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Energy Digital Twin applications: A review

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ABSTRACT

Digital Twin-based (DT) decisions are becoming increasingly popular in several areas, and the energy industry has been exploring the advantages of this approach. By creating synchronised virtual models that mirror the physical systems' behaviour, decision-makers can make more efficient and quicker decisions. In this case, this work aims to evaluate relevant papers in this area considering their objectives, application fields, adopted techniques and tools, as well as to discuss the advantages and challenges of this approach. Though a Systematic Literature Review (SLR), the main scientific databases were explored, and relevant articles were selected for analysis based on search criteria. Some crucial findings were highlighted, including the state of the art of the theme and important discussions considering energy generation, storage, transmission, and consumption subsystems. The main methods and tools adopted by the analysed literature were also evaluated and the objectives, advantages, and limitations stood out. The results of this SLR provide valuable insights for researchers and practitioners in the field and can be used to identify gaps in the current literature and provide directions for future research. It is important to mention that this work fills a gap in the literature considering the need for theoretical studies that provide a theoretical and conceptual basis for researchers and professionals in the field of Energy DTs.

1. Introduction

The energy sector faces numerous challenges and developments in the current global scenario, including energy efficiency, sustainability, and security of energy supply [1,2]. With the increasing demand for electricity and the need to reduce carbon emissions, exploring innovative solutions to optimise the performance of existing energy systems and planning for future expansion and advancements is crucial [3,4]. Digital technologies play an essential role in addressing these challenges, and the concept of Digital Twin (DT) is one of the most promising solutions proposed in recent years [5].

A DT is a virtual replica of a physical system that simulates its behaviour and performance [6,7]. The virtual model could be synchronised with real-time data from the physical system, allowing for real/near-real-time monitoring and analysis of system performance [8]. This concept has grown fast in the last two decades; however, many challenges and opportunities remain. Cameron et al. [9] reviewed the oil and gas industry literature to analyse how the DTs can be more sustainable, maintainable, and useful. In the same sector, Knebel et al. [10] recently performed a systematic review of cloud and edge computing and data management to support DT applications. The authors concluded that most studies deal with theoretical or partial implementations of DTs, and cloud/edge computing are critical in enabling DTs applications in the Oil and Gas industry.

Using DTs in the energy sector, or simply Energy Digital Twin (EDT), can revolutionise how energy systems are managed, leading to improved energy efficiency, reduced downtime, and lower maintenance costs [11]. The application of EDTs is rapidly growing, with numerous studies and research projects undertaken in various domains, such as renewable energy [12], energy storage [13], energy distribution [14], and energy consumption and management [15]. Previous literature presents some overviews in this area. Examples include reviews about DTs in energy management systems [16–18], energy conversion systems [7,19], electric grids [20], energy storage and battery manufacturing [21,22], and building energy consumption [23]. Moreover, Ghenai et al. [24] conducted a literature review on DT's benefits in the energy sector, highlighting its applications in generation, consumption, and storage. More details about these reviews are addressed in Section 2.3.

By analysing these reviews and other related works [9,10], it is possible to identify a lack of review studies focused on DT's applications

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across the four sides of the energy supply chain (generation, transmission/distribution, storage, and consumption), compiling and discussing important aspects of EDTs, such as the problems characteristics, adopted techniques and tools, advantages, challenges and opportunities. Therefore, this Systematic Literature Review (SLR) aims to address these aspects through a comprehensive analysis of relevant papers from five research databases (Scopus, Web of Science, ACM, IEEE Xplore, and SciELO).

The study addresses four research questions: RQ1: What is the current State of the Art? RQ2: Which are the main objectives and applications? RQ3: Which techniques and tools are used in DT development? and RQ4: What are the Advantages and Challenges associated with the approach? The answers to these research questions comprehensively are necessary to understand DTs' status and its future potential in the energy sector.

The results of this SLR are expected to provide valuable insights for researchers and practitioners in the field. The findings of this study can be used to identify gaps in the current literature and provide direction for future research in the field of EDTs. Moreover, this paper could guide practitioners to make informed decisions about the appropriate methods and tools for their DT projects according to their specific problem characteristics, leading to improved performance and cost savings.

Although other reviews explore similar topics, this paper differs since it promotes a systematic review of the DTs' studies throughout the entire energy sector's value chain. In other words, the analysis is not limited to a specific application or tool, addressing new issues and research questions and providing a background for professionals and researchers. Therefore, this paper systematically investigates the current knowledge in the field based on important steps that comprise searching/screening of the literature, analysis/synthesis of the selected papers, and discussion of the results.

The remainder of this paper is divided as follows: Section 2 presents the theoretical background of the work. Section 3 shows the research method applied in this systematic review. Section 4 presents the paper's results, findings, overall discussion, and technical remarks. Finally, the conclusions of the work are highlighted in Section 5.

2. Theoretical background

2.1. Digital Twins

Digital Twins (DTs) are virtual replicas of physical systems and can be used to mirror their behaviours and support decision-making [25]. Initially proposed by Shafto et al. [26] to reference virtual copies of physical equipment from the American Aerospace Agency (NASA), the DT concept spread quickly and became a valuable tool for the production systems of goods and services [27,28]. The DTs-based decisions can be applied in various industries and sectors, such as manufacturing, logistics, service, healthcare, and energy [28].

The DT model can incorporate data from various sources, including sensors, machines, and other devices, to create a comprehensive and accurate model of the physical [29]. Moreover, DT models can be developed using and integrating several technologies, including simulation, machine learning, big data, cloud technology, and the internet of things (IoT) [21,27]. By combining these technologies, analysts and developers can create highly sophisticated DTs that can mirror the behaviour of complex systems and processes.

According to Tao and Zhang [25], a typical DT has four main components: (i) Physical System (PS), (ii) Virtual System (VS), Service System (SS), and DT Data (DTD). The PS is based on processes, machines and materials, while the VS consists of virtual models that can describe the behaviour of the PS overtime. The SS include the communication structure that allows the integration between the physical and virtual environments, and, finally, the DTD refers to a set of data and information transmitted between both. Fig. 1 illustrates the DT structure.

By using DTs to mirror and simulate real-world scenarios, companies can gain valuable insights into how their products and services perform under different conditions. Therefore, it is possible to optimise the overall operations [21]. Alam and Saddik [29] state that DT can be used to support decision-making in three approaches: (1) diagnosis, which aims to evaluate past decisions; (2) monitoring, aiming to monitor and control the processes; and (3) prognosis, where the objective is to anticipate and predict behaviours.

DTs in manufacturing have been widely used to simulate the production process, identifying potential bottlenecks or issues and helping decision-makers optimise their production processes, reduce costs, and improve their product quality [30]. On the other hand, in healthcare and services applications, DTs can simulate individuals' behaviour (such as patients and clients), allowing decision-makers to perform informed decisions [21]. DTs that replicate logistics process can be used to simulate traffic patterns and warehouse operations to optimise decisions related to routes of vehicles and replenishment management, for example [31]. Finally, Onile et al. [16] highlight the applicability of DTs in the Energy Industry.

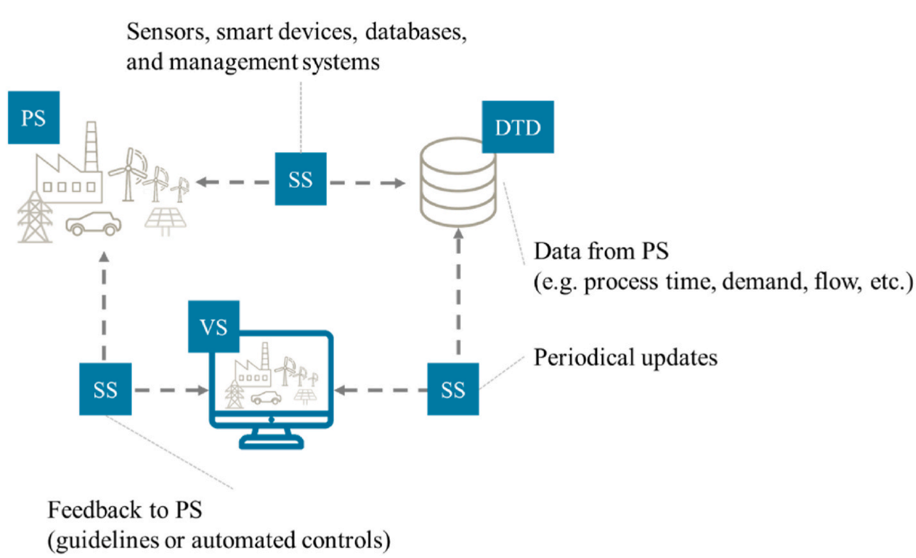

Fig. 1. Typical DT structure.

2.2. Energy Digital Twins

Decisions in the energy sector usually involve complexities and high risks, mainly due to the involvement of numerous stakeholders, large investments in infrastructure, sensitivity to weather events, and direct impact on several supply chains. This feature requires techniques capable of transforming this complexity and a large amount of available data into concise decision-making analyses [32,33]. Examples of these techniques include regression methods to forecast consumption [34], production planning models [35], and blockchain technology to power exchange [36].

According to Kooning et al. [7] and Singh et al. [37], the DT technology has gained popularity in the energy industry over the past few years since it can be used to monitor and optimise the performance of assets, predict failures, and plan maintenance and replacement activities. In this case, for Ghenai et al. [24], digitalisation contributes to improving the security, efficiency, and durability of energy systems and one of the most important and efficient digital solutions used in the energy sector is DT. The authors complement that, among the numerous advantages of DT technology adoption in the energy industry, the improvement of asset performance, higher profits and efficiencies, and less harmful effects to the environment stand out.

