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REVIEW **Open Access**

Digital Twins of smart energy systems: a systematic literature review on enablers, design, management and computational challenges

Ali Aghazadeh Ardebili[1,2*], Marco Zappatore[2*], Amro Issam Hamed Attia Ramadan[2], Antonella Longo[2*] and Antonio Ficarella[2]

*Correspondence:
ali.a.ardebili@unisalento.it;
marcosalvatore.zappatore@unisalento.it; antonella.longo@unisalento.it

[1] Department of Research and Development, HSPI-Roma SpA, Rome, Italy
[2] Department of Engineering for Innovation, University of Salento, Lecce, Italy

Abstract

Background: Energy systems, as critical infrastructures (CI), constitute Cyber-Physical-Social Systems (CPSS). Due to their inherent complexity and the importance of service continuity of CIs, digitization in this context encounters significant practical challenges. Digital Twins (DT) have emerged over the recent years as a promising solution for managing CPSSs by facilitating real-time interaction, synchronization, and control of physical assets. The selection of an appropriate architectural framework is crucial in constructing a DT, to ensure integration of enabling technologies and data from diverse sources.

Objectives: This study proposes a Systematic Literature Review (SLR) to examine technological enablers, design choices, management strategies and Computational Challenges of DTs in Smart Energy Systems (SES) by also analyzing existing architectures and identifying key components.

Methods: The SLR follows a rigorous workflow exploiting a multi-database search with predefined eligibility criteria, accompanied by advanced searching techniques, such as manual screening of results and a documented search strategy, in order to ensure its comprehensiveness and reliability, More specifically, research questions are first defined and then submitted as queries to scientific digital libraries (i.e., IEEE Xplore, Scopus, and WoS) selected due to their coverage and reliability (Google Scholar was excluded for the presence of grey literature and non-peer-reviewed material). Then, inclusion and exclusion criteria are established to filter the results and shortlist the significant publications. Subsequently, relevant data are extracted, summarized, and categorized in order to identify common themes, existing gaps, and future research directions, with the aim of providing a comprehensive overview of the current state of DTs for SESs.

Results: From the proposed DT-based solutions described in the selected publications, the adopted architectures are examined and categorized depending on their logical building blocks, microservices, enabling technologies, human–machine interfaces (HMI), artificial intelligence and machine learning (AI/ML) implementations, data flow and data persistence choices, and Internet-of-Things (IoT) components involved. Additionally, the integration of edge-cloud computing and IoT technologies in literature are studied and discussed. Finally, gaps, opportunities, future study lines, and challenges of implementing DTs are thoroughly addressed. The results achieved also pave the way for a forthcoming design pattern catalog for DTs in CPSSs capable of supporting the engineering and research communities, by offering practical insights on implementation and integration aspects.

Conclusion: The proposed SLR provides a valuable resource for designing and implementing DTs of CPSSs in general and of SESs in particular. Furthermore, it highlights the potential benefits of adopting DTs to manage complex energy systems and it identifies areas for future research.

Keywords: Digital Twin, System architecture, Complex system, Cyber-Physical System, Cyber-Physical-Social System, Internet of energy, Energy IoT, Edge-Cloud Continuum, Smart energy system

Introduction

Today, Energy Systems (ES) represent complex infrastructures essential to any society, with necessity of high reliability and resilience (Rocha et al. 2015). Scientific researches have consistently shown that the optimal way to operate an ES is by making it *smart*, a concept supported by numerous studies over the last decades (Huebler and Rush 1983) and further validated by recent works (Lund 2018). More generally, the rapid growth of digitization (Ku et al. 2020), industry 4.0 (Uygun and Aydin 2021), and IoT (Wang et al. 2021a), alongside socio-technical and socio-ecological transformations, as well as the evolution of traditional Cyber-Physical Systems (CPS) into comprehensive Cyber-Physical-Social Systems (CPSS), underscore the need for sustainable and intelligent systems to be designed and deployed. In the domain of ES, these systems are called Smart Energy Systems (SES) (Lund et al. 2017)

One of the emerging technologies showing promising potential to render complex systems intelligent is the Digital Twin (DT). This technological paradigm involves the computerization and creation of autonomous digital systems. In this article, the definition of DT provided by Massel (Massel and Massel 2020) and by the Digital Twin Consortium (Consortium 2021) is considered, by taking into account the model of an industrial CPSS:

“DT is a component of CPSS that couples with the physical real-world entities and the stack-holders through bidirectional information channels to present the state of the entire system, store data, monitor the system, and automate its operation employing Artificial Intelligence.”

The main purpose of this study is to fill the significant absence of a systematic architecture design pattern catalog for the *digital twinning* (i.e., the creation of a DT for a real-world object, process, or system) of CPSS critical infrastructures focused on SES. In addition, we aim at formulating a research roadmap for the implementation of DTs in SES. To achieve this, we will propose a Systematic Literature Review (SLR) that follows a specific and rigorous approach: the (SLR) is conducted to provide a better understanding of the DT in SES, and the identification and classification of the corresponding system architecture. Therefore, the main objectives of the SLR are as follows:

- O1: Enhance the understanding of DT in SES
- O2: Identify and classify system architectures for DT in SES
- O3: Determine what challenges and gaps are faced in bringing DT into action
- O4: Highlight what potential research directions currently exist for advancing the application of DT in SES

To this aim, a set of research questions (RQs) ("Exclusion/inclusion and screening procedure" section, Table 2) has been meticulously crafted to address each objective delineated within the methodology section.

To ensure the integrity of the review process and mitigate bias, we prioritize clarity and validity, considering them alongside suitability, as outlined by Booth et al. (2012), as key attributes of this review. Additionally, given that this review relies on keyword-based article extraction, we dedicate a subsection ("Quality assessment of reviews" section) to address quality assessment, validity, and auditability of the process. The findings indicate that the incorporation of DT in energy systems represents a recent and burgeoning area of study. Nevertheless, literature have increasingly focused on the effectiveness of DT applications, leading to a surge in publications. After identifying the diverse architectural patterns employed in the digital twinning of energy systems, the architectures are classified into two-layer, three-layer, four-layer, and hyper-layer architectures. Finally, to illustrate their practical application, we present a case study involving the design and implementation of a specific architectural pattern in a real-world scenario. The chosen case study focuses on the digital twinning of a smart photovoltaic panel (PV), employing a service-oriented architecture and leveraging the edge-cloud computing paradigm along with IoT technologies. This case study exemplifies the efficacy and feasibility of employing such architectures in the SES domain.

Overall, this work aims at proposing several contributions in terms of academic research and practical applications in the energy domain. Most importantly, it identifies the scarcity of empirical studies and the lack of real-world implementations of DT in SES as two of the most critical research gaps in the existing literature. This allows directing future investigations to the less-researched areas, such as addressing the integration of DT in operational settings or studying the impacts of a DT on the efficiency and reliability of SES. A further contribution is the focus given to aspects as crucial as data acquisition, integration, and scalability when DT architectures are considered: the proposed RQs are specifically defined so that those key aspects are not overlooked in this review. We also aim not only to ascertain the difficulties associated with the design and deployment of DT of SES, but also to provide researchers and practitioners with useful suggestions for innovative solutions that can raise the performance of DT in real-time energy management. Furthermore, this study promotes an interdisciplinary approach wherein insights from cyber-physical systems and approaches coming from the computer science domain can be integrated into energy research, thus facilitating better collaboration opportunities and more robust solutions.

The manuscript is organized as follows. "SLR methodology" section describes step by step the methodology adopted in this SLR. "Results and analysis" section presents the findings of the in-depth analysis, while it includes also "System architecture patterns identification" subsection, which discusses system architecture patterns, and "Logical architecture components" subsection, which provides a detailed description of logical architecture components, defining the building blocks and the layers. This is followed by "Discussion" section, which covers integrated synthesis of findings ("Integrated synthesis of findings" subsection) and the integration of DT with the smart grid ("Scalability and integration with smart grid" subsection). "Gaps and future studies" section offers insights into gaps and future research directions, while "Conclusion" section draws the conclusions.

SLR methodology

The methodology adopted for this SLR is grounded on the format suggested by Smith et al. (2011), whereas the outline of its processing steps is adopted from an approach approved in the software and systems domain (Szvetits and Zdun 2016). Similarly, the keyword selection complies with a technique largely implemented in SLRs in the engineering sector (Aghazadeh Ardebili and Padoano 2020).

Data sources and search stages

The scientific works examined in this SLR were collected by searching three digital libraries, namely IEEE Xplore, Scopus, and Web of Science. Two main search phases were performed, as depicted in Fig. 1, where the SLR outline is illustrated:

1. the primary search phase collects the core information about the state-of-the-art in the addressed domain by querying the selected digital libraries as specified in Table 1;
2. The secondary search phase is aimed at answering the research questions listed in Table 2.

Since this SLR centers on the application of DTs in the field of energy systems engineering, our primary focus encompasses complex energy systems. Consequently, we have incorporated in our search process documents related to: (1) the implementation of DTs, (2) the maturity level of sub-systems; (3) the energy system as a whole unit; and (4) the evaluation, analysis, and enhancement of system efficiency. Moreover, the research scope extends to the domains of Engineering and Social Studies. As for the document types considered, we have included research papers published in conference proceedings and journals, reviews, book chapters, and books. The two main keywords used in the advanced query search submitted to the selected digital libraries are "Digital Twin*" AND "energy system*".

The choice of the digital libraries Web of Science (WoS), Scopus, and IEEE Xplore in researching DT technologies for SES (Table 1) was based on their extensive coverage of this scientific domain, the reliability of their content, and the availability of advanced search functionalities. More specifically, WoS offers multidisciplinary access to peer-reviewed articles and robust citation analysis, thus ensuring any academic investigation is wholesome. Similarly, Scopus is the world's largest abstract and citation database, offering a vast collection of scientific literature including journals, conference papers, and patents with advanced analytics for research trends. Finally, IEEE Xplore was also considered because its focus is on topics pertaining to engineering and technology.

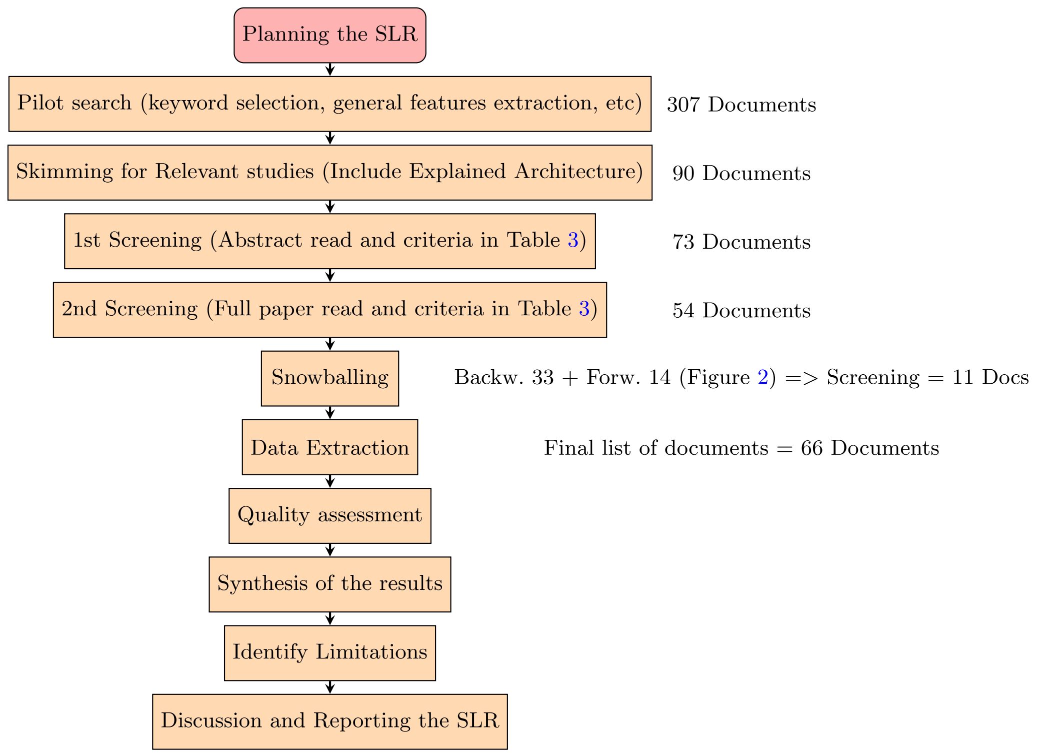

Fig. 1 The flowchart shows the outline of the steps of the SLR in this study. In the snowballing step, the process depicted in Fig. 2 is employed. Backward snowballing identifies 33 documents, while forward snowballing identifies 14 documents. After conducting a duplication check and screening process on 47 documents, 11 documents are selected to be added to the final list of articles. The final list consist of 66 articles

Table 1 Search queries in different databases

Database	Search query
SCOPUS	TITLE-ABS-KEY ("energy system*") AND "Digital Twin*"
WOS	#1 TI=("Digital Twin*" AND "energy system*")
	#2 AK=("Digital Twin*" AND "energy system*")
	#3 AB=("Digital Twin*" AND "energy system*")
IEEE	"Abstract":"Digital Twin*" AND "energy system*" OR
	"Document Title":"Digital Twin*" AND "energy system*" OR
	"Author Keywords":"Digital Twin*" AND "energy system*"

These libraries, considered all together, provide a broad, reliable, and detailed foundation on which to base the study of recent developments and applications in this field. It is also important to point out that when considering such digital libraries, the sets of documents returned could be overlapping, thus making duplicates removal an indispensable stage of our SLR. Also, the adopted query was structured depending on the advanced query's syntax required by each digital library but the same structer was kept, as we searched for the contemporary presence of at least a keyword related to the technological enabler (i.e., "Digital Twin") and at least a keyword about the target domain (i.e., "energy systems"). Furthermore, we did not include in the query any other synonyms of "Digital Twin" or "energy system", since a preliminary analysis we performed in the digital libraries confirmed that there are no synonyms that could alter significantly the number of papers collected. Noteworthy, Google Scholar was not included as a viable digital library in our SLR. This is due to some of its limitations: first, it does not offer homogeneous scientific coverage (since not all academic journals and databases are indexed in that search engine). Second, it also includes non-peer-reviewed material, thus bringing items from the so-called grey literature in the results and increasing the potential issues during the quality control phase of the returned papers. Third, the algorithms used for its search function are not publicly known and the results might be unreliable or unpredictable. Fourth, it does not offer advanced filtering and search functionalities, thus hindering the application of the defined inclusion/exclusion criteria. In addition, duplicate results and inconsistent metadata are also provided by Google Scholar, thus diminishing its reliability.

Finally, after delving into the implementation of DT in energy systems, system architecture patterns are extracted from the shortlisted and analyzed documents.

Exclusion/inclusion and screening procedure

As depicted in Fig. 1, the primary search stage, conducted in early 2024, unveils the freshness of the topic, as the less recent paper returned was published in 2018. Then, all the documents gathered from the three queried digital libraries are reviewed and duplicates are removed. As our primary focus is on the current state-of-the-art and roadmap for implementing DT in SES, we then defined a list of several Research Questions (RQs) to guide the final selection of relevant studies and data extraction. The RQs (detailed in Table 2) are based on the main objectives of the research, listed in the introduction, and serve a two-fold purpose:

Table 2 Matching between research objectives and research questions that guide the SLR on DT for SES, particularly focusing on architectures

Research objective	Research questions (used in full-paper screening)
O1: Enhance the understanding of DT in SES	1. What are the core concepts and definitions for DT in SES?
	2. How has digital twinning been conceptualized and applied in different domains within SES?
	3. What frameworks and methodologies have been developed/employed for implementing DT in SES?
	4. What are the most cited DT platforms and tools in SES?
	5. How does digital twinning contribute to enhance the resilience, efficiency, and sustainability of SES?
	6. What are the technologies enabling digital twinning of SES?
O2: Identify and classify system architectures for DT in SES	1. What are the main types of system architectures used for digital twinning in SES?
	2. How are data acquisition, integration, and processing handled within different system architectures?
	3. What are the key components and subsystems involved in DT architectures for SES?
	4. How do different architectural approaches address challenges such as scalability and interoperability?
	5. What are the emerging trends and innovative approaches in system architectures for digital twinning in SES?
O3: Determine what challenges and gaps are faced in bringing DT into action	1. What are the main themes, trends, and gaps in the existing literature on digital twinning in SES?
	2. Where do different studies operationalize digital twinning in SES?
	3. What are the key findings, insights, and recommendations derived from previous research on digital twinning in SES?
	4. What are the implications/applications of digital twinning within SES?
	5. What are the implications/applications of DT for energy policy, regulation, and decision-making?
	6. What are the ethical, legal, and social implications of digital twinning in SES?
O4: Highlight what potential research directions currently exist for advancing the application of DT in SES	1. How can the insights gained from the SLR on digital twinning in SES be translated into actionable recommendations?
	2. What are the key challenges and barriers to the adoption of digital twinning in SES?
	3. What are the emerging technologies and methodologies that can enhance digital twinning in SES?
	4. How can stakeholders collaborate to promote interdisciplinary research in digital twinning for SES?
	5. How can interdisciplinary approaches and collaborations contribute to advancing knowledge and innovation in digital twinning for SES?

