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Review

Digital Twins for Enhancing Efficiency and Assuring Safety in Renewable Energy Systems: A Systematic Literature Review

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Abstract: As the demand for sustainable energy solutions grows, there is a critical requirement for continuous innovation to optimize the performance and safety of renewable energy systems (RESs). Closed-loop digital twins (CLDTs)—synchronized virtual replicas embedded with real-time data and control loops to mirror the behavior of physical systems—have emerged as a promising tool for achieving this goal. This paper presents a systematic literature review on the application of digital twin (DT) technology in the context of RESs with an emphasis on the impact of DTs on the efficiency, performance, and safety assurance of RESs. It explores the concept of CLDTs, highlighting their key functionalities and potential benefits for various renewable energy technologies. However, their effective implementation requires a structured approach to integrate observation, orientation, decision, and action (OODA) processes. This study presents a novel OODA framework specifically designed for CLDTs to systematically identify and manage their key components. These components include real-time monitoring, decision-making, and actuation. The comparison is carried out against the capabilities of DT utilizing the OODA framework. By analyzing the current literature, this review explores how DT empowers RESs with enhanced efficiency, reduced risks, and improved safety assurance.

Keywords: digital twin; renewable energy systems; safety assurance; production efficiency

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1. Introduction

Driven by escalating environmental concerns and surging energy demands, the world is increasingly turning its eyes to green energy. This shift is poised to be further fueled by the anticipated surge in smart grid and microgrid technologies, amplifying renewable energy generation capacity. However, the reality of our current situation cannot be ignored. In 2020 alone, the globe consumed 36.5 billion barrels of oil (roughly 100 million per day), 3.8 billion tons of coal, and 3.95 trillion cubic meters of natural gas [1]. Burning one metric ton (i.e., 1000 kg) of fossil fuel releases approximately 3.15 metric tons of carbon dioxide (CO_2) into the atmosphere.

The persistent and substantial demand for fossil fuels perpetuates adverse environmental impacts, contributing to the ongoing degradation of our planet's ecosystems. Just the summer of 2023, four major climate records were shattered: the hottest day ever recorded, the hottest June globally, unprecedented marine heatwaves, and record-low Antarctic Sea ice [2]. Moreover, scientists warn that exceeding a crucial warming threshold in June 2023 served as an alarming indication of how much hotter it could be if we do not take action on climate change [1]. To address climate change by reducing CO_2 emissions, there is a growing need to shift away from fossil fuels and transition toward cleaner and more sustainable energy sources [2,3]. Renewable energy has grown in popularity in recent decades as a result of public concern about global warming and decreasing fossil fuel supplies. Several renewable energy-generating technologies, utilizing wind, solar, and tidal generation, have been commercialized [4]. However, hydrogen, as an efficient energy carrier and a clean, environmentally kind fuel, is gaining increased attention from developed and developing countries [5].

Despite the significant advantages of renewable energy sources, they are subject to certain limitations. One such limitation is the discontinuity of generation caused by seasonal variations, as most renewable resources rely on climate conditions [6]. For instance, solar energy systems encounter issues due to the intermittent and variable nature of sunlight, requiring efficient energy storage solutions for continuous power generation. Moreover, hydrogen poses inherent safety, health, and environmental (SHE) challenges. It has high flammability and explosive potential when mixed with air in specific concentrations and necessitates robust containment, ventilation, and monitoring systems [5].

Past incidents highlight various risks. Notably, on 1 June 2019, an unauthorized valve repair attempt at an Air Products facility in Santa Clara, U.S.A., led to an uncontrolled release of 250 kg of high-pressure hydrogen, emphasizing the dangers of accidental discharges [7]. Similarly, a gas control equipment malfunction on a liquefied hydrogen tanker in Hastings, Victoria, Australia, on 25 January 2022, resulted in a gas flame [8], further illustrating the need for meticulous operational protocols and safety measures. These cases underscore the vital role of diligent engineering design, operational procedures, and emergency response planning in mitigating SHE risks associated with hydrogen production, handling, transportation, and usage.

Fortunately, ongoing advancements in computer technologies enabled researchers to address difficulties observed in improving efficiency, performance, safety, and effectiveness of RESs faced in renewable and sustainable energy systems [6]. DT emerges as a promising technology, holding the potential to revolutionize RESs and unlock significant efficiency gains across industrial, residential, commercial, and transportation sectors [9]. By enabling comprehensive real-time monitoring, accurate simulations informed decision-making, and data-driven optimization, DTs can empower RESs to operate more flexibly, adapt to dynamic conditions, and navigate fluctuations in production efficiency and safety [9,10]. Consequently, their rapid adoption can facilitate the transformative shift towards more resilient and efficient RESs [9].

The concept of the DT, comprising a physical entity, a virtual counterpart, and the interlinking data connection, has gained significant traction in recent years. Its potential lies in leveraging computational techniques enabled by the virtual model to optimize the performance of its physical counterpart. This growing interest stems from the DT's abilities to provide real-time monitoring, facilitate data-driven decision-making, and enable closed-loop control of physical systems [9]. Figure 1 depicts a closed-loop digital twin (CLDT) architecture characterized by bidirectional information flow between the physical and virtual domains, facilitated by physical-to-virtual (P2V) and virtual-to-physical (V2P) connections. A CLDT goes beyond simply replicating a physical system; it establishes a dynamic feedback loop between the digital model and the real-world system. This enables real-time monitoring and analysis of operational data, allowing for continuous adjustments and optimizations [11,12]. This closed-loop design empowers the DT to not only provide insights into the current state and real-time performance of the physical counterpart (product, process, or infrastructure) but also dynamically anticipate its future behavior under various operating conditions and potential scenarios [11]. It offers a transformative approach to managing energy systems. By enabling real-time optimization, enhancing efficiency and sustainability, and fostering resilience and adaptability, they hold the key to revolutionizing the energy sector [13]. Further research and development in this area are crucial to unlocking the full potential of CLDTs for enhancing efficiency and safety and ensuring a secure, efficient, and sustainable energy future.

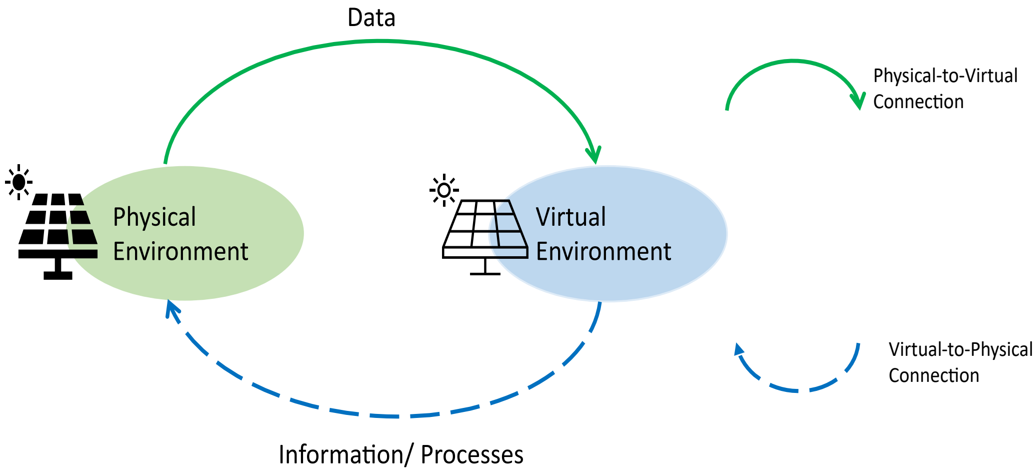

Figure 1. Closed loop digital twin architecture with a bidirectional flow of information.

RESs are recognized for their sustainability and potential to address climate change. However, enhancing their production efficiency and ensuring safety assurance are pivotal considerations for fostering their widespread adoption. Production efficiency is described as the ratio of actual energy output to the theoretical maximum output of an RES under ideal conditions. It reflects how effectively the system utilizes its potential resources [14]. It maximizes energy output while minimizing losses, downtime, and operational costs [15]. Additionally, the safety assurance of RESs is described as measures to minimize the potential risks associated with the operation and maintenance of RESs. By prioritizing measurable production efficiency and safety factors, stakeholders can enhance RESs, implement responsible practices, and amplify their widespread adoption for a sustainable future. DT plays a crucial role in enhancing production efficiency and ensuring safety in RESs [16]. The implementation of DT technology in the energy industry, especially in RESs, has several benefits, including increased asset performance, higher profitability and efficiency, and fewer adverse environmental consequences, i.e., safety, etc. Real-time data from physical assets are used to update the virtual model's parameters, boundary conditions, and dynamics, leading to an accurate representation of the actual entities being modeled, which can provide better decision-making and increase the production efficiency and safety of the RESs [10,11].

While there is a strong theoretical basis supporting the potential of DTs to optimize RESs, practical implementation faces challenges due to limited access to real-time data [5]. The gap between theoretical understanding and real-world application represents a significant barrier to fully utilizing the benefits of digitalization in the renewable energy sector [5,9]. Overcoming this gap is essential for translating theoretical knowledge into practical deployments that enhance the efficiency and performance of RESs.

This study addresses two research questions: research question (RQ)1: What is the current state-of-the-art of DTs for enhancing production efficiency and safety assurance in RESs? Research Question (RQ)2: What literature gaps exist regarding the utilization of DTs for enhancing production efficiency and safety assurance in RESs?

This paper presents a systematic and comprehensive review that encompasses the role of DT in improving production efficiency and safety assurance in RESs. Moreover, this paper introduces CLDTs, including the key functionalities and potential benefits of renewable energy technologies.

By adopting this systematic approach, this paper offers a critical evaluation of the current state of the art in the field and facilitates further exploration of DTs within the renewable energy sector. More specifically, the main contributions of this paper include the following;

1. An overview of the primary RES-related DT research projects and energy-saving applications that may help develop the DTs of RESs. This study aims to highlight the RESs benefiting from DT applications, frameworks, and architectures.
2. An OODA loop framework of a DT. The requirements will be assessed, and the DT components will be identified, including real-time monitoring, decision-making, and actuation, which are described in more detail in Section 4.2.
3. A comprehensive comparison of the most popular DT platforms in the market (i.e., Amazon Web Services IoT TwinMaker (AWS TwinMaker), Azure Digital Twins (ADT), and Eclipse Ditto (Ditto)). We describe them and their unique features.

The remainder of this paper is divided as follows: Section 2 explores the concept of DT. Section 3 presents the related work of existing reviews in RESs using DTs. Section 4 presents the research methodology applied in this systematic review. Section 4.1 presents the DT taxonomy and Section 4.2 presents the proposed OODA framework for identifying the DT components for efficient RESs. Section 5 presents the systematic review outcome, findings, overall discussion, and technical remarks, and Section 5.4 presents a comparison of three prominent DT solutions. Finally, the conclusion is highlighted in Section 6.

2. Digital Twins

DTs are virtual representations of physical systems, enabling the emulation of their behaviors and facilitating informed decision-making [10]. The concept was initially introduced by Shafto et al. [17] to describe virtual duplicates of NASA's (American Aerospace Agency) physical equipment, and it quickly gained acceptance. DT has evolved into a valuable tool across various industries for optimizing the production of goods and services [10]. DT offers several advantages over traditional techniques in various domains, particularly in integrating and analyzing real-time data from physical assets or systems. This capability provides up-to-date insights into performance, condition, and behavior, allowing for timely decision-making and proactive interventions [18]. DT leverages data analytics and modeling techniques to predict future behavior and performance. By combining historical data, real-time monitoring, and advanced algorithms, DTs can forecast potential failures, optimize performance, and suggest preventive actions [13]. Traditional techniques often rely on reactive approaches (that is, addressing issues after they occur), whereas DTs enable proactive decision-making. They enable continuous monitoring, analysis, and optimization of assets, systems, or processes. These capabilities are particularly valuable in sectors such as energy, manufacturing, and infrastructure, where centralized management and optimization are crucial for efficient operations [9,19]. These advantages make DTs powerful tools for decision-making, performance optimization, and risk mitigation across a wide range of industries and applications.