DTs can monitor and help to optimise the performance of power generation, transmission, and distribution systems or simulate building energy management systems [20,23,38]. By creating a DT of a power plant or a building, it is possible to simulate and analyse the system's behaviour in near/real-time, identifying improvements to increase efficiency and reduce energy consumption.

DT technology in energy systems can transform energy operations, considering production, distribution, and consumption, by making it more sustainable and efficient [39]. In this case, the work of Gheinai et al. [24] argues that DT-based decision approaches can be adopted in four main fields in the energy industry: (A) Energy supply/production systems (i.e. photovoltaic equipment, wind turbines, hydroelectric plants, and microgrids); (B) Energy demand/consumption (i.e. building applications and industrial systems); (C) Energy for Transportation (i.e. electric vehicles and engines); and (D) Energy storage (i.e. Batteries).

Furthermore, Yu et al. [18] classify Energy DT applications into three main groups related to the application phase: (i) Design phase, where it is possible to carry out analysis in order to evaluate and validate new assets; (ii) Operation phase, where it is possible to monitor and control processes, predict behaviours, as well as optimise the systems' results; and (iii) Service phase, where DT can be used to maintenance planning and fault detection during the processes operation.

Considering the Design phase, by creating a DT of a proposed power plant or transmission line, for example, it is possible to simulate and analyse the behaviour of the system under different operating conditions in order to optimise the design aiming to obtain maximum efficiency and minimum costs, as illustrated by Stennikov et al. [40]. Moreover, Yu et al. [18] complement that DT can also be used for retrofitting existing processes and plants to improve product quality, production rate and energy efficiency. According to the authors, around a third of applications of Energy DTs are related to the Design phase.

Considering the adoption of DTs during the Energy Operation phase, the DT can be utilised to monitor, analyse, and predict the performance of the system during its life cycle, allowing to optimise energy production, reduce downtime, and improve the efficiency of the entire energy value chain [38]. According to the authors, since DTs can monitor the energy demand, it is possible to predict behaviours considering several scenarios and different factors/variables that may influence the systems, and adjust the system's parameters in near/real-time.

Finally, in the Service phase, Ghenai et al. [24] highlighted the importance of DTs in the predictive maintenance of energy systems. In this case, by analysing near/real-time data from sensors, IoT devices, databases, and other sources, a DT can detect potential issues before they become critical and recommend proactive maintenance activities to prevent downtime and reduce costs. Moreover, Falekas and Karlis [41] align with this idea and state that adopting DTs in the service phase may result in lower costs throughout the life cycle of the systems, saving time and money through maintenance and fault detection support systems based on DTs. In addition to these practical applications, it is important to highlight that DTs also have the potential to facilitate collaboration and knowledge sharing across different parts of the energy value chain. By creating a common DT platform that all stakeholders can access, it is possible to improve communication and coordination, reduce errors, and improve the decision-making process, as highlighted by Chen and Huang [42].

2.3. Related reviews

Regarding reviews that discuss EDT applications, an exploratory search was conducted on the Scopus database, covering journal articles published up to January 2023. In this stage, a search for related reviews that address the Boolean logic ("Digital Twin" AND "Energy" AND "Review") was conducted. Ten papers were found and evaluated during

Table 1
Summary of reviews in Digital Twins and energy.

Paper	Research Method	Focus	Keywords
Onile et al. [16]	LR	Energy Management Systems	"Energy services" AND "Innovation"; "Energy Services" AND "Digital Twins"; "Energy service" AND "Recommendation"; "Energy services" AND "Consumer behaviour"
Lamagna et al. [17]	LR	Energy Management Systems	Not specified
Kooning et al. [7]	LR	Energy Conversion Systems (Wind)	Not specified
Bortolini et al. [23]	SLR	Consumption	"Digital Twin" AND "Building" AND ("Energy Efficiency" OR "Energy Performance")
Sifat et al. [20]	Not specified	Grids	Not specified
Ghenai et al. [24]	LR	Generation, Storage, and Consumption	Not specified
Yu et al. [18]	SLR	Industrial Energy Management	"Digital Twin" AND ("Process Heat" OR "Process Industry" OR "Decarbonization" OR "Decarbonization" OR "Reboiler" OR "Evaporator" OR "Heat Exchanger")
Chen et al. [19]	Survey	Energy Conversion Systems	Not specified
Ayerbe et al. [22]	Not specified	Battery Manufacturing	Not specified
Semeraro et al. [43]	SLR	Storage	"Digital Twin" AND ("Energy Storage" OR "Battery Storage" OR "Pumped Hydro Storage" OR "Thermal Storage" OR "Supercapacitors" OR "Capacitors" OR "Compressed Air Energy Storage" OR "Magnetic Energy Storage" OR "Fuel Cells")
This paper	SLR	Generation, Storage, Transmission, and Consumption	"Digital Twin" AND ("Energy planning" OR "Energy operations" OR "Renewable energy" OR "Energy storage" OR "Energy supply" "Energy Generation" OR "Energy production")

LR – Literature Review, SLR – Systematic Literature Review.

the exploratory search, as summarised in Table 1. It is worth mentioning that this section does not aim to present all the existing reviews in the area but provided an understanding of previous studies and insights about the theme used in the research protocol definition. Therefore, some keywords that may be synonymous of the adopted terms were not considered in this exploratory phase. On the other hand, for SLR, all relevant terms were included in search engines.

The first review article was published in 2021, portraying the contemporary nature of the topic. Onile et al. [16] provide a review of the applications of DT in energy management, including energy services, recommendation systems, and demand-side management. The authors reviewed papers from IEEE Xplore and Scopus databases and summarised several case studies and real-world applications. In the same topic, Lamagna et al. [17] present a review of DTs for smart energy management systems, covering various aspects of energy management, including demand response, energy efficiency, and renewable energy integration.

Also, looking at the consumer side, Bortolini et al. [23] conducted a SLR of DTs' applications for building energy efficiency. It discusses DTs' benefits and limitations in improving building energy efficiency, including energy savings, costs, and occupant comfort. Yu et al. [18] perform an SLR of DTs' application in the industrial field. The authors summarise data from 53 papers and propose a classification framework for DTs in industrial energy management. They also highlight its potential to improve energy efficiency and reduce industry costs and the challenges concerning data management and modelling complexities.

Chen et al. [19] present a survey of DT techniques used in energy conversion systems. The paper discusses the concepts of the layers of DTs, i.e., the Foundation Layer (hardware and software platforms), Data Interaction Layer (gathering, transmission, storage, and processing), Modelling and Simulation Layer, and Application Layer (e.g., renewable energy integration, electric vehicle charging, and energy storage systems). Regarding renewable energy generation, Kooning et al. [7] review modelling techniques for DTs of wind energy conversion systems, emphasising model fidelity and computational load. It recommends a hybrid modelling approach combining physics-based and data-driven models as the most promising technique for creating efficient and high-fidelity DTs of wind energy systems.

Semeraro et al. [43] conducted a SLR about DT applied to energy storage. Analysing 50 papers from the Scopus database, the authors provide a detailed overview and insights regarding the application contexts, the life cycle phases, the functions, the architecture and the components, and the research challenges. Ayerbe et al. [22] focused on the digitalisation of the battery industry. They cover the benefits and challenges concerning battery manufacturing digitalisation, such as quality control improvements, production efficiency, and cost reduction.

Linked to energy transmission and distribution, Sifat et al. [20] reviewed the state-of-the-art and proposed a framework for creating a DT for power grid applications. This paper addresses features like the grid evolution over time, challenges, opportunities, and future directions of the DTs' application in electrical grids. Ghenai et al. [24] presented a literature review covering DT's concept and benefits in the energy sector, focusing on its applications in energy generation (e.g., fossil to renewables), consumption (e.g., transportation, buildings, and industrial), and storage (e.g., Mechanical, thermal, battery, and hydrogen). The paper also discusses the challenges of this technology, such as the need for standardised data models and increased interoperability between different systems.

Notably, the previously mentioned papers and others were the basis for this research. Although these reviews deal with similar topics, this paper differs from the others since it promotes a systematic review of the DTs' studies throughout the entire energy sector's value chain, not limited to a specific application or tool. In this case, other issues and research questions not addressed in previous works are addressed in this article, generating a solid basis for researchers and professionals in the field.

3. Research method

SLR is a methodology that involves collecting, understanding, synthesising, and evaluating scientific works to generate the theoretical-scientific basis required to comprehend a particular topic [44–46]. According to Denyer et al. [47], SLR assists researchers in conducting all methodological steps, including problem definition, method selection, data collection, and analysis, which helps to minimise flaws in work conclusions and provides greater clarity on the research procedures used. Unlike traditional literature reviews, the SLR is a research method that follows a predetermined procedure to answer specific questions using existing literature.

The methodology adopted in this article is based on the studies of references [48–50] and is divided into four steps: planning research questions; searching/screening; analysis/synthesis; and results and discussions. This paper's research protocol, presented in the following sections, was developed through a panel of specialists. The panel was done with 4 PhDs with extensive knowledge in simulation, DTs, energy planning and operations, optimisation modelling, and PhDs students researching correlated themes.

