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Review article

Digital twin technology and artificial intelligence in energy transition: A comprehensive systematic review of applications

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ABSTRACT

The transition to reliable, affordable, and sustainable energy is a continuing global challenge still shaped by the goals of carbon neutrality and mitigation of environmental impact. Achieving this transition will require a high degree of management skill, underpinned by advanced digital technologies, and new practice approaches. The use of Digital Twin (DT) technology, combined with Artificial Intelligence (AI) revolutionizing the management, maintenance, and real-time monitoring of renewable energy systems. This systematic literature review follows the PRISMA methodology to analyze 42 high-impact studies, providing a comprehensive synthesis of DT applications in the energy sector. The results reveal that AI-powered DT models enhance predictive maintenance efficiency leading to a 35 % reduction in unplanned downtime an 8.5 % increase in energy production, 98.3 % accuracy in fault detection and a 26.2 % reduction in energy costs. However several challenges remain, including high implementation costs, cybersecurity risks, and the complexity of integration. This study provides a clear perspective on this technology its applications, and the solutions it offers. It highlights existing challenges and future directions for leveraging digital techniques to accelerate the transition towards intelligent and sustainable energy systems.

1. Introduction

In the last century, humanity has seen rapid economic growth with an engrossing amount of swallowed energy and raw materials. This classical development model, depending heavily on conventional energy sources such as coal, oil, and gas, dredges up irreparable damage to land and human health. While effective in supporting the early industrialization, this approach has shown to be long-term unsustainable; pollution in this way has soared, and ecosystems have taken to degrading (Starkey et al., 2022; Li et al., 2023a). Such problems have engaged the world into rethinking energy development toward sustainability, a shift which has been hastened by geopolitical tensions such as that of the Russo-Ukrainian conflict, defeating global supply chains and calling for the urgency of energy transition (Li et al., 2023a). Fig. 1 illustrates the worldwide distribution of greenhouse gas emissions by country, with the major contributors being China, the USA, and India. Such emissions signal an urgent need for the countries to transition to renewable energy solutions in curbing the environmental menace. Across the world, the transition to renewable energy sources has become a central topic of international debate, driven by increasing awareness of climate change and its consequences (Starkey et al., 2022).

Change Performance Index (CCPI), an independent tool monitoring climate mitigation efforts across 63 countries and the EU, exemplifies this urgency. Established in 2005, the CCPI fosters public and political debate on climate policies, promoting transparency and comparative analysis of countries' efforts in reducing greenhouse gas emissions (Climate Change Performance Index, 2024).

Governments and international organizations continue to address the ever-growing energy demand fueled by demographic expansion, economic growth, and changing behaviors of consumers. This demand,

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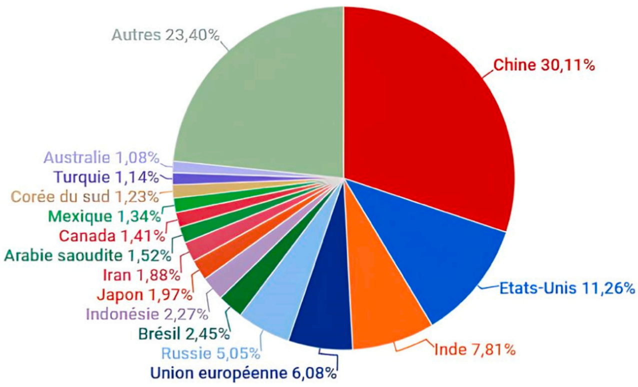

Fig. 1. Global greenhouse gas emissions by country in 2023 (million tonnes CO2 equivalent, MtCO2e).
Source: (R. T. l'Europe, 2024).

which is expected to grow by some 40 % between 2006 and 2030, showcases the need for sustainable solutions (Starkey et al., 2022; Rapport annuel mondial sur l'énergie, 2024). Oftentimes, consumption increases will lead to environmental impact issues; therefore, it makes it obvious that there must be something done for both green energy and efficient resource management.

