

Review Article

Harnessing the future: Exploring digital twin applications and implications in renewable energy

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ABSTRACT

The extensive use of conventional oil and gas energy resources has significantly impacted the planet, accelerating global warming and climate change. A key solution to this issue is the shift from fossil fuels to renewable energy (RE) sources. However, integrating renewable energy for transportation, power generation, and energy storage presents challenges due to its intermittent nature and reliance on external factors. A digital twin (DT) is an effective way to tackle these challenges. This technology utilizes adaptive models to simulate the real-time performance of physical systems in a digital environment, helping to predict and prevent potential system failures. This paper comprehensively reviews the latest research on the context, applications, lifecycle, functions, and architecture of digital twin technology in renewable energy systems.

1. Introduction

The global population is projected to rise significantly. This, in return, results in more land usage and encourages migration to large cities in search of a higher standard of living [1]. Consequently, global energy consumption is expected to rise by 60–80 %, doubling the emissions in urban cities [2–4]. However, one of the primary contributors to climate change is the reliance on fossil fuels in different energy and industrial sectors [5]. In general, fossil fuels are natural resources produced from hydrogen and carbon. Until now, fossil fuels have supplied around 80–84 % of the world's power generation [6]. Fossils consist of decomposed animals and plants that are dead and buried underground. Fossil fuels in transportation and power generation fields emit toxic greenhouse gas, leading to global warming, air pollution, and accelerated climate change [7,8]. Therefore, one excellent alternative to conventional sources is investigating renewable energy technologies [7–9]. Renewable energy is zero-emission green energy [10] and is extracted from environmental sources [11]. Renewable energy depends on environmental sources, such as geographic location, weather, and season. This heavy reliance on these factors is limiting the development of renewable energy.

Renewable energy sources encompass biomass, solar, hydroelectric,

wind, and geothermal energy. Solar energy, derived from the sun's radiation, is utilized for heating and electricity production. As the largest renewable energy source worldwide, solar power accounts for 2 % of the total renewable energy available globally [12]. Sunlight energy is converted directly into electricity using photovoltaics (PV) [13]. Concentrated solar power (CSP) indirectly generates electricity by concentrating sunlight using many mirrors or lenses into a focal point [14]. Wind energy converts the wind's kinetic energy to generate electricity [15,16]. The wind turbine can be installed onshore on the land and offshore on the sea as fixing or floating. The two primary types of wind turbines are vertical-axis wind turbines (VAWT) and horizontal-axis wind turbines (HAWT) [17]. The HAWT rotates parallel to the wind stream, capturing the maximum amount of wind energy. However, utilizing the HAWT is limited to the location of stable airflow with no considerable fluctuation. In the VAWT, the axis rotation is perpendicular to the wind motion. In contrast, to the HAWT, the VAWT can get the wind from any direction, operating at a turbulent wind stream location with a lower power generation rate [18]. Hydroelectric energy is a type of energy that produces power from the flow of water, harnessing the effects of gravity and elevation [19]. Nevertheless, hydroelectric energy is associated with high construction costs, negative environmental impacts on the water quality [32], and adverse influence

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on the nearby animal habitats. Biomass energy is a type of energy that is composed of organic material from decomposed animals and plants. Biomass energy can be extracted from various solid, liquid, and gaseous sources, for instance, municipal solid waste, animal manure, vegetable oils, agriculture crops [20], and methane. Geothermal energy is extracted from the interior heat of the earth's core for heating, cooling, and electricity generation. In the last decade, there has been a consistent increase in the use of renewable energy across various applications [21, 22]. However, the high initial infrastructure cost and the slow power generation rate pose challenges to using renewable energy sources. Furthermore, some renewable energy sources depend on climate conditions and thus require an energy storage system to account for the intermittent energy supply [23]. As a result, most of the power generation is still supplied from conventional sources due to these limitations of renewable energy sources [24]. Consequently, it is crucial to create a new strategy and technology to deal with and overcome the drawbacks of renewable energy through understanding, studying, and analyzing the behaviour of the parameters of each system during the design phase, production phase, and services phase of the useful lifecycle of the renewable energy system. The digital twin technology reflects and virtually represents the physical system, using real-time data to simulate the physical system, predict how the operation will perform, detect and prevent future failures, and optimize the system [25–28]. Moreover, other digital technologies will enhance the energy efficiency, save costs, carry out predictive maintenance, improve operations, and prolong the system's lifetime [29]. A primary function of a digital twin in renewable energy is to gather real-time data from onsite sensors to model or reproduce the operations of the physical system in a virtual setting [30]. The digital twin relies on vast amounts of data to accurately predict the real-time behavior of the physical system [31]. The digital twin was first studied in the NASA Apollo program [32], where technical trouble caused an explosion of the supplier oxygen tank that crippled the engine of the spacecraft. In 2002, Grieves [33] proposed the earlier concept of the digital twin and divided it into three major parts: the real physical space, the virtual space of the physical part, and the connecting link between these spaces. Before this, in 1991, Gelernter [34] discussed the same concept for modelling a specific physical system via software miming the physical system called 'Mirror Worlds'. In 2010, the first official appearance of the term "Digital Twin" started appearing in NASA's roadmap reports [35]. In 2011, the U.S Air Force developed a digital twin to predict fatigue, maintenance, and design of the aircrafts [36,37]. Fig. 1 depicts the timeline of the developments of the digital twin technology. After 2011, the context application of the digital twin propagated to several fields, including oil and gas applications [38], healthcare [39–41], shipping and maritime [42], manufacturing [43, 44], city management [45,46], aerospace [47–49], and transportation [50,51].

The digital twin can be developed for each type of renewable energy system during the system's lifecycle phases [52] to serve a specific task [53–56]. Therefore, applying the digital twin in the renewable energy sector can be complex and challenging due to the vast amounts of data required. The data required is related to the physical system, including the real-time data, the geometry of each component, weather data, historical forecasting, experimental and practical data, and previous issues from former applications [57].

This review focuses on the application of digital twins in renewable energy systems, an area not yet fully explored. It highlights the potential benefits and challenges of applying DTs in such systems, paving the way for future research. This paper employs a new research methodology to identify the main research aspects. Text mining and topic modeling are the key modelling techniques used to analyze, extract, and summarize information from papers and four main research areas have been detected and addressed. The first aspect addresses the context of where to use a Digital Twin in renewable energy. The second aspect pertains to the life cycle, focusing on when a Digital Twin should be applied in this field. The third aspect emphasizes the rationale for utilizing a Digital Twin in renewable energy. The fourth aspect discusses the digital twin architecture, detailing how to implement a Digital Twin for renewable energy systems. For this reason, the section on 'Where' relates to the context and types of renewable energy. The sections on 'When' and 'Why' outline the lifecycle phase in which the digital twin is developed and its primary functions. The section on 'How' illustrates the architecture and structural layers of the digital twin. Finally, this review identifies key research outcomes and future directions in digital twin applications for renewable energy systems.