Using DTs to mimic and simulate real-world situations allows industries to gain valuable insights into how their products and services perform in different scenarios [10]. Alam and Saddik [20] explain that DTs can support decision-making in three main ways: diagnosis, monitoring, and prognosis. Diagnosis involves evaluating past decisions, monitoring focuses on controlling processes, and prognosis aims to anticipate and predict behaviors [10].

In manufacturing, DTs are commonly used to simulate production processes to help identify potential bottlenecks or issues, enabling decision-makers to optimize production, cut costs, and enhance product quality [21]. In healthcare, DTs can simulate individual behaviors, such as patients or clients, aiding decision-makers in making informed decisions [22]. For logistics, DTs can replicate processes like traffic patterns and warehouse operations [23]. This allows decision-makers to optimize vehicle routes and manage replenishment effectively. Finally, Onile et al. [24] emphasized the usefulness of DTs in the energy industry. Section *DTs in Renewable Energy Systems* provides a detailed description of the utilization of DT in energy systems.

DTs in Renewable Energy Systems

An energy system's DT is a system that combines analytical and physics-based modeling techniques to simulate each energy system component [9]. The power production unit's design limitations under various operating situations, such as variations in meteorological data, ambient temperature, humidity, changeable load, fuel mix, etc., may be found using these models, which, in turn, can be used for new and existing energy systems [9,25,26]. The results of these DT models can enhance the energy system's performance, reliability, availability, maintainability, and flexible operation when combined with cutting-edge prediction, control, and optimization approaches [27]. The models can improve efficiency for various operating scenarios while considering multiple trade-offs by employing data from the sensor's network. Moreover, DTs can be combined with algorithms for decision-making to enable real-time modification and control. DT applications for energy systems include enhancing production efficiency, operational safety, cyber security, asset management, performance, and cost optimization, using advanced edge computing techniques, and processing "big data" via clouds and specialized platforms [9].

Future energy systems in the energy production industry will be more complicated due to the integration of various renewable energy sources. These will include features like Power-to-X, electrolysis to hydrogen, on-site hydrogen storage, and the use of pure or mixed hydrogen. Figure 2 shows the global primary energy consumption. In 2019, approximately 16% of the world's primary energy was derived from low-carbon sources, including nuclear and renewable energies (e.g., hydropower, wind, solar, bioenergy, geothermal, wave, and tidal energy), constituting 11.4% and 4.3%, respectively. While hydropower and nuclear energy contribute significantly to low-carbon energy, there is notable growth in the utilization of wind and solar sources [28]. DT architecture is a critical technology to support these energy systems in achieving high reliability, availability, and maintainability (RAM) at reduced costs. Another energy-related use for DT involves energy savings in the construction, transportation, industrial, and service sectors [9]. However, DT publications for energy systems, i.e., fossil fuel and RESs, are extremely limited [9]. We found three articles on fossil fuel energy systems [29–31]; five on RESs [32–35]; and two on nuclear energy systems [36,37], as shown in Table 1.

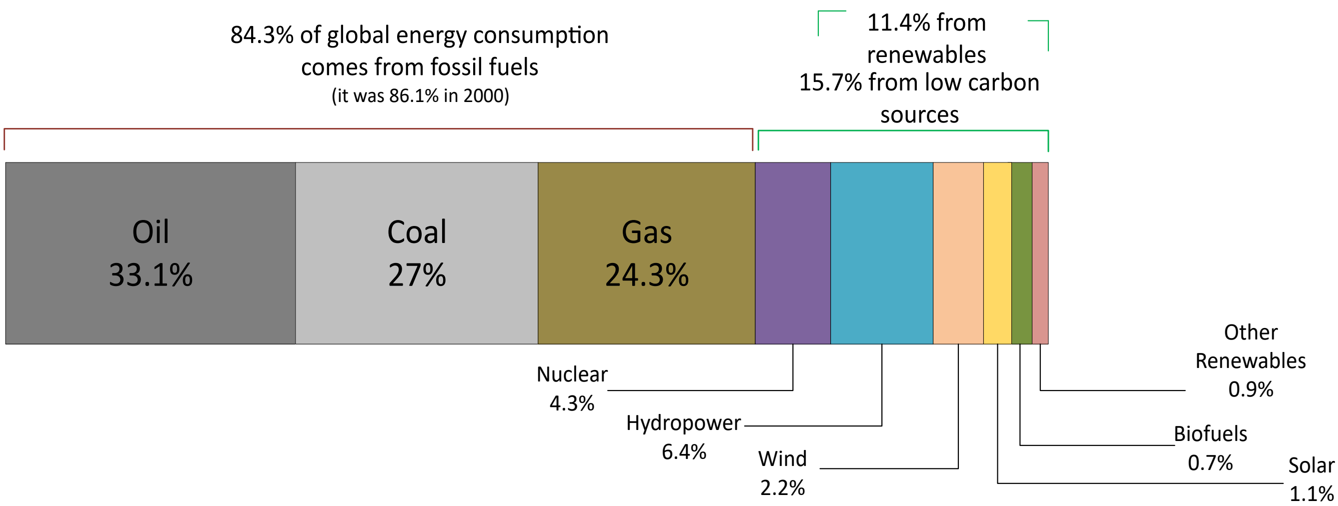

Figure 2. Global primary energy consumption in 2019. Data source: [28].

In nuclear energy systems, DTs are utilized in predicting service life and modeling decommissioning processes [36]. On the other hand, thermal energy systems leverage DTs for hybrid modeling and development methods to improve real-time performance monitoring and system optimization [29,30]. The application of DTs extends to RESs, including offshore wind turbines and synchronous machine generators, where they forecast the remaining useful life of components and identify current magnitudes in generators [34,35]. In the case of photovoltaic (PV) panel-level power converters, DTs are effectively employed for real-time fault detection and identification [33].

Table 1. Number of publications on DTs for different energy systems.

Energy Systems	No. of Publications	Years
Renewable Energy System	1 2 1	2016 2018 2019
Fossil Fuel Energy System	1 1 1 1	2020 2019 2020 2021
Nuclear Energy System	1 1	2016 2019

Despite the increasing applications of DTs in energy systems, quite a few challenges persist. These challenges affect decision-making processes, operational safety, data security, the need for accurate data, data handling, management issues, limited generalizability, obtaining key characteristic parameters, restricted applicability, and a predominant focus on fault detection without sufficient emphasis on remediation strategies. Although there has been significant progress in implementing DTs in energy systems, certain areas still require improvement. These include enhancing operational safety, improving production efficiency, refining data integration and management practices, and developing comprehensive strategies for addressing faults. It is imperative to comprehensively understand the current state of DT applications, recognize their potential benefits, and acknowledge the challenges associated with their implementation in RESs.

Table 1 indicates limited research on DT for energy systems compared to other complex systems. However, at the component level of energy systems, several articles on DT exist [9]. As discussed in Section 5, all of these studies lacked sufficient information regarding the reliability and comprehensiveness of their DTs as well as the information regarding artificial intelligence, supporting technologies, and physics-based models that were utilized. Section 3 will discuss and provide a review of related work utilizing DTs in RES research.

3. Related Work

In this section, we review papers that were based on secondary or tertiary studies, i.e., literature review, systematic literature review, etc. The search was conducted with the following terms: 'digital twin' AND 'literature review', AND 'production efficiency', OR 'safety', 'digital twin' AND 'renewable energy', AND 'safety', 'digital twin' AND 'literature review' OR 'survey' AND 'renewable energy' OR 'production efficiency' OR 'safety' and 'digital twin models' AND 'operations'. We performed initial screening based on the titles, keywords, and abstracts, resulting in the selection of 15 articles (involving both SLR and literature reviews) for related work. We then compare the papers based on their application domains and services, as shown in Table 2. Upon completing this step, we identified that reviews are specific to different topics or applications, and to the best of our knowledge, there is no review paper addressing the production efficiency and safety assurance of the RESs using DT.

Table 2. Review of related work: utilizing DT in research.

Reference	Research Method	Focus	DT Services
Jones et al. [11]	SLR	Not specified	Identify and discuss 13 characteristics of the DT, including physical entity/twin, virtual entity/twin, physical environment, virtual environment, State, realization, metrology, twinning, twinning Rate, physical-to-virtual connection/twinning, virtual-to-physical connection/twinning, physical processes, and virtual processes.
Agnusdei et al. [38]	SLR	Safety management	Enhance process performance, and simulation modeling
Semeraro et al. [22]	SLR	Smart manufacturing	Improved decision-making, analytics, and simulations
Melesse et al. [39]	SLR	Industrial operations	Predictive maintenance and after-sales services
Dos et al. [40]	SLR	Manufacturing, healthcare, construction, and service	Production and energy efficiency, improved decision-making, customer satisfaction, and enhanced safety
Yu et al. [41]	Literature review	Industrial energy management	Energy management and optimization, better servicing and maintenance
Ghenai et al. [16]	Literature review	Energy industry	Improved asset performance, higher profits and efficiencies, monitoring, autonomous control, and intelligent management of battery packs, prediction of energy storage performance
Nguyen et al. [42]	SLR	Supply chain management (SCM)	Real-time monitoring and evaluation of large-scale complex systems, simulation and optimization, and assembly process planning
Corallo et al. [43]	SLR	Smart Manufacturing	Decision-making, real-time optimizations, predictive maintenance, fault diagnosis, and predicting equipment's lifetime.
Somers et al. [44]	SLR	Testing (cyber–physical systems)	Enhanced visualization, proactive state prediction, autonomous systems, modeling complex interactions, and improved testing techniques.
Osadcha et al. [45]	SLR	Construction	Improved monitoring of structural health, a better understanding of the building's life cycle, improved decision-making, reduced costs, and improved efficiency
Van et al. [46]	SLR	Not specified	Predictive maintenance, real-time representation of the physical machine, and remote monitoring and control
Carvalho et al. [47]	SLR	Environmental sustainability	Intrusion detection, anomaly detection, monitoring (remote and on-site), virtual commissioning, autonomy, and predictive analytics
Errandonea et al. [48]	Literature review	Aeronautics automotive, energy industry, naval, health and smart manufacturing	Predictive maintenance, proactive maintenance, condition-based maintenance, remote maintenance, and real-time monitoring
Bortolini et al. [49]	Literature review	Building operation and maintenance	Energy efficiency optimization design, and occupants' comfort
This paper	SLR	RESs	Enhancing production efficiency and safety assurance, closed-loop DT, real-time monitoring, informed decision-making, actuation, and predictive maintenance

Jones et al. [11] presented 13 characteristics of the DT and provided a comprehensive framework for its functioning. Seven key areas for future research were identified, including aspects such as perceived benefits, use cases, and data ownership. Additionally, the paper introduced an eight-dimensional model for DT planning based on its purpose, supporting the findings of the study. Agnusdei et al. [38] analyzed existing fields of applications of DTs for supporting safety management processes in order to evaluate the current state of the art. A bibliometric review was carried out through VOSviewer to evaluate studies and applications of DTs in the engineering and computer science areas and to identify research clusters and future trends.

Semeraro et al. [22] presented the results of a systematic literature review on DTs in manufacturing. A total of 150 papers were reviewed, of which 35 were in the fields of the factory of the future, Industry 4.0 technologies, cyber–physical systems, and predictive manufacturing. The remaining 115 papers were in the DT field. The research challenges identified in the literature were organized into three categories: (1) DT application, (2) DT lifecycle and functions, and (3) DT architecture and components/technologies. Melesse et al. [39] investigated the application of DT models in industrial operations, particularly in the domains of production, predictive maintenance, and after-sales services. The paper provided insights into industrial practitioners, researchers, and experts on the specific roles of DT models and the challenges of implementing these models in the aforementioned domains. Van et al. [46] investigated the state-of-the-art in predictive maintenance using DTs. Moreover, 42 studies were included in the review, which revealed insights into the objectives, platforms, approaches, and challenges of using DTs for predictive maintenance. The findings from the SLR contribute to both academic and industry knowledge by identifying critical design considerations and challenges. These include computational burden and data complexity, which are crucial aspects for guiding future research efforts in this domain.