- Final screening: During the full-paper review stage, articles that fail to provide explicit answers to the RQs are excluded.
- Data extraction: The RQs also guide the data extraction process, ensuring to capture the most pertinent and relevant information from the selected studies.

The first screening is conducted based on the document's relevance to the domain of application and its matching to the RQs.

In the second screening, inclusion/exclusion (Inc./Ex.) Criteria are employed to retain or eliminate the documents from the review process: they are outlined in Table 3 in terms of type and attributes.

The inclusion and exclusion criteria of this SLR have been carefully selected to include studies that are comprehensive, relevant, technically sound, and compliant with the research objectives listed in the introductory section. Inclusion criteria aims at selecting documents that: (1) are written only in English, to avoid any issues of accessibility and comprehensibility; (2) belong to the main document types and source types, to get a complete scope of research outputs; (3) address all subject areas, to encompass the broadest spectrum of research studies, ranging from engineering and computer science to environmental studies. Exclusion criteria establish that a paper must be discarded if: (1) there is no focus on DT implementation (i.e., low relevance); (2) it does not detail any defined method of DT implementation (i.e., not enough actionable insights); (3) its length is less than 1500 words (i.e., lack of details and inadequate depth of the study). Moreover, short reports, essays, and extended abstracts are ruled out in advance because they are not detailed enough and could plausibly lack of rigorous methodology. In this respect, the documents may be excluded if they fail to answer any research question to ensure that our SLR keeps its focus and relevance.

Then a third stage is performed with both forward and backward snowballing to identify relevant research papers, as depicted in Fig. 2. This approach follows the method introduced by Wohlin (2014) and also outlined in Ardebili et al. (2023). Backward snowballing starts with initial articles and examines their references to find more relevant sources. Forward snowballing looks at the citations of initial articles to find newer publications. Using this process, researchers can identify seminal works and recent advancements in the field, thus ensuring a more comprehensive review of the literature.

After the 3-stage screening process described above, 66 documents were selected for the full-paper study. This relatively low amount of selected papers suggests a significant gap in the empirical studies and implementation of DT in current testbeds or microsystems. For example, during the years 2022 and 2023, 53 works were dedicated

Table 3 Inclusion (Inc.) and exclusion (Excl.) criteria

Type	Criteria description	Abs.*	Met.	Struc.
Inc.	English			X
Inc.	All Doc. type			X
Inc.	All source type			X
Inc.	All subject area			X
Excl.	Doc. without focus on DT implementation	X	X	
Excl.	No defined Method of DT implication		X	
Excl.	Less than 1500 words		X	
Excl.	Short Report, Essay, Extended Abstract			X
Excl.	Doc. does not answer any RQ	X	X	

*Abs, criteria applied to the document abstract; Met, Methodology; Struc, Document structure

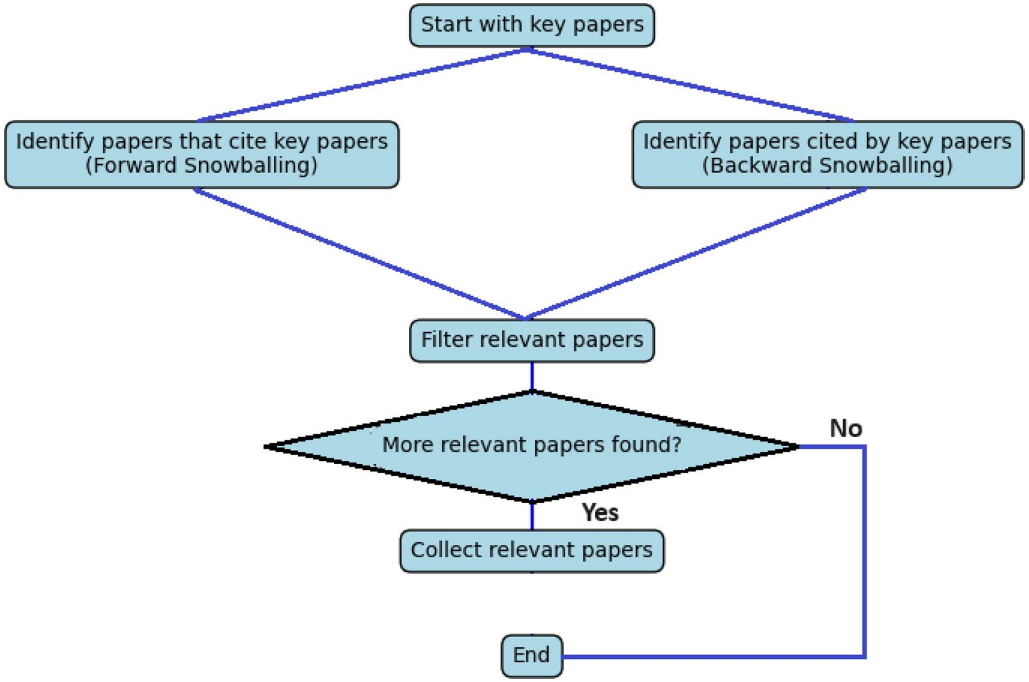

Fig. 2 The adopted forward/backward snowballing process (Ardebili et al. 2023)

to in-depth examinations of the implementation of DT in energy systems. Surprisingly, only 7 of these papers conducted practical experiments and validation, while the remainder focused on proposing models, architectures, and simulation applications.

Keyword analysis and clustering

A multi-step process of clustering and grouping similar keywords was performed using two widely-known Python libraries, specifically: `scikit-learn` and `nltk` This process is aimed at facilitating efficient keyword classification as well as synonym detection for various applications, and it is outlined in Fig. 3. First, the data undergoes preprocessing (Step 1), which involves tasks such as converting keywords to lowercase, removing punctuation, tokenization, and lemmatization using `nltk`. Next, the preprocessed keywords are vectorized (Step 2) using the TF-IDF Vectorizer from `scikit-learn`. After vectorization, K-Means Clustering is applied (Step 3) to group the vectorized keywords into clusters. Then, within each cluster, cosine similarity is calculated (Step 4) to detect synonyms. Finally (Step 5), due to a large number of keywords not belonging to any group, the clusters with a high quantity of keywords are retained.

Subsequently, manual adjustments and modifications are made based on the concept and scope of the keywords to form cohesive groups. Notably, the "Standards" cluster lacks a group of similar keywords, as articles in that domain predominantly employ identical terms without variations like synonyms or words from the same family.

Quality assessment of reviews

The quality of the SLR is assessed through three criteria detailed in Table 4: for each criterion, the main purpose and a short description are provided as well. We also declare that there were no deviations from the initial protocol, and no changes in inclusion/exclusion criteria during the entire process.

Results and analysis

This section will examine the reviewed articles in our SLR by considering several analysis dimensions. In addition to overall numerical insights, we will consider how smart decision support systems are addressed in the articles. Then, we will discuss what application areas for DT in SES and what system architectures are proposed in the articles.

Overall insights

The queries submitted to the selected digital libraries returned a certain amount of articles, whose distribution by year of publication is depicted in Fig. 4-Left. If we do not consider the value for the year 2024 (which only covers the first quarter of the year as it refers to the moment of writing this SLR and which, nevertheless, almost equals the number of articles published in 2022, thus suggesting a further increase for the rest of the year), a sharp and constantly increasing trend is clearly visible. Additionally, the distribution of articles by authors' affiliation country (Fig. 4-Right) identifies China, the US, the UK, and Germany as the most prolific countries (with China having more articles published than the sum of the other three countries). It is evident that the United States and China are very dominant in terms of publications, thus indicating how they are contributing significantly to energy informatics research and development. As for

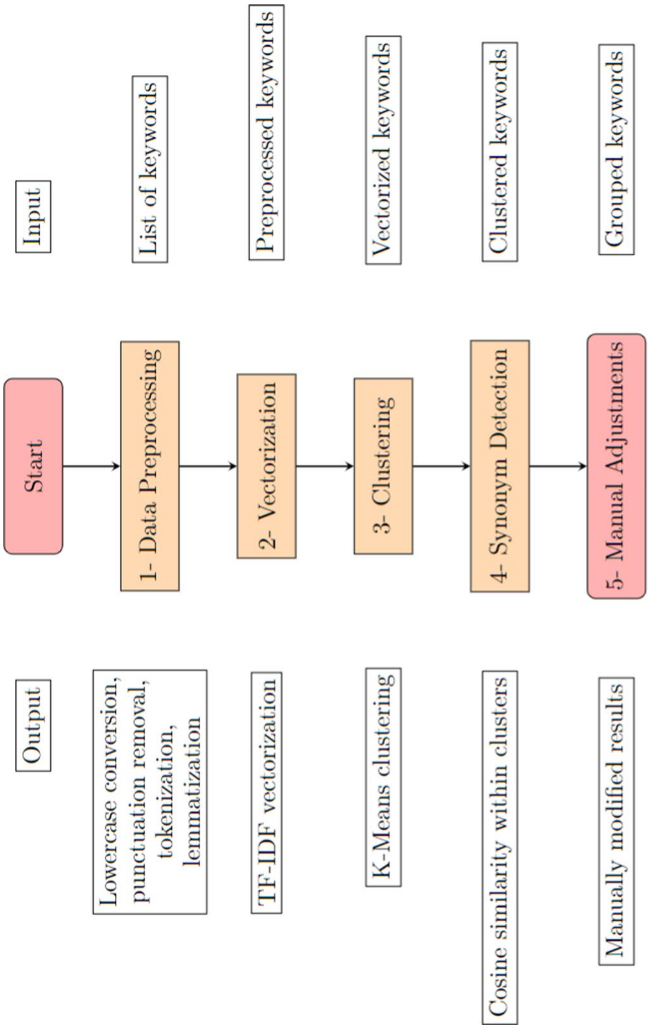

Fig. 3 Keyword analysis and clustering process via `scikit-learn` and `nltk` Python libraries

Table 4 Quality assessment criteria adopted in the SLR

Criteria	Purpose	Short description
Clarity	Making the approach reusable	The review is structured systematically and the general procedure of data extraction, databases, and screening criteria is detailed
Validity	Avoiding selection bias	Publication Bias and Selection Bias in SLR are considered and avoided by following a strategy based on the use of three different digital libraries and inclusion/exclusion criteria
Auditability	Ensuring credibility, transparency, reliability	The auditability of this SLR refers to the transparency and comprehensibility of the review process, allowing others to assess and replicate the study. Aiming to draw the maximum transparency, terminology is explained in detail, the outline of the steps for search strategy and methodology is detailed in "SLR methodology" section

the US, various funding agencies (e.g., the Department of Energy and the National Science Foundation) further support this leadership by the United States. As for China, the growth in publications is fueled by targeted strategic research in new technologies and energy infrastructure projects, which are supported by the government's "Made in China 2025" plan. European countries also reported a high research activity, particularly Germany and the UK, which benefited from collaborative projects under the Horizon 2020 framework. However, this geographical distribution underlines that in energy informatics, different regions may have different focus and resources.

As for the keywords, the occurrence of keyword pairs reveals that "Digital Twin" and "AI" appear together in documents more frequently than other word combinations, as indicated by the horizontal bar chart shown in Fig. 5. Studying the contribution of these articles (with the same word combinations), we can conclude that AI is more and more adopted as it enhances traditional systems by providing real-time data analysis, predictive maintenance, improved security through anomaly detection, optimized resource allocation, adaptability to changing conditions, and integration with IoT devices, leading to enhanced operational performance and cost savings. In addition, we can also ascertain that the most frequent combinations are: (1) *proactive maintenance* with *anomaly/fault detection* with 7 occurrences; and (2) *smart grid and microgrid*, with 5 occurrences. The frequent co-occurrence of the terms "Digital Twin" and "AI" in the literature highlights the growing interest in using AI technologies within applications for DT in SES for real-time data analytics, predictive maintenance, and anomaly detection to make energy systems more efficient and reliable. Being such *hot topics*, "Digital Twin" and "CPS", they also suggest that the research is rapidly moving toward more complex data-driven models that give real-time insights and unprecedented decision-making capabilities to the researchers and the stakeholders involved. Moreover, such combinations of keywords represent the newest trends in smart grids, system resilience, and resource management, where AI and DT technologies play a central role.

Highly repeated keywords are shown in Fig. 6, which shows how *Data Analytics*, *Cyber-Physical Systems*, *Internet of things*, and *Smart Grid* are used the most. This approach identifies frequently occurring original keywords within a corpus of SES

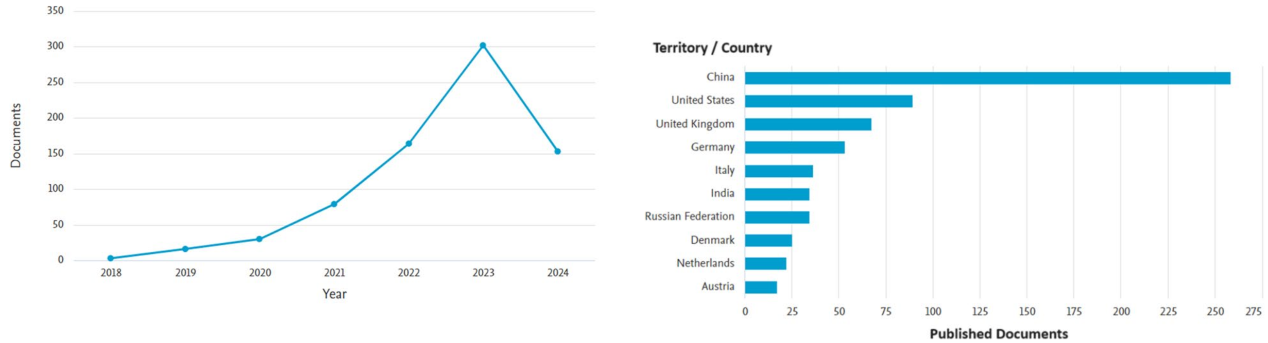

Fig. 4 Distribution of articles by publication year (on the left; the value for the year 2024 refers to its first quarter only) and by authors' affiliation country (on the right)

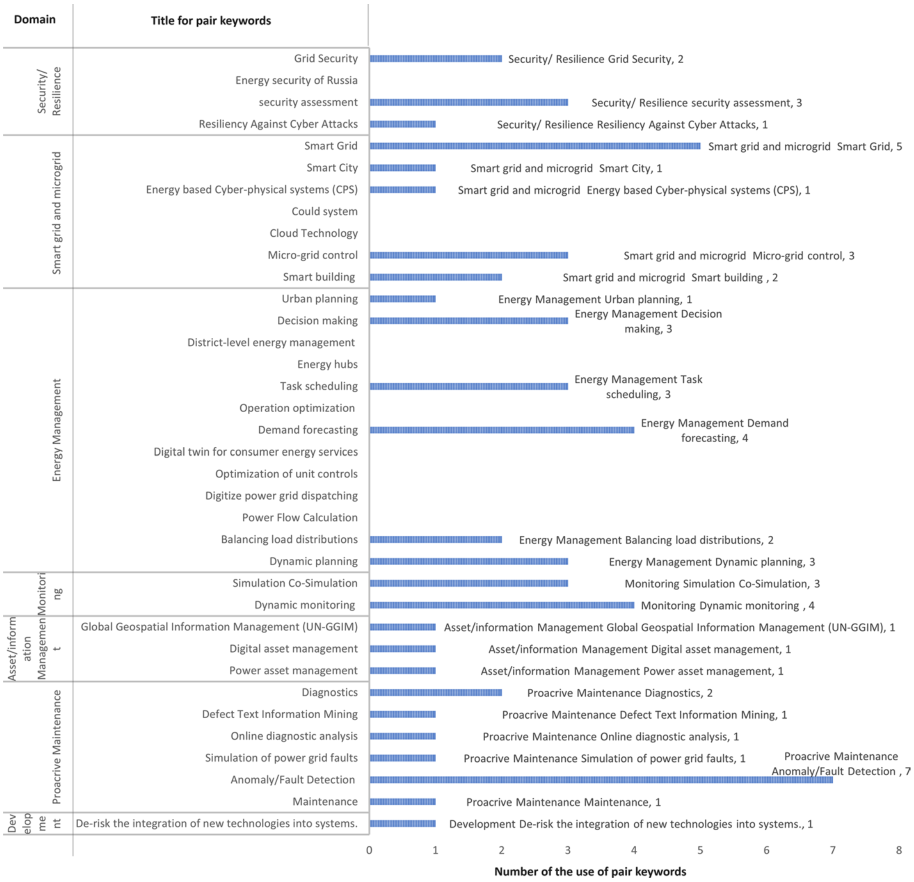

Fig. 5 Distribution frequency of keyword pairs combinations. Each pair is listed at the end of the corresponding bar on the right side of the chart. A categorization with a specific name for each pair and a general name for the keywords from the same domain are also reported on the left side

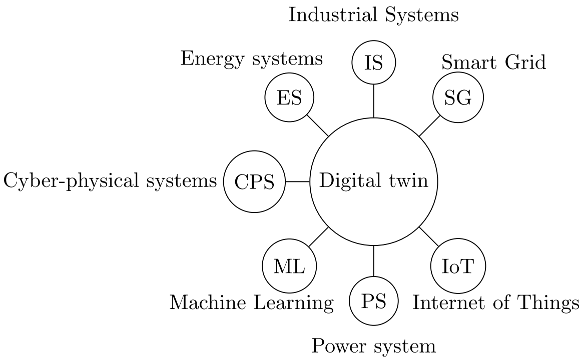

Fig. 6 Highly repeated keywords (the radius of each circle quantifies the number of studies). "Digital Twin" is the most prevalent keyword, followed by CPS and IoT (for all the acronyms, please refer to Table 21)

studies. By examining these keywords, and the application domain of the articles that they belong to, we can pinpoint areas where DT technologies are being actively conceptualized and leveraged.