2. Research methodology: text mining and topic modelling

This literature review centres on previous literature on the digital twin technology and its applications, functions, and architecture in the renewable energy sector. The literature review is primarily conducted across the Scopus database, encompassing various peer-reviewed interdisciplinary research studies. The state-of-the-art methodology follows a three-step process, as shown in Fig. 2: Paper Identification, Text Mining Analysis, and Topic Modelling.

2.1. Phase 1: paper identification

This work explores the recent progress of digital twin technology in the renewable energy sector. Hence, this paper analyses different research studies to examine the digital twin's main applications, functions, and architecture in the renewable energy sector. This analysis was conducted based on research studies extracted from the Scopus database, based on the following Keywords: ("Digital Twin" OR "DT") AND

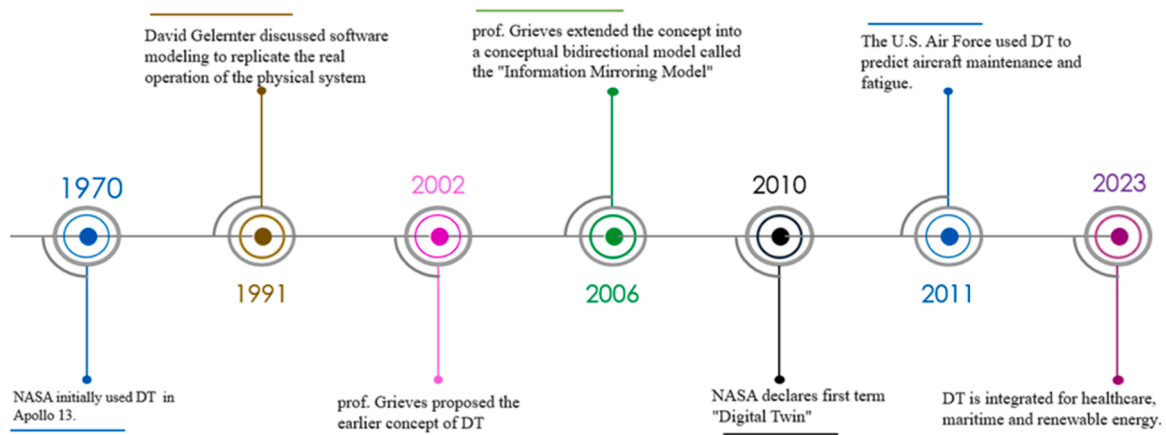


Fig. 1. The sequence of the development of the "Digital Twin".

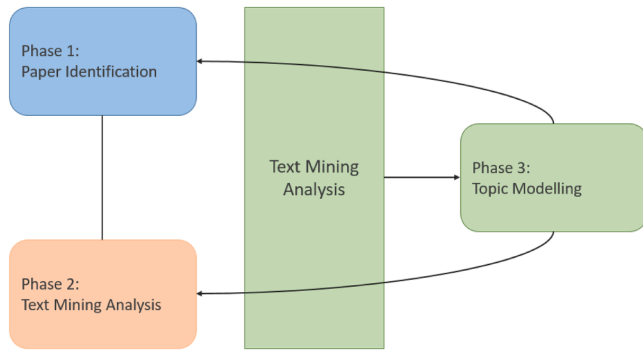


Fig. 2. Research Methodology Workflow.

“Renewable” AND “Energy”). These keywords were used to search the Scopus database for related research studies. The search was carried out by exploring the titles, abstracts, and keywords of research studies stored in the Scopus database. The initial search showed around 487 papers related to the topic. Thereafter, the studies were selected based on the timespan between 2010 and 2024, as before this timespan, the papers did not show high relevance to the topic of this paper. The main language was selected as English. The type of research study was specified as articles, journal papers, conference proceedings, and book chapters.

2.2. Phase 2: text mining analysis

Upon screening and selecting the related studies, a devised technical methodology was employed to investigate the available features and details of the chosen digital twin papers. Specifically, text mining analysis was adopted for this purpose. Text mining involves examining text content to extract valuable information that is utilized for various objectives [58]. The Orange software [59] can be utilized to apply various text mining techniques. The software facilitates the construction of workflows by connecting user-designed or pre-defined elements termed widgets. Hence, Orange software was utilized in this paper to create a model that represents the keywords used in different digital

twin papers encompassing renewable energy systems. Fig. 3 depicts the model created in Orange to analyze the related studies to uncover trends, concepts, and latent associations within these studies.

2.3. Phase 3: text mining analysis: topic modelling

The created model has been modelled to identify the most prominent topics that have been discussed in the chosen studies. In order to create any text mining model, the first step is to use a Corpus widget that imports the Corpus file, which encompasses the used text features. In this case, the imported text features are the author keywords used in selected publications. The Corpus Viewer widget can view these text features. The main widget in this model is the Topic Modelling widget. The Topic Modelling widget is a statistical model that utilises a text mining technique to uncover concealed semantic structure within a body of text. Before modelling the main topics, the author keywords are pre-processed using the Preprocess Text widget. The main topics were modelled using the Latent Dirichlet Allocation (LDA) method. LDA autonomously identifies topic patterns within content, categorises papers accordingly, and gauges their significance in different subjects. LDA results are displayed in the Data Table and Corpus Viewer widgets. As papers commonly involve various topics in differing proportions, LDA also presents the weightage of topics per paper, which can be observed in the Distributions widget.

Even though numerous research studies exist to discuss digital twin technology and its applications in different fields, few studies explore the applications, functions, and architecture of digital twin technology in the renewable energy sector. Hence, this paper focuses on addressing these questions: *Where* (Applications), *When* (Lifecycle Phase), *Why* (Functions), and *How* (Components and Architecture). Therefore, the model created by Orange (Fig. 3) was utilized to explore the primary topics discussed by researchers in this field. The model provided four distinct topics after employing the LDA algorithm. The outcomes of this algorithm are presented in Table 1. The table presents the set of words that represent the four topic modelling. The first topic modelling (T1) contains the words: “**Energy, Solar, Renewable, System, Microgrid, Wind, Vehicle**”, which indicates that a portion of the selected publications discusses the applications of the digital twin in the renewable