Somers et al. [44] highlighted the importance of DT in testing cyber–physical systems, their role in enhancing system reliability and safety, and the need for further research to advance testing methodologies in this domain. Corallo et al. [43] summarized data from 41 papers and proposed the 'hexadimensional shop floor DT' (HexaSFDT) framework for smart manufacturing, integrating physical and digital components. They also describe a need for standardized information models, high-performance data processing, security issues, and improving data exchange interoperability.

Bortolini et al. [49] investigated the application of DTs to improve building energy efficiency. They explored the benefits and drawbacks of DTs in this context, such as their impact on energy savings, costs, and occupant comfort. Yu et al. [41] reviewed the application of DTs in the industrial sector. They analyzed data from 53 papers and proposed a classification system for DTs in industrial energy management. Their findings highlighted the potential of DTs to improve energy efficiency and reduce industrial costs, while also noting challenges related to data handling and complex modeling.

Dos et al. [40] focused on the use of simulation, particularly discrete event simulation (DES) and/or agent-based simulation (ABS), as DTs, to facilitate decision-making processes. The review highlighted ongoing discussions and uncertainties surrounding simulation models in this research domain, including issues related to the level of autonomy, synchronization, and connectivity within these models. Ghenai et al. [16] presented a literature review on the application of DTs in the energy industry. The focus is on DT applications in energy generation (e.g., from fossil fuels to renewables), consumption (e.g., transportation, buildings, and industry), and storage (e.g., mechanical, thermal, battery, and hydrogen). The paper also discussed the challenges of this technology, such as the need for standardized data models and increased interoperability between different systems.

Nguyen et al. [42] explored the convergence of the physical internet and DT concepts within supply chain management. By employing bibliometric analysis techniques, the authors categorized research articles into 10 key streams, highlighting emerging trends and research frontiers. The study identified areas such as job shop scheduling, smart manufacturing design, and sustainability development as vital points of research. Moreover, it suggested future research directions, emphasizing issues such as business ecosystem development and SC resilience in the context of PI/DT integration. Osadcha et al. [45] reviewed the state-of-the-art research on updating DT geometry in construction, identifying key gaps and challenges. The study explores equipment and data collection methods, as well as data processing techniques. Through an analysis of 56 articles, the study identifies six main research directions, highlighting areas for further exploration and addressing challenges. Emphasizing the importance of updated geometry data in DT, the study also highlights its potential to improve data quality and maximize the benefits of technology in construction.

Carvalho et al. [47] focused on the environmental dimension of sustainability and explored the use of DT systems. Employing a meta-systematic literature review methodology, the authors analyzed 29 articles. Their analysis identified key challenges associated with DT implementation, including a limited understanding of the potential benefits of DTs, a lack of research on lifecycle applications, and technical implementation hurdles. Most importantly, the research highlights a critical gap in existing literature regarding the contribution of DTs to environmental sustainability.

Errandonea et al. [48] explored the growing adoption of DTs across diverse industrial sectors. The authors emphasized the crucial role DTs play in maintenance optimization, a domain with a significant impact on operational performance. The authors highlighted how maintenance activities can directly influence production line efficiency and operator safety, thereby underlining the potential benefits of intelligent maintenance approaches enabled by DTs.

Although these reviews deal with similar topics, this paper differs from the others since it focuses specifically on the application of DT technology in the context of RESs, with a particular emphasis on CLDTs. It highlights the importance of continuous innovation for optimizing the performance and safety of RESs and introduces CLDTs as promising tools for achieving this goal. This SLR outlines the key functionalities and potential benefits of CLDTs for various renewable energy technologies and proposes a novel OODA framework discussed in Section 4. This framework is designed to systematically manage the key components of CLDTs. This review emphasizes the role of DTs in empowering RESs with enhanced efficiency, reduced risks, and improved safety assurance.

4. Methodology

In this section, we present an SLR of existing DT strategies for RESs. An SLR is a well-defined and recognized process for discovering, analyzing, and evaluating relevant information that is linked to a specific research issue in an unbiased manner. For this SLR, we utilize the methodology provided in [50]. Figure 3 shows the SLR overview discussed in this paper.

To review existing publications that discuss the DTs of RESs, we used Google Scholar to search for the relevant publications, where we found 485 publications from the years 2018 to 2022. A search was conducted using a set of keywords, including 'digital twin' AND 'renewable energy systems' AND 'production efficiency' AND 'safety', 'digital twin' AND 'renewable energy systems' OR 'production efficiency', 'Renewable energy' AND 'safety' OR 'digital twin', 'digital twin' AND 'production' OR 'safety' AND 'renewable energy systems'. This review process is structured into six distinct stages, each of which is detailed below.

1. Removal of publications based on secondary and tertiary studies (surveys or review papers).
   Publications can be classified into three categories: primary, secondary, and tertiary studies. Primary studies are original research articles that make research contributions. A secondary study is one that reviews primary studies on a particular research topic. Tertiary studies examine other studies. Therefore, we excluded any articles that were secondary or tertiary studies (e.g., those with the words 'survey' or 'review' in the title). This resulted in the removal of 20 papers.

2. Removal of duplicates.
   In this stage, we first used Excel's duplicate removal function, then manually checked each article title to ensure that no duplicates were present. This resulted in the removal of 42 duplicates.
3. Removal of publications that had never been cited.
   We considered citations as measures of a publication's research impact. Therefore, we excluded any articles that had never been cited. This resulted in the removal of 194 papers.
4. Publications prior to 2018.
   We removed two papers that were published prior to 2018. This was done because publications on digital twins have been rapidly evolving since 2018, and to the best of our knowledge, none of the published papers prior to 2018 in this collection have discussed the production efficiency and safety assurance of RESs using DT. Therefore, we focused on papers published from 2018 onward [39].
5. Removal of publications by non-mainstream publishers.
   We only considered publications from mainstream publishers. This resulted in the removal of 67 papers that were published by non-mainstream publishers. Therefore, we only considered publications from mainstream publishers, including Elsevier, IEEE, ACM, MDPI, and Springer.
6. Manual filtering of remaining publications.
   Finally, we manually checked the remaining papers one by one and found that 110 papers were not relevant to the topic of this survey. After the removal of these papers, we obtained 55 papers for our review.

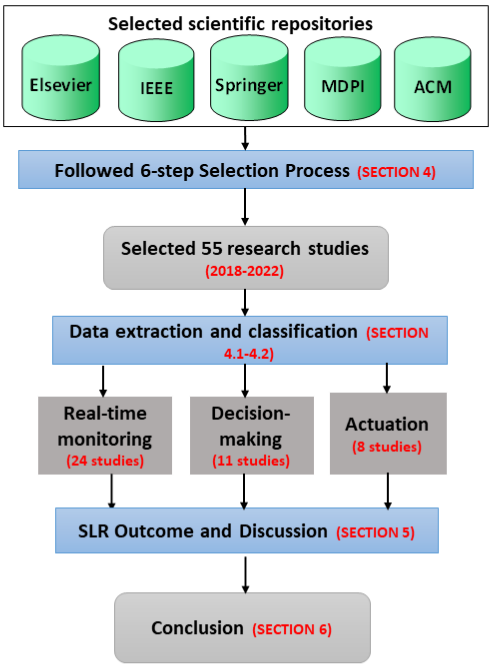

Figure 3. Overview of the SLR conducted in this study.

Figure 4 shows the literature selection and filtration process based on the above-mentioned steps.

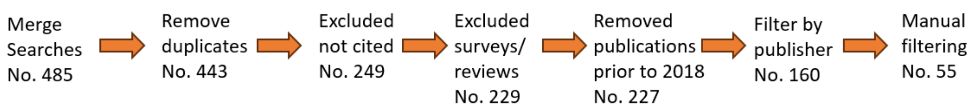

Figure 4. Literature selection process conducted in this study.

It is worth mentioning that the difference in the results between the related work and the SLR sections stems primarily from the types of literature reviewed. The related Work focuses on synthesized knowledge from secondary sources, which generally provide broader overviews and conclusions drawn from multiple studies. In contrast, the SLR targets primary studies that offer specific, direct insights into DT applications in RESs. This focus on primary literature uncovers newer, more detailed findings that have not yet been broadly synthesized in review articles, contributing to the differences in results between these sections.

The outcomes of this SLR are discussed in Section 5. Section 5.1 addresses RQ1 by analyzing and discussing the data obtained from the papers that deal with production efficiency and safety assurance of RESs, i.e., PV systems, wind, hydropower, etc., providing the current state of DT in RESs. Finally, in Section 5.3, we answer RQ2 by presenting the results of the DT taxonomy and OODA framework developed specifically to identify gaps related to CLDTs concerning the utilization of DTs for production efficiency and safety in RESs.

Section 4.1 details the taxonomy of DTs, which served as a foundational framework for our analysis, helping to identify gaps in the literature concerning the utilization of DTs for production efficiency and safety in RESs. By categorizing DT components into physical and digital environments, we gained insights into the essential elements of DTs. Subsequently, the need for CLDTs is outlined in Section 4.2, where their major components are also identified. Furthermore, leveraging the principles of the OODA (observe, orient, decide, act) loop helped us finalize the key components of CLDTs, including real-time monitoring, decision-making, and actuation.

4.1. Reviewing Taxonomy of DT

Figure 5 illustrates the proposed taxonomy to systematically identify gaps within the existing literature discussing DT in RESs. By categorizing the taxonomy into the physical environment and digital environment, we gain insights into the essential components of DT and their interactions. In this taxonomy, hardware constitutes tangible tools in the physical environment (enclosed in continuous green lines), while data and software are elements of the digital environment (enclosed in blue dashed lines).

4.1.1. Hardware

The tangible components and tools, such as sensors for data collection, processors for data analysis, and communication devices for data transfer, are critical in building a DT model and are collectively referred to as the hardware of the DT. Depending on the complexity of the system being modeled and the desired level of authenticity, various hardware configurations may be necessary for a DT. Essential elements frequently observed in a DT's hardware setup include real-time data from the physical asset or system gathered using sensing tools like sensors and data loggers [32]. These sensors can detect a wide range of parameters, including temperature, pressure, humidity, vibration, and more, depending on the application, making them a crucial source of data. The DT model's data communication infrastructure includes Ethernet, Wi-Fi, Bluetooth, and industrial protocols like Modbus or OPC-UA for data transmission. It also encompasses edge computing devices for local data processing, a central platform to host the DT model and execute complex simulations, data storage solutions for large volumes of data, high-performance processors for efficient computations, visualization interfaces for displaying simulations and real-time data, and control and actuation devices for closed-loop system management [9]. The hardware of a DT is crucial for integrating real-world data and simulating complex systems, contributing to better decision-making and optimization in various industries and applications [51].

4.1.2. Software

Software in DT is a vital component that enables the creation, simulation, and management of virtual replicas of physical assets or systems. It integrates data from various sources, including sensors and Internet of Things (IoT) devices, allowing real-time monitoring and visualization. The software employs advanced modeling techniques for accurate simulations, predictive analytics for forecasting future behavior, and optimization to identify inefficiencies and improve performance [52]. It facilitates remote access and collaboration while also ensuring robust security and privacy measures. Overall, DT software enhances asset management, decision-making, and efficiency across industries, playing a key role in the digital transformation of businesses worldwide [53].

4.1.3. Data

In a DT, data play a crucial role as they represent virtual replicas of physical entities, systems, or processes. The data are obtained through various sources and continuously updated to ensure accurate representation. Critical aspects of data in a DT include real-time monitoring, historical data for analysis, integration from multiple sources, data analytics for predictions, visualization for insights, data security measures, cloud-based storage for scalability, data sharing for collaboration, and a feedback loop to improve the physical counterpart's performance. Data form the foundation of a DT, enabling real-time insights, predictive capabilities, and informed decision-making for optimizing physical assets, systems, and processes [54].