More specifically, since a DT provides a data-driven replica of physical entities, the behavior of a digital replica is derived from data processed and transformed through Data Analytics processes (Runkler 2020). Moreover, in energy systems, DT is operating as a system of systems because its functioning is based on two main systems, along with the communications between them: cyber entities in the digital counterpart on one side, and physical entities (i.e., the assets of the energy system) in the physical counterpart on the other side. It is worth mentioning that all architectures adopted for managing these complex systems consider a communication layer to the communication means and protocols. Furthermore, many papers adopt Internet of Things (IoT) to exchange data between cyber and physical entities within a CPS. In such a scenario, the Energy Internet of Things (EIoT) (Muhanji et al. 2019) is a particular type of IoT used in the energy infrastructure. To bring Internet of Things (IoT) in action, the Physical Entity (Ph.E) is embedded with diverse sensors that provide data for Data Analytics and feed them to AI algorithms for making real-time decisions. This process forms a smart system, which in energy sector instantiates the concept of Smart Grid (Markovic et al. 2013). Some examples of smart grids, at different granularity levels, are: a smart house energy grid (Akbari-Dibavar et al. 2020); a group of smart houses in a smart city; the whole electricity and thermal power distribution in a country; the transmission grid plus the transportation in a country (Lund et al. 2017).

Smart decision support system (smart DSS)

In traditional industrial practices, decisions are made by humans and the process of upholding a decision and bringing it to action is quite slow; process-driven decision-making causes human errors, and isolated operations decrease the efficiency (Khan and Turowski 2016; Jimeno-Morenilla et al. 2021). As a solution, Industry 4.0 is seeking to automate the systems and data exchange through the fruitful combination of IoT and smart systems such as DTs. The advantage of a DT compared to monitoring and control systems is the possibility of digitizing the process by exploiting IoT, AI, and Data-driven decision-making to make the system fast and smart (Mohamed 2018; Masood and Sonntag 2020). However, in order to design a data-driven real-time DSS, new infrastructures should be developed for real-time communications.

Table 5 shows the list of the main IoT and DT platform providers, as inferred from the SLR, in terms of owner/founder companies (e.g., Ansys, Autodeks, Bosch, GE, IBM, NASA, and so on), short description, and application examples (e.g, monitoring, optimization, testing, and simulation analysis, for energy, real estate, healthcare, and aerospace. It is important to point out that the popularity of IoT is rapidly increasing, but the same trend is also evident in the energy systems too, where the EIoT concept was introduced in 2010 (Li et al. 2010), but raised considerably in popularity since early 2019 (liu and Bu 2019; Liu et al. 2019a; Zhang et al. 2019; Tian et al. 2019; Shao et al. 2019).

System architecture patterns identification

In this section, we are heading to investigate the architectural patterns of DTs and how their core components are linked and pieced together. Regarding the definition of DT

Table 5 DT providers and IoT tools

Platform	Founder	Description	Application example
Dynatrace	Dynatrace Software company	Artificial intelligence based platform for monitoring and optimization	Palladio Component Models (PCM) (Willnecker et al. 2015)
IoTIFY	IOTIFY.IO	DT testing platform	IoT test system (Goswami 2020; Manivannan and Radhakrishnan 2020; Cunha 2019)
Ansys Twin Builder	Ansys, Inc.	Representation of real entities along with sensors	Wind power generation, DC-DC power converter (Ai et al. 2021), Power Electronics, Power transfer systems for EV charging (Robles et al. 2021)
Autodesk Tandem	Autodesk, Inc	CAD extension to a digital replicadesign for planning and build	Mechanical design (Zemko and Kapustová 2024)
Bosch IoT Suite	Robert Bosch GmbH	A set of IoT applications software package	Power consumption management (Corno et al. 2018), energy harvesting (Dobrev 2020)
Cohesion	Cohesionib	Intelligent real-estate software platform	Critical Building Operations (Cohesion 2021)
iLens	Knowledge Lens	Industrial IoT Platforms	Condition Monitoring (CM) (Bhowmick 2021)
Flutura Decision Science	Flutura Decision Sciences and Analytics	Operational Excellence tool	Diagonostics (Raman 2024)
NASA DT	NASA	Simulation tool for future air force vehicles	Safety and reliabiulity of flight (Glaessgen and Stargel 2012)
Predix	NYSE: GE	Data collection and analysis tools	Livestock farms (Jo et al. 2018), industrial usecase (Augustine 2020)
MindSphere	Siemens AG	Cloud based pen IoT tool	Business digital transformation (Novikov and Sazonov 2019)
ThingWorx	PTC	A cloud based platform to transforms data into information	Piping model (Lee et al. 2016)
Watson IoT Platform	IBM	Cloud based IoT platform	Health monitoring (Kaur and Jasuja 2017)
Ditto	Eclipse Foundation	Abstracting physical entity in virtual world	Consumer choice modeling (Vijayakumar 2020)

provided in "Introduction" section, we recall here that a DT forms a *system of systems* in which all the composing microservices work according to a bi-directional data flow. Consequently, in a complex system, the DT of the whole system is typically composed of smaller DTs, each managing a different service or functionality.

Overall, infrastructures are complex systems with different components that act together to keep the continuous operation of a vital function of the society (Chunlei et al. 2011; Oughton et al. 2018; Rehak et al. 2019). Since in this study we focus on the energy system as a complex cyber-physical-social system (Xue and Yu 2017; Song et al. 2020; Ma et al. 2019), it is important to point out that it is composed by a set of interconnected systems and that it operates in interaction with other components in order to provide a specific service. Moreover, a DT needs to interact with other components of the complex system itself. Therefore, to understand how this system operates, it is crucial to consider how a DT is connected, interacts, and relates to the other components of a SES. Since we can consider the system architecture as a map of connections and dependencies within a specific domain (Mano 1993), we need to address the structure of these connections along with the conceptual model of the system components involved and their interactions. Several different architectures are employed in DTs for SES and we can categorize them depending on how their components are organized into functional *layers* (Tao et al. 2019).

More specifically, in a system architecture, different layers represent various levels of abstraction and responsibilities within the system. In this article, a layer in the context of a system architecture refers to a distinct level of abstraction that separates and organizes different aspects of a system or software application. Each layer is responsible for a specific set of functions and interacts with other layers in a controlled manner, promoting modularity, maintainability, and scalability. A set of layers with interactions between them frame a general architecture.

According to our review, researchers designed and used various layers for DTs in different systems, very often grounding their solutions on DT architectures proposed in other subject areas. For instance, DT-based solutions adopted for the maintenance of industrial systems propose the combination of local function layer, cloud function layer, and cloud layer (Mi et al. 2021). In the manufacturing sector, the CMCO (Configuration design, Motion planning, Control development, Optimization decoupling) bi-level architecture introduces two layers including physical design and logical design (Liu et al. 2021). In the healthcare sector, DTs typically present a data layer, with physical real-time monitoring, and virtual real-time monitoring layers that are used in order to improve scheduling, supervision, and crisis early warning (Liu et al. 2019b).

In the following subsections, we will focus on identifying the layers employed in DT for SES and categorizing the architectures in terms of the number of layers they incorporate. It is worth to point out that some of the diagrams depicting the architectural structures proposed in the following are conceptually inferred and schematized from the original architectures described in the corresponding studies, while the remaining diagrams are just reworked replicas of the existing architectures, so that they exhibit a homogeneous graphical notation in order to provide the reader with a common visual interpretation of each DT architecture. The notation used for these diagrams is reported in Fig. 7.

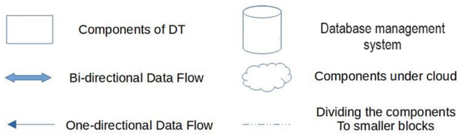

Fig. 7 Graphical notation used for the system architecture diagrams

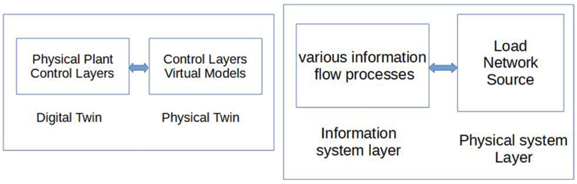

Fig. 8 Two-layer architecture diagram. Right: DT architecture based on EIoT—Left: DT architecture based on Control Layer Context

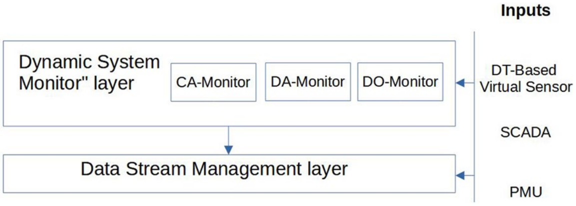

Fig. 9 Two-layer DT architecture diagram based on cyber-physical data stream management

Two-layer architectures

Among all the articles included in this SLR, the studies proposing the most simple DT architecture were based (either by explicit explanation of the authors or by inferring from the proposed technological solutions) on two architectural layers. This architecture decreases the complexity of the system and eases the implementation of DT in a generic CPSS. In some cases, this simplicity also resulted in the decrease of the computational cost (Milton et al. 2020). Milton et al. (2020) employed a two-layer architecture in power electronic converters. As it is shown in Fig. 8-Left, the system refers to a digital and a physical twins. Each twin has embedded control layers. This approach is known as Control Layer Context (Ginn et al. 2015). The embedded control layers are system control, application control, converter control, switching control, and hardware control. Moreover, each control layer has a model inside the DT main layer.

The most recent two-layer architecture is proposed by Zhang et al. (2020a), and it is based on the EIoT concept. In their study, the authors claim to respect the four pillars of the Energy Internet (i.e., Openness, Interconnection, Sharing, and Equality) (Zhang et al. 2020a; Zeng et al. 2017; Yan and Hu 2018). The layers are connected by an Information Communication bi-directional channel. The information system layer in Fig. 8-Right includes energy production information, energy markets information, energy management systems, data collection systems, data storage, analytics, etc. On the other hand, load, network, and source refer to the end users of energy, transmission and distribution of energy, and energy production points, respectively.

Kummerow et al. (2020) implemented a two-layer architecture in a different context. They applied the DT approach to create data-driven monitoring in order to safeguard the CPS against cyber-attacks. They use of data entries from SCADA, PMU, and “DT-Based Virtual Sensor” in the “Dynamic System Monitor” layer in order to discover anomalies in the system. The same data along with the output data of Dynamic System Monitor goes into the “Data Stream Management” layer as it is shown in Fig. 9. The virtual sensor

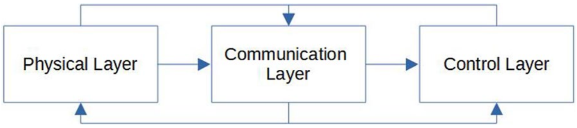

Fig. 10 Three-layer DT architecture diagram with a communication layer

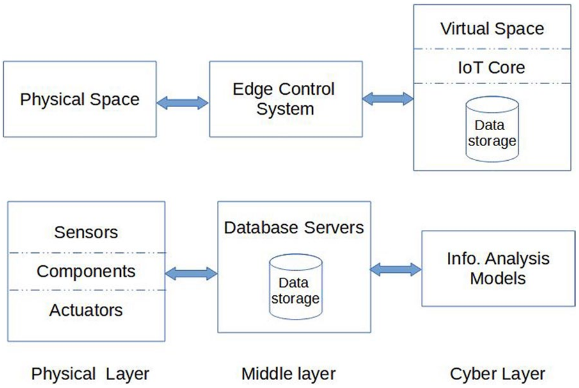

Fig. 11 Three-layer DT architecture diagrams with different middle layer; Top: Saad's architecture (Saad et al. 2020). Bottom: Yang's architecture (Yang et al. 2018)

provides input for the DA-Monitor process that estimates prediction error, while DO-Monitor and CA-Monitor estimate Physical anomaly and Cyber anomaly, respectively.

Three-layer architectures

Three-layer architectures are largely applied in the ES, in several different variants. For instance, Atalay and Angin (2020) and Strasser et al. (2018) employed the same structure for their system architecture; both of these architectures have a communication layer that handles data flow and receives feedback from the other three layers (Fig. 10). Strasser assigned two functions to the control layer, which contains analysis and decision making, respectively. The third layer in Atalay's architecture is named the IT layer. According to the Atalay's architecture, the DT undertakes simulations and optimization by comparing the logical and physical models.

In Saad et al. (2020) (Fig. 11-Top) and in Yang et al. (2018) (Fig. 11-Bottom) a three-layer architecture was also implemented. The major difference between these two architectures is in the middle layer. Saad incorporates three virtual entities in the virtual space cyber layer besides the IoT core and data storage and analytics: physical asset, cyber twin, and shadow twin. Shadow of the Things (ShoT) represents the last healthy desired state of the physical and cyber twins which updates every specific time and is employed in order to provision the Energy CPS. The edge controller exploits the estimated state by shadow to apply desired control action. Alternately in Yang architecture, the middle layer includes only database systems. The target analysis including deterioration, stability, efficiency, etc takes place in the cyber layer using the data-driven models.

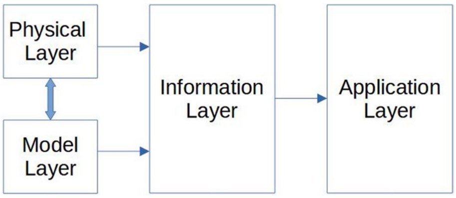

Fig. 12 Four-layer DT architecture diagram

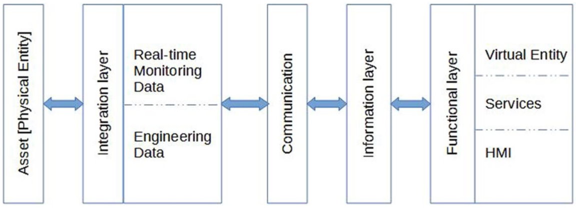

Fig. 13 Steindel GDTA Hyper-layer architecture diagram

Four-layer architectures

There is just one four-layer system (Fig. 12) proposed in the articles reviewed in this SLR, implemented by Pan et al. (2020). In most architectures, the physical entity consists of the physical assets and facilities, conversely, in Pan's system the physical layer includes also the data associated with a physical asset such as its current state, environmental data, rules, asset data, etc. instead, the information layer retains the information that converges Physical layer with DT. The model layer is a virtual mirror of the physical entity and its attributes. The application layer plays the role of a virtual test bed and handles the optimizations and digital management.

Hyper-layer architectures

In this subsection, we propose to identify every system architecture that exhibits four layers or more as a Hyper-Layer architecture. In 2020, Steindel introduced a generic architecture for Industrial Energy Systems (Steindl et al. 2020) as a hyper-layer architecture (depicted in Fig. 13 which, according to the authors of that study, might be customized to make it feasible for any individual system.

Massel and Massel (2020) emphasized the role of data management and IT infrastructure in the DT architecture. In that approach, the focus is on Big Data collection from measurement tools and on the subsequent use in three models within DT, including mathematical models, information models, and ontological models. Since a DT is a data-driven approach, in that article an architecture of the multi-agent intelligent environment (MAIE) were introduced to support DT and digital shadow in power systems. Howard et al. (2022) went a step further by proposing reusable DT agents that can be applied across various scenarios. Figure 14 is an integrated architecture of those DT and IT infrastructures.