3.1. Research questions definition

This paper uses the CIMO-logic framework proposed by Denyer et al. [47]. This framework involves dividing the research questions into four elements using the CIMO-logic method, which includes: In what problems and fields (Context) … the DTs are applied (Intervention) … using which modelling technique (Mechanism) … to improve the system's performance (Outcomes). As such, this paper integrates a SLR with the CIMO methodology to examine EDTs. In this sense, the research questions of this review include.

RQ1. State of the art and trends (Context)

RQ2. Main objectives and application fields (Context/Intervention)?

RQ3. Which techniques and tools are used for DT modelling (Intervention/Mechanism)?

RQ4. Advantages and challenges associated with the approach (Outcomes)

3.2. Searching/screening phase

This SLR researched papers from Scopus, Web of Sciences (WoS), IEEE Xplore, ACM Digital Library, and SciELO since they are considered the main sources of scientific articles and citations on this topic [51,52]. Based on the panel of specialists and the previous reviews, the search keywords were defined as: ("Digital Twin" AND ("Energy planning" OR "Energy operations" OR "Renewable energy" OR "Energy storage" OR "Energy supply" OR "Energy Generation" OR "Energy production")). It is worth mentioning that other related terms were considered but not used since they return an expressive percentage of non-fitting papers (e.g., "Electricity", "Electricity Production", "Energy supply", "Energy Generation", "Energy", "Storage", "Renewable").

At the Screening step, the SLR employed a specific set of criteria that was defined in each search to determine whether an article was eligible: (i) the search terms had to be present in the title, abstract, or keywords of the article; (ii) articles published until January/2023; (iii) only complete articles published in peer-reviewed scientific journals; and (iv) only articles written in English. The meta-search returned 96 documents from Scopus, 62 from WoS, 8 from IEEE Xplore, and nothing from ACM Digital Library and SciELO. Moreover, 64 documents were excluded as duplicates.

Afterwards, the selected papers underwent a quality assessment stage where the title, abstracts, and introduction were carefully examined to identify those aligned with this SLR's objectives. Any articles that failed to meet the previously established research criteria or did not address the application of EDT were excluded. During this process, each document was examined by two researchers, and if these disagreed about the inclusion/exclusion of a paper, a third researcher should evaluate it. Following this stage, 49 articles were deemed suitable for full-text reading. Fig. 2 summarises the searching/screening procedures.

3.3. Analysis/synthesis phase

The 49 articles were evaluated considering sixteen points, grouped into four groups, as illustrated in Fig. 3. Each group are designed to help answer a specific Research Question, in which the "Bibliometric information" is related to the RQ1, the "Context" addressed RQ2, the "Adopted methods and tools" is associated with RQ3, and the "Advantages and challenges" is linked to RQ4.

In this step, one researcher was responsible for extracting the relevant data from each article, while another checked the extracted data for accuracy to avoid personal bias. In the event of discrepancies, a panel of all the researchers was convened to discuss and resolve any issues. Following the data extraction process, the collected data were subjected to descriptive statistics and analysis, as described in Section 4. The data were organised using an Excel® spreadsheet and analysed with Python and RStudio.

3.4. Structure of SLR' results

The results of this SLR are discussed in Section 4, which was divided into four main topics according to the research questions. Section 4.1 presents the state of the art and trends in EDTs. This section addresses the RQ1 by synthesising and discussing the bibliometric data acquired from the papers, i.e., "Authors name", "Author's nationality", "Journals name", and "Publication year". This work adopted the Bibliometrix library on the Rstudio platform to conduct this analysis.

Section 4.2 discusses the context of the EDTs papers, precisely the "main objectives and application fields" (RQ2). For this purpose, the section presents the "Context" data (i.e., the energy subsystem, the production sector, the problem type, the problem characteristics, the application, and the data source). The discussions in this section are segregated into topics according to the energy subsystems, i.e., generation, storage, transmission, and multi-energy systems.

Furthermore, Section 4.3 explores the methods and tools adopted by the authors in their approaches. It is correlated to RQ3 and involves the analysis of "methods and tools" data (i.e., modelling techniques, physical/virtual connection, and synchronisation interval). Section 4.4 aims to answer the RQ4, "Advantages and challenges are associated with the approach", synthesising the advantages and achievements of DTs highlighted by the papers, issues faced during DT development, and the suggested future opportunities. Finally, Section 4.5 compiles the main findings of this work.

4. Results and discussion

To answer and explore the proposed RQs, the following Sections will present important discussions and findings to each question.

4.1. State of the art and trends related to the use of DTs in the energy industry

Among the 49 articles analysed, it is noted that this research area is still recent and little explored since the oldest article analysed was published in 2019. In addition, this is a fertile field of research, given the growth of annual publications. Fig. 4 illustrates the annual publications considering the articles analysed, and the most accentuated growth in the last two years is highlighted. Although the present research was limited to works published until January/2023, it is noted that about 10 % of the articles were published in 2023, demonstrating great potential for this research area to continue to grow in annual publications since more articles are expected to be published from February to December

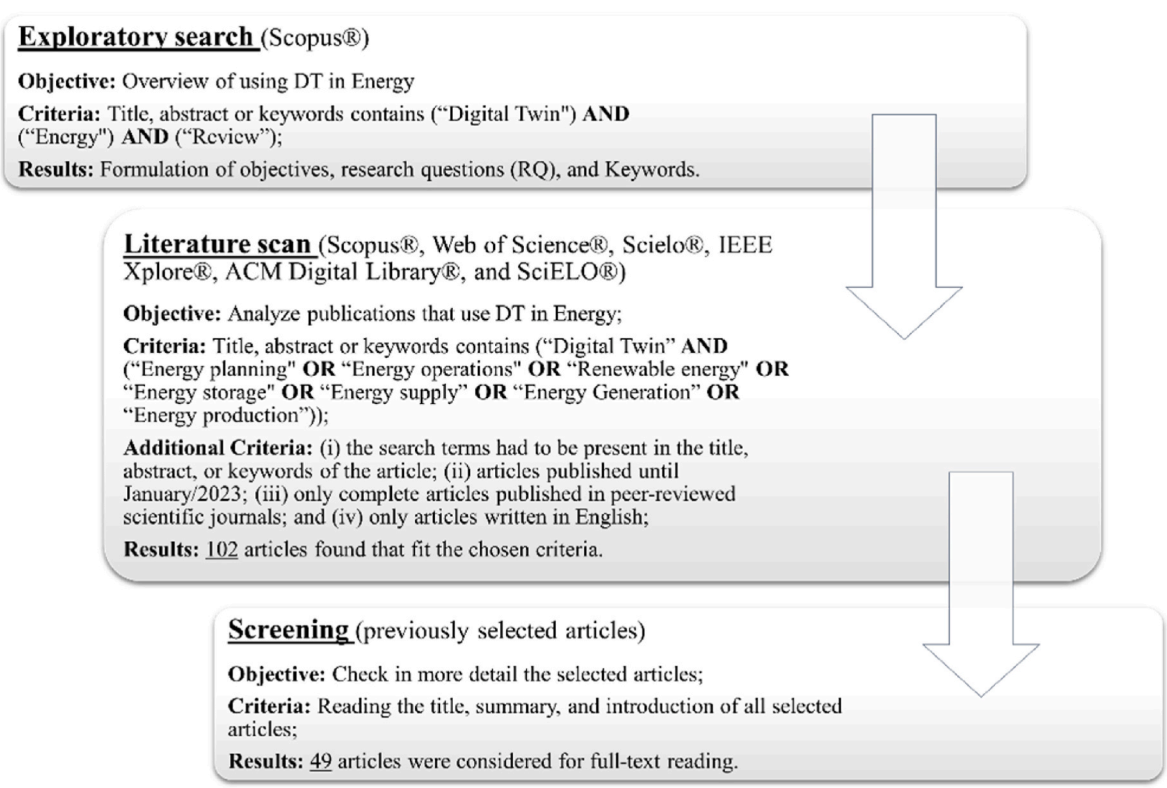

Fig. 2. Searching/Screening procedures.

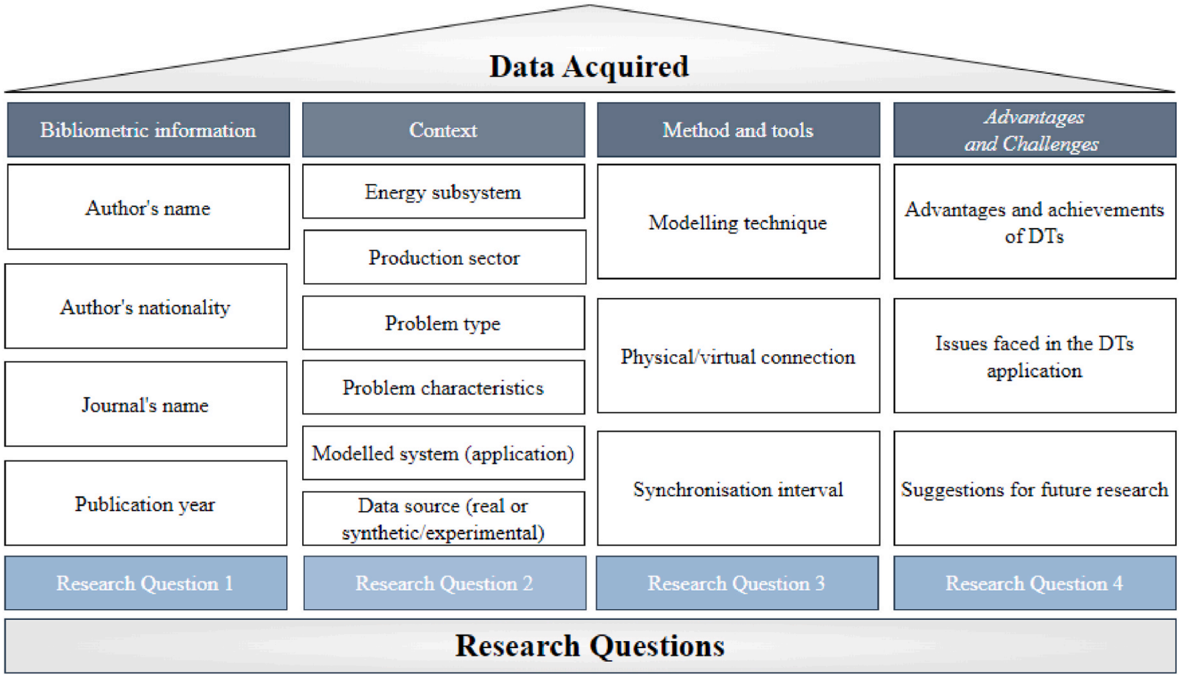

Fig. 3. Main aspects considered for the papers' analysis.

