Enhancing Reliability of Energy Systems with Digital Twins: Challenges and Opportunities

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***Abstract*—Digital Twins enable real-time monitoring through automatic model extraction of complex systems using data from sensors, meters and IoT devices to facilitate valuable decisions. In energy systems, Digital Twins can be integrated to improve system reliability by enabling adaptability to demand fluctuations and system disturbances. With the increasing share of renewable energy sources, reliability and stability of power grids is challenged by intermittent supply, unexpected disturbances, and demand mismatches. In this paper, we explore the use of modelling and simulation for reliability analysis and investigate automation of reliability model extraction for Digital Twins in the context of energy systems. By reviewing Digital Twin applications in energy systems, including energy optimization and predictive maintenance, the paper contributes to the understanding of trends, challenges, and opportunities in improving reliability of energy systems through a comprehensive review of literature and implementation results.**

Keywords—Digital Twins, Reliability, Energy Systems

I. Introduction

Reliability of energy systems is important to ensure stable and uninterrupted supply to meet the growing demands of modern society. However, aging infrastructures, increasing complexities, and integration of renewable energy sources present significant challenges to maintaining reliability [1]. Modeling and simulation play a pivotal role in evaluating reliability of power systems, particularly as the integration of renewable energy sources introduces new complexities [2].

Two fundamental concepts within the reliability of power systems are adequacy and security [3]. Adequacy, also known as resource adequacy, refers to the capability of the electrical grid to meet end-user power demand at any given time, especially during peak demand periods. This involves ensuring a surplus of dispatchable generation capacity and demand response resources to accommodate major equipment failures and fluctuations in power from variable renewable energy sources, such as wind variability [4]. On the other hand, security refers to the ability of the system to maintain the balance between supply and demand in real-time, especially after contingencies, by automatically adjusting generation and removing interruptible loads. Security relies on the availability of operating reserves, historically provided by synchronous generators [4]. However, with the proliferation of inverter-based resources, like solar photovoltaics and grid batteries, ensuring security has become more complex [5].

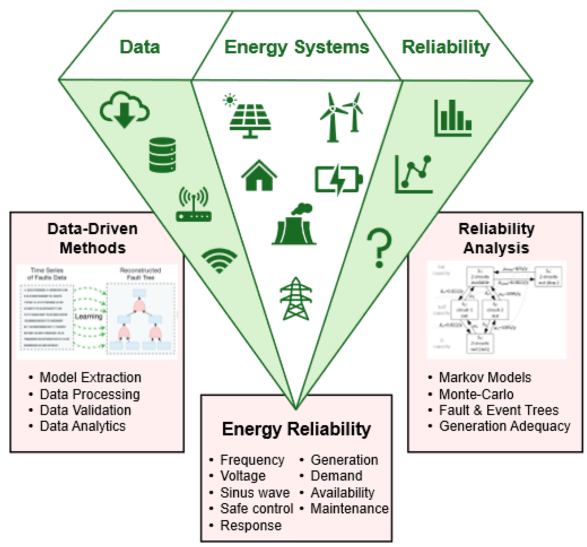

Fig. 1. Integration of data-driven reliability analysis in energy systems.

Modeling and Simulation (M&S) techniques enable the assessment of adequacy and security in power systems, facilitating understanding and improvement of reliability amidst changing energy landscapes and increasing renewable energy integration [2]. Given the central role of data in today's energy industry, data can be used to study the reliability of energy systems through the application of M&S with the aim of improving reliability measures and formulating more effective decisions for more reliable systems. For this reason, data-driven analysis and simulation approaches are becoming increasingly popular in many fields with the aim of extracting system behavior [6]. Fig. 1 illustrates the complementary roles of data-driven methods and reliability analysis in ensuring the security and adequacy of energy systems, emphasizing their integration to achieve reliable performance.

A DT serves as a virtual representation of a physical entity, process, or system, capable of reflecting its real-time behavior through data interaction [7]. For example, in the context of smart grids, a DT acts as a virtual replica of the physical power grid, reflecting real-time grid behavior using data from smart meters and sensors [8]. Implementing DTs for smart grids provides utilities and grid operators with a holistic view of their infrastructure [9]. DTs enable improved monitoring, management, and optimization of power system performance by providing accurate simulation and predictive analytics [10], [11]. Real-time monitoring and advanced analytics can help identify potential problems, predict failures, and improve power systems' reliability and efficiency [12].

Capabilities of DTs can facilitate the transition of power systems, one of the most complex Cyber-Physical Systems (CPS) created by humans, towards a new generation of Industry 4.0 [13]. The advancement of digital transformation involves advanced technologies such as Machine Learning (ML) and Industrial Internet of Things (IIoT). The concept of DT has recently gained prominence as a means of revolutionizing modern energy industry, with potential applications to improve power grid operations, reduce unplanned outages and manage fluctuations in market conditions [14]. By enhancing stability, reliability, and resilience through real-time fault monitoring, power grid DTs emerge as a valuable tool. This transformative technology (i.e., DT) is relevant to microgrid development, where its application promises substantial benefits for long-term planning [15]. Furthermore, DT technology offers a transformative perspective from the standpoint of energy management and monitoring, enabling systems and operators to make optimal and more efficient decisions [10].