In The Royal Borough of Greenwich in London, a smart city initiative supported by local government was triggered in 2016. It is one of the six cities that engaged in the EU-funded *Sharing Cities* project (SHARING CITIES) (EUROCITIES 2021) whose aim was to develop infrastructure solutions for SES. O'Dwyer et al. (2020) studied Greenwich

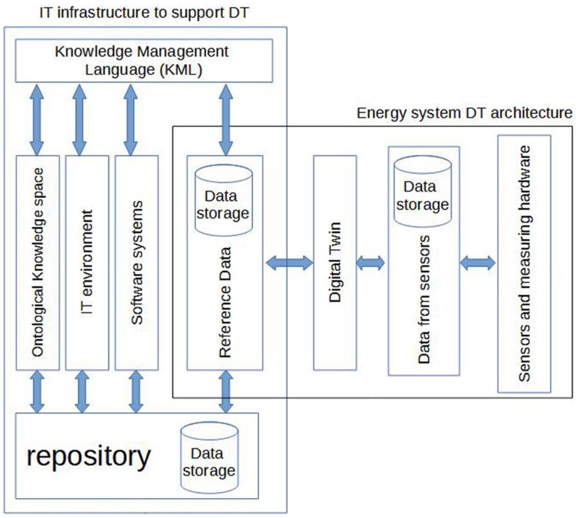

Fig. 14 Massel's DT architecture Massel and Massel (2020) diagram integrated with IT infrastructure architecture

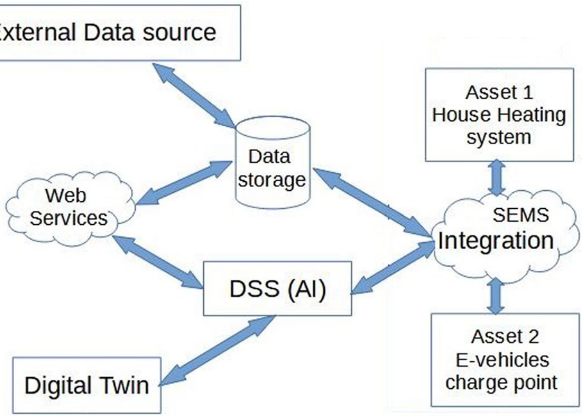

Fig. 15 Generalized Greenwich DT architecture diagram for SEMS and for DSS

residential heating and electric vehicle charge-points, by implementing an architecture, whose diagram is reported in Fig. 15, based on two subsystems considered as assets; each asset has embedded sensors and a data acquisition system connected. In the DT architecture, Sustainable Energy Management System (SEMS) is integrated with simulation tools, ML algorithms, and decision support systems (DSS) for the energy system. Appendix B includes an example of a developed DT for a smart building, with a web-based interface showcased in O'Dwyer et al. (2020).

The Power Systems DT (PSDT) architecture (He et al. 2019b) is designed for the analysis of Power Flow (PF) in cyber-physical Power systems. It has three eminent characteristics closed-loop feedback, data-driven mode, and real-time interaction. PSDT is developed in line with State Grid Electric Internet of Things (SG-eIoT) which is proposed by State Grid Corporation of China. This system empowers the decision makers by providing real-time information on PE and a virtual test bed for the decisions.

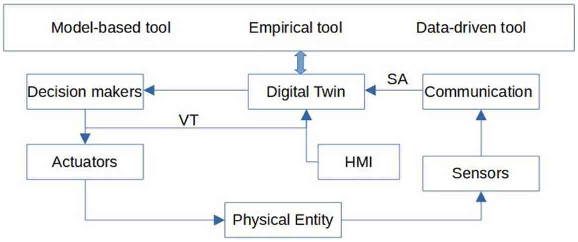

Fig. 16 Power Systems DT (PSDT) architecture

these two tasks are shown in Fig. 16 as Situation Awareness (SA), and Virtual Test (VT). The core of this model is DT, which employs model-based tools (PSS/E,[1] PSCAD,[2] Matpower.[3]...) data-driven enablers (big data, AI, cloud, 5 G...), and empirical tools such as traditional statistics. The continuously active operation of DT increases the reliability of the decisions in the system.

Logical architecture components

Following the GTDA Hyper-layer architecture discussed in "Hyper-layer architectures" section and the logical schema proposed in (Lu et al. 2020) (see Fig. 17) in DT for smart cities scenarios, the components of the architecture are discussed in the following.

The architecture can be divided into logical blocks, each corresponding to identified models. These blocks communicate with each other, as illustrated in the Figures reported in previous section with the data flow symbols detailed in Fig. 7.

There are multiple blocks, each of which is tasked to provide a certain service. In other words, the DT is made up of a federation of microservices, which are intended as services that cooperate to provide an accurate representation of the real-world asset of interest. Therefore, it is crucial to distinguish the different components that are employed in the extracted architectures.

The architecture types that have been identified and discussed in this Section are summarized in Table 6 in order to enable their comparison. Each architecture type is reported in terms of components and layers. The physical asset layer is a consistent component across all architecture patterns identified in the literature. However, a noticeable exception is found in the study by Kummerow et al. (2020), which omits this layer and focuses solely on the data derived directly from the physical asset as input for the layers of the Digital Twin.

In the two-layer architecture, the data layer is embedded in the information system layer (Fig. 8-Right). However, in three-layer architectures with a focus on communication (Atalay and Angin 2020; Strasser et al. 2018), various types of information, such as energy market data, energy management systems, and data from physical assets, are not treated as standalone layers. This limitation makes three-layer architectures less optimal for data-driven solutions. Nevertheless, within the same category, Saad et al. (2020) includes the data layer as part of a general cyber layer. In contrast, with a particular

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[1] https://www.siemens.com/global/en/products/energy/grid-software/planning/pss-software/pss-e.html.

[2] https://www.pscad.com/.

[3] https://matpower.org/.

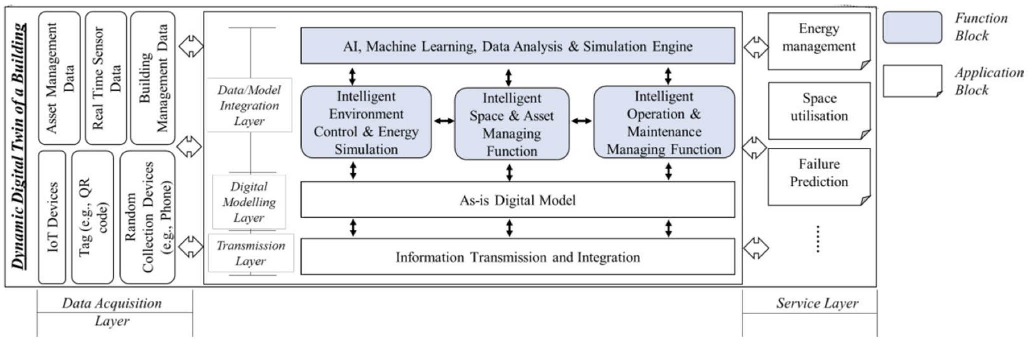

Fig. 17 An example of detailed logical architecture of the DT of a smart building with the micro-services and building blocks (Lu et al. 2020)

Table 6 Architecture comparison according to the existing components

Component/layer	Two-layer	Three-layer	Four-layer	Hyper Layer
Physical entity	✓	✓	✓	✓
Data layer	Figure 8-right	Figure 11	Figure 12	✓
DT layer	✓	✓	✓	✓
Communication layer	–	Figure 10	–	✓
Integration layer	–	–	–	✓
IoT components	✓	✓	✓	✓
Application/functional layer	–	✓	✓	✓
Control layer	–	✓	–	–

The (✓) symbol means that all the architectures in the category specified by the column (discussed in the reviewed articles of this SLR) exhibit the component specified by the row

Table 7 Features of Human–Machine Interface (HMI) for real-time dashboards of DT for SES

Category	Features
Data visualizations (Ferrigno and Barsola 2023; Scheer 2023; Jadhav and Sarnikar 2023; He et al. 2021; Shirowzhan 2022; Pedrosa Cabello 2023)	Graphs and charts, heat maps, 3D models and graphs, Augmented Reality, Virtual Reality, Metaverse
Real-time data feeds (Aheleroff et al. 2021)	Live data streams, alert systems
Interactive controls (Dalibor et al. 2020; Baniqued et al. 2024)	Filters and drill-downs, time range selectors: tools for viewing historical and recent data trends
Metrics and KPIs (Papacharalampopoulos et al. 2020)	Dashlets, performance indicators, realtime KPIs
Geographical information systems (GIS) (Shirowzhan et al. 2020; Adreani et al. 2023)	Maps, location analytics
User interface elements (Steiner 2022)	Dashboard tabs or sections, layouts
Data integration and sources (Redeker et al. 2022)	API integrations, database connectivity
Collaboration tools (Lee et al. 2021)	Annotations and notes, sharing and export options
Predictive analytics and insights (Mihai et al. 2021; Arsiwala et al. 2023)	Trend analysis, forecasting tools, statistical models for future predictions
Control panels and settings (Wang et al. 2021b; Madni et al. 2021)	User permissions and access control, customization settings

emphasis on data storage, Yang et al. (2018) dedicates a middle layer specifically to database servers. The same focus is evident in four-layer architectures as well.

User interface

This subsection focuses on identifying articles that thoroughly describe the features of human–machine interfaces (HMI) in real-time dashboards used for the decision support systems discussed in the articles reviewed in pilot searches of the current study (Fig. 1). The examined features are detailed in Table 7, where they are organized by different functional categories. Each category includes specific features that are essential for effective decision support systems and real-time monitoring applications of DT.

These features are used to extract the information about the HMIs. This ensures that Table 8 only includes studies that provide details about the HMI features and offer comprehensive insights into the capabilities of HMIs. Articles that mentioned

Table 8 HMI and corresponding features discussed in the reviewed articles

Ref	HMI	App Domain	Adv Graph Pres	Real-Time Data	KPIs	GIS	Data Integr	Pred.	Control Panels	Visuals
Steindl et al. (2020)	Interactive HMI	Generic DT Architecture (GDTA)	No	Run-time data and Engineering data	–	–	✓	✓	A micro-service named "Control Services"	General Monitoring Service
Atalay and Angin (2020)	Interactive HMI	Smart Grid Security	–	Historical data and simulation data	–	–	–	Simulation	–	N/A
Kertha Utama et al. (2024)	Interactive HMI	Microgrid DT	Virtual representation	Raw data from data lake	–	–	✓	Adam optimizer	✓	✓
O'Dwyer et al. (2020)	Interactive HMI	Smart buiding	–	Historical data and realtime data	–	–	✓	k-means clustering to forcast generation	✓	✓
Benigni et al. (2020)	SCADA	Power grid simulation	–	✓	–	–	FIWARE	✓	Monitoring and control application in control room	N/A
Andryushkevich et al. (2019)	User Interface	Power system modeling	–	✓	–	✓	N/A	Mathmatical model and simulations	To change the source code, recompile, test, and install the new version of software	Data Visualization (only time series)
He et al. (2019b)	Interactive HMI	Power System (monitoring and dispatch control)	N/A	✓	N/A	N/A	✓	N/A	✓	✓
Haghshenas et al. (2023)	Interactive HMI	Wind Turbine	3D(Unity) and AR	Real-time data streaming from edge	–	–	✓	Vibration, failure, state predictions	✓	2D dashboard
Idrisov et al. (2023)	Monitoring UI	Virtual power plants	–	✓	–	–	✓	N/A	✓	Data visualization (only time series)
Ambarita et al. (2023)	Interactive HMI	Offshore Wind Farms	✓	N/A	–	–	✓	ML for automation	✓	Visualization in the form of 3D, 2D
Clausen et al. (2022)	UI to show the result of simulation	Photovoltaic panels	✓	Raw data from data lake	–	✓	✓	N/A	–	–

Table 8 (continued)

Ref	HMI	App Domain	Adv Graph Pres	Real-Time Data	KPIs	GIS	Data Integr	Pred.	Control Panels	Visuals
Gourisetti et al. (2023)	Interactive UI/GUI	Energy systems	–	Raw data from relational database	–	–	Data orchestration system	Forecasting (mentioned in general)	✓	Data Visualization
Malmedal (2023)	Web based interactive HMI	Wind Turbine	3D simulation with CFD and virtual model with Unity Game Engine	✓	✓	✓	✓	Hybrid analysis and modeling (HAM)	✓	Data Visualization
Clausen et al. (2023)	Interactive GUI	Energy dispatch testbed	–	External Data inputs	–	–	N/A	Dispatch optimizer	✓	Data visualization (only time series)
Værbak et al. (2024)	GUI for mionitotring	Power distribution	–	✓	–	✓	✓	Agent-based simulation (ABS)	–	Monitoring the simulations

Explanation of column headers. Ref, corresponding bibliographical reference. *HMI* Human-Machine Interface; *App Domain* application domain; *Adv Graph Pres* incorporated advanced graphical presentation elements; *Real-Time Data* real-time feeds; *KPIs* thresholds, metrics and KPIs monitoring; *GIS* Geographical Information Systems; *Data Integr* sources/data integration;*Pred* predictive analytics and insights; *Control Panels* setups and settings; *Visuals* data visualizations; *N/A* no information available in the referenced article the presence of an HMI without providing detailed information on its features were excluded from Table 8.

Although incorporating advanced graphical presentation methods into a dashboard can significantly enhance the user's ability to monitor and interact with data,

Table 9 IoT physical components

Article	Sensors	Actuators	Gap in the literature
Strasser et al. (2018)	Network-Enabled Sensors Smart Meters IoT Device Physical Layer Sensors	Traditional Primary Electric Power System Actuators Secondary Variable Actuators Grid Modernization Technologies Smart Devices in Smart Homes and Buildings	No Specific types of Sensors or Actuators were mentioned
Kummerow et al. (2020)	High-resolution PMU (Phasor Measurement Unit)	–	No specific type of actuators were mentioned
Tucker et al. (2018)	Smart sensors	–	No specific type of Sensors were mentioned
Yang et al. (2018)	Pressure sensors Temperature sensor Mass flowrate sensors Ambient temperature and pressure sensors	Control valves of turbines and pumps Frequency control of air fan	
Rasheed et al. (2020)	Sensor Data Integration Sensor Data Augmentation Sensor-Based Monitoring Sensor Networks Sensor Fusion	–	No specific Types of Sensors or actuators were mentioned
Pan et al. (2020)	Smart Sensors	Decision-Making and Control Real-Time Perception and Contro	No specific type of Sensors or Actuators are mentioned
Atalay and Angin (2020)	Smart meters	–	No specific data about sensors and actuators was mentioned
Tzanis et al. (2020)	Smart meters	–	No specific data about sensors and actuators was mentioned
Huang et al. (2021)	Smart sensors	–	No specific data about sensors and actuators was mentioned
Merino-Córdoba et al. (2023)	Specific sensor types mentioned include temperature sensors, humidity sensors, air quality sensors (e.g., CO2), energy sensors, light sensors, and motion sensors	–	No specific data about sensors and actuators was mentioned
Haghshenas et al. (2023)	–	–	No specific type of sensors was mentioned
Ambarita et al. (2023)	–	Robots are mentioned as actuators	No specific type of sensors
Malmedal (2023)	Sensors such as accelerometers are mentioned for monitoring blade vibration and oscillation	–	No specific data about actuators was mentioned
Cespedes-Cubides and Jradi (2024)	RS 485 sensors	–	No specific data about actuators was mentioned

our analysis revealed that there is still a significant gap in bringing VR and AR effectively into action in DT of SES.

IoT components

As anticipated in "System architecture patterns identification" section, IoT components are fundamental to all the architectures discussed. The integration between

Table 10 Key IoT based enablers of Digital Twins

Component	Enabler of	Description
Sensors and Actuators (Figure 9)	Collect Data	Capture real-time data on various parameters such as temperature, pressure, humidity, and motion
	Control Systems	Execute commands from the DT to perform actions, such as adjusting settings or triggering alarms
Connectivity	Wireless Networks	Wi-Fi, Bluetooth, Zigbee, and other wireless communication protocols. (Merino-Córdoba et al. 2023)
	Cellular Networks	4G/5G networks for long-range and high-speed data transmission.Rasheed et al. (2020)
	IoT Protocols	Lightweight protocols designed for IoT communication. [MQTT (Strasser et al. 2018; Tucker et al. 2018; Saad et al. 2020; Atalay and Angin 2020; Malmedal 2023; Ismail et al. 2024) and AMQP (Strasser et al. 2018)]
Edge-cloud Computing	Low Latency (Steindl et al. 2020; O'Dwyer et al. 2020; Saad et al. 2020; Rasheed et al. 2020; Onile et al. 2021; Tzanis et al. 2020; He et al. 2019b; Ismail et al. 2024)	Immediate processing of data near the physical asset.(Strasser et al. 2018; Tucker et al. 2018; Zhou et al. 2019; Zhang et al. 2020a; Tang et al. 2020; Steindl et al. 2020; O'Dwyer et al. 2020; Saad et al. 2020; Scharl and Praktiknjo 2019; Rasheed et al. 2020; Atalay and Angin 2020; Merino-Córdoba et al. 2023; Haghshenas et al. 2023; Ma 2023; Cespedes-Cubides and Jradi 2024; Jradi and Bjørnskov 2023; Bayer and Pruckner 2023)
	Efficiency	Minimizes the amount of data transmitted to central servers
	Enhanced Security	Local data processing reduces exposure to external threats.(Yang et al. 2018; Massel and Massel 2020)
Cloud Computing	Scalability	Easily scale resources up or down based on demand.(Bayer and Pruckner 2023)
	Data Integration	Aggregate data from multiple sources for comprehensive analysis.(Strasser et al. 2018; Tucker et al. 2018; Zhang et al. 2020a; Saad et al. 2020; Conway and Hainoun 2020; Zhou et al. 2020b; Scharl and Praktiknjo 2019; Rasheed et al. 2020; Atalay and Angin 2020; Tzanis et al. 2020; Xie et al. 2019; He et al. 2019b; Huang et al. 2021; Kertha Utama et al. 2024; Ambarita et al. 2023)
	Accessibility	Access data and services from anywhere with internet connectivity. (Ambarita et al. 2023)

the various architectural layers and IoT technologies is essential for the effective functioning of any DT. However, most of the articles do not elaborate on the CPS perspective adequately. Therefore, there is a significant gap in defining the physical components of the (Physical Twins) used in SES. Table 9 summarizes all the components mentioned in the literature reviewed in our SLR and highlights significant missing information regarding the physical twin for each CPSS under study.