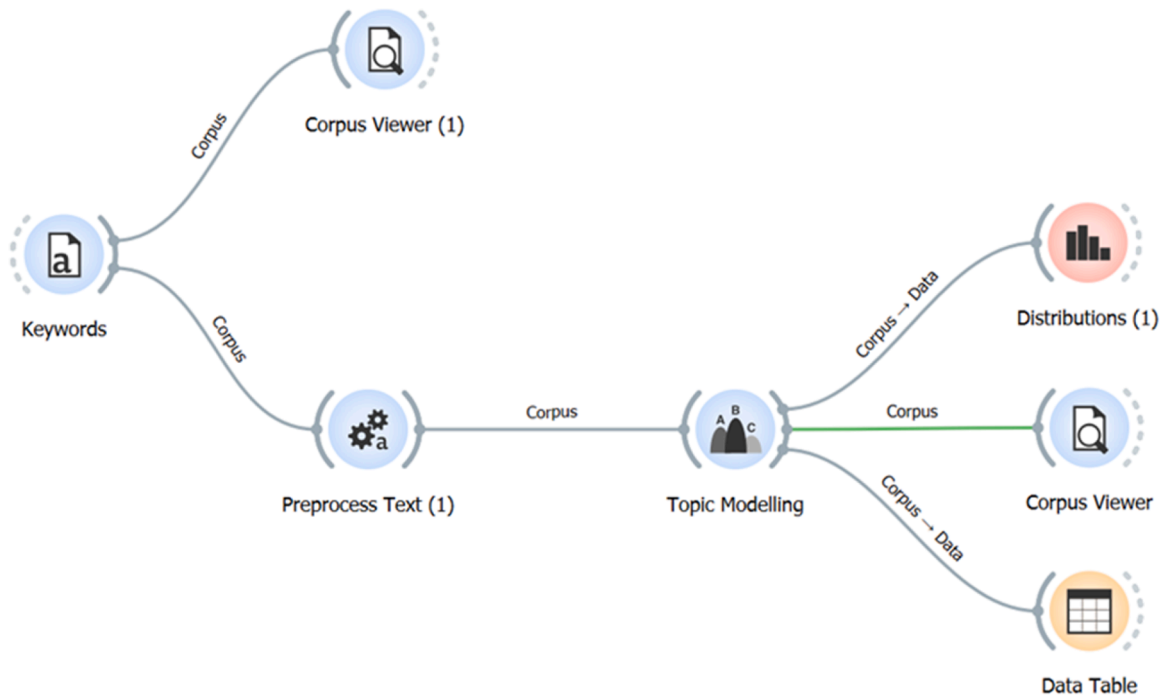


Fig. 3. Model created by Orange software for Topic Modelling.

Table 1

Outcomes from the Data Table widget based on the Topic Modelling technique.

TOPIC	Topic Modelling: Representing Words	Research Outcomes
T1	Energy, Solar, Renewable, System, Microgrid, Wind, Vehicle	Applications 'Where'
T2	Simulation, Artificial Intelligence, Internet, Neural	Components 'How'
T3	Monitoring, Control, Management, Optimization	Functions 'Why'
T4	Design, Computing, Virtual, Modelling, Network	Architecture 'How'

energy sector. These words tend to address the research question 'Where'. The second topic modelling (T2) includes the words: "**Simulation, Artificial Intelligence, Internet, Neural**". These words refer to the main components and elements utilized to build a digital twin for renewable energy systems. This topic modelling tends to answer the research question 'How'. The third topic modelling (T3) consists of the words: "**Monitoring, Control, Management, Optimization**". These words reveal the main functions provided by the digital twin for different renewable energy systems. This topic modelling attempts to underscore the research question 'Why'. The fourth topic modelling (T4) focuses on these words: "**Design, Computing, Virtual, Modelling, Network**". These words are related to the main architecture of the digital twin. Based on these words, it is evident that a typical digital twin architecture includes the following layers: Virtual, Physical, and Network. This topic modelling tends to address the research question 'How'. The outcomes of the LDA algorithm show that the main research topics explored by researchers are the applications, components, functions, and architecture of the digital twin in the renewable energy field. Therefore, this paper addresses these four research topics.

Each paper can include more than one topic of the topics modelled by

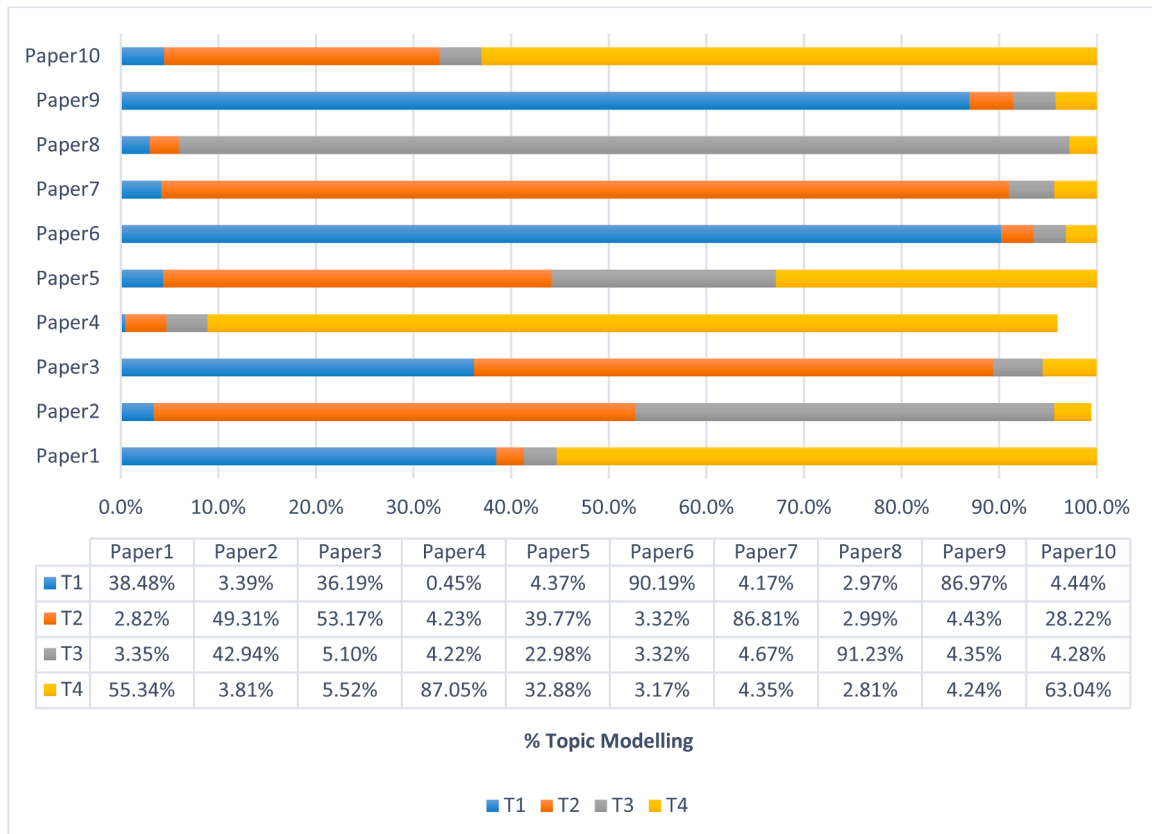
the LDA algorithm. This algorithm autonomously categorizes the selected studies into topics and assesses their significance within each topic, as depicted in Fig. 4. As a result, the figure shows the distribution of topics across a sample of ten research studies. This distribution demonstrates that paper 6 (Polo et al. [60]) and paper 9 (Shen et al. [61]) mostly discuss topic 1 (applications). Meanwhile, paper 4 (Zhang et al. [62]) and paper 10 (Nivarthi et al. [63]) mainly explore topic 2 (components). In this way, the LDA algorithm helps identify the main topics each paper discusses. In this paper, the outcomes of the LDA algorithm are the basis for carrying out a systematic literature review. Each section discusses one of these topics, and the associated papers are selected based on their topic modelling. For instance, papers 6 and 9, in addition to other related publications, are included in section 3.0 which discusses the applications of digital twin technology in the renewable energy sector.