To identify challenges and opportunities in using DTs to maintain reliability of power/energy systems, we performed detailed literature review on the application of data-driven methods in power system reliability analysis and simulation, focused on impactful papers published from 2014 to the present. We begin with a background and related work in Section II, where we outline the current methods for reliability assessment in power/energy systems. This section also addresses the primary M&S techniques used in power/energy systems, and their limitations in reliability assessment. We conclude this section with an overview of the concept of DTs in various power/energy systems and their applications, and advantages. In Section III, we discuss the role of data-driven approaches in applying DTs for enhancing energy system reliability. We, furthermore, present examples from recent research where DTs have been used for reliability analysis in power/energy systems. As a result of our findings, we propose a general framework for DTs for enhancing reliability in power/energy systems. In Section IV, we discuss the challenges and limitations associated with the implementation of DT for reliability enhancement in power/energy systems. In Section V, we present a summary of the key findings from the literature review and discuss future research directions in this area.

II. Background and Related Work

In this section, we provide background on the use of DTs for enhancing reliability of power/energy systems. For this, we review recent advances on reliability, M&S, and DTs in energy systems. To conduct this review, we followed the three-level methodology below. Fig. 2 shows the number of documents obtained after the first level, accumulated over the last 10 years.

Level 1: Keyword search on Scopus and Google Scholar.

Level 2: Screening the documents based on their titles, keywords, and abstracts to select the most impactful studies.

Level 3: Reading and analyzing the selected papers.

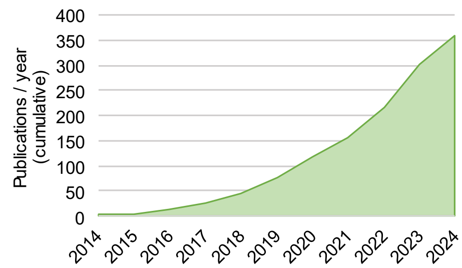

Fig. 2. Cumulative publications in Scopus over the last 10 years related to data-driven reliability analysis and simulation in power systems (as of 10-Jun-2024).

A. Reliability of Energy Systems

Reliable energy is essential for life-saving hospital equipment, communication systems, and building environments, supporting health, safety, and economic security. Energy reliability is defined as the ability of a power system to withstand instability, uncontrolled events, cascading failures, or unforeseen loss of system components [16]. In other words, a reliable energy system can deliver energy securely and adequately to homes, buildings, and appliances, even in the event of physical or cyber disruptions.

Power and energy system failures have a significant impact on the economy, causing significant financial losses and operational disruptions. In the United States, power outages cost about $150 billion annually, according to the Department of Energy [17], underscoring the importance of power system reliability. Utilities face challenges in recovering from severe outages, which affect not only their operations but also the broader economy. As a result, utilities must balance the high cost of grid improvements with the need for reliable power, aiming for an "adequate level of reliability" at a reasonable cost [18]. Digital transformation strategies can help utilities reduce unplanned outages, and enhance reliability and performance [19].

The evolution of power system reliability has undergone significant advancements driven by technological progress, increasing demand for electricity, and a deeper comprehension of system dynamics [20]. In the initial stages, the assessment of reliability was primarily focused on the maintenance of continuous electricity supply in the face of component failures, relying on empirical data and heuristic methods [21]. However, with the increasing complexity of power systems, it became evident that these traditional approaches were no longer sufficient to ensure reliability [22].

The introduction of probabilistic methods by researchers, such as Allan and Billinton, transformed the field, allowing accurate modeling of system reliability by incorporating uncertainties in generation and load [4]. Advanced computational tools have further transformed reliability analysis, allowing detailed modeling of complex systems, including those with renewable energy sources and smart grid technologies [22], [23]. Additionally, the emergence of smart grid technologies further revolutionized this area of power system reliability by enabling real-time monitoring and predictive maintenance strategies, as discussed by Weng et al. [24], who demonstrated how historical data-driven state estimation can improve reliability management in modern power grids. An overview of reliability analysis in CPS has been presented in [25], outlining the need and potential of conducting data-driven reliability assessments in the current era due to the pivotal role played by data.

Two different approaches are used to assess the reliability of power systems: deterministic and probabilistic [3]. Historically, deterministic methods have been employed for planning of aspects such as generation, operation, and network capacity [3]. However, despite the advantages of being simple to perform and requiring less data, these methods do not take into account the stochastic nature of systems' behaviors, including uncertainty in customer load demands and component failures [3]. On the contrary, probabilistic approaches consider uncertain events and random nature of component failures (i.e., failure states). Therefore, probabilistic approaches can handle the variable nature of renewable generation, whereas deterministic approaches usually only consider worst-case scenarios [3].