In the scope of CPSS and with respect to the presence of the physical twin concept, IoT enablers provide the necessary infrastructure, tools, and services to connect, monitor, and manage physical assets in real-time. Key IoT components and enablers of DT are listed in Table 10.

On the other hand, external APIs for a DT are a crucial component that facilitates communication between the DT and various external systems or data sources (Ala-Laurinaho et al. 2021). APIs enable the integration of real-time data, control commands, and analytics results, enhancing the functionality and accuracy of the DT (Robles et al. 2023). For instance, a DT for a PV panel needs to merge environmental data from multiple sources, such as SmartPV's air quality sensors, weather service web APIs, and other relevant inputs. This integration enables further analyses that correlate weather conditions, air quality data, and the PV panel's throughput (Aghazadeh Ardebili et al. 2023b).

A gap was discovered after the analysis regarding external APIs. Since APIs play a crucial role in integrating different components of the energy system, such as data exchange, communication, and integration with other systems, the absence of external APIs can lead to inefficiencies, inconsistencies, and potential conflicts in the energy market, ultimately impacting the overall performance and sustainability of any SES. External APIs were discussed only four times, as follows. First, in Ma (2023) the author mentioned API interfaces as part of the IoT system architecture. The different IoT system architectures and its layers are illustrated graphically in Fig. 18

Second, as for the contribution of (Gourisetti et al. 2023), the topic of external APIs is explored in conjunction with the integration of third-party systems and services in the digital realm. Nonetheless, the third occurrence is in (Ambarita et al. 2023), where the authors described the integration of RESTful API Connectivity to establish automatic storage and communication protocols for linking physical assets to digital assets represented by Asset Administration Shell (AAS). Finally, the fourth article discussing APIs

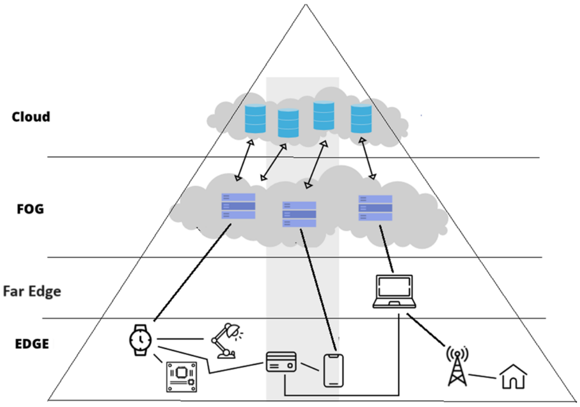

Fig. 18 Difference Between Edge layer, Far Edge, Fog, and cloud layer

is (Scheibe et al. 2019), where the authors explored the use of external APIs within the cosimulation framework, specifically focusing on inter-process communication through shared memory for power system analysis. That article also specifically discusses the use of event handles in the context of shared memory, thus allowing processes to wait for specific events while minimizing the overhead imposed by the operating system.

Finally, the bidirectional communication between the components (facilitated by a potential comunication layer) in the edge-cloud architecture is crucial is very important. Other than providing a message-brokering service, it also enables an on-premise persistence mechanism used to keep a record of the low-level data (either raw sensor readings or servos actuation commands) forwarded by the message broker (Somma et al. 2023). Our SLR showed that four kind of distributed architectures are implemented in the literature, as summarized below.

- Cloud Architecture: Centralized computing model where data and applications are hosted on remote servers, providing scalable resources over the internet (Armbrust et al. 2010; Marinescu 2013).
- Edge Architecture: Computing model that processes data closer to its source to reduce latency and improve real-time data handling (Satyanand et al. 2018; Shi et al. 2016).

Table 11 IoT system architectures in the reviewed articles

Paper	Cloud	Edge	Far edge	Fog	SES type
Strasser et al. (2018)	✓	✓	–	–	EIoT
Cui et al. (2020)	✓	✓		✓	DT for Power System Steady-state Modelling, Simulation, and Analysis
Zhou et al. (2019)	✓	✓	✓	✓	PowerGrid
Zhang et al. (2020a)	✓	✓	–	–	OADT power grid
Steindl et al. (2020)	✓	✓	–	–	Packed-Bed Thermal Energy Storage (PBTES)
O'Dwyer et al. (2020)	✓	✓	–	–	Multi-Vector
Zhou et al. (2020a)	✓	✓	–	–	Real-Time Online Analysis for Power Grid
Atalay and Angin (2020)	✓	✓	–	–	Smart Grid
Xie et al. (2019)	✓	–	–	–	Electrical DT in Smart Grid
Merino-Córdoba et al. (2023)	✓	✓	–	–	IoT based indoor air quality
Haghshenas et al. (2023)	✓	✓	–	–	DT for offshore wind farms
Kertha Utama et al. (2024)	✓	✓	–	–	Microgrid
Ambarita et al. (2023)	✓	✓	–	–	Offshore Wind Energy
Ma (2023)	✓	–	–	–	Virtual Energy Ecosystem
Jørgensen et al. (2023)	✓	✓	–	–	Smart Power Distribution
Nashirul Haq et al. (2023)	✓	–	–	–	Microgrid
Gourisetti et al. (2023)	✓	–	–	–	DT
Malmedal (2023)	✓	✓	–	–	Small-Scale Wind Power Generation
Cespedes-Cubides and Jradi (2024)	✓	✓	–	–	DT and IoT For buildings
Jradi and Bjørnskov (2023)	✓	–	–	–	DT for buildings
Bayer and Pruckner (2023)	✓	✓	–	–	Local Energy System
Ismail et al. (2024)	✓	✓	–	–	DT

- Far-Edge Architecture: It extends edge computing by placing processing capabilities at very remote locations, often in distributed environments (Baccarelli et al. 2020; Zhang et al. 2020b).
- Fog Architecture: Decentralized model that extends cloud capabilities to the network edge through intermediate fog nodes (Bonomi et al. 2012; Buyya et al. 2017).

The findings in the literature regarding the distributed architecture are reported in Table 11.

From Table 11, it is evident how cloud-based approaches reported in the reviewed literature represent the majority of the studied approaches, followed by edge-based solutions that come second except in Xie et al. (2019), Ma (2023), Gourisetti et al. (2023),Nashirul Haq et al. (2023) and Jradi and Bjørnskov (2023), which only discusses cloud-based approaches. the significant difference was to find a far-edge approach that was reported in Zhou et al. (2019). It discusses the dynamic Virtual (Software) Model: The dynamic virtual model within the OADT approach can be considered far-edge-based as it mirrors the physical power grid in real-time, potentially at the far edge of the network where data is generated. In the same work, A fog-based approach focused on Complex Event Processing: Fog computing, which extends cloud capabilities to the edge of the network, is often associated with complex event processing to analyze data closer to the data source. This aligns with the event-driven nature of the system architecture. Fog-based approaches appeared another time in the work of Cui et al. (2020) and it discussed the following aspects Digital Space refers to the digital counterpart of physical elements, represented as a Digital Twin, which is used for simulations and analysis purposes. Human experience refers to the utilization of human expertise and knowledge in interpreting and utilizing data for decision-making. Tools and methodologies for modeling, simulating, and analyzing the power system using data from the Internet of Things (IoT).

Artificial Intelligence (AI) and Machine Learning (ML)

The key advantage of Digital Twins (DT) over traditional monitoring and control systems is their ability to use AI. These algorithms not only provide data-driven decision support but also facilitate a two-way flow of information between the physical asset and digital replica (Fang et al. 2012; Panajotovic et al. 2011). This interaction engages consumers by analyzing consumption patterns and customer relationship system (CRS) information (Park et al. 2014; Gangale et al. 2013) empowering the social impact on the cyber-physical-social system.

Using ML methods is essential in constructing DT. Table 12 shows the variety of the applications of ML. According to our analysis of the tools implemented in the reviewed studies, Python is widely used in DT applications (Al-Geddawy 2020; GALVÃO 2020; Rodemann and Kitamura 2020; Bhowmik et al. 2019; Körber and Frommel 2019; Yun and Park 2021; Protic et al. 2020; Zabala et al. 2020; Zhu et al. 2020) and it can be considered as the predominant programming language for deploying machine learning

Table 12 Machine Learning applications in DT (DT) of energy systems

Author	Application	Use case	SES domain
Seo et al. (2021)	Predictions	A big data analysis system utilizing the machine learning framework in KNIME (an open source data analysis platform) for smart operation	Water Column-Wave Energy
Yang et al. (2018)	Data Driven Modeling	Modeling the components in thermal power plants	Thermal Power Plants
Snijders et al. (2020)	State Prediction	Use of Machine Learning for Digital Twins to predict a battery's responsiveness	Energy Storage
Tzanis et al. (2020)	Fault Prediction	ML model in fault diagnosis in distribution grid	Distribution Grid
Haghshenas et al. (2023)	State Prediction	ML algorithms are being used to monitor and predict asset condition and behavior	Offshore Wind Farms
Kertha Utama et al. (2024)	Electricity Load Model	ML algorithms are being used for short-term electricity load forecasting	Energy Consumption
Malmedal (2023)	State Prediction	Machine learning finds relationships from simple sensor time-series data to replace too complex or even nonexisting monitoring methods for wake effects, blade root bending moment, and blade tip-tower clearance	Single Wind Turbine
Ambarita et al. (2023)	State Prediction	Predict the expected behavior of the healthy system, to be compared with the factual one	Offshore Wind Farms
Xie et al. (2019)	Demand Forcasting	Ordinary differential equation (ODE) based solutions yield acceptable levels of accuracy for wide range of prediction horizons	Energy Consumption
Zhou et al. (2019)	Anomaly Detection	Perform security assessment to enhance the DT's built-in intelligence for security assessment purposes	Smart power grid
Hu et al. (2020)	Wind speed prediction	Prediction of wind speed and wave height, compared with alternative approaches including persistence model, ARIMA, LSTM, BO-LSTM, and EEMD-LSTM models	wind power plant
Yitmen et al. (2021)	Building lifecycle management	Adapted model of CDT for BLM, focusing on applicability, interoperability, and integrability	Smart building energy system
Agostinelli et al. (2021)	Energy management	Deployment of cost-effective IT infrastructure	Smart Building
Lopez et al. (2021)	Intelligent authorization	Monitoring platforms and architecture decentralization	Smart Grid

Table 12 (continued)

Author	Application	Use case	SES domain
(Fan et al. 2021)	Urban disaster management	Integrating AI with DT for disaster management	Smart City
Molinaro et al. (2021)	Computational Fluid Dynamics (CFD)	Simulation Digital Twin (SDT) using hybrid physics-informed and data-driven modelling	Predictive maintenance
Chen et al. (2021)	Maintenance	Wind Turbine Operation	Wind power plant

Articles that do not exclusively detail the implementation of machine learning in a use case have been excluded from this table

algorithms in DT. Neural Networks (NN) are the most popular solutions for SES, leveraging AI to empower DT.

Neural Networks (NN) are the highly used ML algorithms, designed to identify relationships through clustering and classification purposes (mostly for maintenance). In general, within the results, NNs are used in a supervised manner with training data or in an unsupervised manner when the target set is unknown (risk assessment of the grids). Eight types of NNs are used in DT to learn from historical data. However, many studies did not specify the machine learning model, programming language, or libraries used in their DT implementations. Table 13 provides a summary of the algorithms, theoretical foundations, applications, and their use in DT of SES.

Data flow

Unidirectional data flow (also known as one-way data flow or monodirectional data flow) restricts data movement to a single direction, whereas bidirectional data flow allows data to flow freely back and forth between components. In a monodirectional data flow, information is transferred only in one direction—from the the physical asset to digital shadow- primarily for monitoring or analysis. In contrast, bidirectional data flow involves a two-way exchange between a Digital Twin and the physical asset, allowing for real-time updates and feedback in both directions. Figures 19 and 20 illustrates the difference in these two concept.

Data flow that is detailed in Table 14 refers to the direction along which data travels between components. However, bidirectional flow can introduce complexity but many advantages are inferred from a general comparison of the case studies, and the features of the DT with bidirectional data flow in Table 14, which are shown in Table 15.

In Kummerow et al. (2020), it was mentioned that SCADA systems typically employ bi-directional data flow, wherein control commands are dispatched from the control center to field devices, while data from sensors and devices are transmitted back to the control center for the purposes of monitoring and analysis. When it comes to evaluating cyber-physical data streams, there can be a two-way exchange of data between monitoring systems (like SCADA and PMU clients) and the data stream assessment module. This allows for real-time analysis and feedback. Another approach is found in Zhou et al. (2019), which explored the data flow in the context of the Online Analysis Digital Twin (OADT) method for analyzing

Table 13 Neural network algorithms used in DT in energy systems

No.	Type	Description	Application in DT	Programming language	Library
1	Neural Network (NN) (Type: N/A)	Inspired by neural network in human brain and mimic its functioning approach to learn	Simulation model to create a converged Loadflow snapshot (Zhou et al. 2020a)	N/A	N/A
2	Artificial neural network (ANN)	Feed-forward neural network based on Multi-Layer Perceptions, which process execute only onwards (Aggarwal 2015) The third generation of ANN- Spiking Neural Networ (Taherkhani et al. 2018)	Converged Loadflow snapshot (Snijders et al. 2020) Measurement-based system (Baboli et al. 2020) Consumer behavior modeling (Onile et al. 2021) Fault identification (Tzanis et al. 2020)	Python Matlab	Python-Keras
3	LSTM (Long-Short Term Memory)	A particular Type of RNN in which recursion take place contingent upon time series (Houdt et al. 2020)	Defect Text Information Mining (Zhou et al. 2020b)	Python	jieba
4	Temporal Convolutional NN TCN	A type ofDeep Artificial NN to detect temporal patterns (Bai et al. 2018) (He et al. 2016) (Dumoulin and Visin 2016)	Anomaly Detection (Snijders et al. 2020)	Python	keras
5	Stochastic Neural Networks	Restricted Boltzmann Machines (RBM)(Larochelle et al. 2012)	Anomaly Detection (Rasheed et al. 2020)	Matlab, R, Python, Julia	
6	Recurrent Neural Network (RNN)	A particular type of ANN that nodes facilitate by feedback loops aim to obtain sequential information (Mandic 2001)	An LSTM in RNN class is employed in (Zhou et al. 2020b) (row 3 of this table)	Python	Jieba PyTorch torchdiffeq Keras
7	Deep Neural Network (DNN)	Hybridization Technique (Maulik et al. 2019) (Reichstein et al. 2019) (Xie et al. 2019) considers Recurrent Neural Network in the family of DNN	Unexpected behavior detection (Rasheed et al. 2020)	Python	PyTorch torchdiffeq
8	Natural Language Processing (NLP)	NLP based on Neural Networks and LSTM algorithms (Ruder 2018) (Young et al. 2018)	Power text process through information mining (Zhou et al. 2020b) NLP as a mode of interaction in Human-Machine interface concept (Rasheed et al. 2020)	Python	N/A

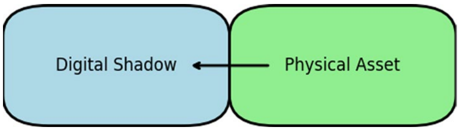

Fig. 19 Monodirectional data flow from Digital Shadow to Physical Asset

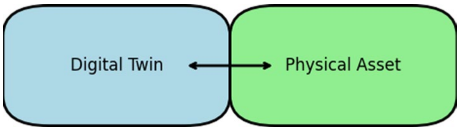

Fig. 20 Bidirectional data flow among Digital Twin and Physical Asset

Table 14 Data flow

Article	Unidirectional	Bidirectional
Kummerow et al. (2020)	–	✓
Zhou et al. (2019)	✓	–
Zhang et al. (2020a)	–	✓
Steindl et al. (2020)	–	✓
Saad et al. (2020)	–	✓
Zhou et al. (2020a)	✓	✓
Andryushkevich et al. (2019)	✓	–
Tzanis et al. (2020)	✓	–
Xie et al. (2019)	✓	–
Huang et al. (2021)	✓	✓
Merino-Córdoba et al. (2023)	✓	–
Haghshenas et al. (2023)	–	✓
Kertha Utama et al. (2024)	–	✓
Idrisov et al. (2023)	–	✓
Ma (2023)	–	✓
Jørgensen et al. (2023)	–	✓
Nashirul Haq et al. (2023)	–	✓
Clausen et al. (2022)	–	✓
Gourisetti et al. (2023)	–	✓
Malmedal (2023)	–	✓
Jradi and Bjørnskov (2023)	–	✓
Bayer and Pruckner (2023)	–	✓