Building upon this understanding, we sought to develop a framework that would enable the effective implementation of CLDTs for RESs. We utilized the OODA loop—a decision-making model known for its agility and adaptability—to develop a DT framework for the specific challenges and opportunities in RESs. In the following section, we describe in detail the OODA framework and its components.

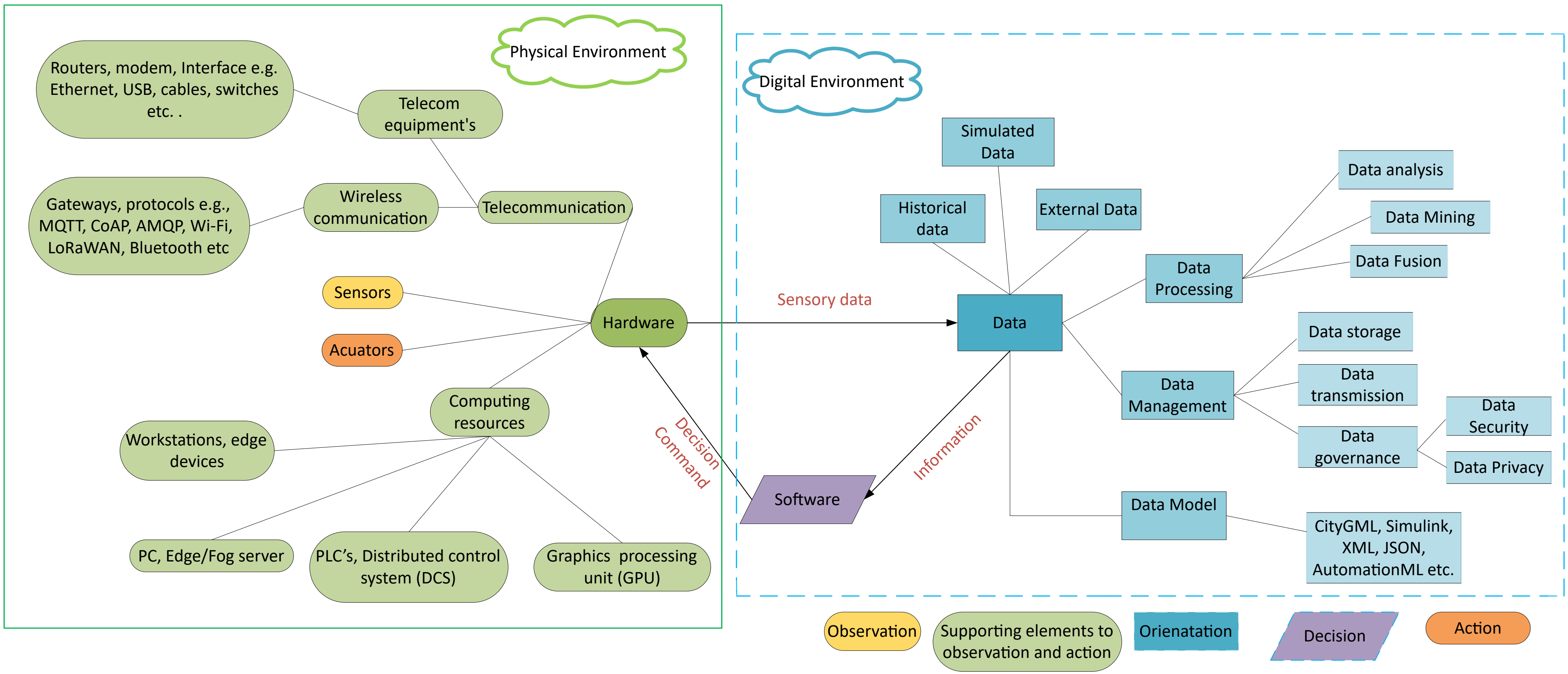

Figure 5. DT taxonomy with three aspects—hardware, software, and data—categorized into the physical environment and digital environment.

4.2. Proposed OODA Framework for CLDT

In this section, we present a DT framework based on the OODA loop, a decision-making model encompassing the following four stages: observe, orient, decide, and act. The OODA loop, originally developed for military applications, has been widely adopted in various fields due to its effectiveness in situations requiring quick thinking, strategic planning, and rapid adaptation to new information [55,56]. By applying the OODA loop, we identified the key components of a CLDT: real-time monitoring, decision-making, and actuation.

Figure 6 shows the OODA framework for DT. Such an application consists of the following four phases: Observation involves collecting IoT data; orientation includes analyzing information and providing decision support; decision pertains to making appropriate decisions, and action consists of an actuation that is based on the decisions made [50]. The figure illustrates how observation and action reside in the physical environment, as they involve tangible tools like sensors and actuators as also highlighted in Section 4.1. Conversely, orientation and decision belong to the virtual environment. Observation captures real-time data, which are then transferred to the orientation stage for analysis and comparison with historical data. This process leads to decision support, culminating in actual decision-making. Finally, the decision command is transmitted to the Action stage for actuation. From action to event feedback, the system monitors the outcomes of these actions and captures feedback on events. This feedback is then transmitted back to Observation, completing the closed-loop cycle.

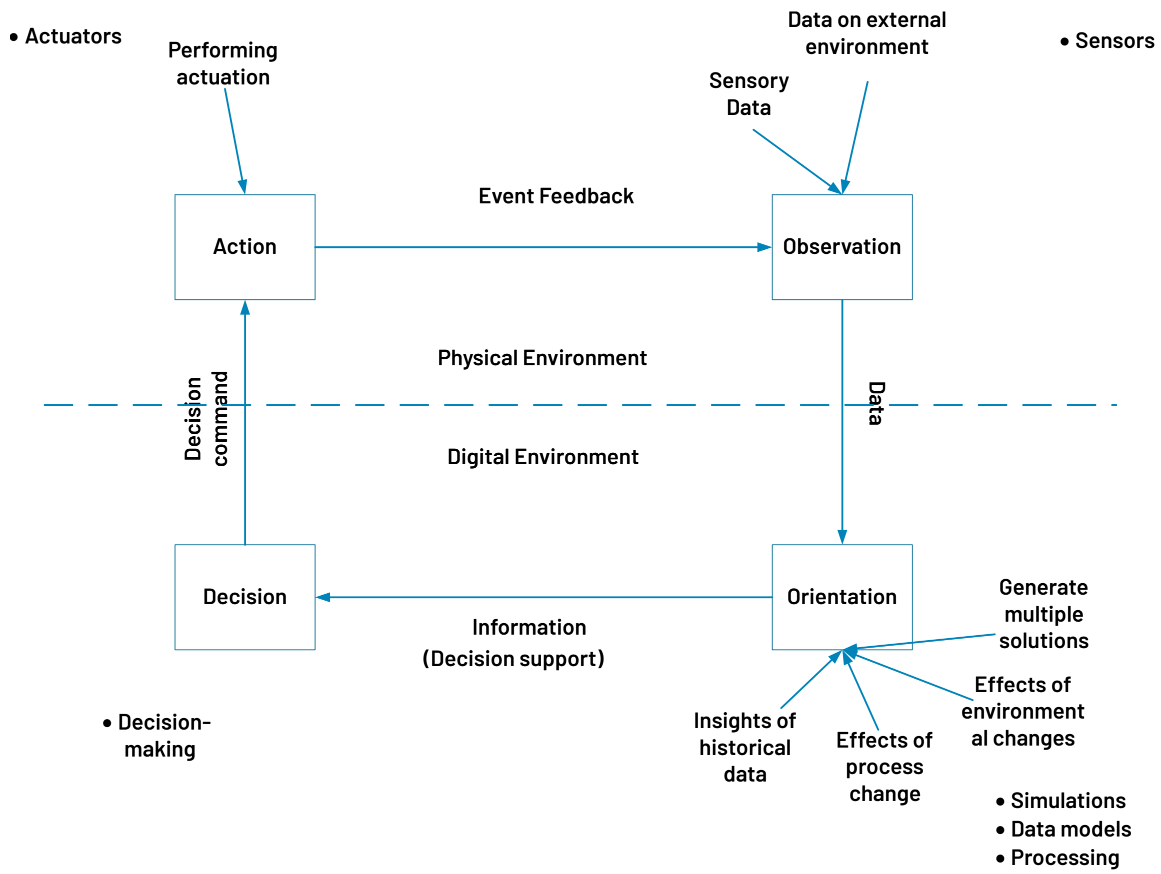

Figure 6. OODA framework for the DT.

4.2.1. Real-Time Monitoring

Real-time monitoring involves the ongoing observation and tracking of a system, process, or data stream as events take place. Real-time data must be collected, analyzed, and displayed in order to provide timely information on the state, performance, or behavior of the monitored system [57,58].

Real-time monitoring differs from traditional monitoring in that it provides a continuous, low-latency stream of relevant and up-to-date data from which administrators can quickly identify and resolve major issues. Alerts can be sent to appropriate personnel—or even automated systems—for remediation more promptly. By recording real-time monitoring data over time, organizations can identify and predict trends and performance [57].

4.2.2. Decision-Making

Decision cycles in energy systems are being disrupted by the proliferation of data, new data sources, and computation speeds, all in a more uncertain economic environment. Each decision involves a careful assessment of the potential benefits and risks associated with different energy strategies [59]. The chosen strategy not only affects immediate energy production and consumption but also has long-term implications on sustainability, regulatory compliance, and market positioning. Effective decision-making in this context is essential for driving innovation, ensuring environmental responsibility, and maintaining economic viability within the energy industry. In this new environment, the DT is the key to successful decision-making [59]. Making better and faster decisions that can be executed perfectly every time is vital for delivering better performance in RESs [60].

4.2.3. Actuation

The process of transforming a control signal or instruction into physical action or motion is referred to as actuation [61]. Actuation involves the use of actuators to start or stop movement, mechanical processes, or other desired physical reactions in the context of control systems [61]. In response to an input signal, actuators are devices that may produce mechanical motion or carry out a certain activity. They are in charge of converting energy, whether it be thermal, electrical, hydraulic, or pneumatic energy, into mechanical motion or force. Actuators are frequently employed in a wide range of applications, such as industrial, automation, robotics, heating, ventilation, air conditioning (HVAC), aerospace, and aviation, as well as medical equipment.

In order to implement CLDT for enhancing production efficiency and safety assurance in RESs, it is essential to have these three components. Figure 7 illustrates the OODA framework with physical-to-virtual (P2V) and virtual-to-physical (V2P) communication. The highlighted text in red displays the components of CLDT, and the arrows represent the flow of data from observation to action. As the data transition from observation to orientation, they move from the P2V environment. Then, when the decision command is issued for action, the information flows from the V2P environment, and then from action to event feedback; the system monitors the outcomes of these actions and captures event feedback. This feedback is then transmitted back to observation completing the closed-loop cycle.