3. Digital twin applications and contexts in renewable energy

Digital twin technology can be used for various purposes in the lifecycle of renewable energy. Specifically, as presented in Fig. 5, most papers focus on applying wind systems and solar energy in different applications. However, fewer researchers have studied hydroenergy, geothermal, and biomass applications.

3.1. Uses of digital twin technology in wind turbine systems

Several studies discussed the digital twin technology in onshore and offshore wind turbine energy systems. The wind turbine data acquisition from the sensors in the physical facility plays an essential role in enhancing the performance of the facility's operations. These sensors enable continuous monitoring and controlling of the system. As a result, Shen et al. [61] developed a data-driven digital twin to monitor the

**Fig. 4.** Topic Modelling distribution based on a sample of the selected papers.

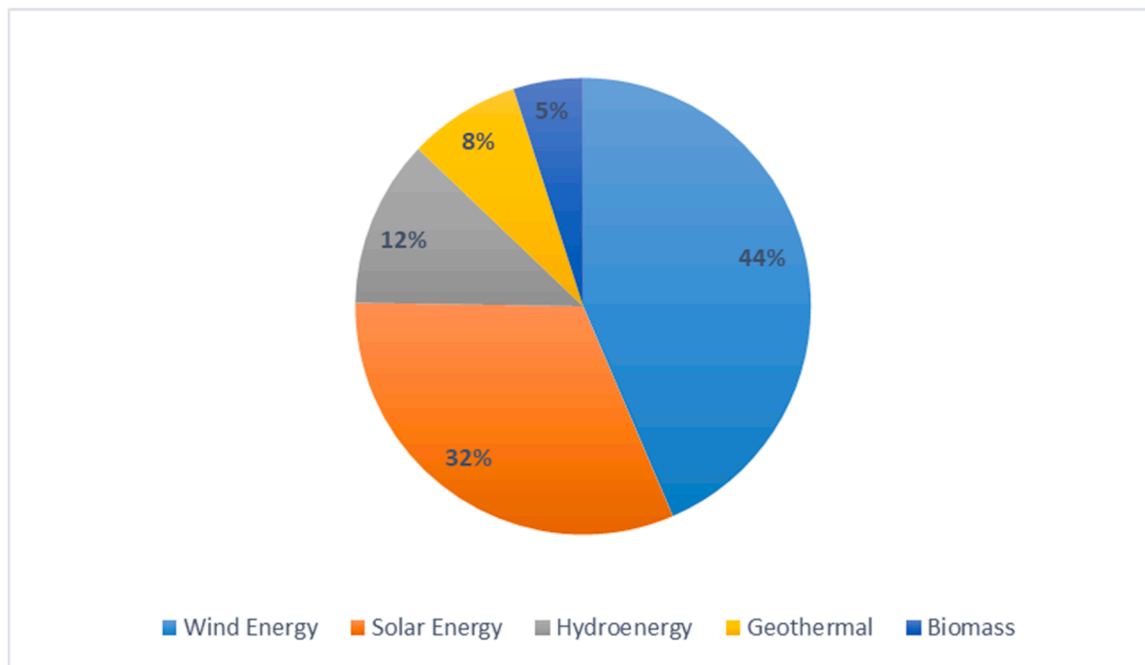


Fig. 5. The proportion of published papers addressing the integration of digital twin technology with renewable energy systems.

sensors' statuses and then verify the accuracies of the measurements acquired by these sensors. Furthermore, the digital twin technology can be developed to extend the useful life of an onshore wind turbine by carrying out accurate early fault detection for the system's components. This was illustrated in a study by Pimenta et al. [64], which aimed to create a digital twin model for an onshore wind turbine to predict fatigue damage, power output, internal forces, and thrust forces. In contrast, offshore wind turbines are constructed in challenging environments with high operational and maintenance costs. On another note, offshore wind turbines are built-in facilities because they require high operational and maintenance costs. Hence, Johansen et al. [65] designed a DT to control the system's status. Furthermore, the digital twin was utilized to carry out.

For instance, there is a lack of applications in predictive failure analysis and real-time optimization for offshore wind turbines. Scalability is an issue, especially when it comes to successfully integrating digital twins into huge wind farms.

3.2. Uses of digital twin technology in solar energy

The digital twin has different applications for solar energy generation plants. Hereof, the digital twin estimates the unknown factors related to PV panels, such as solar irradiance, voltage, current, and output power. This was illustrated by Razo et al. [66] in a study conducted to develop a digital twin model for optimizing the function of seven unknown parameters related to a PV system. The Digital twin can be used to make predictions PV parameters. Consequently, Polo et al. [60] implemented a digital twin model for PV systems applied in green buildings to accurately predict power generation and analyze the impact of shading and geometric factors on the overall efficiency of the PV. Another use of digital twin technology for PV applications in green buildings is for fault detection. Jain et al. [67] designed a digital twin model for a PV system in a smart building-integrated photovoltaics (BIPV) system for fault detection. Another application is for Solar cars. Solar cars are vehicles that are powered by the energy from the sun, typically through the use of photovoltaic cells that convert sunlight into electricity. Some solar cars are also being developed for commercial use, although they are not yet widely available on the market. The limited commerciality of solar cars is due to their low output energy rate, area

usage, and intermittent energy supply. Thus, several researchers attempted to employ the digital twin technology to monitor and manage the energy supply in solar cars. For instance, Suita et al. [68] developed a digital twin to describe the different conditions to maximize the power tracking of solar cars and enhance energy consumption. Furthermore, understanding the energy flow between the components of a solar vehicle is required to solve the issues related to energy management in solar vehicles. Wherein, Bai et al. [69] demonstrated a digital twin model to simulate the energy flow between the components of a solar car. The simulation enables the digital twin to calculate the power consumption in each component of the solar vehicle in order to identify the appropriate energy management strategy. In addition to solar vehicles, agrophotovoltaics are other applications of the digital twin technology. Agrophotovoltaics is a mature technology that combines power generation from PV panels with agriculture production. The integration between agrophotovoltaics and the digital twin technology has been facilitated by Zohdi et al. [70]. Using a numerical model, the authors developed a digital twin to analyze the agrophotovoltaic hybrid system's different features.