That fact, together with public dissatisfaction in response to the rising consumption, has pushed quite a number of industries in many countries to invite the development of renewable-energy solutions. Industries in many countries consume over 27 % of total energy production and have been often blameworthy for the public during energy shortages (International Energy Outlook, 2024). The importance of optimizing energy use has become crucial among measures including demand-capping, cooperative planning (Khattabi and Amrane, 2022; Tao et al., 2019). Renewable energy powers in their various channels, instead, have become of great interest. Indeed, in 2023, neither solar nor wind energy delivered any less than 473 GW of the world's total renewable energy-capacity increase, supplying 73 % and 24 % of it, respectively (Climate Change Performance Index, 2024; Rapport annuel mondial sur l'énergie, 23, 2024). Under present-day momentum, the International Energy Agency (IEA) projects that up to one-third of current total renewable energy capacity could be virtually tripled by 2030, thus offering a significant step forward in addressing climate challenges ('Rapport annuel mondial sur l'énergie, 23, 2024).

The energy transition encompasses extensive structural transformations of the systems of energy generation, transmission, consumption, and distribution-hence its minimal impact on the environment. While numerous reviews have explored the potential of DT technology across various sectors, this article focuses exclusively on their application within the energy domain. By addressing the integration of AI with DT technologies, this review offers a unique perspective tailored to the specific challenges and opportunities in energy systems. This includes managing the intermittency of renewable energy, optimizing resource utilization. By narrowing the scope to energy applications, this review aims to provide a focused analysis and actionable insights for researchers and practitioners in this field.

This transformation will require governments, citizens, and economic actors to be innovative and to engage in the politically tricky work of switching (Bayer and Pruckner, 2023). The situation with climate change has shown that Morocco is vulnerable to it, and this prompted the establishment of a National Committee on Climate Change in 1996, shortly after its ratification of the United Nations Framework Convention on Climate Change in 1995.The adoption of the first greenhouse gas response plan took place in 2009. Energy generation in the mix here is projected to reach 52 % clean energy only by 2030, thus showing the adoption of energy transformation by the country (Khattabi and Amrane, 2022).

In industry 4.0, one of the key technologies helping to spark this transition is the DT-a digital replica of physical assets or systems for real-time performance improvement insights. A largely nascent technology applied mostly to date in the domain of large- scale solar energy systems affords its application in proactive and predictive asset management (Yuan and Xie, 2023). Growth in worldwide interest in terms of the scientific output on digital twins is reflected in geographic distribution.

This technological advancement is eliciting increasing worldwide interest, as evidenced by the geographical distribution of scientific output on digital twins in the energy sector. Fig. 2 illustrates these research efforts by country.

This map shows that a certain number of countries have made substantial contributions to research on digital twins applied to the energy sector. Representing a global drive to promote energy transitions within that framework of new technologies.

Digital twins combined with artificial intelligence pave the way to smart energy systems. AI-based applications, especially in machine learning and deep learning, leverage data from power generation systems to predict faults, optimize energy utilization, and support better decision-making (Khan et al., 2019; A survey on artificial intelligence assurance, 2024). Together, these technologies address critical challenges such as intermittency in renewable energy and the ability to integrate it efficiently into the grids. For instance, the Digital Twin can simulate solar or wind energy production based on weather forecasts made by AI models, which aids in improved utilization or planning of other resources (The Future of Industrial Communication, 2024). These technologies, however, still face barriers such as the security of information and data, high costs of implementation, and interoperability across platforms within the energy industry (A survey on artificial intelligence assurance, 2024).

Adding to operational improvements, digital twins enable simulation of new concepts and analyses of the impact of strategic decisions, as well as the promotion of sustainable solutions, actually being pivotal enablers of the energy transition by fast-tracking the commissioning of renewable energy and optimization of resource use via algorithm-and technology-enhanced feedback (Li et al., 2023a; Wang and Liu, 2024; Artetxe et al., 2023).

Although Digital Twin (DT) technology has been widely explored across various sectors, and despite its potential in the energy domain, which facilitates management, it still presents specific challenges that require particular attention. These consist of high implementation costs giving rise to considerable hardware, software, and expertise investments (Sehrawat et al., 2023), complexity of integration with existing infrastructures, cybersecurity and data protection risks (Heluany and Gkioulos, 2023), and lack of universal standards for ensuring DT solutions interoperability and scalability.

In order to gain insight into these challenges, this review will look at the various approaches taken in what the literature discussed regarding applying digital twins in the energy sector, examining solutions and the limitations of these solutions. Additionally, the review will highlight and encourage discussion of the principal methodologies devised for predictive maintenance and energy management via AI, and will note the technological, regulatory, and economic barriers that exist to limit full-scale adoption.

This study seeks to address the following key research questions:

1. How do DT technologies combined with AI transform energy systems?
2. What are the development methods for this technology?
3. What are the limitations and barriers to its large-scale adoption?
4. Which artificial intelligence algorithms are applied, and for what purpose?