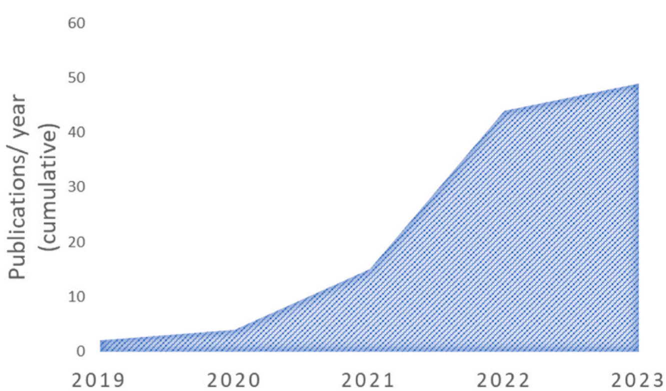

Fig. 4. Cumulative publications per year considering the use of DTs in the Energy industry.

2023.

The papers were published in 34 scientific journals, and Table 2 presents the top 10 sources. The first five journals presented correspond to about 36.7 % of works, and the journal Energies is highlighted as the prominent scientific journal considering the papers analysed (about 16 % of the works). Furthermore, it is noted that most journals have just one publication in the area, which indicates that this is a multidisciplinary field that can fit with many other research areas and journals.

Furthermore, this paper also analysed the works regarding the main authors. About 206 authors were found, and only 12 were associated with two or more papers, as summarised in Table 3. In addition, only one author was associated with three articles, which might demonstrate that the researchers do not produce articles continuously in this area. Moreover, the country's scientific production was evaluated. Fig. 5 illustrates that, among 18 countries, China, USA, and United Kingdom stood out as the most relevant countries in this research field, considering the evaluated works.

4.2. Main objectives and application fields

Table 4 and Fig. 6 summarise some important information about the objectives and application fields considering the analysed papers. The following sections present each energy subsystem's application in detail. The discussions are segregated according to the energy subsystems (Generation, Storage, Transmission, Consumption, and Multi-Energy systems).

Table 2
Top 10 scientific journals considering the use of DTs in the Energy industry.

Rank	Journal	No. of papers	%	CUM (%)
1	Energies	8	16.3 %	16.3 %
2	IEEE Access	3	6.1 %	22.4 %
3	Sustainability	3	6.1 %	28.6 %
4	Applied Sciences	2	4.1 %	32.7 %
5	Energy Reports	2	4.1 %	36.7 %
6	IEEE Transactions on Industrial Informatics	2	4.1 %	40.8 %
7	International Journal of Hydrogen Energy	2	4.1 %	44.9 %
8	Batteries	1	2.0 %	46.9 %
9	Energy	1	2.0 %	49.0 %
10	Applied Energy	1	2.0 %	51.0 %
	Others	24	49.0 %	100.0 %

Table 3
Top Authors considering the use of DTs in the Energy industry.

Rank	Researcher	No. of Articles	Rank	Researcher	No. of Articles
1	A. Bassam	3	7	R Tariq	2
2	S. Agostinelli	2	8	H Wang	2
3	A Cetina-Quiñones	2	9	Q Wang	2
4	Y Chen	2	10	Y Zhuang	2
5	F Cumo	2	11	X Zhu	2
6	S Kaewunruen	2	12	T Zohdi	2
			Another 194 researchers		

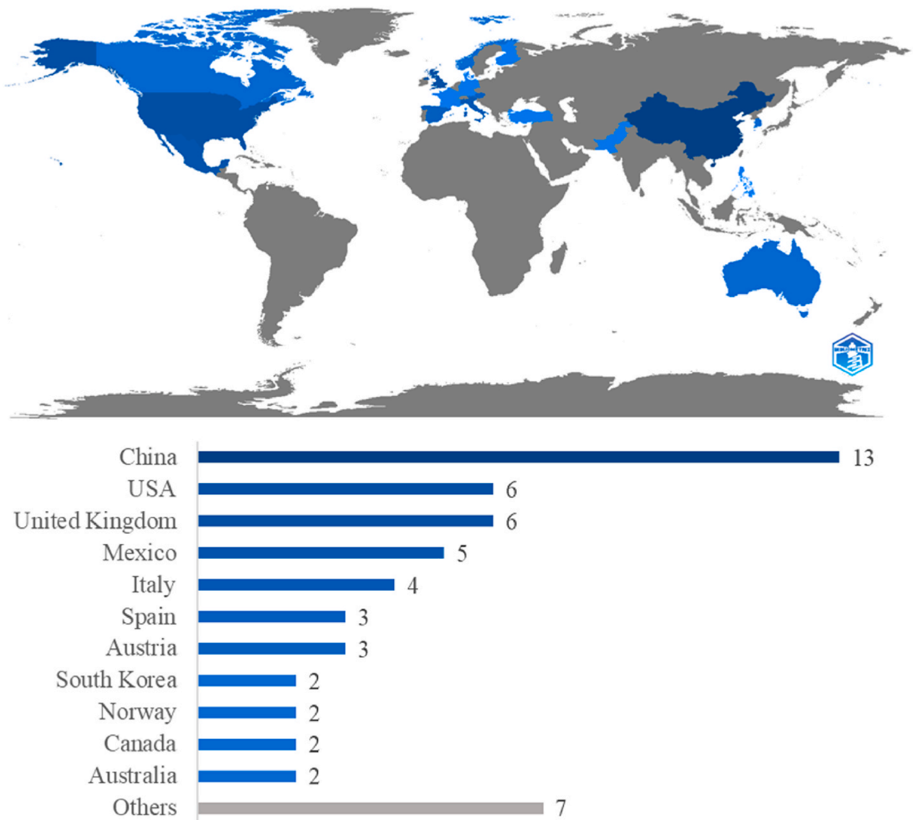

Fig. 5. Country scientific production considering the use of DTs in the Energy industry.

4.2.1. Applications of Digital Twins in energy generation

Approximately 20.4 % of the papers exclusively focused on applications in energy generation systems. Several works explored the design of energy systems, wherein DTs are utilised to evaluate potential solutions before their actual implementation. This concept is presented in references [12,53–55]. These references align with Liu et al. [56], who emphasise the role of DTs in testing solutions, proposing different scenarios, conducting what-if analyses, and validating system behaviour during the design and planning stages. The design of energy generation systems can be found in many application domains, such as renewable sources like photovoltaic systems [12,53] and wave conversion systems [55].

Many papers also focused on Control and Monitoring activities, where the DT is used periodically to support decisions. Control applications are associated with short-term decisions, where systems parameters are controlled based on DT results. Some applications are associated with heating/cooling systems [57,58] and Electrolyser cells [59]. In Monitoring applications, the DT is used to evaluate the systems over time, supporting decisions during the systems life cycle, such as in fault detections and behaviour forecasting. In this case, some papers focus on monitoring photovoltaic systems [60] and wind turbines [61]. Finally, considering the data used in the applications, about 40 % of the papers used real data, while the others adopted synthetic or experimental data to analyse and validate their proposals.

Furthermore, some examples of the use of DTs in energy generation systems are highlighted, such as the work proposed by Isied et al. [12], who developed a DT for optimised agro-photovoltaic greenhouse design. Katsidoniotaki et al. [55] proposed a DT to predict the mooring force in wave energy converters during extreme wave conditions, providing higher efficiency and lower cost. Moreover, Arafet and Berlanga [60] developed an AI-based DT for a photovoltaic solar farm to efficiently detect anomalies and reproduce system behaviour using sensor-based time series analysis and processing. Also, considering applications in other energy generation sources, Fahim et al. [61] proposed a deep learning-based DT to forecast wind speed and predict power generation for wind turbines, leading to effective energy consumption planning.

4.2.2. Applications of Digital Twins in energy storage

In the energy storage subsystem, all evaluated works were focused on short-term decisions, and papers associated with control and monitoring purposes are noted. In this case, there are studies with reduced scopes, such as a virtual representation of batteries [13,62], power plant station [63], and Heating/Cooling systems [64], as well as wider scopes, with virtual models of electrical microgrids [65]. However, some works did not limit their modelling scope to energy storage systems, such as the work proposed by Park et al. [65]. Design/planning approach was not observed among the investigated papers that focused only on storage subsystems. Regarding the data used, most of the papers (about 85 %) adopt experimental/synthetic data instead of real data [13,62–64]. This fact aligns with Zhou et al. [66], who stated that a lack of real data is one of the biggest challenges regarding adopting DTs in energy systems applications.