Based on these findings, Digital twin technology in solar energy still faces several shortcomings. One significant gap is the limited focus on advanced applications such as real-time optimization of energy output, early fault detection, and predictive maintenance tailored to photovoltaic systems.

3.3. Uses of digital twin technology in hydroelectric energy systems

Hydroelectric energy is one of the most efficient types of renewable energy. Hydroelectric energy can be continuously produced with zero-emissions [71]. However, hydroelectric energy production is associated with the high construction costs. Due to the high construction and maintenance costs, monitoring and controlling hydropower plants is necessary to enable continuous preventative maintenance. Zhao et al. [72] develop a digital twin framework to detect early fault for hydropower plants. Moreover, hydroelectric energy production comes with the threat of potential flooding [73]. Hence, Hongqun et al. [74] developed a digital twin based on 3D laser for a virtual simulation of the Fuchunjiang Hydropower Plant in China to forecast the occurrence of flooding. The simulation includes the hydropower house, main

equipment like the generator, the internal foundation structure, and the different flood disaster scenarios, including the emergency and maintenance plans. Similarly, Moussa et al. [75] built a digital twin for hydropower generator systems for monitoring their operations and carrying out accurate diagnostics. There is limited research on using digital twins for optimizing real-time water flow management, turbine efficiency, and energy output at this research stage.

3.4. Uses of digital twin technology in geothermal energy system

Geothermal energy generates heat and power by using underground temperature [4]. Geothermal energy does not require an energy storage system to store excess energy [4,76]. Due to the disadvantages posed by the high costs of the drilling and bugging processes, the digital twin technology is needed to mitigate these drawbacks [77]. The digital twin provides continuous real-time control over these processes to overcome such hurdles. Osinde et al. [78] built a digital twin to simulate the drilling process and gather real-time data to diminish the costs incurred from the drilling and bugging processes. Moreover, the digital twin has been developed to mimic the performance of a heat pump and enhance the performance of a geothermal power plant. Accordingly, Smirnov et al. [79] implemented a digital twin to study and optimize an underground heat pump. Moreover, the digital twin technology was able to predict and detect any faults in the physical equipment, mitigate sudden system failure of the heat pump, and enhance the decision-making process. Digital twin technology in geothermal energy systems has several gaps. Key areas include limited reservoir performance optimisation exploration, real-time subsurface conditions modelling, and predictive maintenance for geothermal plants.

3.5. Uses of digital twin in the biomass

Biomass is composed of organic materials such as waste and wood. Biomass can be directly heated to generate electricity or indirectly used to produce biofuel [80]. Even though the application of digital twins in biomass is limited, the digital twin technology can be applied in the biomass industry to optimize the performance of biomass power plants, predict equipment failures, and improve the overall efficiency. For instance, Jennifer [81] developed a digital twin for a biomass-fired tower boiler to optimize its performance and provide high-fidelity simulation models.

Digital twin technology in biomass energy systems has several gaps. These include limited studies in optimizing biomass supply chains, such as feedstock logistics, storage, and processing. Real-time monitoring and predictive maintenance for biomass conversion systems, like anaerobic digesters or combustion plants, are underexplored.

4. Lifecycle of the digital twin and its functions in renewable energy

This section discusses when it is appropriate to implement a digital twin for renewable energy applications and the different functions of a digital twin. Generally, the digital twin is employed in the design, production, and service phases [52] to serve various tasks at each phase [26, 82]. During the design phase, the digital twin is used to optimize the design of renewable energy systems before they are implemented. In the production and service phases, the digital twin plays a role in monitoring, simulating, and predicting the performance and behavior of these systems.

4.1. Lifecycle of the digital twin and its functions in the wind energy system

Digital twin technology is implemented for onshore and offshore wind energy systems during the design and service phase to carry out various functions. During the design phase, the digital is used to design a

virtual representation of the physical wind system before building it. The most common functions of the digital twin at the design phase are illustrating the properties of the controlling factors, estimating unknown parameters, and ensuring the system's reliability. Some of these functions were reflected in a study by LeBlanc1 and Carlos [83]. In this study, a digital twin model was built to predict and test the aerodynamic and structural properties of the blade and tower. Moreover, these characteristics were utilized to estimate the reliability of the wind turbine's vertical axis.

Occasionally, during the production phase, the material of wind systems undergoes serious fatigue damage due to the frequent twisting and bending in the foundation, tower, and blade. In order to solve this issue, a study was facilitated to develop a digital twin model for the onshore wind turbine. The digital twin was able to predict the fatigue damage in the components of the wind system, such as the blade and foundation, and then estimate the output power to identify the optimal state and proper monitoring condition [64]. Similarly, Sivalingam et al. [84] displayed the functionality of a digital twin in accurately estimating the remaining useful life of a floating offshore wind turbine system to reduce the time and cost of maintenance and operations. Furthermore, according to Branlard et al. [85], the functions of a digital twin during the production phase to be expanded into real-time system monitoring and rapid and accurate estimations of wind turbines. During the service phase, the digital twin is employed to test the accuracy of the estimations conducted during the design phase to match the system during actual operation. Finally, little attention is given to the full life-cycle of turbines, such as considerations for recycling, decommissioning, and overall sustainability impacts.

4.2. Lifecycle of the digital twin and its functions in solar energy

In the design phase, the digital twin is developed to estimate the characteristics of the power plant, such as the output power, voltage, current, and load [66]. This was evident in a study carried out by Massel et al. [86] to estimate the most crucial parameters for designing a solar power plant. The authors used the digital twin to design a database software for the solar power plant and develop a mathematical model to obtain the output power, efficiency, temperature of the solar panel, photo stream, output voltage, and current. Similarly, Tariq et al. [87] employed a digital twin to optimize the geometric variable of the solar chimney geometric parameter during the design phase of building a solar chimney. On the other hand, during the production and service phases, the digital twin is utilized to facilitate fault detection and accurately estimate the outputs of a PV system. This was illustrated in a study conducted by Jain et al. [67]. In this study, the authors proposed a digital twin model for PV systems in a smart building-integrated photovoltaics system (BIPV) for carrying out fault detection and estimation of the characteristic output of the PV system. In other words, during the production and service phases, the digital twin provides data to guide decision-makers to evaluate the model [82]. Lifecycle considerations, including panel recycling and long-term sustainability, remain underexplored.

4.3. Lifecycle of the digital twin and its functions in the hydroelectric

The digital twin was mainly developed for hydroelectric energy systems during the production and service lifecycle phases to guide decision-makers to the optimal scenario for optimally operating the system and predicting upcoming failures and hurdles. Some of these functions were presented in a study conducted by Yan et al. [88] to develop a digital twin that will predict future failures and employ predictive maintenance for the generator. The study was conducted to ensure the stability of the electric generator. Furthermore, during a hydroelectric power plant's production and service phases, the digital twin was employed to simulate the different operations, observe the load conditions, monitor, study, and test the system's reliability [75]. The

digital twin was developed to simulate hydropower plants to observe the generator's performance and the internal foundation structure. The simulation can also show different scenarios of natural disasters that can potentially occur and present several emergency and maintenance plans [74]. Economic feasibility studies and lifecycle considerations, including dam sustainability and long-term environmental impacts, are also lacking.