The distinctive nature of this study stems from its systematic approach, derived from a thorough assessment of 42 high-impact scientific studies providing a holistic evaluation of applications,

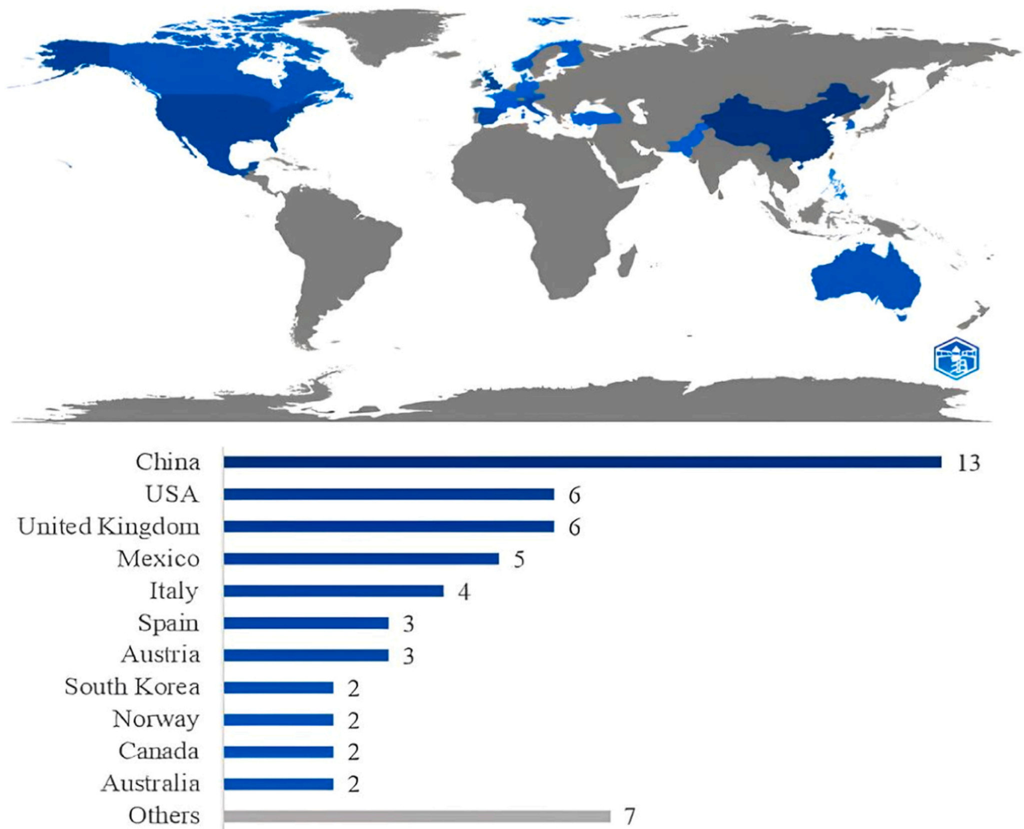

Fig. 2. Country scientific production considering the use of DTs in the Energy industry (do Amaral et al., 2023).

challenges, and future prospects. Unlike previous reviews that focus on specific technical aspects, this work offers a global perspective, shedding light on cross-cutting issues related to DT integration in the energy sector and outlining key research directions for the future.

The results of this SLR will help identify existing gaps in the current literature and guide future research into technology development environments. In addition, this article can help practitioners to make informed decisions about the methods and tools best suited to their technology development projects in the energy framework, based on the specific characteristics of their problems, leading to improved performance and cost savings.

This paper is organized into several sections. Section 2 explains the theoretical framework, including introducing artificial intelligence in the energy sector, digital twins, and human-machine interaction of the digital twin. Section 3 describes the methodology used for the systematic literature review. Section 4 then analyzes and discusses the collected results, which involve analyzing the categories of articles studied, the methods for developing digital twins, the most frequently used algorithms, and the significant challenges facing the implementation of AI and digital twins in the energy sector. Lastly, Section 5 discusses future perspectives, and Section 6 concludes the research by summarizing the important findings and implications of this research.