Deterministic reliability analysis includes criteria, such as N-1 redundancy, where critical components are duplicated to ensure system functionality in events of failures [3]. Otherwise, load shedding strategies are employed to prevent overloading by temporarily cutting off non-essential loads during peak demand [4]. The principal drawback of deterministic criteria is that they may result in the over-design of power systems, thereby failing to consider economic and risk factors.

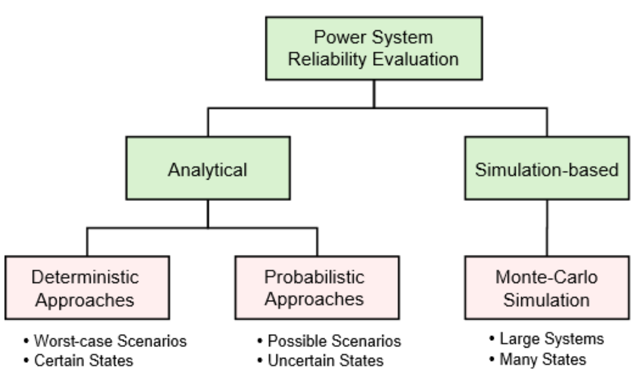

Fig. 3. Reliability assessment methods for power systems.

On the other hand, probabilistic reliability analysis are not easily interpreted without translating results into actionable reliability indicators [3]. Reliability indicators are parameters that quantitatively assess an aspect of power system reliability [3], such as the number, duration, or frequency of failures. It is impossible to assess all aspects using one indicator and no approach always works best. Probabilistic reliability analysis of power systems is discussed in detail in the textbook by Tuinema et al. [3]. This textbook provides a comprehensive introduction to reliability models for components, small systems and large systems using a range of methods including reliability functions, Markov models, fault/event tree analysis and Monte Carlo simulation. Fig. 3 shows the main categories of reliability assessment methods for power systems.

Several reliability indices are commonly used to evaluate the reliability of power systems [3]. For example, utilities measure their performance measures using:

1. System Average Interruption Frequency Index (SAIFI)
2. System Average Interruption Duration Index (SAIDI)
3. Customer Average Interruption Duration Index (CAIDI)
4. Customer Average Interruption Frequency Index (CAIFI)
5. Average Service Availability Index (ASAI)
6. Average Energy Not Supplied (AENS)

B. *Modeling & Simulation for Reliability in Energy Systems*

Advances in reliability of energy systems rely heavily on their M&S techniques. Subramanian et al. [26] review key M&S developments in the field of energy systems and categorize contributions into computational, mathematical, and physical models, while also exploring hybrid approaches. They emphasize hybrid models that integrate process systems engineering and energy economics provide a holistic view by combining technical and economic perspectives. This classification shows how different models address different aspects of energy systems to improve reliability. Key applications include optimal design, demand and price forecasting, sustainability analysis, and consideration of emerging technologies. Continued research to refine these techniques is essential to address the growing complexity of modern energy systems and ensure energy reliability.

In the face of future uncertainties, reliability of energy systems is a critical concern for both researchers and practitioners. Niet et al. [2] address this issue by improving the reliability of energy system scenarios through integrated modeling. The authors review existing modeling paradigms—energy economics, capacity expansion, and power sector planning—and discuss the benefits of combining them into a single framework to leverage their respective advantages. While integrated modeling can enhance representation of system interactions, it also increases complexity and risks creating "black box" models that lack transparency and trust. The authors emphasize that increasing model complexity requires careful consideration to maintain transparency and trustworthiness. They recommend avoiding overly complex models and focusing on clear modeling purposes and best practices to ensure clarity and transparency. Continued research in this area is crucial to address future challenges effectively.

Adinolfi et al. [27] propose a unique method for power system reliability assessment that integrates component and system reliability metrics for a comprehensive evaluation. This method adapts Reliability Prediction Models (RPMs) for different equipment such as power lines, transformers, circuit breakers, and renewable energy systems. The effectiveness of the method is demonstrated in grid reliability assessment by integrating it into a software application for practical implementation. The authors introduce the "Load Feeding Reliability" indicator, which evaluates the failure rate of all possible paths feeding a given load unit, thereby measuring the reliability of power supply to specific loads. This indicator helps identify unreliable systems and improve power system design, planning, and control, thereby increasing the reliability of grids and microgrids. The study underscores the importance of detailed and integrated modeling for the reliability of complex power systems and highlights the need for continued research in this area.