4.4. Lifecycle of the digital twin and its functions in the geothermal

Digital twin technology has been developed to perform several functions during geothermal power plants' production and service lifecycle phases. During the production and service phases, the digital twin can be employed to detect fault, monitor the system in real-time, optimize the system, and provide accurate predictions. The digital twin is used for rapidly detecting faults in the drilling process, as it is considered as the most expensive process in a geothermal power plant. Hence, Osinde et al. [78] developed the digital twin for real-time monitoring and simulating the drilling process to reduce incurred costs and prevent future failures. Furthermore, in a study conducted by Smirnov et al. [79], the digital twin was developed to monitor an underground geothermal heat pump in real-time. The digital twin was developed to optimise the system after providing several simulations using the acquired real-time data. There is a lack of lifecycle studies addressing sustainability, well longevity, decommissioning processes, and insufficient economic feasibility assessments for large-scale implementation.

4.5. Lifecycle of the digital twin and its functions in biomass

Digital twin technology can digitally represent a biomass power plant during the production and service lifecycle phases. During the production and service phases of a biomass power plant, the digital twin can provide highly accurate simulations of the plant to improve its performance. Jennifer [81] developed a digital twin model to improve the performance of a biomass boiler at the Atikokan power plant. The digital twin obtained accurate high-fidelity simulations of the boiler's operations. Economic feasibility and lifecycle analysis are lacking in current implementations, particularly focusing on waste management, sustainability, and scalability.

5. Digital twin architecture and components in renewable energy

After examining the existing research on integrating digital twin technology with renewable energy systems, it can be concluded that there is no standardized architecture for developing a digital twin [57]. Nonetheless, the composition layers and functions of the digital twin are consistent across all renewable energy systems. The digital twin consists of three main layers: the physical layer, the network layer, and the digital layer. Fig. 6 displays the basic elements of the digital twin architecture. Zhang et al. [62] provides a general architecture that can be followed for all renewable energy systems. The authors offer a hybrid simulation of different renewable energy sources via real-time data and online monitoring. The physical space is composed of a physical sub-system, remote sensor, graphical display, and real-time simulator. The primary function of the real-time simulator is to simulate the behavior of different components of the hybrid system. However, the simulator requires a powerful Central Processing Unit (CPU) and a Field Programmable Gate Array (FPGA) to produce an accurate model. The physical setup includes a generator, controllable loads, energy storage devices, power electronic converters, Li-ion batteries and supercapacitors, and energy sources like PV and diesel engines. The data from the hybrid simulation platform are visually displayed on a monitor to depict the entire system's operation. Artificial Intelligence (AI) and Machine Learning (ML) technology significantly enhance the functionality of digital twins in renewable energy systems. AI and ML algorithms are used for real-time problem detection, energy generation optimization, and predictive maintenance. For instance, AI algorithms maximize grid integration and storage management, while machine learning models predict energy production from wind and solar systems depending on meteorological conditions. By examining sensor data to find anomalous patterns, these technologies also help in anomaly detection, which makes it possible to discover system breakdowns early. Furthermore, AI-powered optimization algorithms can increase operational effectiveness by dynamically modifying parameters to optimize energy output and cut expenses.

Notwithstanding their potential, issues including model interpretability, processing demands, and data quality, still exist. However, AI and ML are critical to advancing and implement digital twin capabilities, offering more accurate, adaptive, and efficient solutions for renewable

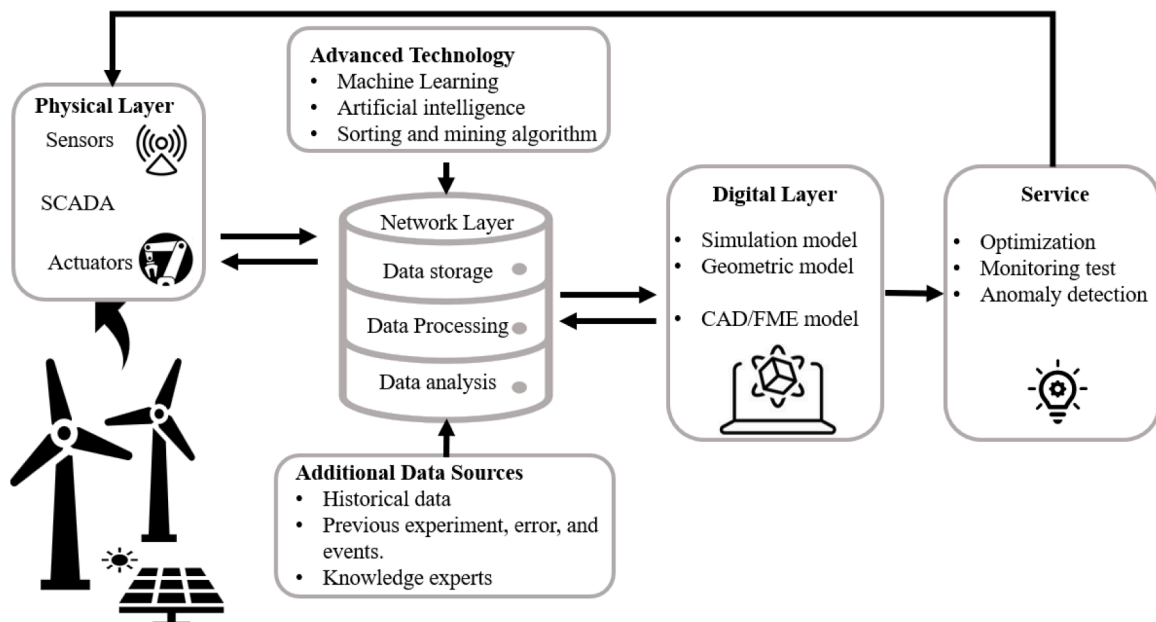


Fig. 6. The architecture of a Digital Twin.

energy management.