Table 15 Unidirectional and bidirectional data flow comparison

	Unidirectional	Bidirectional
Operation	Monitoring	Reacts to actions (by updating the view and then the model) and control actions
Advantages	Faster development, easier maintenance, fewer components	Real-Time Synchronization, Dynamic Optimization, Adaptive Learning and Evolution
Disadvantages	Can be less flexible and provides only real-time surveillance	More complex compared to Unidirectional, debugging challenges, lower resilience, High Computational and Network Requirements, Increased Latency, Scalability Challenges, Cost

power grids online. The text highlights the significance of reducing data transfer while simulating in order to improve system efficiency. The article compares the traditional method of online analysis, which involves exporting data from storage to create a snapshot of the current grid operation state and then sending it to an application for simulation, with the approach used in the OADT framework. The data flow in the context of the OADT approach for power grid online analysis is predominantly unidirectional. Furthermore, Zhang et al. (2020a) discussed the concept of bidirectional data flow in relation to the Energy Internet and DT technology. The data flow within the DT framework is characterized as bidirectional, interactive, and real-time, with data being exchanged between physical systems and virtual models in both directions. While the contribution of Steindl et al. (2020) outlined a Bidirectional data flow within the DT framework for industrial energy systems. The Information Layer collects, enhances, and associates data with contextual information, demonstrating the movement of data from multiple sources towards the Shared Knowledge base.The Smart Data Service guarantees that communication protocols are transparent to the higher layers of the architecture, indicating a two-way flow of data and exchange of information within the system. additionally, Saad et al. (2020) described the presence of a two-way movement of information within the DT framework for networked microgrids in the context of the Internet of Things (IoT) which represents a bidirectional flow of data. This bidirectional data flow entails the exchange of information between sensors attached to physical assets and controllers associated with cyber assets. It enables communication in both directions, facilitating the operation, control, and security of the system. While the article of Zhou et al. (2020a) on the other hand discussed what is known to be a unidirectional flow of data. The work of Andryushkevich et al. (2019) had its primary focus on the unidirectional transfer of data from the physical system to the DT model, which was used to facilitate different functionalities and applications within the power systems domain. Nonetheless, in Tzanis et al. (2020) the article primarily describes a unidirectional data flow, where data is transmitted from the smart meters to the control center. This data is then analyzed and used for real-time fault prediction in the smart grid system. As for the work of Xie et al. (2019) the data flow consists of streams of sensor data transmitted by advanced metering infrastructures (AMIs) within digital replicas of power grids. Data flows primarily in unidirectional, from sensors to the DT framework, where it is analyzed and used for decision-making processes. Additionally, in the work of Huang et al. (2021) represents a bidirectional flow of data. As for the work in Merino-Córdoba et al. (2023) the dataflow in the IoT system architecture for indoor air quality monitoring and energy-related data in buildings is unidirectional. It involves the collection, transmission, and storage of sensor data for analysis. The sensors gather data, which is subsequently transmitted to EDS concentrators for the purpose of storage and subsequent processing. Subsequently, the data is conveyed to a central server for the purpose of storage and analysis. The work in Haghshenas et al. (2023) stated that the OPC-UA mode explicitly refers to bidirectional data transfer, enabling communication between the physical asset and its DT in both directions. Nonetheless, Kertha Utama et al. (2024) focused on ensuring a continuous and uninterrupted flow of data to enable accurate and immediate modeling, with a greater inclination towards bidirectional communication. The work in Idrisov et al. (2023) tends to have a bidirectional dataflow. Furthermore, the work in Ma (2023) stated that the dataflow is bidirectional, as it involves interconnected databases and communication protocols for smooth integration and communication between various Digital Twins and existing systems. In Jørgensen et al. (2023), it was mentioned that the dataflow goes both ways (bidirectional), as it includes gathering data from the physical twin and analyzing it to forecast future states. As for the work in Nashirul Haq et al. (2023), it was mentioned that the dataflow is bidirectional, as it involves the exchange of data between devices using different protocols. Additionally, in Clausen et al. (2022) the work emphasized the importance of bidirectional communication to ensure real-time data feed between the PV and DT, allowing for seamless instruction exchange to facilitate smooth operation. In Gourisetti et al. (2023) it was mentioned that the dataflow involves bidirectional movement of information, encompassing data preparation, verification, validation, and data-driven actions between the physical and digital dimensions. Nonetheless, in Malmedal (2023) it was mentioned that transferring data between physical and digital systems involves a bidirectional flow of information. Furthermore, Jradi and Bjørnskov (2023) clarified that creating a semantic knowledge network in NGSI-LD enables the construction of a DT data model, which in turn facilitates the integration of data related to building data, energy, and human behavior. As a result, the data flow enables bidirectional communication, facilitating the exchange of information between the building components and the DT platform for decision support services. Finally, in the work of Bayer and Pruckner (2023) it was found that the data flow is bidirectional in order to facilitate the feedback loops and real-time adjustments based on simulation results.

Persistence layer

The persistence and communication layer is a crucial component in any software architecture. Since DT is based on real-time streaming data and historical data, a data persistence layer is always expected in DT architectures for managing the storage and retrieval of data from databases, other storage systems, or external APIs. It ensures that data is saved consistently and can be accessed efficiently by various parts of the application. Key functions of the persistence layer should include:

- Data storage and database management system
- Data cleaning, preparation
- Transaction management
- Big data management
- Data type/structure: managing the saving of data to databases, whether relational (SQL) or non-relational (NoSQL).

These points could be considered a research gap as they were mentioned only in three article. In Malmedal (2023), data storage was mentioned to be carried out by MySQL. In Merino-Córdoba et al. (2023), several types of data storage were mentioned such as relational databases (e.g., MySQL, PostgreSQL, or Microsoft SQL), time-series databases (e.g., InfluxDB, Prometheus, and TimescaleDB), and NoSQL databases (e.g., MongoDB, Cassandra, and Apache HBase). While in Atalay and Angin (2020) dynamic knowledge database to store monitoring data and model the behavior of a cloudlet in the smart grid system was discussed as a way of data storage.

The persistence layer is often implemented using Object-Relational Mapping (ORM) tools like Hibernate for Java or Entity Framework for.NET (Ricci et al. 2022; Epiphaniou et al. 2023; Flammini 2021), which help in mapping application objects to database tables and vice versa, simplifying database interactions. However, in the reviewed articles in energy systems, the view of the authors was from a long shot and the authors do not mention the low-level technical detail.

Discussion

Integrated synthesis of findings

DT architectures in energy systems range from the simplest two-layer structure to highly detailed, even hyper-layer models. Each of these architectures has different benefits and challenges. Two-layer architectures have ease of implementation, but limited scalability. The three-layer architectures maintain a middle way on the level of complexity and manageability. While four-layer models allow detailed optimization with higher costs, and the hyper-layer architectures are tailored for very complex systems with large data requirements. Case studies examples of this are given by the Greenwich Smart City initiative and DTs for power systems, which demonstrate their applicability. However, data integration and interoperability remain critical challenges. The following subsections are going to discuss individually the comparison of different layers and their practical implementation followed by case studies examples. Furthermore, the integration challenges associated with each component will be also considered, particularly in the context of IoT and data layers, as well as the role of standardization and protocols in ensuring interoperability between different components.

As for the Case studies addressed in the reviewed articles, the Greenwich Smart City Initiative (EUROCITIES 2021) is very significant as its DT architecture was developed along with SEMS, simulation tools, machine learning algorithms, and decision systems for energy management. This case shows the practical application of DT in residential heating and electric vehicle charge-points and also offers a complete and detailed perspective.

DT for power systems is another case study that has been developed for the power flow analysis of cyber-physical power systems, featuring closed-loop feedback, data-driven mode, and real-time interaction. All of the above features are consistent with the State Grid Electric Internet of Things (SG-eIoT) (He et al. 2019a).

As for the so-called integration layer, it is found that it exists solely within the hyper-layer architecture, which emphasizes detailed architectures that consider the integration of technologies within a separate layer. In many architectural designs, actuators and sensors are indeed treated as integral components rather than being segregated into separate layers. This approach acknowledges their direct interaction with the environment and their crucial role in collecting data and effecting changes in the system. By incorporating them directly into the architecture, it facilitates a more cohesive understanding of how the system operates and how it interacts with its surroundings. Finally, the application or functional layer is mentioned in most of the architectures, except two-layer architectures. The reason these architectures are designed for DTs is that they are intended for monitoring, not controlling, the system.

Moving forward to a crucial point that treats the challenges introduced by the data integration layer, one of the key challenges is the Variability of data format and schema when several sources are involved, with different schemas and structures for JSON or XML payloads. To make them compatible and coherent, strong data transformation processes are needed. Quality and consistency of data is one of the major challenges to ensure that the accuracy, consistency, and reliability of data from these diverse sources are guaranteed. There might be several problems in the data, including duplication, missing values, or inconsistencies in format. Real-time processing is addressed because many applications require the real-time processing and analysis of data. Many applications also need high-performance data processing systems that process large data amounts very quickly and efficiently.

Finally, interoperability means that different components of an IoT system must interact with one another. To this purpose, standards provide common protocols and formats that enable such interoperability, allowing devices and systems to communicate more easily and exchange data. The technologies that are really contributing to standardize the communication among the different IoT devices and services include widely adopted protocols, such as MQTT for messaging or CoAP for constrained devices. These protocols define how much data is structured, transferred, and received; hence, the involved components always interact correctly. As for what concerns data formats, the adoption of JSON or XML enable uniformity in data representation and hence make integration of data from different sources or systems easier.

Practical implications

This section bridges the gap between theory and practice, showing the tangible benefits of the DT.

Industrial applications of DT

The application of DTs in SES is rather recent, as they represent a relatively new technological approach.

Figure 21 shows that DTs are used mostly for Energy Management purposes, Maintenance, and Smart Grid/micro grid (SG) management, while there is a notable absence of studies focusing on the edge-cloud continuum, which is most of the times just mentioned by researchers but almost never presented as a main case study, thus denoting another potential research gap.

Moreover, Fig. 22 shows that most of the studies cited in the reviewed articles are in the scope of Smart Grids and that, overall, different sectors and domains are addressed not homogeneously. A closer look on the scope of the studies leads us to identify important gaps inside each main scope too. For instance, in the energy Storage scope, only two

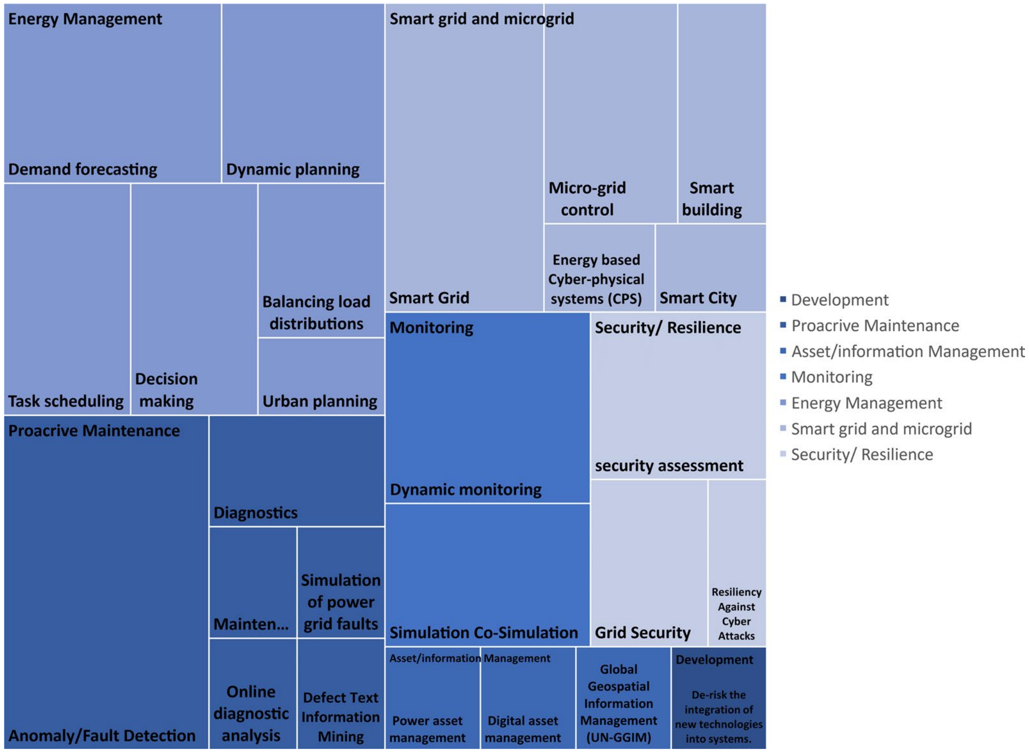

Fig. 21 Treemap of deployment domains for DT in SES by their category: anomaly/fault detection (in proactive maintenance systems) and demand forecasting (in energy management systems) are the most addressed in the reviewed papers

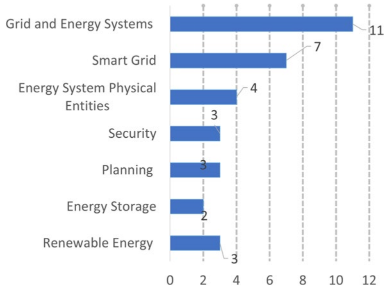

Fig. 22 Highly Cited DT Applications in Energy Systems. The vertical axis represents the most frequently cited applications, while the horizontal axis indicates the number of citations each application has received in the shortlisted articles

works investigated the application of DT for battery design, functioning management and control(Pileggi et al. 2019; Snijders et al. 2020). On the other hand, due to established laws on emissions, UN Agenda 2030, upraising focus on SDGs, socio-ecologic transition of energy infrastructures, etc., the environmental factors and climate action became a must. This imposed the energy planners to think about a socio-ecologic transition in energy production, transmission, and distribution, besides hybrid systems that provides the possibility of integrating small green energy producers to the main energy grid. However, Fig. 22 illustrates that the potential of DT to enhance the sustainability and resilience of the energy system is not studied well, which is another research line for future works. Only two researches studied the renewable and sustainable energy (Andryushkevich et al. 2019; Fokaides et al. 2020), while one article investigated multi-energy systems (Tang et al. 2020).

Nevertheless, several challenges were also identified, mainly in the implementation of DT technology for SES. More focused research has been done regarding some applications, such as the management of energy and smart grids, leaving aside the investigation of the potential use of DTs in other critical applications, such as optimal management of energy storage systems and insertion of renewable energy. Another noticeable gap is the underexploitation of Cloud Technology which, though mentioned, has not been central in the focus of the articles reviewed. Besides, more varied and detailed research is needed regarding the few types of physical entities of the energy systems, such as transformers and turbines. Filling these gaps would require: (a) future studies to explore the application of DT across a more extensive range of physical entities in the energy domain; (b) investigating further the integration of emerging technologies like 5 G/6 G for better communication; c) more emphasis to the environmental impact and the sustainability of energy systems.

Benefits for practitioners and adoption

In terms of benefits and drawbacks of the different architectures considered in "System architecture patterns identification" section, we start by considering the advantages of two-layer architectures. First, they allow reducing the overall complexity of the system is, hence easing its implementation. Computational costs may potentially be reduced. Both digital and physical twins are two-layered with regard to control, hence improving modularity and therefore manageability. As for the potential disadvantages, the scalability of the resulting platform is low due to the number of the layers; in addition, they could not support systems that have too much complexity and might need multiple layers for appropriate abstraction and separation of functionality.

As for the Three-layer architectures, their core benefit is the possibility to Retains a delicate balance between complexity and manageability. Moreover, the addition of a third layer (i.e., communication layer) for the flow of data, analysis, and decision-making is also helpful in the majority of cases. Furthermore, the architecture proposed by Saad et al. (2020) has a stronger middle layer with physical, cyber, and shadow twins to provide the system with more resilience and accuracy in control. The potential drawbacks of three-layer architectures are given by their increased complexity (i.e., more coordination between the layers is required) and by the fact that they can be more resource-demanding.

When four-layer architectures are considered, one of their key potential advantages is the possibility to have a More fine-grained, detailed separation of tasks in the system, as in the case of the architecture presented in (Pan et al. 2020). However, in terms of drawbacks, these architectures exhibit an Increased complexity, hence possibly higher costs of the implementation; more sophisticated integration and maintenance are also required.

Finally, hyper-layer architecture main advantage is to offer a Very detailed and customized approach for the specific system under consideration, as well as the possibility to enable extensive data management and integration into IT infrastructure; moreover, DT agents can be reused in different scenarios. The corresponding drawbacks are given by a considerable complexity, which also requires substantial resources for its development and operation.

Furthermore, regarding practical implications, two-layer architectures are frequently applied to simple Energy Systems or components where there is a need for minimum layers, such as power electronic converters, and basic monitoring of CPSS. Three-layer architectures applicability is more appropriate for medium complexity systems that require a balance between abstraction and practical implementation (e.g., by introducing a communication layer to manage data flow more effectively) in order to manage more properly IoT devices, data storage and data analytics functionalities (Atalay and Angin 2020), which represent the most widely investigated scenario of DT for SES. Four-layer architectures are more suitable for comprehensive system management and demand for a separation between the physical model and the informational model [e.g., the physical layer data integrated in the architecture proposed in (Pan et al. 2020)]. Finally, hyper-layer architectures are indicated for managing highly complex systems that require a high degree of customization, with extensive data management and integration with IT complex infrastructure, as it happens for large industrial energy systems.