For example, Shen et al. [67] proposed a DT for thermal analysis of cell-to-pack battery systems. The DT was used to predict temperature response under fast charging and cooling conditions and for battery design optimisation. Steindl et al. [64] developed a DT for flexible and optimised operation of industrial energy systems, applying it to a thermal energy storage system. Deng et al. [63] also explored the use of DTs in energy storage systems. They proposed a metaverse-driven remote management scheme for energy storage power stations using a DT model capable of predicting power load. Finally, it is worth mentioning the work proposed by Jafari and Byun [13], who proposed a DT-based solution for effectively managing lithium-ion batteries in electric vehicles through predictive modelling and situational awareness.

Table 4
Subsystems, sector, and application characteristics considering different objectives of the EDTs.

Energy subsystems	Control	Design/ Planning	Monitoring	Total	Acc.
Generation	16 (19.0 %)	13 (15.5 %)	5 (6.0 %)	34 (40.5 %)	40.5 %
Consumption	14 (16.7 %)	8 (9.5 %)	–	22 (26.2 %)	66.7 %
Energy Storage	10 (11.9 %)	5 (6.0 %)	3 (3.6 %)	18 (21.4 %)	88.1 %
Transmission	6 (7.1 %)	1 (1.2 %)	3 (3.6 %)	10 (11.9 %)	100.0 %
Sector					
Electricity Production	4 (8.2 %)	4 (8.2 %)	4 (8.2 %)	12 (24.5 %)	24.5 %
Residential	3 (6.1 %)	5 (10.2 %)	–	8 (16.3 %)	40.8 %
Multi-energy system	6 (12.2 %)	2 (4.1 %)	–	8 (16.3 %)	57.1 %
Electrical grids	3 (6.1 %)	–	3 (6.1 %)	6 (12.2 %)	69.4 %
Industrial/ Commercial	4 (8.2 %)	–	1 (2.0 %)	5 (10.2 %)	79.6 %
Transport/ Logistics	1 (2.0 %)	3 (6.1 %)	1 (2.0 %)	5 (10.2 %)	89.8 %
Energy Storage	3 (6.1 %)	–	–	3 (6.1 %)	95.9 %
Agricultural	–	2 (4.1 %)	–	2 (4.1 %)	100.0 %
Modelled system/object					
Microgrid	8 (16.3 %)	3 (6.1 %)	2 (4.1 %)	13 (26.5 %)	26.5 %
HVAC[a]	5 (10.2 %)	2 (4.1 %)	1 (2.0 %)	8 (16.3 %)	42.9 %
Building	4 (8.2 %)	4 (8.2 %)	–	8 (16.3 %)	59.2 %
Photovoltaic system	1 (2.0 %)	3 (6.1 %)	2 (4.1 %)	6 (12.2 %)	71.4 %
Electrical distribution system	1 (2.0 %)	–	2 (4.1 %)	3 (6.1 %)	77.6 %
Battery	1 (2.0 %)	1 (2.0 %)	1 (2.0 %)	3 (6.1 %)	83.7 %
Power Plant/ Station	2 (4.1 %)	–	–	2 (4.1 %)	87.8 %
City	–	2 (4.1 %)	–	2 (4.1 %)	91.8 %
Others	2 (4.1 %)	1 (2.0 %)	1 (2.0 %)	4 (8.2 %)	100.0 %
Problem characteristic					
System Control and Operations	12 (24.0 %)	1 (2.0 %)	4 (8.0 %)	17 (34.0 %)	34.0 %
System Design and Sizing	–	11 (22.0 %)	–	11 (22.0 %)	56.0 %
Schedule and coordination	11 (22.0 %)	–	–	11 (22.0 %)	78.0 %
Forecasting	1 (2.0 %)	1 (2.0 %)	2 (4.0 %)	4 (8.0 %)	86.0 %
Fault detection	1 (2.0 %)	–	3 (6.0 %)	4 (8.0 %)	94.0 %
Current State and Scenario Analysis	–	3 (6.0 %)	–	3 (6.0 %)	100.0 %

[a] Heating, Ventilating and Air Cooling (HVAC).

4.2.3. Applications of Digital Twins in energy transmission

Literature about DTs and Energy Transmission is scarce, with only a few papers exploring this subject. All papers focused on grid modelling, which aims to monitor and control the operations. In this case, the DTs support short-term decisions, such as fault detection [14,68] and scheduling [69]. In the same way as the other subsystems, the difficulty in using real data is highlighted; in this case, just one of the previous papers adopts this approach [14]. Finally, This SLR did not find papers focusing on DTs to support the transmission systems' design/planning phase.

Lopez et al. [14] discussed a fault detection system for microgrid low-level components using a DT, where the model can operate in real-time to support decisions. Furthermore, considering uncertainty and risk assessment, Hong et al. [69] proposed AI-based DT to manage energy in networked microgrids. Finally, the work proposed by Khan et al. [68] proposed an intrusion detection system for power distribution systems that utilises a DT model to analyse physical data for attack detection.

4.2.4. Applications of Digital Twins in energy consumption

Considering the use of DTs in Energy Consumption subsystems, it is noted that most of the previous literature explored residential scopes, modelling heating/cooling systems [54,70] and building features [71,72]. Regarding the decision frequency, most of them present short-term decisions where the DTs support systems control to optimise energy consumption [70,71]. On the other hand, there are applications based on punctual decisions, such as the works proposed by Kaewunruen et al. [73] and Tariq et al. [54], who focused on the use of DTs only in the design/planning phase of the systems in order to optimise the energy consumption. Finally, about 40 % of the works adopted real data.

Examples of this approach include: Gourlis and Kovacic [74] discussed the development of a DT ecosystem for existing industrial facilities to optimise energy and resource efficiency; moreover, Zohdi [15] developed a flexible DT framework for energy management systems with genetic-based machine learning optimisation, and the objective is to maximise overall efficiency and minimise overall losses; Fathy et al. [71] proposed a DT of the energy system that includes a household digital mirroring, allowing energy optimisation and flattening daily energy demand levels while reducing energy costs; finally, Gong et al. [70] used a community-level DT to develop generic water heater load curves and estimate the potential of regulating electric water heaters as a major component of a hybrid residential energy storage system, reducing energy consumption.

4.2.5. Applications of Digital Twins in multi-energy systems

In addition to the described papers, several other authors explored the adoption of DTs in energy systems considering a broader scope and integrating two or more subsystems (generation and/or storage and/or transmission and/or consumption), as highlighted in Fig. 7. In this case, two or more subsystems are integrated into one model. For example, ElSayed et al. [75] and Hosseini Haghighi et al. [76] explored the use of DTs in energy generation and consumption to carry out punctual analyses during the systems project. On the other hand, Soderang et al. [77] and Cetina-Quinones et al. [78] evaluated the DT applicability in generation/storage systems for short-term and punctual decisions, respectively. Arraño-Vargas et al. [79] proposed a DT considering generation and transmission systems to control their operation. Finally, there are papers that considered all subsystems, such as the works proposed by Tang et al. [80] and Fan et al. [3].

Approximately 37 % of these works are dedicated to use DTs in the design/planning phase, where punctual analyses were carried out to obtain optimal parameters and characteristics of equipment, products, and systems, such as Kaewunruen et al. [73] and Mohammadshahi et al. [81]. The rest of the papers adopted the DT to support the systems through monitoring [66,82] and control, such as the work proposed by Agostinelli et al. [5] and Kohne et al. [83]. Considering the study object,

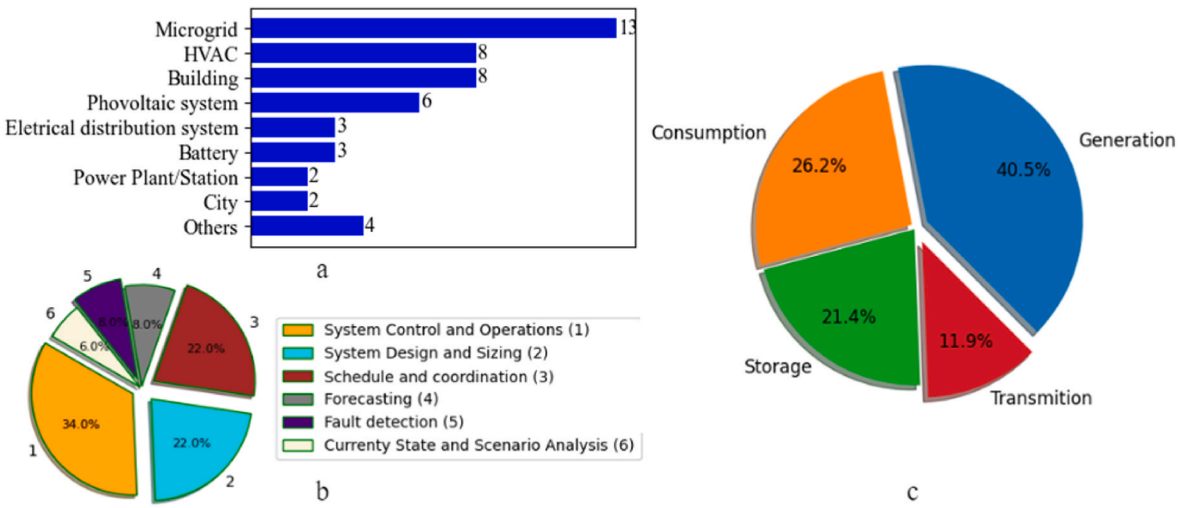

Fig. 6. Papers stratification according to the modelled system (a), problem characteristic (b), and energy subsystems (c).