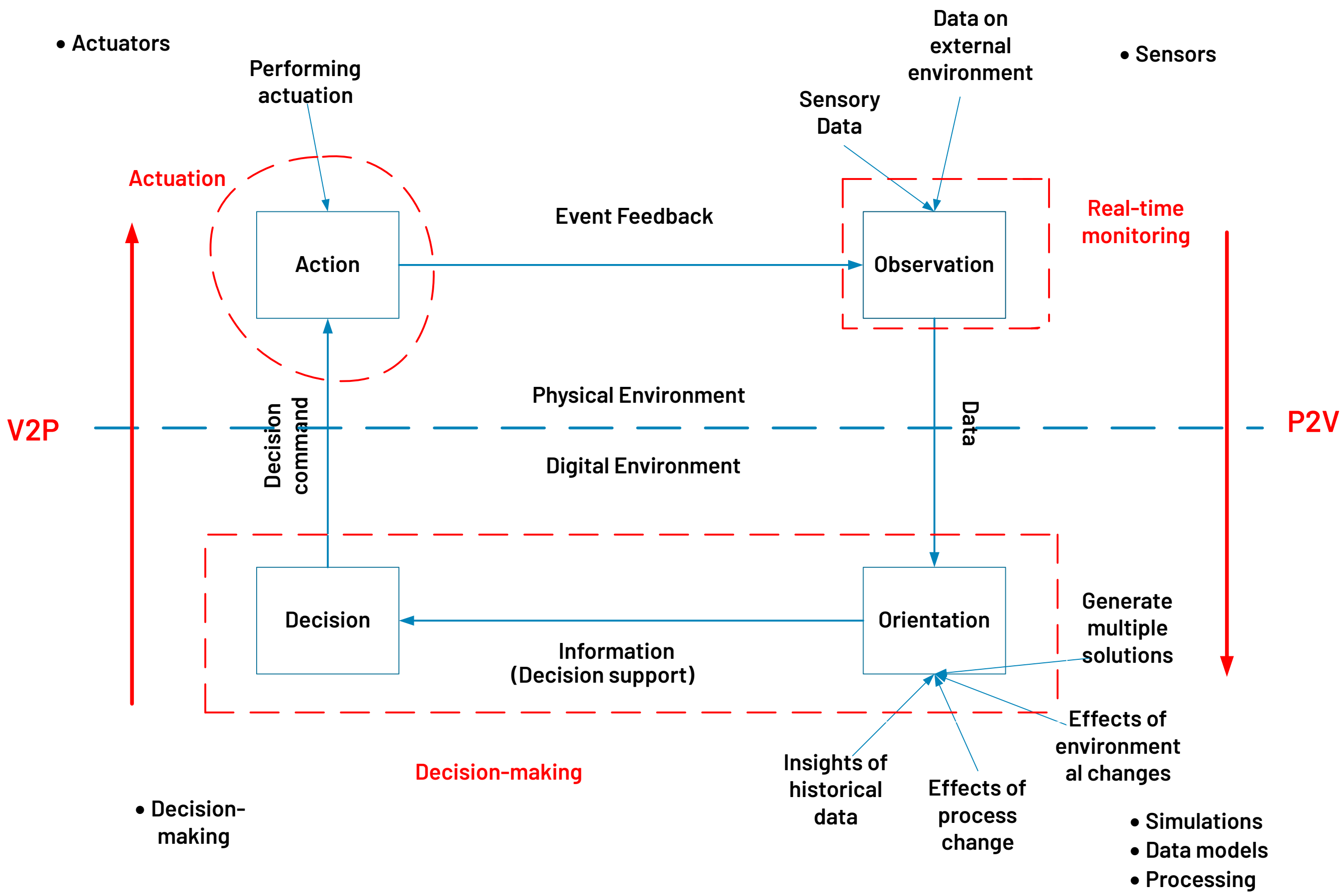

Figure 7. OODA framework, highlighting P2V and V2P connections.

5. SLR Outcome and Discussion

The following sections will present detailed discussions and findings to answer and explore the research questions raised in Section 1.

5.1. Overview of DT Research on the Production Efficiency of RESs and Energy-Saving Applications

In the energy sector, the development of DT technology is rapidly evolving. As previously discussed, only a limited number of publications have reported on these initiatives thus far. The objective of this section is to provide a detailed analysis of DT for production efficiency in RESs, specifically addressing the first half of RQ1 ("What is the current state-of-the-art of DT for enhancing production efficiency in RESs?"). The applications of DTs in this context include enhancing efficiency in the production and distribution of electricity across various energy sectors, such as nuclear, renewable, and conventional energy, as well as in automobiles, energy storage, batteries, and energy project planning. This section also explores DT applications in smart energy systems and energy cyber–physical systems. We review all publications that utilize DT to improve production efficiency in RESs and other energy-saving applications. Figure 8 illustrates the stratification of papers based on the systems modeled using DT. The second half of RQ1, focusing on safety assurance in RESs, will be covered in Section 5.2.

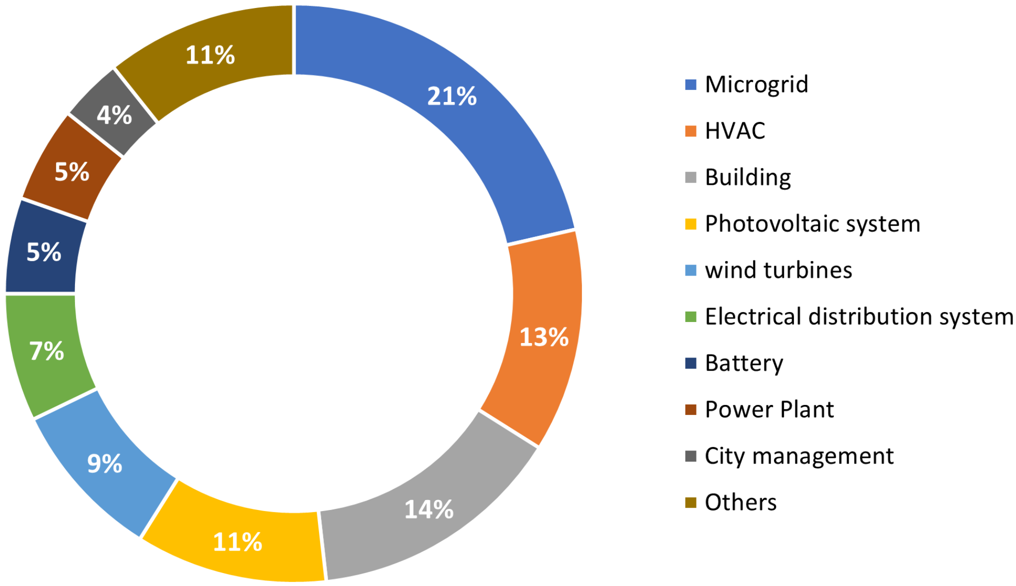

Figure 8. Paper stratification based on the modeled system.

Zohdi et al. [62] computed solar power flow with a reduced order model of Maxwell's equation, and performed simulations to maximize the power absorbed by the panels by considering varying multi-panel inclination, panel refractive indices, sizes, shapes, heights, ground refractive properties, etc., and optimized the system using genomic-based machine learning (ML) algorithm. Moreover, Fahim and Sharma [63] followed the 5D modeling approach, which refers to a physical entity, virtual representation, data curation, communication scheme, and services (PE, VR, DC, CS, and Ss), to monitor the wind turbines and identify wind speed based on advanced temporal convolutional neural network (TCN) and k-nearest neighbors (KNN) regression. They used the wind forecast to predict the power generation for the month through the 5G-next generation-radio access network (5G-NG-RAN) assisted cloud-based model for analyzing the wind farm. Pimenta et al. [64] dealt with optimizing wind energy by creating models and performing simulations for increasing production efficiency. Howard et al. [65], Kaewunrue et al. [66], and Tagliabue et al. [67] proposed a DT framework for modeling, controlling, and optimizing cyber–physical systems of the greenhouse production process. The framework is based on the Smart Industry Architecture Model (SIAM), which provides a systematic approach for the exchange of data and information between the different layers of the model. The proposed framework is evaluated using a case study of a greenhouse production process. The results show that the framework can be used to improve energy efficiency and productivity of the greenhouse production process.

Some researchers [32,59,68] have discussed the necessity of developing a DT for renewable energy generators. He and Ai [69] proposed a framework that emphasizes the importance of leveraging technologies such as big data, artificial intelligence, 5G, cloud computing, and IoT to enhance the capabilities of the power system digital twin (PSDT). By integrating data-driven and model-based tools, the PSDT aims to improve system understanding, decision-making, and overall grid management in the power sector. Zaballos and Briones [70] proposed a BIM model with an IoT-based wireless sensor network for environmental monitoring and motion detection to obtain insights into occupants' level of comfort to improve efficiency. Zhao et al. [71] presented a dynamic cutting parameter optimization method for low carbon and high efficiency based on DT. Compared with traditional static optimization methods, this method can dynamically find optimal cutting parameters in light of the real-time sensing data of the machining conditions. The case study shows that the method can reduce the processing time by 5.84% and carbon emissions by 6.1%. However, this study still has limitations, mainly including the smart perception of machining conditions and the continuous evolution of optimization models driven by sensing data. In the case study, cutting parameters are dynamically optimized based on real-time sensing data for the smoothness of the cutting force, without considering other machining factors such as surface roughness, accuracy, tool life, etc.

Li et al. [72] and Merkle et al. [73] proposed a DT for battery management systems to improve the computational power and data storage capability using cloud computing. The proposed model-based battery diagnostic algorithms with adaptive extended H-infinity filter (AEHF) and particle swarm optimization (PSO) for SOC (state-of-charge) and SOH (state-of-health) estimations were implemented on two different types of batteries, i.e., lithium–ion and lead–acid batteries. Security and privacy of data were assured using MQTT and TCP/IP protocols. Battery modeling, experimental set-up, and validation are performed. Park and Byeo [74] utilized the NARX algorithm (a dynamic neural network) and the multivariate adaptive regression splines (MARS) for the optimal scheduling (charging/discharging) process for an energy storage system (ESS) to minimize electricity bills. Brosinsky et al. [75], Pan and Dou [76], and Brosinsky and Song [26] proposed a framework of PSDT with the main components being data-driven, closed-loop feedback, and real-time interaction. A DT construction of a CNC machine tool was presented by Zhao and Fang [71], which utilized an optimization method for cutting parameters to reduce carbon emissions from manufacturing processes. Furthermore, there are several publications considering DT such as building information modeling (BIM) [66] and simulations [33,64,65], etc. Therefore, there is a need to consolidate research to retain a unified understanding of the topic and to guarantee that future research efforts are built on sound foundations.

The number of energy-related DT publications has been increasing rapidly, with the USA, China, and the European Union taking the lead as shown in Figure 9. Moreover, the research papers on DT in the energy industry were published in 34 scientific journals. Table 3 shows the top 10 sources. The first five journals make up around 36.7% of the papers, with the journal Energies being the most prominent, making up about 16%. Most journals only have one publication in this field, indicating that it is a diverse area that fits with many other research topics and journals [10].

Among all the articles reviewed, it is evident that this research domain remains relatively new and under-explored, with the earliest publication on DT for RESs dating back to 2019 [33]. However, there is a clear indication that it is an emerging field, with an increasing number of publications in recent years showcasing a growing interest and recognition of the potential of DT in enhancing RESs.

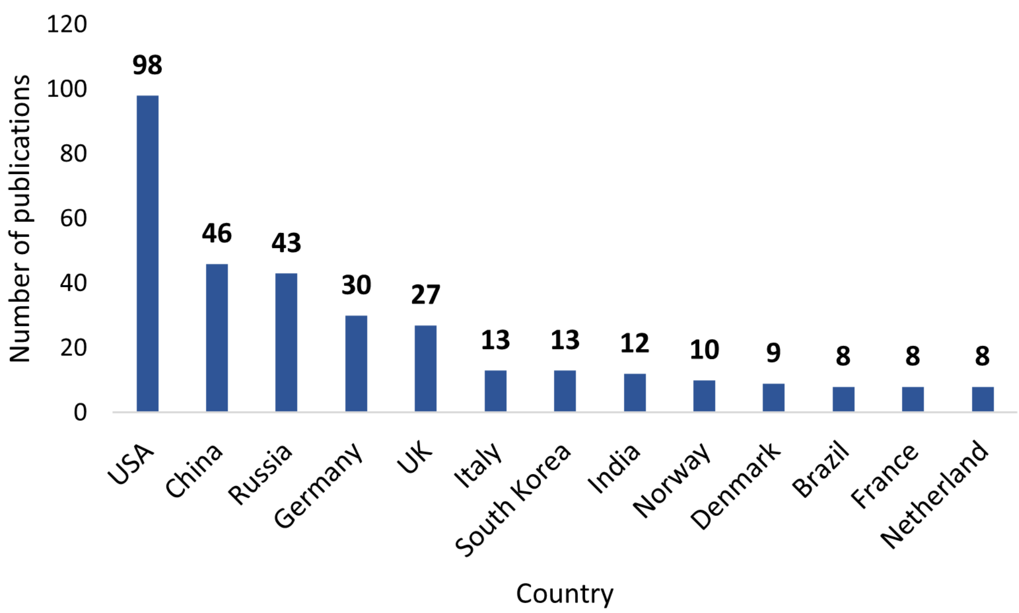

Figure 9. Energy-related DT publications by country.