Data-driven methods have emerged as powerful tools for enhancing power/energy system reliability. Bertozzi et al. [28] explore how these approaches can improve power system stability and control by enabling real-time analysis of large operational data sets to predict potential failures. The paper discusses methods such as Koopman spectral analysis, physics-informed neural networks (PINNs), and sparse identification models that extract and analyze system dynamics from raw data. Machine learning algorithms can identify patterns and anomalies in historical data, enabling predictive control decisions and timely intervention to reduce downtime and improve reliability. Key findings highlight the effectiveness of these methods in improving grid stability, frequency support, and power oscillation damping. In addition, the authors advocate the integration of model-based and data-driven control techniques, combining their strengths to adapt to variations and uncertainties. Their work underscores the potential of data-driven modeling and simulation to revolutionize power system reliability and calls for further research to fully exploit these technologies.

Quantitative reliability modelling of power systems presents several challenges due to their inherent complexity [4]. Factors, such as high redundancy, varying component reliability and the dynamic nature of outage events, contribute to this complexity [4]. Identifying and quantifying the probability and impact of outage events is a challenging task, particularly when major interruptions involve dependent outage events that are not easily modelled probabilistically [4]. In addition, load shedding mechanisms (typically triggered by insufficient system frequency or undervoltage) and the role of human interaction in the control room further complicate modelling processes [4]. Despite these challenges, probabilistic assessment provides valuable data-driven insights that improve decision making by reducing the reliance on subjective judgement [3]. Qualitative methods utilize models, diagrams, and other visual tools to analyze and understand the reliability of a system and its components [29]. Conversely, quantitative methods employ mathematical and statistical techniques to evaluate the system's and its components' reliability [29]. Combining both qualitative and quantitative reliability assessment approaches provide a comprehensive reliability assessment of CPS [29].

Traditional modeling approaches in energy systems typically do not address the complexity and dynamic nature of modern power grids. For instance, the traditional modeling approaches may not account for the variability and uncertainty inherent in renewable energy sources, such as solar and wind power, leading to less accurate reliability predictions. Additionally, these approaches typically focus on individual components in isolation rather than considering the interconnectedness and interdependencies within the entire system. Consequently, these models may not provide accurate predictions of system failures or insights into potential areas of vulnerability.

The evolving landscape of energy systems, characterized by increased penetration of renewable energy and advanced grid technologies, necessitates more sophisticated modeling techniques that can dynamically adapt to changing conditions and integrate a holistic view of system interactions. Investment in research and development of modeling and simulation are crucial for building stable and reliable energy systems as they grow in complexity.

The need for integrated modeling techniques is becoming increasingly apparent, necessitating innovative, data-driven, and probabilistic modeling approaches that can better capture the complexity of modern energy systems and improve their reliability. Therefore, based on the reliability methodologies explored in our literature review, we selected examples to illustrate data-driven reliability modeling for improvement of reliability in different energy system applications. The reviewed papers are presented in Table I and classified according to the reliability model, application, data, reliability assessment method and key performance indicators (KPIs) used.

C. *Digital Twins for Energy Systems*

Digital Twins (DTs) are sophisticated, dynamic digital replicas of physical systems that continuously update and evolve through real-time data and expert knowledge. This concept was first introduced by Michael Grieves in 2002 [7] and has since evolved to encompass advanced technologies such as smart sensors, IoT, 5G communications, cloud platforms, and Artificial Intelligence (AI) [8]. In energy systems, DTs serve as virtual entities that replicate the properties, behaviors, and interactions of physical energy assets such as power plants, grids, and substations [8]. They enable real-time monitoring, performance optimization, and predictive maintenance by creating a continuous feedback loop between the physical and virtual worlds [13], [30].

DTs are transforming energy systems by enhancing efficiency, reliability, and sustainability across various sectors, including power generation, transmission, distribution, energy storage, industrial management, and smart cities. DTs are increasingly used in various facets of energy systems to improve cybersecurity, efficiency, sustainability, and reliability [10], [31]. This section explores the various applications of DTs across different energy systems, highlighting key studies and their findings.