5.1. Digital twin architecture for wind energy

The digital twin architecture for wind energy is closely tied to the operation and performance of wind turbines. Branlard et al. [89] discussed the digital twin architecture when the digital twin was employed to predict a specific characteristic. The authors aimed to identify and predict the characteristics of wind energy, such as wind speed, torque, thrust, and load under various conditions, by comparing the model's performance to actual operations. The system includes physical sensors to measure torque, rotor speed, pitch, and tower top acceleration, which are integrated with supervisory control and data acquisition (SCADA) units. The digital twin combines this measurement data with numerical models to estimate the characteristics, using a linear state space model and Kalman filter algorithm to validate the estimated values. Simulations were run using the OpenFAST tool and TurbSim, with a Kaimal spectrum and exponential coherence model. Similarly, another study focused on onshore wind turbines created a digital twin platform to predict and validate factors such as fatigue damage, power output, internal force, and thrust force. Pimenta et al. [64] developed a digital twin for an onshore wind turbine that allows for ongoing assessment of the turbine's characteristics under different loads and identification of accumulated fatigue damage. The model also provides suggestions for operation and monitoring strategies. The physical system consists of a 1.8MW VESTAS V100 wind turbine, SCADA units, and sensors such as accelerometers and extensometers placed on the turbine tower and blades to gather information on the structure, aerodynamics, and geometry. The FAST software is used to simulate the system by constructing a FEM to depict the structural and aerodynamic properties of the wind turbine's components, including the tower, blade, and foundation. Mechanical statics information is obtained from the geometric properties of the tower and blade and fed into the FAST software as input from sensors. The aerodynamic characteristics of the blade are also required as input for the simulation of blade actions and operations. A 2D CFD model was also created using ANSYS Fluent to calculate the blade's aerodynamics properties using equations such as the Reynolds Average Navier Stokes Equations (RANS).

On the other hand, other researchers focused on developing the digital twin technology to mitigate system failures and accurately detect faults. For instance, Li & Shen et al. [61] used a highly advanced digital twin platform that runs in real-time to detect, correct and rebuild faulty, inaccurate or missing wind speed measurements from sensors in a wind farm. The platform employs spatiotemporal correlations of wind speed measurements across multiple wind turbines on the farm to identify patterns in both space and time. The proposed method includes four stages: estimators, verifiers, setters and selectors. The method also employs the use of Multi-Turbine Wind Speed Correlations (MTWSCs), a SpatioTemporal Network (STN) and Mathematical Statistics Theory (MST) to extract, estimate and verify the spatial and temporal features of the measurements. The process starts with inputting the measurements from physical onsite sensors into the estimator, which uses a combination of a Convolutional Neural Network- Bidirectional Long Short-Term Memory model CNN-BiDLSTM deep network to identify the temporal and spatial features of wind speed. The measured data is input into the CNN to extract the spatial feature, which is then transferred to the BiDLSTM to obtain the temporal feature. The final output calculated by the BiDLSTM network represents the wind speed. The Frobenius norm is used to compare the measured value with the estimated wind speed to determine the error in the estimator stage. In the verify stage, the estimated data is checked using a change point algorithm to calculate each measurement's mean, variance, and change rate. In the setter stage, the average absolute percentage error (MAPE) is used to compare the estimated data and the actual measurement in case of possible errors in the estimated data. Lastly, if the mean absolute error is higher than the standard in the selector stage, the digital twin will use the estimated data

for monitoring and control. However, if the estimated value exceeds the standard, the digital twin will store the data for future comparison.

5.2. Digital twin architecture for solar energy

The digital twin architecture for solar energy entails developing a virtual model of the physical solar energy system, incorporating elements such as solar panels, inverters, and other components. This virtual model can be used to simulate the system's performance, predict its behavior under different conditions, and optimize its operations. The digital twin can also be connected to control systems, such as inverters, to monitor the solar energy system. This can be used to optimize the performance of the system and reduce the cost of operations as illustrated by Razo et al. [66]. Using a Genetic algorithm and weather data, the authors discussed using a digital twin to optimize photovoltaic (PV) system parameters. The physical space of the digital twin architecture was the PV system, including the onsite sensors to measure the property of a solar panel, ambient temperature, and satellite-derived irradiance to obtain the annual irradiance and weather data. The digital twin simulated the PV system through a series of models, beginning with an irradiance model that takes into account factors such as albedo, angle of incidence, azimuth, and tilt angles. The next steps in the simulation include the DC and AC power models, which calculate the PV efficiency based on the input irradiance and ambient temperature. The Genetic algorithm was then used to optimize the PV system by comparing simulation results with measured data and adjusting parameters such as the albedo, tilt, and azimuth angles, as well as the DC and AC power. The process continued until the best PV parameters were determined, using the least square method. The measured data was then compared to the simulated data using the Heydenreich model.

On the other hand, Nivarthi et al. [63] proposed a digital twin for forecasting power generation and detecting faults in solar and wind energy systems using machine learning and transfer learning. The system utilizes a large amount of previous data, including weather and fault information, to train a deep neural network model. This model is then used to identify patterns of normal behavior, and any deviations from this normality is identified as an anomaly. The system was able to estimate missing sensor data and detect faults in the power system.

5.3. Digital twin architecture for hydropower energy

Digital twin technology in hydropower systems can provide a virtual representation of the physical construction, pipeline network, concrete foundation, and cost analysis of the entire system before its implementation as hydroelectric construction is one of the most expensive types of renewable energy construction [90]. A study by Z. Zhao et al. [72] proposed a digital twin data-driven framework for hydropower plants for fault diagnosis using artificial intelligence and big data. The digital twin model enables the platform for self-discovery, self-construction, and self-optimization based on various data sources such as system information, regulation, standard operations, previous experiments, and expert knowledge related to the hydropower plant. The digital twin framework includes four main layers to meet the requirements. Firstly, the digital twin gathers and organizes data from various sources in the data acquisition layer. The extracted data is transformed and stored in a database as TXT, XML, JSON, and EXCEL files. In the model-building layer, the digital twin uses data from the previous layer to build a meta-model using meta-modeling tools and Natural Language Processing (NLP) with knowledge extraction and various models like conversion, library, and fusion. Next, in the model calculation layer, the digital twin processes the data through comparison and sorting algorithms, event reasoning, attribute reasoning, relation reasoning, and representation learning algorithms. Finally, in the application model layer, the digital twin is oriented towards various functions such as fault diagnosis, intelligent alarms for emergencies, and early alarms for crises to manage risk.

5.4. Digital twin architecture for geothermal energy

Research on applying digital twin technology in geothermal energy is relatively limited. due to various factors, including the high cost of drilling for geothermal applications. Osinde et al. [78] proposed a digital twin to carry out real-time monitoring and online control to optimize the drilling operations of a geothermal power plant. The twin model's goal is to depict the geometric characteristics of the physical system and its main functions using Siemens NX 12.0.2 integrated with Mechatronic Concept Designer (MCD) to generate a CAD model, resulting in a strong system representation. Then, the Communication Platform uses Open Platform Communication (OPC) and KEP servers to facilitate and ensure the synchronized transfer of data between the virtual and physical spaces. Moreover, the PLC programming software uses the Total Integrated Automation (TIA) portal to program the hardware PLC and integrate it with Artificial Intelligence and Cloud Computing to realize online communication.