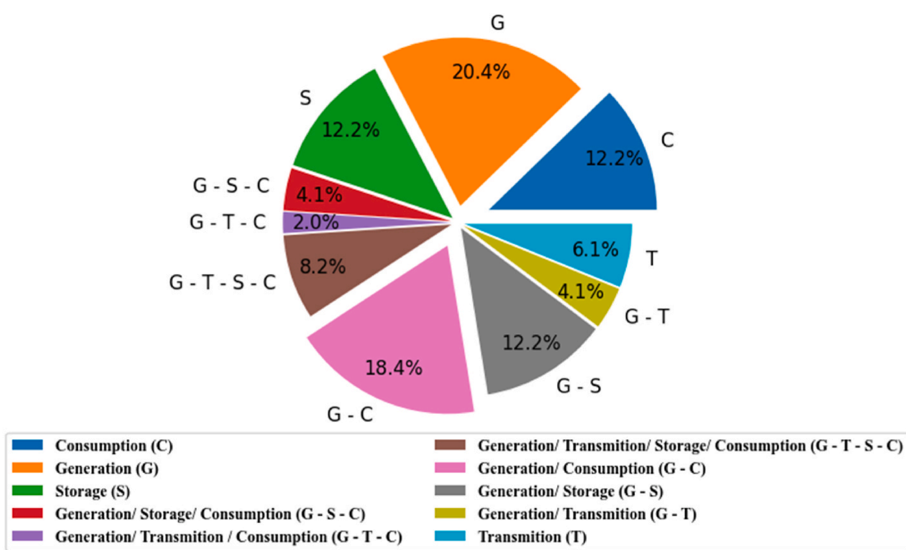

Fig. 7. Energy subsystems addressed by the authors.

several approaches were found, including the modelling of buildings [84], vehicles [85], heating/cooling systems [86], microgrids [40,87], and renewable generation systems [88,89], among others. Finally, it is important to highlight that among the papers that explore two or more subsystems, most of them adopt real data.

To demonstrate the broad scope of works considered in this topic, it is possible to highlight some examples, such as You et al. [90], who proposed a DT-based day-ahead scheduling method to improve the coordination of integrated energy systems, reducing operating costs and reducing carbon emission. Moreover, Tagliabue et al. [91] developed a framework for a DT-based and IoT-enabled dynamic approach to sustainability assessment in the built environment, where the objective is to optimise trade-offs with renewable energy production. Teodorescu et al. [62] introduced a smart battery concept and they used a DT for accelerated training and failure prediction. Zhao et al. [86] adopted a DT in an industrial building application, proposing a hybrid model which integrates AI techniques for optimal decisions in direct air-cooling units to reduce coal consumption and CO_2 emissions. In this case, it is important to emphasise that these papers were included in this subsection because they did not solely focus on one energy subsystem but explored broader scopes.

Moreover, the adoption of net-zero energy sources and society's concerns with CO2 neutrality have increased the number of applications of renewable energy sources, such as solar and wind, as presented in Fig. 8 (a) and (b). Studies involving solar energy are mainly related to the design or system control of buildings [84,91] and cities [75,76]. Many authors also propose DT-based solutions to increase the efficiency of photovoltaic systems and smooth the gap between production and demand [53,88,89,92]. Several papers presented problems related to schedule, control, and design in microgrids with renewable energy sources, such as wind, solar, thermal, diesel, and hydrogen. Among the papers, only one studied wind power generation [93], which used Temporal Convolution Neural Network, K-NN regression, and 5G-Next Generation-Radio Access Network to monitor and predict a turbine's wind speed and energy generation.

Conversely, green hydrogen is one of the most promising sources to aid society's transition towards cleaner energy systems, and several DT studies have focused on it. These studies include the short-term control and operation of hydrogen plants (or specific equipment such as Proton Exchange Membrane) or middle-term schedule and coordination of microgrids with photovoltaic, wind and hydrogen production and storage, as proposed by Zhao et al. [59] and Mohammadshahi et al. [81].

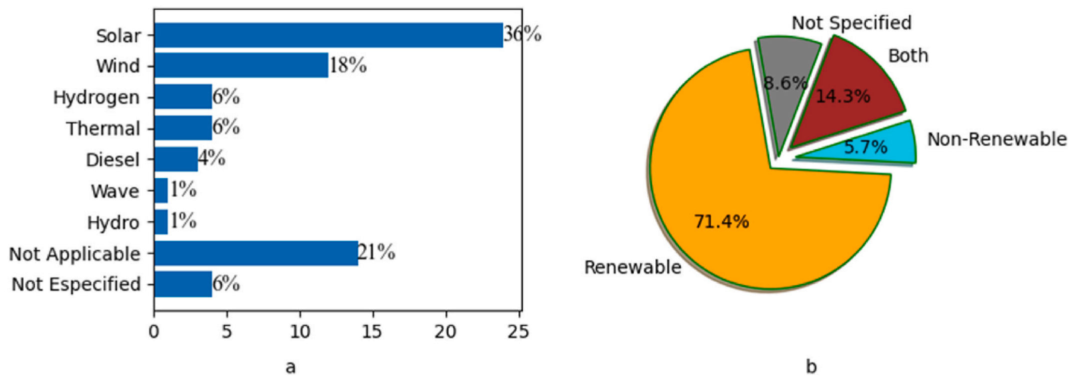

Fig. 8. Energy source (a) and energy source classification (b).

Moreover, the works proposed by Folgado et al. [82], Gronier et al. [87], and Folgado [94] are other examples that are in line with this approach.

Furthermore, some papers addressed the use of thermal plants, such as Geothermal, natural gas, and coal [5,79,86,90]. It is worth mentioning that wave and hydro were just addressed by one paper each. Katsidoniotaki et al. [55] presented a DT model for predicting extreme loads on a wave energy conversion system. The model is based on physics-based simulation (CFD) and metamodels (polynomial regression) to provide real-time predictions of loads on the system. Arrano-Vargas and Konstantinou [79] propose a DT for electrical grid control and operation. Their focus was the electrical distribution system, which was connected to photovoltaic, wind, thermal, and hydro power plants.

4.3. Adopted methods and tools

The technologies/methods used in each problem type are summarised in Table 5. In some topics, the number of occurrences exceeds the number of articles since some authors applied two or more modelling methods, comparing or combining them. E.g., Park et al. [65] compared NARX, Decision Trees, and MARS to operation scheduling of an energy storage system (ESS), while Jafari and Byun [13] combined an Equivalent Circuit model with Extreme Gradient Boost and Extended Kalman Filter to predict the state of health and state of charge of an electric vehicle battery.

4.3.1. Modelling techniques

The first analysed aspect, shown in Table 5 and stratified in Table 6, is the modelling techniques used to create the DTs. In this paper, the class "numerical methods" comprise a set of modelling techniques based on differential equations and/or mathematical modelling, such as Electromagnetic Simulation, finite element method (FEM), Computational Fluid Dynamics (CFD), Gipps' model, Courant–Friedrichs–Lewy method, Linear/Non-linear modelling among others [52].

As highlighted in Fig. 9 (a), most of the studies (41.8 %) applied numerical methods to model their DT, mainly in problems related to the control of microgrids [3,11,15,90] and heating/cooling systems [57,58, 70,83]. E.g., Zohdi [15] used a CFD simulation model to control the energy generation, transmission, and storage for multiple devices, computing the energy balance and determining what the energy supplier must deliver or extract from each device to meet a specific target state considering transmission losses. Kohne et al. [83] use mixed integer linear programming to model an industrial heat transfer station. The model considers various factors such as heat demand, heat supply, and operational constraints to maximise the heat transfer station utilisation while ensuring the system's stability and efficiency.

Also, 14.5 % of the papers employed numerical methods in design/planning problems, e.g., Shen et al. [67] used CFD simulations to model the thermal characteristics of the cell-to-pack battery system to identify potential solutions for better thermal management. Elsayed et al. [75] used Origin-Destination traffic simulation to explore using solar energy to power charging stations for autonomous drones. The authors propose using solar energy to drone power charging stations in smart cities as a sustainable solution for reducing greenhouse gas emissions. Numerical methods-based DTs applied in monitoring problems could be found in electricity distribution, storage, and hydrogen production [14,68,94].

Data-driven methods, which use the system(s) data to fit a machine learning model, were used by 25.5 % of papers. In this case, several machine learning methods were applied, such as Extreme Gradient Boosting [13,86], Support Vector Machines [89], and Generalized Additive Models [87], among others. However, the expressive application of Neural Networks (NN) is highlighted to support short-term decisions since they can model non-linear problems and make faster predictions if compared with numerical models. E.g., Arafet and Berlanga [60] train a recurrent neural network to predict future energy production and identify potential issues in a solar farm system.

Hong and Apolinario [69] used a three-layer feed-forward NN to coordinate interconnected microgrids. Zhou et al. [66] combined physical-model and Convolutional NN to represent the normal behaviour of an AC/DC power system and the uncertainty of renewable energy sources. Moreover, the authors applied principal component analysis to reduce the data dimensionality.