TABLE I. EXAMPLES OF RELIABILITY MODELING FOR ENERGY SYSTEMS USING POPULAR RELIABILITY MODELS

Reliability Model	References	Application	Model Development	Data	Reliability Assessment Approach	KPIs
Markov Models	[32]	Integrated Energy System (IES)	Data-driven, Physics-based	Static data for power and heat loads, system configuration	Monte Carlo Simulation, State Enumeration Method	Loss of Load Probability (LOLP), Expected Energy Not Supplied (EENS), Expected Heat Not Supplied (EHNS)
	[33]	Renewable Energy-Based Microgrids	Data-driven, Physics-based[a]	Static hourly weather data, parameters for components' faults and failures	Monte Carlo Simulation	LOLP, EENS, Loss of Load Expectation (LOLE)
	[34]	Offshore Wind Farm	Data-driven, Physics-based	Static data from wind speed, system configuration	Sequential Monte Carlo Simulation	LOLP, EENS, Energy Utilization Ratio (EUR), Time Utilization Ratio (TUR), Energy Loss (EL)
Hybrid Models (combining discrete-event and continuous models)	[35]	Grid-Connected Solar Photovoltaic System	Data-driven, Physics-based[a]	Static data on weather patterns, parameters for components' faults and failures	Sequential Monte Carlo Simulation	Time-to-Failure (TF), Time-to-Repair (TR), Healthy State Probability
Reliability Block Diagrams	[36], [37]	Microgrids with Hybrid Energy Storage	Data-driven	Static data on failure and repair time of components	Monte Carlo Simulation	LOLP, SAIFI, SAIDI, CAIDI, ASAI
Fault Trees	[38], [39]	Cyber-Physical Systems	Data-driven, Expert knowledge	Streaming data from fault, repair, and failure occurrences	Proxel-based simulation	Reliability and Maintainability Distributions

[a.] The model considers the variability of renewable resources and weather conditions.

1) Power Generation

The emergence of DTs is transforming the field of power generation, enabling more efficient, reliable, and sustainable operations. In the context of power generation, DTs are employed for real-time monitoring and control, improved maintenance strategies, and enhanced energy production. For instance, Choi et al. [40] discuss the implementation of DTs in power generation, emphasizing their role in operational efficiency and predictive maintenance.

Wind Power: The development and deployment of DTs in wind power are significant for monitoring and improving the performance of wind turbines. Pimenta et al. [41] highlight the creation of a DT for an onshore wind turbine, using monitoring data to enhance performance and maintenance. Wang et al. [24] examine the use of DT solutions to enhance the reliability and support the structures of offshore wind turbine, demonstrating the improvements in structural integrity and operational reliability. Real-world applications, such as General Electric's DT for wind farms [42] and DNV GL's WindGEMINI [43], illustrate the practical benefits of DTs in enhancing energy production and reliability.

Solar Power: In the context of solar power, DTs are applied to reduce downtime and optimize fault diagnosis, power point tracking, and asset management. Jain et al. [44] apply fault detection and identification methodologies through a model-based DT to enhance fault diagnosis and reduce downtime for photovoltaic (PV) systems. Moreover, Yalçin et al. [45] investigate the potential of machine learning and DT concepts to enhance the operation of solar PV plants, improving fault detection and system efficiency. Additionally, Wang et al. [46] underscore the significance of DTs in enhancing power output by improving the maximum power point estimation for PV systems.

2) Power Transmission

DTs in power transmission are critical for real-time analysis and improving the reliability of power grids. Yassin et al. [47] provide a comprehensive review that explores the operating principles, communication channels, and challenges of applying DTs in power systems, integrating concepts such as Machine Learning (ML), Big Data (BD), Artificial Intelligence (AI), Cyber-Physical Systems (CPS), and Internet of Things (IoT). Furthermore, Sifat et al. [8] provide frameworks and an overview of the technologies and requirements for implementing DTs in power grids, highlighting their potential to prevent power outages and blackouts. In addition, real-time online analysis of power grids is explored by Zhou et al. [48], showing the potential of real-time online analysis through DTs to improve grid performance and security.

3) Power Distribution & Microgrids

DTs improve the management and reliability of distribution networks. Zhaoyun and Linjun [49] review the current applications and future prospects of DTs in distribution networks applications for fault prediction, real-time monitoring, reconfiguration, and power load forecasting. In addition, the DT approach of Jain et al. [44] enables fault diagnosis in distributed PV systems to reduce downtime. Real-world applications, such as the Norwegian Distribution System Operator's (DSO) Tensio test of a DT of the power grid [50], demonstrate the benefits of this technology.

Microgrids: A microgrid is an independent energy system comprising distributed energy resources and connected loads, capable of operating both independently and while connected to the main grid [51]. Bazmohammadi et al. [15] discuss the application of DTs in microgrids and their role in improving operational efficiency and resiliency, using historical and real-time data through sensor networks and IoT technologies. The applications of DTs in microgrids, explored by the authors, include optimizing operation, maintenance, design, control, operator training, forecasting, fault diagnosis, expansion planning, and policy making. Danilczyk et al. [52] present ANGEL, an intelligent DT framework for microgrid security, highlighting the potential for enhanced protection and operational stability.

4) Energy Storage Systems

DT plays a pivotal role in optimizing energy storage systems. Semeraro et al. [53] explore trends and challenges for various application of DT in energy storage systems (EES), emphasizing their potential in improving storage efficiency and reliability. Further studies by Semeraro et al. [54] and Kharlamova et al. [55] highlight the use of DTs in battery energy storage systems (BESS) for better performance and frequency regulation.