5.5. Digital twin architecture for biomass

The implementation of digital twin technology in biomass systems is limited; however, Jennifer [86] proposed that a digital twin to improve the performance of a biomass power plant. The developed digital twin optimized the 200 MW boiler and enabled real-time control at the Atikokan biomass power plant. The digital twin first identifies and organizes the parameters used for optimization. Then, it creates an accurate simulation of the boiler based on the scientific model of the system and hierarchical validation to improve the system, decrease uncertainty, and provide a reliable prediction of the physical model. The design of experiments (DOE) and high-performance computing (HPC) platforms are employed to optimize and reduce the uncertainty of input data. The simulation of the process is carried out through Large-Eddy Simulation (LES). Since the digital twin simulates real-time data, a faster evaluation of the simulation data is necessary, this is achieved by building a robust surrogate model. The digital twin builds a robust surrogate model using gaussian interpolation regression and a probabilistic approach for each variable. Gaussian interpolation regression ensures fast evaluation and data storage and determines the sources of error in the simulation output. Additionally, the probabilistic approach allows for the calculation of empirical confidence intervals, which helps determine the regions that require refitting and remodeling in the robust model. In order to optimize the boiler's performance, the digital twin utilizes Bayesian analysis to identify the model's uncertainty and predict the posterior operation of the parameter.

6. Conclusions and research direction

This paper represents the state-of-art of published research discussing the integration digital twins with different renewable energy applications. After exploring all these areas, Table 2 is constructed below to summarize the most important findings of this work.

Digital twins are effective instruments for maximizing the efficiency of renewable energy systems, but depending on the features of each energy source, they also have certain drawbacks. These restrictions for wind, solar, geothermal hydroelectric, and energy biomass, are broken down in depth in Table 3.

Every energy source has different restrictions relating to data variability, environmental conditions, and system complexity, even if digital twins have the potential to maximize the generation and management of renewable energy. In order to overcome these constraints and guarantee that digital twins can offer precise and trustworthy insights for decision-making, developments in data gathering methods, modeling methodologies, and processing capacity are needed. For these reasons, the main research outcome and future research directions have been summarized below in three main points:

Table 2

Overview of the analysis.

Aspects	Outcomes
DIGITAL TWIN CONTEXTS/ USE CASES WHERE?	Wind Energy system: - Predict the unknown parameter and optimize the mistaken measurements. Solar Energy: - Use the real-time data from onsite sensors to determine the primary parameter influencing the efficiency and output power. Early material and fault observation. Geothermal energy: - Simulate the entire process, especially the drilling process, which requires cost analysis and fatigue determination to reduce the cost and time of operation. Hydro energy : - Simulate the system to represent the factors that impact the system, and use 3D laser scanning for the old power plants to detect cost-effective fatigue construction. Biomass: - Optimize the performance with a strong understanding of the process and the power plant configuration, like a burner.
DIGITAL TWIN LIFE CYCLE WHEN? DIGITAL TWIN FUNCTIONS WHY?	Design: - Analyze the parameters related to the system - Pick up the best condition before the execution Production: - Real-time data to predict the early behavior of the system. Service: - Fatigue detection of the material and optimization of the system.
DIGITAL TWIN ARCHITECTURE AND COMPONENTS HOW?	Physical layer: - The physical layer includes the renewable energy application with real-time remote sensors, Graphical Display, and a simulator. Network layer: - Transfer the data from the physical assets to the virtual space using sensor data and software. Digital layer: - Including the virtual model for analysis and optimization until the end of the physical assets

6.1. Research outcome #1

Integrating digital twin technology with renewable energy sources poses several challenges. For example, limited research and literature is available on the use of digital twin technology in the field of renewable energy, particularly in areas such as tidal, ocean thermal, wave energy, small and micro hydro. This is largely due to the lack of maturity and limited number of global applications in these areas, as well as a focus on providing temporary and cost-effective solutions for countries and regions with poor infrastructure. To advance the development of digital twin technology in renewable energy, further research is required to explore its diverse applications and to strike a balance between the costs and benefits of implementing this technology across projects of varying scales.

6.2. Research outcome #2

The digital twin enables the creation of a virtual model of a physical system, capable of simulating its performance under various conditions. It also facilitates real-time monitoring, control, and early fault detection. This technology can be applied across the entire lifecycle of physical assets. However, most research on digital twins has concentrated on the design and service phases, primarily due to a shortage of case studies in

Table 3
Digital Twins Limitations for each Renewable Energy Source.

Renewable Energy Source	Digital Twin Limitations: Modelling and Data Constraints
Wind energy system:	1) Modelling and Monitoring Environmental variability, conditions, and factors. 2) Aging Turbines and Wear including blade erosion, gearbox degradation, and electrical system failures. 3) Data Gaps and accuracy in remote or offshore areas where data collection can be sparse or unreliable.
Solar energy:	1) Intermittency and Variability variations in atmospheric conditions, making it hard to predict performance accurately in real-time. 2) Monitoring Panel Degradation and Environmental Factors over time. These factors are not always easy to predict or model, they can significantly reduce system performance. 3) Data Gaps and accuracy in remote or offshore areas where data collection can be sparse or unreliable.
Geothermal energy:	1) Simulating Geological Uncertainty and Conditions for lack of high-quality data. 2) Complexity in modelling the long-term behavior of geothermal systems such as Heat Transfer and fluid flow dynamics over time. 3) Limited Data Availability.
Hydro energy :	1) Complexity in modelling the Water Flow Variability of the Hydroelectric systems . 2) Aging Infrastructure Performance and Data Scarcity. 3) Modelling and Monitoring Environmental and Ecological Constraints.
Biomass	1) Complexity in modelling the biological processes, biomass conversion, and biochemical and thermochemical processes. 2) Simulating the entire Supply Chain of Biomass energy production. 3) Modelling and Monitoring Operational Changes in biomass over time.

the production phase and insufficient collaboration between decision-makers and stakeholders. However, few studies have been published on incorporating digital twin technology throughout all stages of a physical asset's lifecycle. To fully utilize the capabilities of digital twin technology in the future, collaboration between stakeholders and decision-makers is necessary to explore its potential in the production phase. This will allow for a comprehensive, real-time simulation of processes to meet the necessary requirements [91].

6.3. Research outcome #3

Integrating digital twin technology with renewable energy is complex due to the diversity of its functions and the lack of a stable reference. Building a digital twin model involves using advanced machine learning tools and algorithms. Additionally, managing a digital twin requires large amounts of historical and current data, which can be challenging to process and modify. The complexity of the digital twin can be reduced by setting standards for the digital twin architecture.

CRediT authorship contribution statement

Concetta Semeraro: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Haya Aljaghoub:** Writing – review & editing, Methodology, Data curation. **Hamad Khalid Mohamed Hussain Al-Ali:** Writing – review & editing, Conceptualization. **Mohammad Ali Abdelkareem:** Writing – review & editing, Validation, Supervision. **Abdul Ghani Olabi:** Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

Data availability

Data will be made available on request.

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