Table 3. Top 10 scientific journals on DTs in the energy industry.

Rank	Journal	No. of Papers
1	Energies	8
2	IEEE Access	3
3	Sustainability	3
4	Applied Sciences	2
5	Energy Reports	2
6	IEEE Transactions on Industrial Informatics	2
7	International Journal of Hydrogen Energy	2
8	Batteries	1
9	Energy	1
10	Applied Energy	1
N/A	Others	24

5.2. Overview of DT Research on the Safety Assurance of RESs

In this section, we provide a detailed analysis of DT for safety assurance in RESs, addressing the second half of RQ1 ("What is the current state-of-the-art of DT for enhancing safety assurance in RESs?"). Various works propose fault detection and identification methodologies, control logic implementation, and defense approaches for smart grids and distributed systems, highlighting the importance of secure operations. Notably, the literature presents diverse approaches, including cloud-based distributed control algorithms, ML-based fault diagnosis, and prototypes for safety and risk management, such as the hydrogen high-pressure vessel discussed in [5]. However, some prototypes remain untested, emphasizing the need for comprehensive evaluations in developing DTs.

Jain et al. [33] designed a PV panel-level power converter prototype in which a DT estimator was created to capture the real-time characteristic of a PV energy conversion unit (PVECU) and fault signature library for power converter faults, PV panel faults, and electrical sensor faults using Xilinx Artix-7 field programmable gate array (FPGA) for real-time fault detection and identification. Zheng and Liu [77] presented a review of DT for cybersecurity in the smart grid. Onederra et al. [78] presented a novel thermal model of a medium-voltage cable under electrical stress in a wind farm. The model is based on experimental data from previous studies, and it allows us to predict the cable's lifetime under different operating conditions. The model is also able to provide information about the cable's aging state, which can be used to schedule preventive maintenance or replacement. The results of the simulations show that the model is able to accurately predict the cable's failure time, and it can therefore be used as a valuable tool for cable design and maintenance.

Nguyen et al. [79] proposed an advanced holistic assessment procedure using Digital Twins (DTs) and power-hardware-in-the-loop. This approach facilitates the assessment of the impact of distributed renewable energy resources (DRESs) at both local and global levels within their expected deployment environment. The approach was demonstrated via a case study that involved integrating a new PV inverter and load into a high PV penetration microgrid, governed by a coordinated voltage control algorithm. While the DTs were replicated from real devices, it was possible to make adjustments to the topology among them in simulation, without modifying the real connections or interfering with the activities inside the buildings and houses. Lei et al. [80] explored methodologies for realizing a DT of thermal power plants. This article delves into the detailed implementation of the DT from five different perspectives, providing a practical and feasible path for monitoring and controlling the DT via web browsers. The functionalities of a DT thermal power plant are summarized as real-time monitoring, visualization, interactions, algorithm design, and so on.

Saad et al. [81] proposed an IoT-based DT for cyber–physical networked microgrids (NMGs) to enhance resilience against cyberattacks. The cloud-based DT platform is implemented to provide a centralized oversight for the NMG system. The cloud system hosts the controllers (cyber-things) and the sensors (physical things) in the cloud IoT core in terms of the IoT shadow. The proposed DT covers the digital replica for both the physical layer, the cyber layer, and their hybrid interactions. The proposed framework ensures the proper and secure operation of the NMG. Additionally, it can detect false data injection (FDIA) and denial of service (DoS) attacks on the control system whether they are individual or coordinated attacks. Once an attack is detected, corrective action can be taken by the observer based on What-If scenarios that ensure the safe and seamless operation of the NMGs.

Pimenta et al. [64] developed a simulation model for the continuous tracking of accumulated fatigue damage and the evaluation of alternative operation strategies for an offshore wind turbine. This model was capable of making accurate predictions of thrust force and power output using only data from project drawings and theoretical curves. The structural and mechanical properties of the wind turbine were calculated based on the geometric properties of the tower and blades. The aerodynamic properties of different sections of the blades were computed using 2D models created with ANSYS Fluent, which is a powerful computational fluid dynamics (CFD) software tool used for modeling and simulating fluid flow, heat transfer, and chemical reactions. The measured and simulated responses allowed for the identification and validation of structural dynamic properties and static and dynamic internal loads. Table 4 illustrates the citations of safety assurance in RESs using DT. Among the 55 reviewed papers, only 15% of publications have implemented safety assurance. Specifically, three papers discuss equipment safety, another three focus on thermal and electrical safety, and two papers focus on security implementations against cyberattacks. These findings highlight the critical need for further research and attention to safety aspects within the literature, indicating an area that requires greater exploration and emphasis.

Table 4. Breakdown of safety topics covered using DT in energy systems.

Safety Topic Covered	Number of Papers
Equipment safety	3
Electrical safety	2
Thermal safety	1
Security implementation against cyberattacks	2

On the contrary, the DT heavily relies on the Industrial Internet-of-Things (IIoT) for both physical-to-virtual and virtual-to-physical twinning. The use of sensors, including RFID, facilitates data collection, while actuators affect changes in the physical environment. Although the literature emphasizes the importance of data security in this context, it is acknowledged as a broad topic requiring separate research.

While DT stands as a crucial technology within the energy industry, allowing for enhanced efficiency and productivity, predictive system behavior forecasting, and improved safety, challenges remain concerning the practical application of these DT models in real-world scenarios. Despite its significance in energy systems, the development of methods for applying DT models to RESs, notably production, predictive maintenance, and safety, is still in its early stages. Existing literature often comprises theoretical frameworks lacking tangible case studies and comprehensive methodologies. Nevertheless, there are practical instances detailed in certain literature [59]. Consequently, there is a clear need for further research focusing on real case studies to establish methods for effectively integrating DT into the energy industry, thus amplifying its potential impact on RES management operations.

5.3. Analyzing Outcome with DT Taxonomy and OODA Framework

In this section, we delve into the outcomes of our investigation into the application of DTs for production efficiency and safety assurance in RESs, building on insights gained from previous sections. Initially, we introduce a taxonomy, as detailed in Section 4.1, to systematically analyze and explore the literature. This taxonomy divides key aspects—hardware, software, and data—into physical and digital environments, providing a structured approach to our analysis. Following this, we utilize the OODA framework, which is tailored specifically for identifying the main components of DTs in RESs. We assess this framework by exploring common challenges and issues related to production efficiency and safety assurance within RESs. Through these analyses, our goal is to provide insights into the potential benefits and challenges of applying DTs in this sector, offering valuable insights for future developments.

Firstly, we investigated the literature using the DT taxonomy, performing a comprehensive analysis of 55 selected primary publications discussed in Section 4. We collected data from these primary studies and evaluated them based on predefined capabilities. Our analysis outlined the essential tools and components necessary for implementing real-time monitoring (RTM), decision-making, and actuation within DT systems. For example, real-time monitoring requires the utilization of sensors, computing resources, user interfaces, and communication protocols. Decision-making relies on a combination of simulation techniques, data processing methods, real-time monitoring capabilities, ML algorithms, and data modeling approaches. Lastly, actuation involves the integration of real-time monitoring, decision-making processes, and actuators. Table 5 shows the distribution of DT implementation across a constructed taxonomy of the physical environment (i.e., hardware) and digital environment (i.e., software and data). By analyzing this collected data, we were able to identify gaps in the literature concerning CLDTs for production efficiency and safety assurance of RESs.

Furthermore, we conducted a comparative analysis of primary publications against these DT components, utilizing the OODA framework. The results of this analysis are presented in Figure 10. Addressing RQ2: ("What literature gaps exist regarding the utilization of DT for enhancing production efficiency and safety assurance of RESs?"), our findings reveal significant gaps. Specifically, 27% of the publications claim real-time monitoring (RTM) capabilities; however, notably, only 7% of publications explicitly mention and include all the tools necessary for effective RTM. Additionally, only 16% of the publications have achieved decision-making capabilities, and a mere 13% involve actuation components. Interestingly, to the best of our knowledge, none of the papers focusing on RESs comprehensively encompass all three components required to realize a CLDT. This highlights significant gaps in the literature concerning P2V and V2P communication in RESs.

Table 5. Distribution of DT implementation across a constructed taxonomy of the physical environment (i.e., hardware) and digital environment (i.e., software and data).

Digital Twin Aspects				**Number of Papers**
Physical environment	Hardware	Sensors		42
		Computing Resources		25
		Communication protocols		17
		Edge devices		8
Digital environment	Software	Decision-making		11
		ML algorithms		15
	Data	Data processing	Data analysis	20
			Data fusion	18
			Data mining	15
		Data management	Data storage	17
			Data privacy and security	12
			Data collection	37
		Simulations		40
		Data models		25

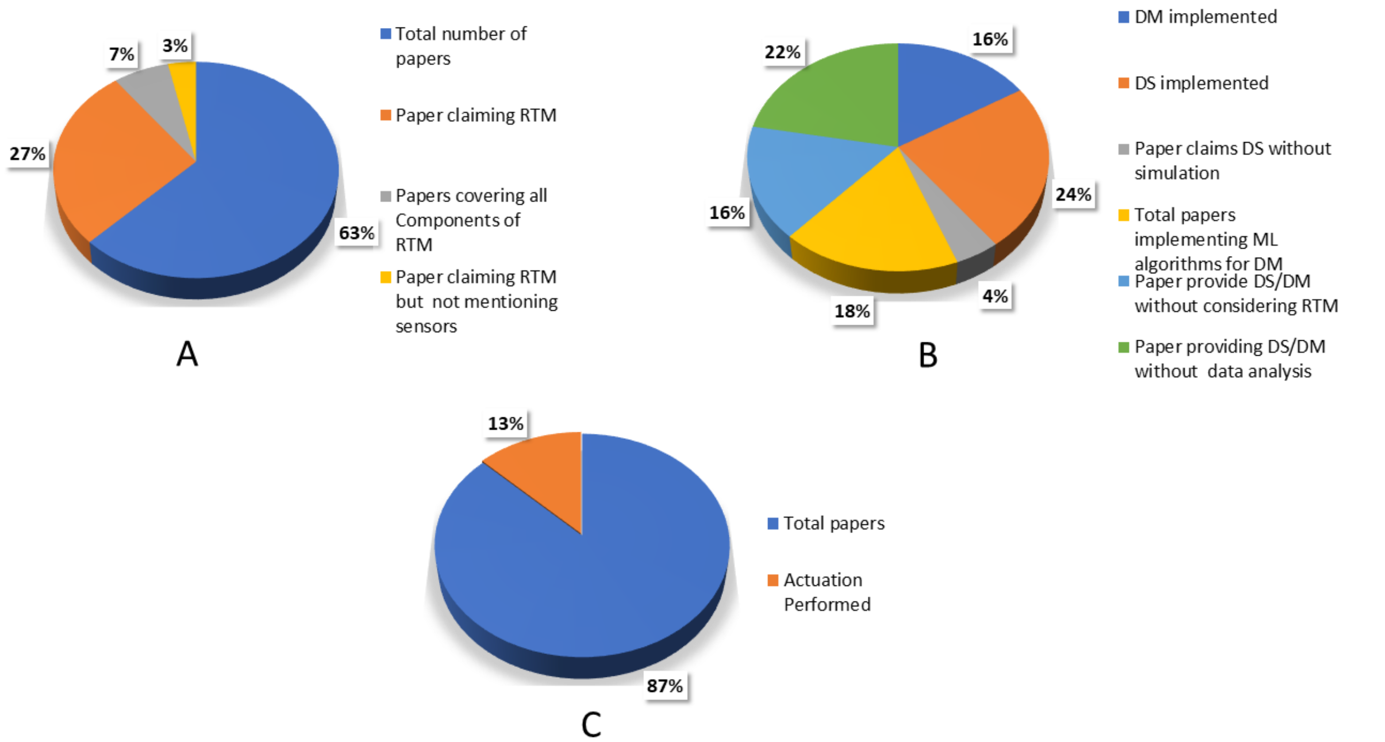

Figure 10. Results obtained from the OODA framework for (**A**) cites of real-time monitoring in the literature; (**B**) cites of decision-making in the literature; (**C**) cites of actuation in the literature.