5) Industrial Management

In industry, reliability of systems is directly linked to the energy consumption. DTs in industrial energy management are increasingly implemented for improving energy efficiency and sustainability of industrial systems. Yu et al. [56] classify the different types of DTs used in industrial energy management, summarizing the applications of energy DTs throughout an industrial site's lifecycle. Khodadadi and Lazarova-Molnar [57] analyze data requirements of energy-oriented DT for industrial energy efficiency through a case study system.

6) Smart Cities

Smart cities are inseparable from energy systems. Employing a smart city DT applies to all energy systems within the smart city. Jafari et al. [10] review the potential of DT technology in the management and energy systems of smart cities, such as transportation and power systems, and show the key role of DT in improving the operation of smart cities.

III. A Framework for Data-Driven Digital Twins for Reliability Analysis in Energy Systems

The DT concept is becoming increasingly important for improving the reliability and stability of power grids, especially with the integration of renewable energy technologies [9], [58], [59]. DT frameworks for power systems can be classified as model-based, data-driven and hybrid, based on the modelling technique [47]. Since DTs update underlying models in near-real-time with system changes based on data, data-driven DTs are emerging as a good solution for improving the reliability of power systems where timeliness is important [60]. Applications of extracted models from energy system data through DTs can be supporting predictive maintenance, fault diagnosis using fault trees [38], security evaluation, operation management, monitoring, and control [15].

Data-driven approaches alone may not be sufficient to ensure energy system reliability. Dynamic system models complement data-driven methods to accurately capture and predict system behavior under different operating conditions [60]. For example, Chakraborty and Adhikari [61] proposed a hybrid approach that combines physics-based and data-driven methods to track and predict the multiscale evolution of system parameters. Similarly, Tzanis et al. [11] developed a hybrid DT model for smart grid fault prediction by combining data-driven machine learning with model-based transient state estimators. This hybrid approach improves fault prediction and predictive maintenance, ensuring robust performance, effective real-time fault detection, and accurate predictions by leveraging the strengths of both modeling techniques.

Security of Operation: Enhancing the security of operation in energy systems involves advanced technologies and proactive strategies to minimize the frequency and impact of unplanned outages and disruptions. Possible advances using data-driven DTs include real-time grid monitoring and control systems that utilize data analytics and IoT sensors to detect faults early and enable swift corrective actions. Smart grid technologies, augmented with data-driven DTs, can facilitate dynamic grid reconfiguration and rapid fault isolation, ensuring quick restoration of service during disruptions. Additionally, microgrid solutions and distributed energy resources (DERs), integrated through DT frameworks, enhance local resilience and reduce dependency on centralized infrastructure. Robust cybersecurity measures, including continuous monitoring and threat detection through DTs, protect against physical and cyber threats. These innovations collectively ensure uninterrupted energy supply, safeguard critical infrastructure, and maintain the reliability of energy systems under diverse operational conditions.

Adequacy of Supply: Data-driven DTs hold significant potential for bolstering supply adequacy in energy systems by improving the integration and management of renewable energy sources and energy storage technologies. Advanced forecasting and grid management techniques for renewables, alongside data-driven insights from DTs, enhance grid stability and reduce supply variability. Innovations in battery storage and grid-scale solutions like pumped hydro, monitored and optimized through DTs, support reliable peak demand management and the integration of intermittent renewable sources into the grid. These advancements contribute to enhanced energy efficiency and reduced emissions, ensuring a stable and adequate energy supply.

Data-driven approaches, such as machine learning and process mining, are used in DTs for various reliability improvements in power systems. Djebali et al. [9] highlight the use of AI and ML in DTs for smart grids, focusing on predictive maintenance, energy optimization, and demand response to improve decision making and system reliability. Chakraborty and Adhikari's [61] hybrid approach combines physics-based and data-driven methods for dynamic system analysis, using machine learning algorithms such as mixture of experts (ME) and Gaussian process (GP) to update DT models and make future predictions, with the ME-GP-based DT providing superior results compared to the GP-based twin.

Anomaly detection algorithms and dynamic system modeling, as proposed by Sleiti et al. [60] improve the reliability and maintainability of power plants by utilizing real-time data. In addition, Shi et al. [62] developed a data-driven model for power system anomaly detection using random matrix and free probability theory, which improves the accuracy and sensitivity of system anomaly detection.

