "Prediction of the battery state using the digital twin framework based on the battery management system," *IEEE Access*, vol. 10, pp. 124685–124696, 2022.

[118] G. Zhao, Z. Cui, J. Xu, W. Liu, and S. Ma, "Hybrid modeling-based digital twin for performance optimization with flexible operation in the direct air-cooling power unit," *Energy*, vol. 254, Sep. 2022, Art. no. 124492.

[119] K. Dröder, P. Bobka, T. Germann, F. Gabriel, and F. Dietrich, "A machine learning-enhanced digital twin approach for human–robot-collaboration," *Proc. CIRP*, vol. 76, pp. 187–192, 2018.

[120] T. Cheng, X. Zhu, F. Yang, and W. Wang, "Machine learning enabled learning based optimization algorithm in digital twin simulator for management of smart islanded solar-based microgrids," *Sol. Energy*, vol. 250, pp. 241–247, Jan. 2023.

[121] S. Cao, V. Dinavahi, and N. Lin, "Machine learning based transient stability emulation and dynamic system equivalencing of large-scale AC–DC grids for faster-than-real-time digital twin," *IEEE Access*, vol. 10, pp. 112975–112988, 2022.

[122] Baeldung. (Nov. 2022). *Inter-Process Communication*. [Online]. Available: https://www.baeldung.com/cs/inter-process-communication

[123] J. Han, Q. Hong, M. H. Syed, M. A. U. Khan, G. Yang, G. Burt, and C. Booth, "Cloud-edge hosted digital twins for coordinated control of distributed energy resources," *IEEE Trans. Cloud Comput.*, vol. 11, no. 2, pp. 1–15, Apr. 2023.

[124] Y. Chen, F. Zhao, X. Chen, and Y. Wu, "Efficient multi-vehicle task offloading for mobile edge computing in 6G networks," *IEEE Trans. Veh. Technol.*, vol. 71, no. 5, pp. 4584–4595, May 2022.

[125] K. M. Alam and A. E. Saddik, "C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems," *IEEE Access*, vol. 5, pp. 2050–2062, 2017.

[126] H. Liao, Z. Zhou, N. Liu, Y. Zhang, G. Xu, Z. Wang, and S. Mumtaz, "Cloud-edge-device collaborative reliable and communication-efficient digital twin for low-carbon electrical equipment management," *IEEE Trans. Ind. Informat.*, vol. 19, no. 2, pp. 1715–1724, Feb. 2023.

[127] J. Xie, R. Yang, S.-Y. R. Hui, and H. D. Nguyen, "Dual digital twin: Cloud–edge collaboration with Lyapunov-based incremental learning in EV batteries," *Appl. Energy*, vol. 355, Feb. 2024, Art. no. 122237.

[128] Z. F. Huang, K. Y. Soh, M. R. Islam, and K. J. Chua, "Digital twin driven life-cycle operation optimization for combined cooling heating and power-cold energy recovery (CCHP-CER) system," *Appl. Energy*, vol. 324, Oct. 2022, Art. no. 119774.

[129] D. Bayer and M. Pruckner, "A digital twin of a local energy system based on real smart meter data," *Energy Informat.*, vol. 6, no. 1, p. 8, Mar. 2023.

[130] H. Jamil, Y. Jian, F. Jamil, M. Hijjawi, and A. Muthanna, "Digital twin-driven architecture for AIoT-based energy service provision and optimal energy trading between smart nanogrids," *Energy Buildings*, vol. 319, Sep. 2024, Art. no. 114463.

[131] S. H. Dolatabadi, M. Ghorbanian, P. Siano, and N. D. Hatziargyriou, "An enhanced IEEE 33 bus benchmark test system for distribution system studies," *IEEE Trans. Power Syst.*, vol. 36, no. 3, pp. 2565–2572, May 2021.

[132] X. Song, H. Cai, J. Kircheis, T. Jiang, S. Schlegel, and D. Westermann, "Application of digital twin assistant-system in state estimation for inverter dominated grid," in *Proc. 55th Int. Universities Power Eng. Conf. (UPEC)*, Sep. 2020, pp. 1–6.

[133] M. Landen, K. Chung, M. Ike, S. Mackay, J.-P. Watson, and W. Lee, "DRAGON: Deep reinforcement learning for autonomous grid operation and attack detection," in *Proc. 38th Annu. Comput. Secur. Appl. Conf.*, Dec. 2022, pp. 13–27.