By considering the fundamental components required for RTM, such as sensors, computational resources, interfaces, and communication protocols, several opportunities in this area emerge. Some studies concentrate on RTM, while others investigate methods for accomplishing continuous RTM. DTs, which are virtual replicas of real-world systems, rely on RTM to function. They constantly exchange data with the actual system, which enables predictive maintenance. This implies that minor problems can be addressed before they become major issues and cause downtime. Overall, RTM provides a wide range of advantages for RESs. It can improve efficiency, lower risks, expedite design processes, simplify complicated systems, allow for faster adjustments, increase productivity, and lead to better decision-making. It can also improve safety and make the entire system more adaptable and competitive.

However, there are relatively few studies that validate and quantify these perceived advantages over existing procedures and systems. Few publications demonstrate substantial improvements beyond current standards. Notably, the implementation of RTM has been detailed in [25,33,66,72,75,81–83]. While many publications leverage sensor networks and IoT devices for RTM, some opt for supervisory control and data acquisition (SCADA) due to its capability to collect real-time data from remote locations and transfer it promptly.

Furthermore, in the literature, decision-making is often referred to as decision support, as seen in [65], where the author proposes the interactive DT (InDT) and utilizes various decision analysis techniques to provide decision support. Decision support and decision-making are interconnected concepts, differing in their focus and purpose. Decision support focuses on providing assistance, information, and tools to enhance decision-making capabilities, while decision-making refers to the actual process of selecting a course of action from available alternatives.

For instance, Zohdi et al. [62] propose decision-making and planning for household energy consumption to improve the efficiency of energy production. The system employs a distributed reinforcement learning (RL) method that runs in the virtual digital world to optimize household appliance schedules before applying the end result to physical assets.

The proposed RL-based rescheduling method is validated using synthetic data, yielding corresponding results.

A limited number of publications in the RESs explore the implementation of actuation within CLDTs, highlighting the need for a more comprehensive approach. Closing this gap is essential to establish a V2P connection and attain a fully automated DT for RESs. Therefore, emphasizing the V2P connection becomes imperative to realize a closed loop. A holistic platform that integrates actuation, real-time monitoring, and decision-making is essential. As demonstrated in [64], where the Power System Digital Twin (PSDT) is introduced with a data-driven approach, closed-loop feedback, and real-time interaction. However, this architecture lacks comprehensive evaluation.

5.4. The Comparison of Available DT Platforms in the Market against the DT Components Identified Using the OODA Framework

In our study, we focused on enhancing production efficiency and safety in RESs using DT technology, we conducted a comprehensive comparison of various DT platforms available on the market, each with its own set of features [84]. In this context, we conducted a comparative analysis of three prominent DT solutions: AWS TwinMaker, ADT, and Ditto. These platforms offer distinct features and functionalities, ranging from real-time monitoring and predictive analytics capabilities to data storage and security measures. By conducting this comparison, we aimed to provide RES operators with valuable insights into the strengths and weaknesses of different DT platforms. This information can guide their decision-making process when selecting the platform that best suits their needs and goals.

AWS TwinMaker and ADT are prominent offerings from leading cloud providers Amazon Web Services (AWS) and Microsoft, respectively, in the competitive cloud computing market [84–86]. They offer pre-built platforms with features catering to a broad range of DT use cases. Ditto is an open-source framework gaining traction. Its open-source nature allows for customization and flexibility, appealing to users who require specific functionalities beyond what pre-built platforms offer [87]. Ditto stands out among open-source DT platforms due to its unmatched flexibility [88]. The open-source nature allows deep customization and integration with existing tools, while strong security features ensure data protection [87]. While requiring more development expertise compared to user-friendly options, Ditto's active community, scalability, and cost-effectiveness make it a compelling choice for projects prioritizing customization and control over their DT development [87,88]. Table 6 presents a comparison among the three mentioned platforms regarding their real-time monitoring capabilities in the context of DT and highlights the features they support and those they do not support. Similarly, Tables 7–10 compare platforms regarding their support for protocols, decision-support, decision-making, and actuation, highlighting both the features they support and those they do not support.

Table 6. Comparison of DT platforms against real-time monitoring.

Platforms	Supported	Not Supported
AWS TwinMaker	Amazon Kinesis Data Stream/Analytics for real-time data stream processing. AWS TwinMaker provides alerts based on data visualization to determine when data or forecasts are out of expectations [89]. Devices that are NOT directly connected to the Internet access AWS IoT Core via a physical hub	Primarily designed for online operation, real-time data are required for visualization and functionalities, causing limited support for offline functionality [90]. While devices connected to a private IP network can access AWS IoT Core with the help of a physical hub as an intermediary, devices using non-IP radio protocols such as ZigBee or Bluetooth LE are not directly supported by AWS IoT Core. They need a physical hub as an intermediary between them and AWS IoT Core for communication and security

Table 6. *Cont.*

Platforms	Supported	Not Supported
ADT	Comprehensive monitoring with dashboards and Azure services–like monitor, logic apps, and time series insights for comprehensive monitoring and real-time alerts about events or anomalies [91]. The platform also enables 3D visualization of the CPS and its physical space	Large enterprises might not find ADTs suitable due to limitations in handling high traffic and potential beta-version issues.
Ditto	Eclipse Vorto is a platform aiming to define twin specifications and automatically generate code (e.g., based on the Ditto framework). It makes use of information models that are assembled by abstract and technology-agnostic function blocks [90]. In addition to the persistent mode, Ditto has a 'live' channel which lets an application communicate directly with a device. Using a live channel, Ditto acts as a router forwarding requests via the device connectivity layer to the actual devices. This channel can also be used to invoke operations (like e.g., "turn the light on now") on the device and accept a response back from a device. Ditto search services could be used by an application that wants to create a dashboard to show the real-time data of a fleet of devices. Ditto allows for the mapping of different device data into a consistent, lightweight JSON model. This allows Ditto to provide a consistent interface for a heterogeneous set of devices [90].	N/A

All three platforms provide core functionalities for building and managing DTs including data modeling, connectivity with devices and sensors, and data visualization. However, they differentiate themselves in various aspects: AWS TwinMaker emphasizes graphical user interface (GUI) and ease of use, making it attractive for users with less technical expertise [86]. ADT focuses on integration with Azure services and offers features like state synchronization and edge deployment [86]. These features are valuable for scenarios requiring real-time data and distributed processing. Ditto prioritizes flexibility and an open-source approach, allowing for customization and integration with diverse tools and platforms. This caters to users who need tailored solutions beyond the limitations of pre-built platforms [88,90]. Additionally, AWS TwinMaker targets businesses of all sizes, focusing on ease of use and rapid deployment [85]. ADT primarily targets enterprises already invested in the Azure ecosystem, leveraging existing infrastructure and services [86]. Ditto appeals to a broad range of users, including individual developers, research institutions, and companies seeking a customizable and open-source solution. Therefore, comparing these three platforms provides a comprehensive overview of different approaches to DT development, catering to various needs and technical expertise levels.

Table 7. Comparison of DT platforms against protocols.

Platforms	Supported	Not Supported
AWS TwinMaker	MQTT ensures real-time transmission of data streams [89]. Other protocols supported include HTTP, Web Sockets, and LoRaWAN	AWS IoT does not support the following packets for MQTT 3: PUBREC, PUBREL, and PUBCOMP (these packets are part of the QoS 2 (assured delivery) mechanism in MQTT, which involves multiple message exchanges for confirmation). By omitting them, AWS IoT simplifies its implementation and potentially improves overall efficiency.)AWS IoT does not support the following packets for MQTT 5: PUBREC, PUBREL, PUBCOMP, and AUTH.AWS IoT does not support MQTT 5 server redirection. While AWS IoT does not support QoS 2 through these packets, it offers alternative mechanisms for ensuring message delivery with varying levels of reliability: shadow service and retries [92].
ADT	IoT Hub supports protocols such as MQTT, AMQP, and HTTPS for device communication [93]. If the device does not support one of these protocols, it is possible to adapt both incoming and outgoing traffic using Azure IoT Protocol Gateway	IoT Hub has limited feature support for MQTT. If the solution needs MQTT v3.1.1 or v5 support, it recommends MQTT support in Azure Event Grid.
Ditto	AMQP 0.9.1, AMQP 1.0, Apache Kafka 2. x, HTTP (invoking external webhooks), MQTT 3.1.1, MQTT 5 [87,94]	It does not define or implement an IoT protocol in order to communicate with devices, i.e., Ditto itself does not handle the specifics of how data are exchanged between devices and the platform. By not defining its own protocol, Ditto maintains protocol agnosticism. This allows it to integrate with diverse devices that utilize different communication protocols like MQTT, CoAP, or proprietary protocols used by specific manufacturers.

ADT is a platform-as-a-service (PaaS) that provides enterprise-grade solutions for IoT connectivity [93]. It allows the modeling of assets, systems, or entire environments, keeping DTs live and up-to-date through Azure IoT [84]. Azure Synapse Analytics tracks the history of DTs, extracting insights to predict future states. The Azure OpenAI and Azure ML platforms support the development of autonomous systems that continuously learn and enhance their capabilities [84]. Microsoft Mesh enables presence and shared experiences from any location on any device.

Comprehensive monitoring with dashboards and Azure services—like Monitor, Logic Apps, and Time Series Insights—facilitates real-time alerts about events or anomalies [91]. The platform also enables 3D visualization of the CPS and its physical space. IoT Hub supports protocols such as message queuing telemetry transport (MQTT), advanced message queuing protocol (AMQP), and hypertext transfer protocol secure (HTTPS) for device communication [93]. If the device does not support one of these protocols, it is possible to adapt both incoming and outgoing traffic using Azure IoT Protocol Gateway [95]. Azure IoT Edge extends the capabilities of Azure IoT Hub by allowing the processing and analysis of data at the edge devices themselves. This is beneficial for scenarios requiring low latency, offline capabilities, or reduced cloud dependency [91]. Data analysis is provided using various services such as Azure Time Series Insights, Stream Analytics, ML, Cognitive Services, advanced analytics, and algorithms [91,95].

Table 8. Comparison of DT platforms against decision-support.

Platforms	Supported	Not Supported
AWS TwinMaker	Amazon Athena and Amazon Quick Sight are used for data analysis. AWS TwinMaker also supports the importation of multi-source and heterogeneous data [89,96]	Consistent rendering performance in the AWS TwinMaker scene is not supported due to hardware dependence. The AWS TwinMaker scene (provides a visual context for the data connected to the service) rendering performance is hardware-dependent. Performance varies across different computer hardware configurations [90].
ADT	Azure IoT Edge extends the capabilities of Azure IoT Hub by allowing the processing and analysis of data at the edge devices themselves. This is beneficial for scenarios requiring low latency, offline capabilities, or reduced cloud dependency [91].	The ADT platform does not directly support the message Routing and Rules Engine. Integration with Azure IoT Hub or Azure IoT Central is recommended.
Ditto	provides web-based simulation capabilities. Ditto structures the data sent by devices via Hono into digital IoT Twins [94]. It offers APIs to deal with Things, Features, Policies, Things-Search, Messages, and CloudEvents. There is also the option to use the Ditto Protocol [97]. Ditto will save the most recent values of a device in a database. This allows DT to query the last reported value of a device. A DT can also establish that it needs to be notified when the value changes. Based on a change, devices can also be notified if an application wants to change something in the device.	The integration of simulations or behavioral models is not directly supported and requires external tools or programming, potentially adding complexity [97].

Table 9. Comparison of DT platforms against decision-making.