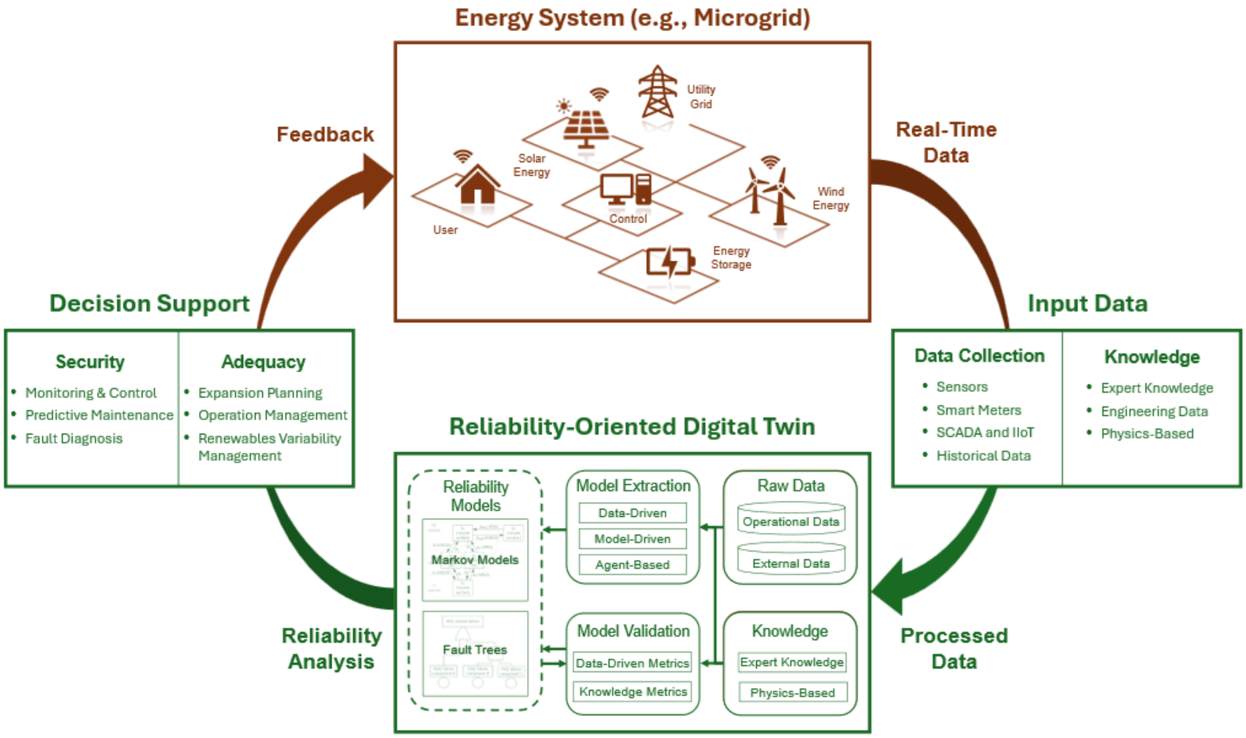

Fig. 4. Proposed framework for DTs for enhancing reliability in power/energy systems.

In addition, Nguyen et al. [63] used a Power Hardware-In-The-Loop (PHIL) setup to integrate DTs for real-time monitoring and operational optimization of renewable energy resources. Song et al. [64] proposed a multi-level system of DT systems (SDTS) using BD and AI to improve grid stability and resilience. IoT and machine learning, highlighted by Jafari et al. [10] enhance real-time data management and analysis in smart grids and transportation systems to improve overall reliability and efficiency.

For example, Wang et al. [65] developed a data-driven DT framework for real-time monitoring, fault diagnosis, and operation optimization of offshore wind turbines. In addition, the DT developed by Jain et al. [44] uses model-based fault detection and identification methods to improve fault diagnosis and reduce downtime for PV systems. Several other studies have proposed five-dimensional DT (5D-DT) framework for power systems and energy sector applications consisting of five key layers ("physical system", "virtual system", "connection", "data" and "services") [15], [30], [31], [49], [66].

Based on our findings, we propose a general data-driven DT framework for reliability enhancement of energy systems, illustrated in Fig. 4 The components of the framework are explained below.

Energy System: The energy system component encompasses the physical infrastructure of power plants, transmission lines, substations, distribution networks, microgrids, or energy storage systems. These systems are equipped with data collection technologies such as sensors, smart meters, Supervisory Control and Data Acquisition (SCADA) systems, and IIoT devices. These technologies enable collection of essential operational data for further processing and analysis.

Input Data: Input data is automatically collected and processed from operational data from sensors, smart meters, SCADA systems, IIoT devices, historical records, and expert knowledge. This component ensures data quality and relevance for model extraction, providing a robust foundation for reliability analysis by the DT.

Reliability-Oriented Digital Twin: DT extracts reliability models from input data using data-driven, model-driven, or hybrid approaches to analyze energy system reliability. Machine learning and other data-driven techniques can be used to extract fault tree and Markov models from real-time data fir fault detection and diagnosis in energy systems [45], [62]. In addition, model-driven approaches incorporate physical laws and engineering principles to simulate system behavior [2]. On the other hand, hybrid approaches combine both data-driven and model-driven extraction methods, for example, using physics-based models to study system dynamics and machine learning to adjust parameters in real-time [11], [60], [61]. Furthermore, validation of DT ensures that model accuracy in reflecting real-world conditions [67], [68]. Finally, DT models are used to analyze reliability indicators that support decision making, enabling dynamic monitoring, predictive maintenance, fault diagnosis, and safety evaluations.