[134] Q. Li, Z. Cui, Y. Cai, Y. Su, and B. Wang, "Renewable-based microgrids' energy management using smart deep learning techniques: Realistic digital twin case," *Sol. Energy*, vol. 250, pp. 128–138, Jan. 2023.

[135] J. Chen, Y. Gan, H. Zhou, J. Zhong, and C. He, "Intelligent coordinated control strategy of distributed photovoltaic power generation cluster based on digital twin technology," in *Proc. 4th Int. Conf. Electr. Eng. Control Technol. (CEECT)*, Dec. 2022, pp. 236–240.

[136] Z. Shen, W. Xu, W. Li, Y. Shi, and F. Gao, "Digital twin application for attach detection and mitigation of PV-based smart systems using fast and accurate hybrid machine learning algorithm," *Sol. Energy*, vol. 250, pp. 377–387, Jan. 2023.

[137] W. Cao and L. Zhou, "Resilient microgrid modeling in digital twin considering demand response and landscape design of renewable energy," *Sustain. Energy Technol. Assessments*, vol. 64, Apr. 2024, Art. no. 103628.

[138] Y.-Y. Hong and G. F. D. Apolinario, "Ancillary services and risk assessment of networked microgrids using digital twin," *IEEE Trans. Power Syst.*, vol. 38, no. 5, pp. 1–15, Sep. 2022.

[139] J. C. Olivares-Rojas, E. Reyes-Archundia, J. A. Gutiérrez-Gnecchi, I. Molina-Moreno, J. Cerda-Jacobo, and A. Méndez-Patiño, "Towards cybersecurity of the smart grid using digital twins," *IEEE Internet Comput.*, vol. 26, no. 3, pp. 52–57, May 2022.

[140] B. Xu, J. Wang, X. Wang, Z. Liang, L. Cui, X. Liu, and A. Y. Ku, "A case study of digital-twin-modelling analysis on power-plant-performance optimizations," *Clean Energy*, vol. 3, no. 3, pp. 227–234, Nov. 2019.

MD RAFIUL KABIR received the B.Sc. degree in electrical and electronic engineering from the Ahsanullah University of Science and Technology, Dhaka, Bangladesh, the M.Sc. degree in electrical engineering from the University of Toledo, and the Ph.D. degree from the Department of Electrical and Computer Engineering, University of Florida. He is an Assistant Professor with the School of Engineering and Technology, Central Michigan University. Before that, he was an Electrical Engineer with Horizon Global Americas, MI, USA, where he worked in the design and development of OEM trailer brake controllers used in automobiles. At the University of Toledo, his research was on renewable energy applications. His research interests include the Internet of Things, digital twins, automotive safety and cybersecurity, and healthcare applications.

DIPAL HALDER (Graduate Student Member, IEEE) received the bachelor's degree in electrical and electronic engineering from the Khulna University of Engineering and Technology, Bangladesh, the master's degree in computer aided engineering from Eastern Michigan University, and the advanced master's degree in embedded system security from Grenoble INP, ESISAR, France. He is currently pursuing the Ph.D. degree with the RISING Laboratory, University of Florida. Furthermore, he was an Research and Development System Engineer Intern with Groupe SEB, France. His research interests include system-on-chip (SoC) design and hardware security.

SANDIP RAY (Senior Member, IEEE) received the Ph.D. degree from The University of Texas at Austin. He is a Professor with the Department of Electrical and Computer Engineering, University of Florida, Gainesville, FL, USA, where he holds an Endowed IoT Term Professorship. Before joining the University of Florida, he was a Senior Principal Engineer with NXP Semiconductors. Prior to that, he was a Research Scientist with the Intel Strategic CAD Laboratories. He is the author of three books and over 100 publications in international journals and conferences. His current research targets correct, dependable, secure, and trustworthy computing through the cooperation of specification, synthesis, architecture, and validation technologies. He has served as a technical program committee member for over 50 international conferences. He was the Program Chair of ACL2 2009, FMCAD 2013, and IFIP IoT 2019. He was a Guest Editor of *IEEE Design and Test*, IEEE TRANSACTIONS ON MULTI-SCALE COMPUTING SYSTEMS, and ACM TODAES; and an Associate Editor of Springer HaSS and IEEE TRANSACTIONS ON MULTI-SCALE COMPUTING SYSTEMS.