Scalability and integration with smart grid

The relationship between logical architecture components and Smart Grid Integration requires a smooth exchange of information, collection, and analysis of data, and storage capabilities. This enables the real-time monitoring, optimization, and control of energy distribution. Nonetheless, the integration of smart PV systems into the fabric of smart city grids extends to the broader context of interconnected smart cities, forming a

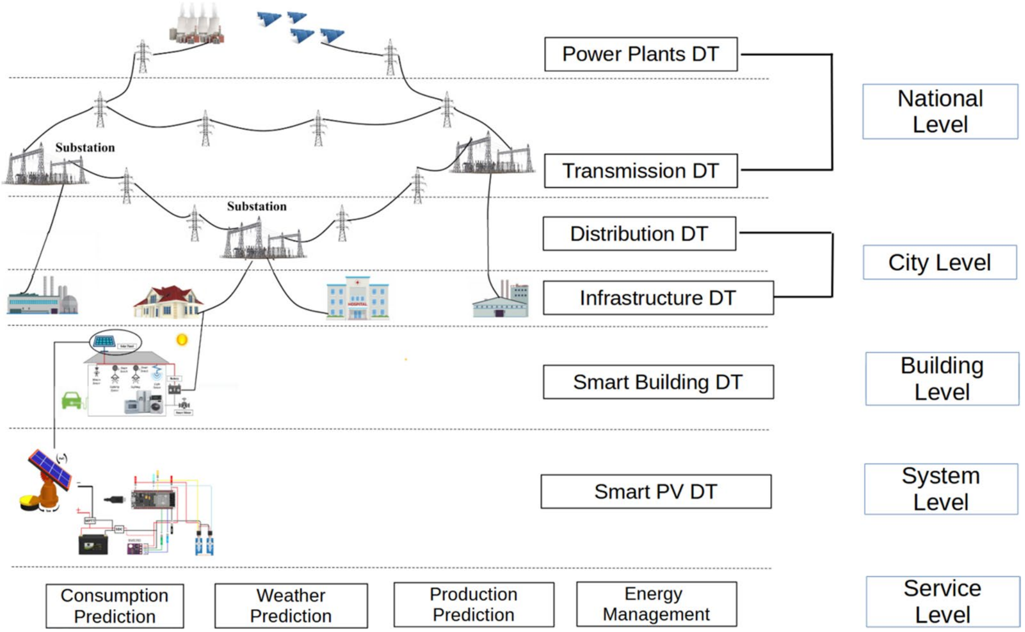

Fig. 23 A typical smart grid scenario seen as a hierarchy of sub-DTs and services

cohesive smart national grid (Lu et al. 2020). At this large scale, smart systems and their subsystems intricately interconnect the physical, social, and business dimensions. The synchronized deployment of Information and Communication Technology (ICT) infrastructure on both national and city levels also enables the extraction of intelligence from diverse datasets. Moreover, it facilitates the effective management of physical assets within energy systems at various scales.

Viewed as an integrated asset, a city encompasses diverse sub-DT, including buildings, utilities and transportation infrastructure. At the smart building level, a DT is conceived as a collection of integrated DTs, comprising both production and consumption assets. Delving further into the asset level, a DT encapsulates a spectrum of services. For instance, the DT of a smart PV panel seamlessly integrates various services. The hierarchical architecture presented in Fig. 23 illustrates the connectivity of these services at different levels, ranging from services to buildings, from cities to the entire national level. In this context of SES, the national level typically involves power plants and transmission networks, the smart city level incorporates solutions to optimize urban energy use, while the smart building level manages energy in individual buildings (as shown in Fig. 17) and the system level uses DT for specific components. Finally, the microservices level breaks down functionalities into independently deployable services, offering flexibility and scalability. A two-dimensional integration across these levels is crucial: horizontal integration connects systems within the same level, whereas vertical integration ensures compatibility and data exchange between levels, creating a cohesive and efficient smart energy ecosystem.

This intricate architecture comprises four key sub-services: (1) data acquisition from the dynamic environment and weather prediction, (2) production prediction based on weather forecasts, 3) consumption simulation and prediction, and (3) an energy management system.

Impact on business operations

According to the outcomes of our literature review, the impact of DT on Business Operations (BO) is not studied widely in the energy domain, as it has been most prominently observed in the area of digital transformation, as highlighted by Novikov and Sazonov (2019). DT facilitates this transformation by creating virtual replicas of physical assets, enabling businesses to simulate, analyze, and optimize their operations in real-time. This capability allows for more informed decision-making, enhanced process efficiency, and the ability to predict and mitigate potential issues before they occur, thus making DT a suitable and profitable solution to be considered.

In addition, the study by Lu et al. (2020) examines how SES and their subsystems intricately interconnect the physical, social, and business dimensions through the synchronized deployment of Information and Communication Technology (ICT) infrastructures at both national and city levels. In such a complex landscape, DT technology can significantly influence these systems by providing a real-time, integrated view of all the interconnected dimensions. Therefore, it can enhance the coordination and optimization of resources, improve the resilience of systems, and, from a wider perspective, support the sustainable development of smart cities.

Environmental and societal implications

The proposed case study, which dealt with the DT of a smart PV panel also represents a useful example of how the adoption of DT-based solutions can have positive implications at both the environmental and societal levels in the energy domain.

For instance, the application of the DT technology to PV panels can enhance significantly the sustainability and efficiency of the overall energy system, since the DT can integrate environmental data from diverse sources, including embedded Smart PV's air quality sensors as well as weather service web APIs. Consequently, the availability of heterogeneous data to be merged facilitates advanced analyses that can correlate real-time weather conditions, air quality metrics, and the PV panel's performance throughput (Aghazadeh Ardebili et al. 2023b).

Moreover, by incorporating sophisticated AI algorithms and accurate weather predictions, the DT can also enable optimized energy management, precise scheduling, and strategic planning within hybrid energy grids comprising both PV panels and wind turbines, thus eventually leading to a more sustainable energy infrastructure capable of adapting to dynamic environmental conditions and energy demands.

If considered from the same viewpoint, a DT can positively impact emissions and influence positively on the other environmental parameters (O'Dwyer et al. 2020; Hledik 2009; Pratt et al. 2010; Elkhorchani and Grayaa 2016), thus behaving also as a promising tool to enhance system resilience and sustainability at the same time(Saad et al. 2020).

General and computational challenges in implementing Digital Twins

One of the determining factors when dealing with DTs, independently from the specific domain they are going to be applied to, is the amount of potential challenges that their implementation can yield, in terms of overall complexity and computational demands.

The outcomes of our literature review showed that, on the one hand, most of the articles do not explicitly mention any specific challenges, while, on the other hand, they commonly refer to general types of challenges such as "complexity challenges", "security challenges", "sustainability challenges", "demand prediction challenges", and "future energy systems challenges". However, some articles also highlight particular challenges and suggest specific solutions or propose areas for future study.

In order to systematize the analysis of the specific challenges reported in the literature so far, they have been listed in Table 16, along with the proposed solution and the corresponding reference(s). Similarly, Table 17 categorizes the computational challenges connected to the implementation of DTs, by also providing a short description for each category and the corresponding reference(s).

In Table 16, we can see that several different types of general challenges have been identified in the literature, ranging from technical difficulties (such as data collection and integration, real-time communication, and scalability), to more conceptual challenges (like determining the optimal model detail and fostering human–machine interaction). The solutions proposed by the respective authors demonstrate a trend toward leveraging advanced technologies, including in-memory computing, hybrid modeling, and machine learning, as well as promoting collaborative approaches, and the use of Digital Twin frameworks. This highlights the importance of a multi-disciplinary approach

Table 16 General challenges identified in the reviewed articles and corresponding solutions proposed by the respective authors

No.	Challenge	Proposed solution	Refs.
1	Data movement issues in big data processing	In-memory computing in DT	Zhou et al. (2019)
2	Technical challenges in data collection, fusion, and processing for Energy Internet	N/A	Zhang et al. (2020a)
3	Management challenges in centralized data and integration across energy sources	Advanced DT models for data integration	Zhang et al. (2020a)
4	Handling complexity of interconnected energy systems	Integrated Energy Management Tool	O'Dwyer et al. (2020)
5	Real-time simulation challenges for power-electronics converters	Improved simulation frameworks for real-time analysis	Benigni et al. (2020)
6	Planning and management of modern energy demands amidst market changes	Collaborative solutions with automated and data-driven processes	Conway and Hainoun (2020)
7	Ensuring security of supply during a sustainable transition to renewables	Utilization of Industry 4.0 capabilities to enhance resilience	Scharl and Praktiknjo (2019)
8	Determining the optimal detail-level for DT power system models	Balanced models to manage complexity while retaining accuracy	Brosinsky et al. (2018)
9	Data management challenges in digitalization and big data	Deployment of DT and Big Data technologies	Rasheed et al. (2020)
10	Real-time communication in energy networks	Use of data compression techniques and 5G technology	Rasheed et al. (2020)
11	Real-time modeling challenges in complex systems	Hybrid and data-driven models, reduced-order modeling techniques	Rasheed et al. (2020)
12	Large-scale computational demands in DT systems	Edge, fog, and cloud computing architectures for enhanced scalability	Rasheed et al. (2020)
13	Interaction challenges between machines and users	Advanced interfaces using HMI, NLP, VR, and AR technologies	Rasheed et al. (2020)
14	Complexity in assembling Digital Twin components	Use of simple programming scripts in languages like Python and Matlab	Andryushkevich et al. (2019)
15	Information isolation issues in central heating systems	Frameworks based on open architecture for integrated services	Onile et al. (2021)
16	Social interaction challenges between human and machine systems	Social computing paradigms to foster human-machine collaboration	Onile et al. (2021)
17	Data collection and integration difficulties in energy systems	Consistent and coherent spatio-temporal data spaces	Merino-Córdoba et al. (2023)
18	Interoperability, connectivity, scalability, and other network challenges	Ongoing research and development in this area	Merino-Córdoba et al. (2023)

N/A the corresponding article does not propose or suggest any promising or sufficiently detailed future research line to address the challenge

in addressing the complexities associated with modern SES and DT. Moreover, the comprehensive overview in Table 16 allows stakeholders to focus on both the technical and management aspects to drive innovation and efficiency.

Similarly, the implementation of a DT presents a variety of computational challenges, as listed in Table 17, which span across multiple domains and stem from the inherently complex, high-fidelity models of SES, which necessitate of advanced computational methods and models.

Table 17 Computational challenges in Digital Twin implementation

Computational challenge	Description	References
Data Complexity and Integration	Managing large volumes of data from various sources and integrating them into a cohesive model	Redeker et al. (2022); Chakraborti (2024); Strasser et al. (2018); Tucker et al. (2018); Zhang et al. (2020a); Saad et al. (2020); Conway and Hainoun (2020); Zhou et al. (2020b); Scharl and Praktiknjo (2019); Rasheed et al. (2020); Atalay and Angin (2020); Tzanis et al. (2020); Xie et al. (2019); He et al. (2019b); Huang et al. (2021); Kertha Utama et al. (2024); Ambarita et al. (2023)
Reduced-Order Modeling (ROM) and Microservice Architecture	Simplifying large-scale dynamical systems while preserving essential dynamics	Jradi and Bjørnskov (2023); Bayer and Pruckner (2023); Peterson et al. (2024); Gourisetti et al. (2023)
High-Performance Computing (HPC)	Utilizing HPC for handling extensive simulations and computations	of Sciences (2023); Eklund et al. (2023)
Edge Computing	Distributing computational tasks to edge devices to reduce latency and improve efficiency	Strasser et al. (2018); Tucker et al. (2018); Zhou et al. (2019); Zhang et al. (2020a); Tang et al. (2020); Steindl et al. (2020); O'Dwyer et al. (2020); Saad et al. (2020); Scharl and Praktiknjo (2019); Rasheed et al. (2020); Atalay and Angin (2020); Merino-Córdoba et al. (2023); Haghshenas et al. (2023); Ma (2023); Cespedes-Cubides and Jradi (2024); Jradi and Bjørnskov (2023); Bayer and Pruckner (2023)
Parallel and Cloud Computing	Leveraging parallel processing and cloud resources for scalable and efficient computations	Armbrust et al. (2010); Marinescu (2013); Bayer and Pruckner (2023); Strasser et al. (2018); Tucker et al. (2018); Zhang et al. (2020a); Saad et al. (2020); Conway and Hainoun (2020); Zhou et al. (2020b); Scharl and Praktiknjo (2019); Rasheed et al. (2020); Atalay and Angin (2020); Tzanis et al. (2020); Xie et al. (2019); He et al. (2019b); Huang et al. (2021); Kertha Utama et al. (2024); Ambarita et al. (2023)
Multiscale Modeling Techniques	Bridging processes at different scales using advanced mathematical methods	Bayer and Pruckner (2023); Gunasegaram et al. (2021)
Virtual Populations	Creating synthetic data and virtual models	Aghazadeh Ardebili et al. (2023a); Antil (2024); Nivarthi (2022); Papyshev and Yarime (2021); Aghazadeh Ardebili et al. (2023c)
Metamodels in CPS and DTs	Developing data-driven approaches to reduce computational cost and complexity	Zhou et al. (2020a); Kertha Utama et al. (2024); Tzanis et al. (2020); Yang et al. (2018); Zhou et al. (2019); Onile et al. (2021); Steindl et al. (2020); Hu et al. (2020)

Since a DT should include complex knowledge models to integrate information from the physical world, one of its most characteristic features is the capability to represent and capture vast amounts of data from the physical world. Therefore, in order to process and manage large datasets there has to be a drastic development in IoT, AI, and simulation techniques (Chakraborti 2024). As a consequence, new modeling paradigms became crucial over the recent years in the design and development of sophisticated DTs allowing accurate predictions and real-time control.

One of the key computational challenges in this field has been in developing reduced-order models (ROMs) that focus on reducing the size of large complex systems. In the majority of dynamical systems, ROMs reduce dimensionality while conserving major dynamics and structure. One such approach has been found useful in process engineering where conventional methods are not very powerful in handling spatial and temporal complexities (Peterson et al. 2024). Probably, the most popular ROM technique is the reduced basis (RB) method, which consists of projection onto a subspace of relevant basis functions in order to drastically reduce high-fidelity problems and enable efficient approximation (Peterson et al. 2024).

Furthermore, the integration between high-performance computing and edge computing can help overcome DTs' computational load, especially when shifting from single entities to entire cities with several interacting components (of Sciences 2023). It is possible to put parallel computing and cloud computing resources to work, diminishing the problem of computations via algorithms that distribute computational tasks across many processors or servers (Eklund et al. 2023).

The generation of synthetic data, and their comparisons to real life data raise some of the most important computational and mathematical challenges (Antil 2024). This ranges from transport simulations over statistical correlations to machine learning models for outcome prediction. In view of this practice for CPS and DT, less resource-intensive approaches are demanded, such as data-driven metamodels, to meet such challenges (Parnianifard et al. 2022).

Finally, intrinsic methodologies for multiscale modeling (i.e., to link processes across different scales) are essential to the appropriate representation of systems within DTs. These approaches involve the use of sampling, projection, and homogenization

Table 18 Open RQs that remained unanswered (or answered partially) after this SLR and that are suitable for further investigation

Research goal	Unanswered research questions in the literature
O1: Enhance the understanding of DT in SES	• How does digital twinning contribute to enhancing the resilience, efficiency, and sustainability of SES?
O2: Identify and classify system architectures for DT in SES	• How do different architectural approaches address challenges such as scalability and interoperability? • What are the emerging trends and innovative approaches in system architectures for digital twinning in SES?
O3: Determine what challenges and gaps are faced in bringing DT into action	• What are the implications/applications of DT for energy policy, regulation, and decision-making? • What are the ethical, legal, and social implications of digital twinning in SES?
O4: Highlight what potential research directions currently exist for advancing the application of DT in SES	• What are the emerging technologies and methodologies that can enhance digital twinning in SES? • How can stakeholders collaborate to promote interdisciplinary research in digital twinning for SES? • How can interdisciplinary approaches and collaborations contribute to advancing knowledge and innovation in digital twinning for SES?

techniques that are important in transforming information at different scales (Gunasegaram et al. 2021).

Gaps and future studies

In order to streamline the implementation of the aforementioned DT architectures on a broader scale, various gaps, research lines, and challenges have been identified during the proposed SLR and the development of the DT alongside the construction of the test bed. The next two subsections delve into an in-depth exploration of these challenges, elucidating the intricacies encountered. Following this, the subsequent sections will elaborate further upon the forthcoming research directions, providing detailed insights into the prospective study lines aimed at effectively implementing the DT within the context of ES and SES.