Decision Support: This component translates the DT output (i.e., reliability analysis results and indicators) into actionable recommendations and adjustment measures, providing feedback into the energy system. The decision support component is divided into security and adequacy: Security focuses on monitoring, predictive maintenance, and fault detection; while adequacy covers expansion planning, operation management, and managing renewables variability. With the assist of reliability analysis using real-time data, the DT detects and diagnoses failures and recommends actions to prevent future disruptions and optimize performance [15], [49]. Decisions are implemented through advanced control algorithms and real-time optimization, enabling dynamic adjustments based on current conditions [28]. By providing continuous feedback and implementing adaptive control measures, the DT enhances the overall reliability of the energy system, ensuring it can meet both current and future demands.

IV. Challenges

Having discussed the benefits of the DT technology, in the following, we discuss the challenges and limitations associated with data-driven DTs for reliability of energy systems:

A. Data Quality and Availability

Effectiveness of DTs is highly dependent on the accuracy and consistency of the data they receive. Advanced data analysis techniques are needed to pre-process noisy raw data and improve data quality [15]. Any errors or inconsistencies in the sensor data can lead to inaccurate models and predictions, which can affect the reliability of energy systems [69].

B. Connectivity and Real-Time Management

Ensuring that data is collected in real-time and can be efficiently processed without delay is critical to maintaining the accuracy and responsiveness of DT models. In energy systems, this is particularly challenging due to the need to continuously update DT models with data from diverse, geographically dispersed sources such as wind turbines, solar panels, and grid sensors, all without latency issues [70]. Delays can result from incompatibilities in data collection, communication speeds, and processing infrastructure [10], [47]. Managing large and diverse data streams is complex and requires robust communication networks and processing capabilities to ensure timely updates and accurate representation of physical system changes [9].

C. Standardization and System Complexity

There is a lack of standardized methodologies and generic modeling and validation criteria for developing and implementing DTs across different energy systems [10], [47]. The complexity of energy systems, with their diverse components and varying operating conditions, further complicates standardization efforts. This can lead to inconsistencies, as well as increased costs and inefficiencies when developing and implementing DTs across different types of energy systems, such as electrical grids, wind farms, and solar power plants [9], [49].

D. Implementation Costs

The initial implementation of DTs involves significant costs, including specialized software, infrastructure, and ongoing maintenance. It requires large amounts of data and sensors, which are directly proportional to processing costs. Renewable energy generation technologies such as wind and solar already face high operation and maintenance (O&M) costs. DTs can help optimize maintenance strategies and predict failures, but the initial implementation of DT technology can be costly and resource intensive [71].

E. Cybersecurity

The implementation of DTs in energy systems introduces cybersecurity risks. Unauthorized access and data manipulation can lead in severe consequences, including grid instability, energy theft, and large-scale power outages. Although reliability-oriented DTs aim to enhance system reliability, this reliability is also critical for overall security. However, DT integration with control systems of critical infrastructure, such as power grids, makes them prime targets for cyber-attacks. Consequently, robust cybersecurity measures are essential to protect energy systems from potential threats and ensure the reliability and security of the energy infrastructure [9], [10].

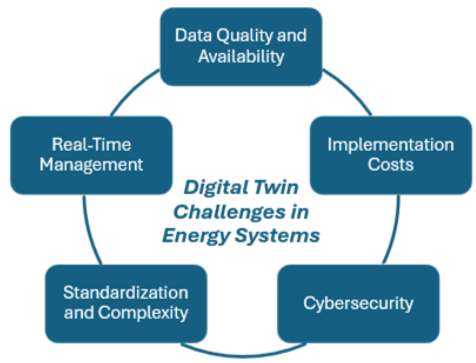

Fig. 5. Challenges of DT implementation in energy systems.

V. Conclusions and Outlook

The goal of our comprehensive literature review was to explore the role of Digital Twins (DTs) in enhancing reliability of energy systems. DTs facilitate real-time monitoring, predictive maintenance, and optimization of operations, which are crucial for adapting to the complexities introduced by the integration of renewable energy sources. Data-driven approaches, combined with advanced modeling and simulation techniques, have demonstrated considerable promise in improving system reliability by enabling accurate predictions and proactive interventions. However, the implementation of DTs faces challenges such as data quality, real-time data management, standardization, and high initial costs.

Future research should focus on developing standardized methodologies and protocols for implementing DTs across various energy systems to ensure reliability and stability. Additionally, there is a need for hybrid approaches that integrate both data-driven and physics-based methods to capture the dynamic behavior of complex systems more accurately. Future case studies should aim to demonstrate the practical applications of DTs in diverse energy systems, highlighting the benefits and addressing the challenges of scalability and cybersecurity. Continued advancements in ML and IIoT technologies will further enhance the capabilities of DTs, paving the way for more resilient and reliable energy infrastructures.

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