Building Information Models (BIM) and Building Energy Models (BEM) are also well applied in industrial and residential building design and control studies. Concerning building design, Kaewunruen et al. [72] used BIM to redesign existing buildings to meet a net-zero goal, minimising energy consumption and maximising energy generation by improvements of building envelope, HVAC system, and renewable energy sources (photovoltaic and wind). Zhao et al. [84] also analyse an existing office building, using Scan-to-BIM technology and the Carbon Emission Coefficient method, and propose a retrofit plan to achieve nearly zero-energy building status.

Moreover, Hosseinihaghighi et al. [76] created an urban building energy model for characterising and structuring urban GIS data for housing stock energy modelling and retrofitting. Agostinelli et al. [5] associate BIM, BEM, CFD simulation, and GIS models to control and improve building energy management. The proposed CPS gathers data in real-time by IoT, smart metered devices, System on Chip (SoC), and protocols (e.g., Elettra and Proxy). Therefore, the system uses k-means and Naïve Bayes Classifier to cluster and classify the apartments by consumption similarities and provide recommendations or actions to reduce the energy consumption, energy purchased from the grid, and CO_2 emitted.

In the logistic sector, Agostinelli et al. [95] also combine BIM, BEM, CFD simulation, and GIS models for status analysis and scenario evaluation of a port area. The authors also idealise a DT model connected via IoT technology to a zero-energy port renewable energy system operation. Related to industrial buildings, Gourlis and Kovacic [74] presented

Table 5
Adopted methods per problem type.

Modelling	Control	Design/ Planning	Monitoring	Total	Acc.
Numerical Methods	12 (21.8 %)	8 (14.5 %)	3 (5.5 %)	23 (41.8 %)	41.8 %
Data-Driven	7 (12.7 %)	2 (3.6 %)	5 (9.1 %)	14 (25.5 %)	67.3 %
BIM/BEM	2 (3.6 %)	4 (7.3 %)	–	6 (10.9 %)	78.2 %
Metamodel	1 (1.8 %)	3 (5.5 %)	–	4 (7.3 %)	85.5 %
OPAL	2 (3.6 %)	–	1 (1.8 %)	3 (5.5 %)	90.9 %
GIS	1 (1.8 %)	1 (1.8 %)	–	2 (3.6 %)	94.5 %
Agent-based Simulation	1 (1.8 %)	–	–	1 (1.8 %)	96.4 %
Discrete-event simulation	1 (1.8 %)	–	–	1 (1.8 %)	98.2 %
Not Specified	–	–	1 (1.8 %)	1 (1.8 %)	100.0 %
Physical/Virtual Connection					
IoT	6 (12.2 %)	1 (2.0 %)	1 (2.0 %)	8 (16.3 %)	16.3 %
Local Sensors/ Database	4 (8.2 %)	–	2 (4.1 %)	6 (12.2 %)	28.6 %
Local Database	2 (4.1 %)	–	3 (6.1 %)	5 (10.2 %)	38.8 %
Data management system	4 (8.2 %)	–	1 (2.0 %)	5 (10.2 %)	49.0 %
API	1 (2.0 %)	–	–	1 (2.0 %)	51.0 %
Hardware-in-the-loop	–	–	1 (2.0 %)	1 (2.0 %)	53.1 %
Not applicable	2 (4.1 %)	15 (30.6 %)	–	17 (34.7 %)	87.8 %
Not specified	5 (10.2 %)	–	1 (2.0 %)	6 (12.2 %)	100.0 %
Synchronisation Interval					
Real-Time	13 (26.5 %)	–	7 (14.3 %)	20 (40.8 %)	40.8 %
Near Real Time	4 (8.2 %)	–	–	4 (8.2 %)	49.0 %
Daily	1 (2.0 %)	–	1 (2.0 %)	2 (4.1 %)	53.1 %
Weekly	–	–	1 (2.0 %)	1 (2.0 %)	55.1 %
Non-synchronised	3 (6.1 %)	16 (32.7 %)	–	19 (38.8 %)	93.9 %
Not specified	3 (6.1 %)	–	–	3 (6.1 %)	100.0 %

BIM – Building Information Model; BEM – Building Energy Model; GIS - Geographic Information System; ABS – Agent-based Simulation; DES – Discrete Event Simulation.

a framework integrating DES, BEM, and Genetic Algorithm to optimise energy efficiency and identify potential issues with the industrial facilities. The framework integrates data (such as equipment and process status, production plan, Indoor/outdoor weather, and energy consumption) from sensors and databases to perform real-time energy system control.

Another method found in the literature is metamodelling. According to Amaral et al. [97], metamodelling is the approach to developing a representative model of an expensive model, i.e., a model of a model. It is recommended in cases where the highly accurate model cannot provide a good response in a desirable time interval. E.g., Zhao et al. [71] use a multi-physical model (by Finite Element Method) to generate data to train a metamodel (information model). Then, this metamodel is used to evaluate different control strategies for Proton Exchange Membrane Electrolyser cells in hydrogen production. Moreover, Katsidoniotaki et al. [55] fit a polynomial regression metamodel over a high-resolution (and time-expensive) CDF model to predict extreme loads on a wave energy conversion system. Other studies also used the OPAL simulator as the virtual counterpart for a physical system real-time monitoring/control [14,79,91], and GIS [5,95], DES [74], and ABS [40], mainly associated with the previously mentioned modelling methods.

4.3.2. Physical/virtual connection and synchronisation

The second and third topics of Table 5 are related to communication between the physical and virtual twins. Regarding the approach used to connect the DT with the physical system data, as shown in Fig. 9 (b), most of the studies that cover this topic applied IoT technology concepts (16.3 %), as the works proposed by Agostinelli et al. [5] and Han et al. [11]. Other examples of this approach can be found in the works proposed by Fathy et al. [71], Chen et al. [85], and Tagliabue et al. [91]. IoT is a pillar of the fourth industrial revolution and refers to a network of physical devices, homes, vehicles, and other items via sensors, software, and connectivity to enable them to gather, exchange, and connect data over the internet. Other 12.2 % of the papers used local sensors and databases (e.g. Refs. [70,74,92]), and 10.2 % referred to local databases as the only source of data connection (e.g. Refs. [60,64,89]). Also, data management systems, such as SCADA, were adopted by 10.2 % of the works (e.g. Refs. [40,68,69]). Furthermore, some papers do not address connections between DT and Physical systems, such as in design/planning problems (e.g. Refs. [78,96]) or middle/long-term control (e.g. Ref. [87]).

Regarding the data synchronisation time interval between the physical/virtual model, most studies update their models in real-time (40.8 %) or near real-time (8.2 %). This SLR considered near real-time DT updated with a time interval equal to or less than an hour. Fan et al. developed a DT of a university microgrid to monitor and control the energy systems in real-time, gathering and processing several data types, such as demand, weather forecast, PV, and wind energy generation. Teodorescu et al. [62] propose a Physics-Informed Neural Network connected via wireless to gather data (current, voltage, surface, and core temperature) from batteries in energy storage stations and predict failures in the system.

Zohdi [15] uses a CFD simulation model as a DT updated in near

Table 6
Modelling technique versus applications.

Modelling	Building	Microgrid	HVAC	PV	Battery	Electrical distribution	Other
Numerical Methods	[5,71,95]	[3,11,15,81,90,96]	[57,58,70,83]	[12,53,88]	[13,67]	[68]	[75,77,85,94]
Data-Driven Model		[65,69,80,87]	[64,78,86]	[60,89]	[13,62]	[66]	[61,63]
BIM/BEM	[5,72,74,95]						[76]
Metamodel	[73]		[54]				[55,59]
OPAL	[91]	[14]				[79]	
GIS	[5,95]						
Not Specified				[92]			
ABS		[40]					
DES	[74]						

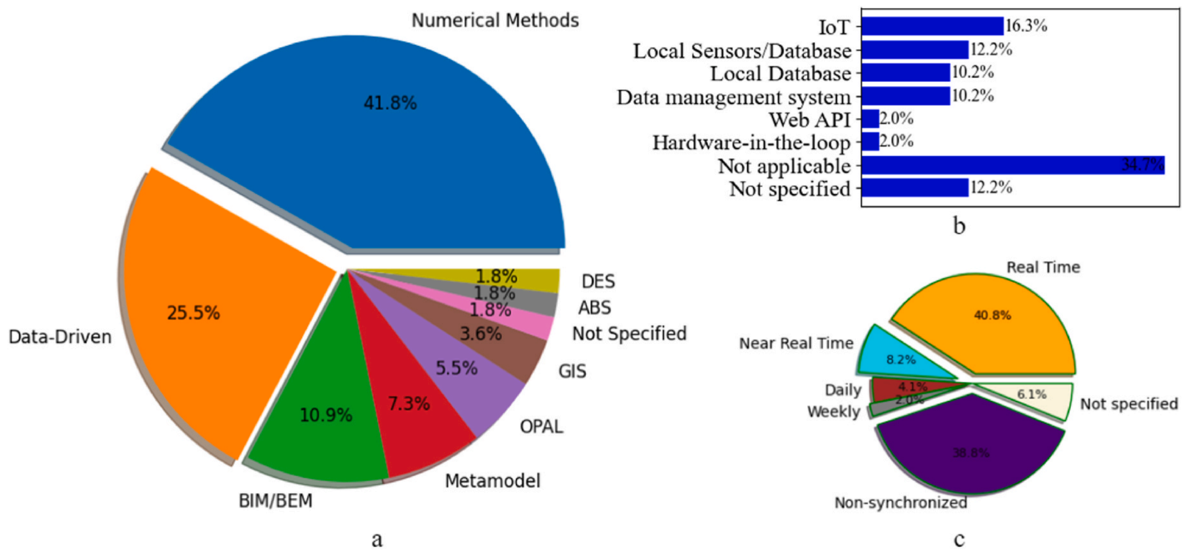

Fig. 9. Modelling techniques (a), physical/virtual connection (b), and synchronisation interval (c).

real-time with energy demanded and generated for each device in a data centre microgrid. Other examples of real-time and near-real-time synchronisation can be found at [15,40,63,77,86,92]. Some authors also updated their models daily (e.g. Ref. [83]) or weekly (e.g. Ref. [61]). It is worth noting that there is no better or recommended updated time interval, depending on the decision-making window required by the problem.