Significant gaps

This SLR revealed significant gaps in the Body of Knowledge (BOD). For instance, unanswered RQs. These RQs represent gaps in current knowledge and hold considerable potential for future research endeavors in this domain. Table 18 summarizes these RQs, highlighting areas where existing literature falls short of providing conclusive answers.

An important research gap that remains unaddressed is the impact of DT on the resilience of SES. Although Fig. 5 shows that "security" and "resilience" are common keywords in the reviewed articles, the resilience of the system is neither quantified nor analyzed in-depth when DT are employed compared against a system without DT. This highlights a significant gap in understanding the influence of DT on the resilience of SES. Furthermore, there is no quantification of the improvement in efficiency or sustainability of the system [regarding the 17 Sustainable Development Goals (SDGs) of UN (Griggs et al. 2017)].

Another relevant gap in the current state of the art pertains to benchmarking and ranking scalability and interoperability within DT architectures. None of the reviewed articles have employed two or more architectures for the same asset to propose benchmarking methodologies or quantify thresholds and performance indicators. This absence underscores the need for future research to develop comprehensive benchmarking frameworks that can evaluate the scalability and interoperability of DT architectures effectively.

Also, there is a significant gap in the architecture of DT for higher levels of a SES in the grid. No article suggests an architecture for the DT of the system at the National Level or at the City Level (shown in Fig. 23). The majority of the architectures refers to system level and few architectures are for Building level (Fig. 17). In addition, there is a lack in standardization efforts across the reviewed articles. The only noticeable observation is the popularity of hyper-layer infrastructures. However, it is worth noting that simpler architectures may offer greater resilience, especially for less complex assets. This is because fewer building blocks and microservices translate to fewer components prone to disruption and fault. Thus, future research should explore the trade-offs between complexity and resilience in DT architectures to inform more effective design choices.

As for RQs referring to O3 (i.e., *determine what challenges and gaps are faced in bringing DT into action*), it seems that there is a significant gap in addressing the impact of energy policy, regulation, and decision-making of DT for SES.

Another gap was found regarding microservices as this solution was mentioned only four times in the reviewed articles. This can be considered a relevant issue as microservices are essential for optimizing energy consumption and enhancing the overall efficiency of energy systems. The lack of microservices can result in inefficiencies, inconsistencies, and potential conflicts in the energy market, ultimately affecting the overall performance and sustainability of the energy system (Araújo et al. 2024). More specifically, microservices were mentioned as follows. In (Ma 2023), the IoT system architecture incorporates a microservices architecture, similar to that of a network architecture. In Gourisetti et al. (2023), the article discusses the use of microservices for creating applications that are both modular and scalable in the digital realm. In Jradi and Bjørnskov (2023), authors have collaborated on creating a cutting-edge energy modeling framework in Python. This framework, based on ontology, is designed to be reusable and serves as a foundation for generating hybrid energy models. Nonetheless, in Bayer and Pruckner (2023) microservices are described as an effective approach to modularize the system architecture, enabling scalability and flexibility in managing various components of the Digital Twin.

During the SLR, it was also noted that a gap regarding the broker type is present. The lack of a broker type can impede the seamless integration of various sectors, such as electricity, heating, cooling, and transportation, which are vital for an optimally functioning energy system. A strong and inclusive framework is necessary to integrate these sectors, encompassing all essential components, such as brokers. The lack of a specific type of intermediary can result in inefficiencies, discrepancies, and possible disputes in the energy market, ultimately affecting the overall effectiveness and durability of the energy system as mentioned in Savvidis et al. (2019). Broker type was mentioned only one time in the contribution of Kummerow et al. (2020), which described the use of a

Table 19 Technical challenges in the multi-generation systems identified in the reviewed literature

References	Open challenge
Yang et al. (2018); Baboli et al. (2020); Pan et al. (2020); He et al. (2019b); Benigni et al. (2020); Zhou et al. (2019)	Operational complexities, uncertainties and the accuracy of digital mirror
Rasheed et al. (2020); Zhou et al. (2019)	Security risks
Yang et al. (2018); Zhou et al. (2020a); Atalay and Angin (2020)	Real-time response
Zhou et al. (2019)	Distance between Physical entities and control units
Yang et al. (2018); Zhou et al. (2020a)	Major reliable decisions must be made through complex simulations
Benigni et al. (2020)	Multidisciplinary systems integration
Brosinsky et al. (2018); Andryushkevich et al. (2019); Pan et al. (2020); Atalay and Angin (2020)	Data collection and management systems
Atalay and Angin (2020)	Communication between the entities

Table 20 Future research opportunities about DT in ES domain

Reference	Suggestions for future research
Pileggi et al. (2019)	DT capacity in control parameter estimation for system calibration applications
Kummerow et al. (2020), Pileggi et al. (2019)	Implement the DT effect on KPI's in real-life use-case
Strasser et al. (2018)	(1) The impact of DT on machine-to-machine communication. (2) Innovative implementation of DT in cybersecurity. (3) Big data analytics issues in DT
Massel and Massel (2020)	DT as a future Critical Entities (CE) of IT sector
Steindl et al. (2020)	(1) DT capacity as asset management support tool—Asset Administration Shell (AAS). (2) DT capacity as Service management support tool. (3) Further studies on Ontologies
Snijders et al. (2020)	Privacy-secure test of DT in real-life cases
Fokaides et al. (2020)	(1) Further study on digitization by design through DT.(2) Adoption of DT by decision makers
Zhou et al. (2020b)	DT for Artificial Inspection
Scharl and Praktiknjo (2019)	(1) DT and transparency in ES. (2) DT and system efficiency. (3) DT and demand flexibility
He et al. (2019b)	(1) DT and agile system reaction in disruptions
Tzanis et al. (2020)	(1) Realtime measurement, data processing, fault identification through DT. (2) Reduce computation time
Xie et al. (2019), Clausen et al. (2022)	(1) Solar and Wind energy production prediction. (2) Model depth and its impact on prediction errors
Huang et al. (2021)	(1) Further study on DT modeling. (2) Further study of DT applications in CPS. (3) Further studies on dynamic real-time interactions in DT model

message-broker system based on Apache Kafka to achieve optimal and resilient handling and examination of diverse data streams.

Finally, many of the reviewed articles either fail to address or only partially address some RQs (Table 18) like emerging technologies and methodologies, stakeholders collaboration and interdisciplinary research in digital twinning for SES. Since those RQs were designed through a pilot search (not limited to the Energy Systems domain), answering them would be an opportunity to significantly enhance digital twinning in SES.

Open challenges and future works

Although the implementation of DT technology is increasing, many challenges remain, particularly in the ES/SES domain. With the rising popularity of household energy production and smaller energy farms, multi-generation systems are expected to become a common feature of future energy grids. However, creating the coupling for these systems through DT and bringing data-driven solutions into action still presents technical difficulties (Suslov et al. 2019). The technical challenges identified in the literature are summarized in Table 19.

Overall, the implementation of DT of SES is still in the infancy stage and it is necessary to identify future needs. This section lists new research lines by pinpointing gaps specifically related to this domain. Numerous future study topics emerge from the limitations and suggestions in these works and Table 20 outlines potential and preferred studies to guide future research projects on DT oF SES.

As outlined in Table 20, our SLR identifies some key areas for future research in the following aspects. First, real-time data processing and the integration of edge computing with DT systems have been realized as serious challenges. Forthcoming research efforts should be focused on methodologies like real-time data streaming and edge-based analytics in an effort to enhance system responsiveness and decision-making. Second, in terms of scalability and benchmarking, future works should have benchmarking techniques that would measure the scalability and interoperability of different DT architectures: this will outline the quantitative metrics of performance indicators and thresholds for assessing system efficiency. Third, security and data integrity represent another crucial area that needs to be discussed in future research, for instance by considering the integration of blockchain technology into DT systems to raise the level of data security and integrity. From a practical point of view, it will therefore be interesting to understand and clarify how blockchain can be used for immutable data records and safe data exchange among components. Fourth, interdisciplinary approaches should be tackled with dedicated studies that integrate insights from the fields of computer science, CPSS management, and energy informatics in order to fill the current gaps in DT implementations.

Table 21 Acronyms

Acronym	Meaning	Acronym	Meaning
AAS	Asset Administration Shell	AI	Artificial Intelligence
ANN	Artificial Neural Network	AR	Augmented Reality
BOD	Body of Knowledge	BOCR	Analysis of Benefits, Opportunities, Costs, and Risks
CAD	Computer Aided Design	CE	Critical Entities
CI	Critical Infrastructures	CM	Condition Monitoring
CPSS	Cyber-Physical-Social Systems	CFD	Computational Fluid Dynamics
DNN	Deep Neural Network	DL	Deep Learning
DT	Digital Twin	DER	Distributed Energy Resource
DSS	Decision Support System	EIoT	Energy Internet of Things
EI	Energy Internet	Env.S	Environmental Systems
ES	Energy Systems	Inc./Ex.	Inclusion/Exclusion
ICT	Communication Technology	IoT	Internet of Things
LSTM	Long-Short Term Memory	MAIE	Multi-Agent Intelligent Environment
ML	Machine Learning	MQTT	Message Queuing Telemetry Transport
NLP	Natural Language Processing	NN	Neural Network
ORM	Object-Relational Mapping	PF	Power Flow
Ph.E	Physical Entity	PLM	Product Life-cycle Management
PSDT	Power Systems DT	RNN	Recurrent Neural Network
RQs	Research Questions	SA	Situation Awareness
SCADA	Supervisory Control and Data Acquisition	SDGs	Sustainable Development Goals
SEMS	Sustainable Energy Management System	SES	Smart Energy Systems
SGAM	Smart Grid Architecture Model	SG-eIoT	State Grid Electric Internet of Things
ShoT	Shadow of the Things	SLR	Systematic Literature Review
SQL	Structured Query Language	SWOT	Strengths, Weaknesses, Opportunities, and Threats
TCN	Temporal Convolutional Neural Network	VR	Virtual Reality
VT	Virtual Test		

Limitations

The fundamental limitation of this study is the lack of detailed technical features in the reviewed articles. Since the focus of all of the articles is on energy systems in general or a case study in the energy systems domain, many studies fail to provide comprehensive technical details (like communication protocols, ML algorithms, real-time data acquisition and cleaning, database management systems, data types and data structures, communication media, networking solutions, etc.), as their main emphasis is the application of DT in energy systems. Consequently, the identified gaps in this study may be addressed in articles that concentrate more on CPSS and computer science. These disciplines often delve deeper into the technical intricacies that are overlooked in energy system-focused research regardless of the domain of application of DT. Therefore, expanding the review to include literature from these fields might provide a more holistic understanding and fill the existing knowledge gaps. All the acronyms used in this article are listed in Table 21.

Considering two critical areas highlighted in our manuscript but not thoroughly addressed, we propose in this subsection a set of additional RQs related to real-time data processing and scalability within DT for SES, which could be adopted as guidance for further investigations in this field.

- Real-Time Data Processing: The proposed RQ is: *How can advanced data processing techniques be optimized for real-time analysis within DT systems in energy systems?* A pertinent example involves investigating the integration of edge computing technologies into DT frameworks to enhance real-time data processing capabilities. This research could focus on how edge-based processing reduces latency and improves data throughput, thereby facilitating more responsive and accurate decision-making in real time.
- Scalability: For this aspect, we propose the following RQ: *What are the primary factors influencing the scalability of DT architectures in large-scale energy systems?* An example inquiry could examine the scalability mechanisms of DT architectures utilizing containerization and microservices. This could involve analyzing the impact of container orchestration tools, such as Kubernetes, on the efficiency of scaling DT solutions under varying loads and across different geographical locations.

As for what concerns the research gaps to address in real-time data processing and scalability within DT research, we are aware that several pragmatic and technological challenges must be tackled. Some of these challenges are listed below.

- Real-Time Data Processing Challenges: The practical challenge in this domain is ensuring low latency in data transmission and processing, particularly in scenarios characterized by high data volumes and diverse data sources. The technological challenge primarily involves the integration of edge computing and real-time analytics platforms. This necessitates the development of sophisticated synchronization techniques and data fusion methods to effectively manage streams of hetero-

geneous data. Additionally, researchers must tackle issues related to the reliability and robustness of real-time systems operating within dynamic environments.
- Scalability Challenges: Scalability presents practical challenges, such as the need to scale DT solutions to accommodate increasing data volumes and computational loads without sacrificing performance or accuracy. The technical challenges associated with scalability include the complexities introduced by scalable architectures, such as those based on microservices and containerization. Researchers must address resource allocation and fault-tolerance issues while orchestrating distributed components within these architectures.

Finally, there are several technologies and methodologies that can offer promising opportunities for addressing the research gaps identified in our SLR.

- Edge Computing: In terms of relevance, edge computing significantly enhances real-time data processing by facilitating processing closer to the data source, thus reducing latency and bandwidth consumption. Future research could explore the integration of edge computing with DT systems to provide timely insights and control actions in energy systems.
- Containerization and Microservices: Containerization technologies, such as Docker, alongside orchestration platforms like Kubernetes, are crucial for developing scalable and flexible DT architectures. Research in this area could focus on how these technologies support efficient scaling of DT components and manage dynamic workloads in large energy systems.
- Blockchain Technology: Blockchain technology is relevant for enhancing data integrity and security within DT systems, addressing issues related to data handling and system resilience. Future research might investigate the integration of blockchain into DT architectures to create immutable records that enhance trustworthiness in data exchanged among system components.

By focusing on these areas, we can advance the understanding and application of DT systems in energy contexts, ultimately leading to more efficient and resilient energy infrastructures.

Conclusion

This study provides the results of an in-depth systematic literature review about DT for SES in terms of: categories of platform architectures proposed, logical architecture building blocks, microservices, enabling technologies, HMI, AI and ML implementation, data flow and data persistence, IoT components, and exploitation of edge-cloud computing paradigm. Finally, it systematically addresses the gaps, opportunities, future research directions, and challenges in implementing Digital Twins. The implications of DT for SES are numerous in this research. As for the most relevant points to the researchers, we aim at enabling them to develop more fine-grained and resilient models with DT using a the findings of our SLR as guidance about how to integrate various architectures, logical building blocks, and enabling technologies. The detailed categorization of microservices, AI/ML implementations, and data management strategies proposed in this study provides a methodological guideline for further empirical research. This could also pave the way for the creation of a methodological framework to help design experiments and simulations to validate the effectiveness and efficiency of different DT configurations. In addition, we identified important gaps and challenges to current DT implementations (e.g., system resilience, scalability, and benchmarking methodologies), hence providing a clear direction for future research.

While for Practitioners, some of the key findings we proposed are the following. First, implementation guidance is important because highlighting design patterns in a systematic way will aid practitioners in the easier implementation of DT for SES. These guidelines would also support an adequate management of scalability, flexibility, and efficiency of energy systems that will integrate advanced technologies such as IoT and edge-cloud computing. Optimization strategies are also crucial as they provide insights about microservices and containerization technologies to inform the deployment and management of DT systems to be more adaptive to dynamic workloads and diverse operational conditions. Better decision-making, by focusing on AI/ML and data flow management, can help improve the decision-making process by providing timely and accurate insights with respect to system control and optimization.

Finally, we aim at triggering further impacts on the advancing DT technologies in and for SES, such as the improvement of energy efficiency, as DTs allow monitoring and optimization of energy systems at a finer resolution thereby reducing energy consumption and operation costs, improving general goals of energy efficiency and sustainability. Increased resilience, as DTs make energy systems more resilient against disruptions by providing real-time insight and predictive capabilities, could reduce the likelihood of outages and improving system reliability. Environmental benefits, thanks to the optimization of energy systems by DTs, will likely limit the level of greenhouse gas emissions and integrate renewable sources of energy. This is in line with international goals of sustainability and helps in facing challenges related to climate change. Economic growth, thanks to the use of cutting-edge DT technologies will open up innovation opportunities within the energy sector and thus in job creation and economic development.

Overall, this research on DT in SES can have a relevant impact on both theory and practice, as it highlighted important gaps in the literature and came up with specific research questions to explore this scenario better, to engage scientists in testing new ideas, and to motivate practitioners and also policymakers to think up more adequate ways to solve typical problems in the energy domain. Moreover, by showing how interconnected DT and SES are, this study pointed out the importance of activating fruitful collaborations between experts from different fields. Nonetheless, it has been recognized in this work that energy systems, due to their inherent complexity, need considerable amount of input data from many areas and multiple heterogeneous sources in order to create well-rounded solutions, thus casting the need for efficient big data management solutions to support DTs. Furthermore, relevant implications for ethics, law, and society have been also discussed, with also a focus on the need for enabling responsible innovation and fair access to DT technologies. Finally, this work paves the way for future studies on the definition of specific metrics to quantify how DT implementations achieve improvements in energy efficiency and system resilience, for instance by promoting standardized benchmarking methodologies.

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Author contributions
A.A.A. actively contributed throughout all stages of the research, providing substantial input in the conceptualization, methodology, screening, data extraction, analysis, validation and writing; M.Z. actively contributed throughout methodology, validation, proofreading, and writing; A.I.H.A.R.contributed to the data extraction and proofreading; A.L. and A.F. contributed equally to supervision and project administration.

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