Platforms	Supported	Not Supported
AWS TwinMaker	ML models and AI services offered by AWS, such as Amazon SageMaker, allow the development of predictive models. AWS TwinMaker may be seamlessly integrated with Lambda and SageMaker, which offer additional data processing and decision-making capabilities [89]. The Rules Engine enables continuous processing of inbound data from devices connected to AWS IoT Core. One can configure rules in the Rules Engine in an intuitive, SQL-like syntax to automatically filter and transform inbound data.	It primarily focuses on visualization and monitoring, offering limited support and features for automated decision-making based on twin data [91]. Additionally, it does not support a fully integrated simulation engine. (Implementing features like automated decision-making based on DTs and integrated simulation engines can introduce significant complexity to the platform. This can be achieved by developing custom decision-making logic or integrating third-party solutions tailored according to needs).
ADT	Pre-defined conditions and Azure Logic Apps integration–Integrate AI and ML models to analyze data and generate insights for informed decision-making. Responsible AI dashboard—the dashboard offers a holistic assessment and debugging of models so one can make informed data-driven decisions.	N/A
Ditto	Pre-defined rules and custom integrations—decisions can be made through integration with external tools or a rule engine	N/A

Table 10. Comparison of DT platforms against actuation.

Platforms	Supported	Not Supported
AWS TwinMaker	AWS OpsWorks is a configuration management service that provides managed instances of Chef and Puppet. Chef and Puppet are automation platforms that allow one to use code to automate the configurations of servers [98]. OpsWorks lets one use Chef and Puppet to automate how servers are configured, deployed, and managed across Amazon Elastic Compute Cloud (EC2) instances or on-premises compute environments. OpsWorks has three offerings: AWS OpsWorks for Chef Automate, AWS OpsWorks for Puppet Enterprise, and AWS OpsWorks Stacks. Puppet offers a set of tools for enforcing the desired state of infrastructure and automating on-demand tasks [98].	N/A
ADT	Azure Automation—Azure Automation delivers cloud-based automation, operating system updates, and configuration services that support consistent management across Azure and non-Azure environments. It includes process automation, configuration management, update management, shared capabilities, and heterogeneous features [99].	N/A
Ditto	Eclipse Arrowhead is an open-source framework for industrial automation based on service-oriented principles. It allows the creation of a highly flexible System of Systems (SoS) by defining local clouds for connecting application systems running on industrial cyber–physical systems (ICPSs) [87].	N/A

Azure Automation delivers cloud-based automation, operating system updates, and configuration services that support consistent management across Azure and non-Azure environments. It includes process automation, configuration management, update management, shared capabilities, and heterogeneous features [99]. Table 11 shows the comparison of DT platforms against DT modeling, highlighting both the features they support and those they do not support. ADT uses a digital twin definition language (DTDL) to enable users to define their models in their vocabulary, using existing models to inherit from or interact with drawing a graph of DTs [85]. DTDL language is based on JavaScript object notation (JSON) format and a comprehensive set of application programming interfaces (APIs) and tools [100]. DTDL allows defining the model from scratch or inheriting from another. A model is defined by name, ID, and other properties. A DT model can have relationships with other models to exchange data, attach components as other models, and command requests and responses [85,99].

Table 11. Comparison of DT platforms against DT modeling.

DT Modeling		
Platforms	**Supported**	**Not Supported**
AWS TwinMaker	To model the physical environment, one can create entities in AWS TwinMaker that are virtual representations of physical systems, such as a furnace or an assembly line. One can also specify custom relationships between these entities to accurately represent the real-world deployment of these systems. Then connect these entities to various data stores to form a DT graph, which is a knowledge graph that structures and organizes information about the DT for easier access and understanding. As one builds out this model of their physical environment, AWS TwinMaker automatically creates and updates the DT graph by organizing the relationship information in a graph database [92].	N/A

Table 11. *Cont.*

DT Modeling		
Platforms	**Supported**	**Not Supported**
ADT	MS Azure uses a DT definition language (DTDL) to enable users to define their models in their vocabulary, using existing models to inherit from or interact with drawing a graph of DTs [85]. DTDL language is based on JSON format and a comprehensive set of APIs and tools. DTDL allows defining the model from scratch or inheriting from another. A model is defined by name, ID, and other properties. A DT model can have relationships with other models to exchange data, attach components as other models, and command requests and responses [85].	As of October 2023, ADTs primarily support DTDL version 2 for defining DT models. Version 3 support is limited and mainly for viewing models in the ADT Explorer [100]. While it uses DTDL as its modeling language, it does not currently implement all DTDL commands [100].
Ditto	Eclipse DT Suite is an open-source platform that consists of a Vorto text tool for modeling DTs using Vortolang modeling language (a metamodel based on the Eclipse modeling framework (EMF)). Vortolang is composed of information models that define the DT properties and function blocks that define the Operation, Event, configuration, fault, and status information [85].	N/A

The use-case of DTs built using ADT spans various domains such as predictive maintenance, smart buildings, smart cities, energy, agriculture, manufacturing, asset tracking, and management [85].

On the other hand, AWS TwinMaker is a graph-based twin virtualization platform designed for the quick creation of DT [84]. This platform offers efficient tools to generate virtual representations of existing physical systems, integrating real-world data for faster monitoring operations [86]. For authentication, users can choose two-factor authentication via Amazon Cognito or integrate with an existing LDAP setup. Additionally, users can gain in-depth insights into their DTs using Amazon QuickSight [84]. Amazon Kinesis Data Stream/analytics facilitates real-time data stream processing. AWS TwinMaker offers alerts based on data visualization to detect deviations from expected data or forecasts [89,92]. Devices not directly connected to the Internet can access AWS IoT Core through a physical hub [92]. AWS provides ML models and AI services, such as Amazon SageMaker, enabling the development of predictive models. Integration with Lambda and SageMaker enhances data processing and decision-making capabilities [89].

The Rules Engine in AWS enables continuous processing of inbound device data, allowing intuitive filtering and transformation using SQL-like syntax [92]. AWS OpsWorks offers configuration management services, automating server configurations across instances with tools like Chef and Puppet [98]. AWS TwinMaker enables DT model specification using knowledge graphs. To model the physical environment, one can create entities in AWS TwinMaker that are virtual representations of physical systems, such as a furnace or an assembly line. One can also specify custom relationships between these entities to accurately represent the real-world deployment of these systems, and then connect these entities to various data stores to form a DT graph, which is a knowledge graph that structures and organizes information about the DT for easier access and understanding. As one builds out this model of their physical environment, AWS TwinMaker automatically creates and updates the DT graph by organizing the relationship information in a graph database [95]. Use cases for DTs with AWS TwinMaker include predictive maintenance, remote monitoring of infrastructure, energy optimization, and real-time tracking of assets and supply chains [85].

The Eclipse Foundation, operating as a global platform for open innovation and collaboration, presents an open-source framework called Ditto for IoT and DT solutions [84,86]. Ditto assists businesses in building DTs of assets with internet connectivity. As an IoT middleware, it seamlessly integrates into existing backend systems using supported protocols. It provides web APIs for simplified workloads, Microservices with the data store, static metadata management, and a JSON-based text protocol for communication [86]. Table 12 illustrates the additional functionalities of DT platforms, categorized under various aspects such as storage, security, privacy, and more.

To summarize, there is a variety of IoT DT solutions available in the market, each possessing unique capabilities. Nevertheless, making a well-informed decision necessitates a comprehensive understanding of the distinctive features provided by each platform.

Table 12. Additional features of DT platforms.

Features	AWS TwinMaker	ADT	Ditto
Availability zones	AWS's higher market share compared to its competitors has resulted in a wider availability of its services across different zones [85,88]. AWS is the most considerable infrastructure as a service. It supports more than 76 availability zones worldwide (this number is constantly increasing)	MS Azure follows a protocol of maintaining a maximum of 3 AVs (availability zones) in a region. To date, they have 60+ AVs serving 140 countries [100]	N/A
Security and privacy	certain AWS services, such as CloudTrail and Amazon CloudWatch, can be used to set logging requirements to ensure sensitive data sent through API Gateway are captured. Storage modules (such as S3 and Glacier) are encrypted using management keys to ensure data privacy [89]. AWS supports more than 89 security standards and protocols than any other competitor. AWS networks are compatible with GPPDR, HIPAA, NIST, FIPS, PCI-DSS, and other certificates.	Microsoft Azure can provide layered security architecture for different application tiers to restrict public access to API applications, as well as the existence of role-based access control and data encryption for transit and storage. Additional tools like VPN Gateway help protect traffic in Microsoft Azure. Even if someone on the team uses an open internet network, the infrastructure will detect security risks in time. The main network protection tools in Microsoft Azure are Azure Firewall, service endpoints for VNs, and DDoS security measures	Ditto can restrict access to the APIs based on predefined authorization policies. Ditto authorization services protect the privacy and integrity of the device data. Only predefined authorized clients are granted read/write access to individual elements of a Ditto Thing. Clients are authenticated in Ditto using the OAuth 2.0 and OpenID Connect standards.
Storage	Amazon Simple Storage Service (S3) bucket provides secure and scalable object storage [89]. Other storage services include Elastic block storage, Elastic file system, S3 infrequent access (IA), S3 glacier, AWS backup for archiving and backup, storage gateway, AWS import/export disk, AWS import/export snowball, Snowball Edge, Snowmobile for data transport.	Azure Storage Queues are a popular service provided by Microsoft Azure for storing large numbers of messages [91]. Other storage facilities include Azure Blob storage, Azure managed disks, Azure Files, Azure storage cool tier, and archive access tier	Time-series databases (TSDBs) NoSQL database. The DT model represents the physical assets based on the "Thing" provided by the Ditto framework, and the "Thing" is stored on the platform via the NoSQL database. Information such as spatial environments, physical devices, IoT layer tasks, and data with static attributes are managed using a relational database (RDB); data with dynamic attributes are managed through a time series database (TSDB) [87].
Technical traits	Graph-based twin virtualization	State synchronization and edge deployment	Open-source framework for managing DTs
Cost	Small Instance: AWS charges around USD 69/month, for instance, with 2 virtual CPUs and 8GB RAM. Large Instance: AWS offers up to 3.84 TB of RAM and 128 virtual CPUs for USD 3.97 per hour [101].	Small instance: Azure charges USD 70/month for two vCPU and 8 GB of RAM. Large instance: For their more significant instances, they charge USD 6.79/hour for 128 vCPU and 3.89 TB of RAM. Azure Functions pricing is calculated based on per-second resource consumption and the number of executions. Similar to AWS, MS Azure has its own pricing calculator [100]	N/A (Ditto is an open-source platform)

6. Conclusions

This SLR has critically examined the integration of DTs in RESs with a focus on enhancing production efficiency and safety assurance. Our comprehensive analysis of publications from 2018 to 2022 revealed substantial advancements in the application of DTs within the renewable energy sector. However, despite these developments, several critical gaps remain that must be addressed to fully leverage DTs for RESs.

Firstly, while the proposed OODA framework marks a significant step toward operationalizing DTs, there is a substantial need for advancements in data integration and interoperability. Current DT platforms like AWS TwinMaker, ADT, and Ditto offer diverse capabilities, yet they fall short of seamlessly integrating disparate data sources, which is crucial for creating a holistic DT environment.

Secondly, scalability and cybersecurity emerge as paramount concerns. As RESs increasingly rely on DTs for real-time decision-making and actuation, the scalability of these systems must be enhanced to handle large-scale data without compromising performance. Moreover, as the reliance on DTs grows, so does the vulnerability to cyber threats, underscoring the urgent need for robust security protocols that safeguard against potential breaches.

Looking forward, the development of a comprehensive DT platform that accommodates all necessary components to fully realize CLDTs in RESs is imperative. Such a platform should not only integrate safety and efficiency measures but also ensure scalability and robust cybersecurity. Furthermore, standardizing data models and establishing resilient communication protocols are crucial for facilitating effective information exchange between physical assets and their virtual counterparts. Research should prioritize these areas to bridge the current gaps and advance the field toward the next generation of DT applications in renewable energy.

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