Therefore, for RQ3 ("Which techniques and tools are used for DT modelling?"), it is possible to conclude that numerical methods are the most popular modelling technique, driven by studies of system control and design of microgrids, HVAC systems, and buildings. Moreover, Data-Driven methods were the second most popular simulation type, mainly using NNs models to fit the microgrid data. The researchers also more frequently connected the virtual/physical parts by IoT technology updated in real-time.

4.4. *Advantages and challenges in the field*

While DTs have been studied for many years, their application in energy systems problems is a new research topic. As a result, there are still numerous unexplored opportunities, both practical and theoretical, due to the difficulties and challenges that persist with this approach. Addressing the RQ4 ("Advantages and challenges are associated with the approach"), this SLR work analysed papers based on the advantages and drawbacks of using DT in energy and the opportunities highlighted by the authors. The main findings of this analysis are summarised in Table 7.

Table 7
Advantages, issues, and opportunities in EDT.

Features	Findings
Advantages	✓ Allows holistic and detailed analysis of systems under several operational conditions [59,64,66,67,79,92,94].
	✓Allows the reduction of energy consumption, CO2 emissions, and operational costs of energy systems by better managing resources [71,73,76,83,85,86,89,90].
	✓Can find optimal dispatching/scheduling under the uncertainty of energy systems and ancillary services [69,90].
	✓ Monitoring and controlling complex systems in real-time provides coordinated decision-making [11].
	✓ Enables integration with other powerful tools, such as optimisation, sensibility analysis, machine learning, and data mining [15,79].
	✓ Allows quick and consistent identification of systems failures, anomalies, and cyber-attacks [14,68].
	✓ Smoothing the mismatch between energy generation/consumption [88].
Issues	✓ Handle noise, sparse, and non-structured data [66]
	✓ Need for continuous model validation and updating [86,91]
	✓ Requires typically high computational resources [58,79]
	✓ Real-time operations are still a challenge due to the communication latency and model response time [58,77]
Opportunities	✓ Works focused on improving automatic data gathering, preprocessing, and synchronisation [64,70,92].
	✓ Frameworks integrating optimisation and AI with physical-based DT to improve analysis and control capabilities [53,55,83,84].
	✓ Frameworks to build and operate multi-purpose DTs, including predictive control, condition monitoring, fault detection, and scheduling [81].
	✓ Handle with multi-objective problems, considering the divergent stakeholders' interests [59,78].
	✓ Solutions considering macro/micro economic indicators in decision-making [88,89].
	✓ The analysis focused on DT applications' security and data privacy [85].

4.5. *Discussion and remarks*

Considering the mentioned results, this section highlights the main findings of this work. First, concerning energy systems, most of the papers (69.5 %) addressed problems related to energy generation, exclusively or in a broader context (with consumption, storage, or transmission subsystems). In this case, several authors used DT to control systems in real-time, evidencing the importance of telecommunication technologies such as IoT, smart sensors, 5G, and management systems to synchronise the virtual and physical systems with low latency. Also, many papers propose a DT-based solution to monitor the system behaviour or to find the optimal design of complex energy generation systems.

On the customer side, DT approaches to increase buildings' energy efficiency are popular, considering microscale models (i.e., detailing the building characteristics and behaviour over time) or macroscale models (i.e., modelling a city or a condominium without detailing each building unit). Several papers addressed the concept of prosumer, i.e., the entity that both produces and consumes energy. In this context, the authors mainly used BIM/BEM models to analyse and improve the design of new/existing buildings or to coordinate the system decisions to balance the building demand with the energy produced by the local power generation unit. Some papers also propose user recommendation systems based on DT technology.

Moreover, studies that applied a data-driven approach to modelling buildings DT were not found. However, with the crescent presence of smart devices and data management systems in modern buildings, data-driven models (such as neural networks) could be an alternative to the BIM/BEM models, with the advantage of adaptability and quick response of the machine learning methods (compared with high-resolution BIM models). It is worth mentioning that some authors study machine learning methods in buildings but do not use them as the primary DT modelling method.

It also highlighted the expressive number of papers addressing renewable energy as the primary power source or studying renewable power plants directly. However, just one paper cited hydropower plants as an energy source, but the focus was the electrical distribution system. Therefore, it is pointed out that EDT studies focusing on hydropower plants are an excellent opportunity for future research. Hydropower generation is a highly complex system affected by weather conditions (e.g., temperature, precipitation), environmental, economic, and social aspects (e.g., energy and water demand, agricultural, land use, local communities, biodiversity impact), and stakeholders' decisions (e.g., political aspects, other hydropower plants' decisions upper and downstream). Therefore, the DT technology could improve integrated scheduling and coordination between hydropower plants up and downstream, considering the system intercorrelation, precipitation, dam water level, and demand forecasting. Moreover, developing a DT to monitor and control the real-time hydropower plant operation is a potential future direction.

Mainly related to studies of system control and design of microgrids, HVAC systems, and buildings, numerical methods (i.e., Electromagnetic Simulation, FEM, CFD, Gipps' model, among others) are the most employed modelling technique. Data-Driven methods, particularly those utilising NNs models to fit microgrid data, were identified as the second most popular modelling technique. In this case, ensemble methods [98, 99] to combine different models could reduce the DT's prediction bias and improve model capabilities. Also, hyperparameter optimisation methods [100], such as genetic algorithms and particle swarm optimisation, are strongly encouraged for future works involving data-driven models.

It is important that many results of this SLR are in line with other literature reviews that explored the use of EDTs, as presented in section 2.2. In this case, several advantages, issues and opportunities highlighted in this work were also mentioned by some of the authors, such as Onile et al. [16], Yu et al. [18], and Semeraro et al. [43]. However, it is important to highlight that this work addressed a broader scope regarding the keywords and scientific bases with respect to the other reviews. Therefore, many insights presented in this section have not been discussed before, reinforcing the relevance of this work.

5. Conclusion and future perspectives

Considering the growing adoption of DTs in energy applications, it is important to highlight the importance of theoretical studies aiming to systematically explore the literature and evaluate the state of the art of works that adopt such approach. Therefore, it is possible to build a solid base for researchers and professionals in the area, exploring the main characteristics, advantages, limitations, and opportunities for future research. The present work was based on an SLR aiming to explore scientific works published in the main scientific bases to evaluate them regarding the characteristics associated with the use of DTS in energy generation, transmission, storage, and consumption subsystems.

As highlighted, although there are other reviews on the subject, it is noted that the present work complements the current literature by reporting and addressing different research questions, as well as using different search criteria for articles, corroborating for a broader study. Considering the heterogeneity of applications and approaches, a holistic view of EDT studies could help researchers to identify gaps and opportunities to expand the knowledge frontier and improve DT solutions. Therefore, the main objectives of this paper were to discuss the main aspects of EDT, identifying and exploring the state-of-the-art, issues, gaps, opportunities, trends, and future perspectives related to the theme.

Among the 49 articles that were accessed, the first one was published in 2019 and a growing trend of annual publication was observed. Moreover, considering the analysed subsystems, a significant majority of papers concentrated on energy generation, either exclusively or within a broader context, including consumption, storage, and transmission subsystems. In this case, the near/real-time control and monitoring stood out as a promising approach, which reinforces the importance of the emerging technologies that allow the synchronisation between physical and virtual environments.

Furthermore, several scopes were observed, covering industrial and residential applications, with different levels of abstraction and complexity, and involving short-term and long-term objectives. The papers were also evaluated regarding the techniques and tools adopted by the authors, with emphasis on numerical methods, simulation techniques and data-driven tools. Finally, the advantages, limitations and research opportunities were explored, and, among several highlights, it is important to state that, despite the wide applicability of EDTs to support more efficient decisions, there are still important issues to be explored involving the connection and reliability of DT models.

Notably, the present work was limited to analyses involving EDTs in energy generation, transmission, storage, and consumption subsystems. Therefore, broader research scopes are suggested for future reviews, addressing issues and keywords involving renewable energy systems and emerging technologies. In this review, it is possible to highlight some challenges and gaps in EDT literature. This is the case for real-time applications, which may face issues related to communication latency between the virtual and physical systems. Moreover, although the reliability of the DT models over time is a key requirement to provide efficient decisions, DT validation routines are not widely addressed in the literature. Another important issue is related to input data modelling since EDT applications might handle non-structured, noisy, and sparse data.

Furthermore, based on the results of this work, several future practical research opportunities were highlighted, such as the development of: frameworks that integrate optimisation and AI techniques with DTs to enhance analysis and control capabilities; frameworks to build and operate multi-purpose DTs, including predictive control, condition monitoring, fault detection, and scheduling; research focused on improving automatic data gathering and preprocessing; works aiming to integrate emerging technologies (e.g., 5G, IoT, big data, cloud) to improve real-time operation and virtual/physical systems synchronisation; frameworks to access the DTs validity over time; among others.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly® and ChatGPT® in order to revise the text grammar and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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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