2. Theoretical background

2.1. Artificial intelligence in the energy sector

The integration of artificial intelligence into the energy sector is revolutionizing the approach to energy management, efficiency, and sustainability. AI technologies are being utilized to optimize the performance of energy supply, distribution, and consumption, resulting in significant improvements in operational efficiency and a positive impact on the natural environment. The key applications and benefits of AI in the energy sector include, among others, its role in energy management, such as:

- **Demand forecasting:** AI algorithms analyze historical data to make predictions of energy production and consumption patterns, optimally allocating resources and reducing overproduction (Kuzmenko et al., 2024).
- **Smart grids:** AI contributes to the reliability of the grid through optimizing energy distribution and the integration of renewable sources, thus enhancing system stability (Zakizadeh and Zand, 2024).
- **Battery management:** AI optimizes charging and battery performance in electric vehicles and energy storage systems which further enhances sustainability (Mittal et al., 2024).

- **Environmental monitoring:** AI applications allow for real-time responses to environmental effect assessments, increasing both compliance and safety measures taken (Hussain et al., 2024).
- **Predictive maintenance:** AI models, including deep learning techniques, are being used to predict equipment failure with great precision, leading to a 35 % decrease in unplanned downtime and an increase in energy production by about 8.5 % in renewable energy systems (AI-driven predictive maintenance and optimization, 2024). Moreover, it cuts down on maintenance costs greatly, extends the life of critical energy assets, and, above all, allows deep learning models to reach F1 scores higher than 90 % in predictive accuracy (AI-Driven Predictive Maintenance, 2024). By identifying patterns which indicate likely areas of faults, AI scans sundry data, thereby reducing downtime and enhancing the reliability of solar energy systems (Onimisi Dawodu et al., 2024).
- **Optimizing energy production:** The self-learning algorithms, besides predicting energy generation patterns and adapting to environmental changes, boost the competitiveness of renewable sources

against conventional energy sources (Onimisi Dawodu et al., 2024). Integration of AI-powered PV systems with energy storage can lead to an increase in overall efficiency up to 28 %, while the control strategies based on AI greatly reduce the duration and frequency of power outages ('AI-Based Analysis and Prediction of Synergistic Development Trends in U.S, 2024).

2.1.1. Specific AI algorithms used

AI algorithms are significant in the energy sector, particularly in forecasting energy, managing systems, and conducting predictive maintenance. LSTM models, in particular, have been used in forecasting electrical imbalances and electrical energy generation because they are able to process time-series based data and remember long-term dependencies, offering greater forecast accuracy of energy imbalance in the markets (Bârã and Oprea, 2024).

Random Forest models are used in forecasting energy production in microgrids, offering a good balance between computational efficiency and forecasting accuracy. They are also part of hybrid models for solar energy forecasting, contributing to data normalization and outlier elimination (Simankov et al., 2024). In parallel, Support Vector Regression (SVR) is applied to solar energy forecasting, leveraging its ability to model nonlinear relationships in data (Natgunanathan et al., 2023).

Artificial Neural Networks (ANN) are superior in modeling and predicting weather data, solar irradiation and energy usage. ANN is also capable of fault detection and diagnosis for photovoltaic systems, thus enhancing the reliability of the system (Simankov et al., 2024). Additionally, Convolutional Neural Networks (CNN), often combined with LSTM, are used to predict solar energy by extracting both spatial and temporal features from the data, making them particularly effective for managing the stochastic nature of wind energy.

Finally, AI models such as Autoencoder LSTM and Isolation Forest are used for anomaly detection, ensuring reliable operation and efficient maintenance of photovoltaic systems (Idrissi Kaitouni et al., 2024)

To summarize, the application of AI algorithms within the energy sector not only enhances the accuracy of energy forecasts but also enhances the operation/reliability of renewable energy infrastructures while introducing predictive maintenance through innovative concepts such as digital twins.

2.1.2. Performance evaluation of AI solutions in energy systems

Evaluating artificial intelligence (AI) solutions in energy systems plays an important role in optimizing their performance and becomes critical for the sustainable management of energy. The evaluation of AI solutions relies on a number of performance indicators such as accuracy, response time, scale and reliability. The accuracy of an AI model is evaluated using metrics, like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), that quantify how far the predictions made by a model differ from actual values. The accuracy of a model can also be assessed by using the coefficient of determination (R^2) to assess the extent to which the observations match the predicitons made through the AI model (Sehrawat et al., 2023; AI-Driven Predictive Maintenance, 2024; Onimisi Dawodu et al., 2024).

In smart grid real-time management, response time is crucial. AI allows for quick assessment of sensor data and optimizes the dynamic balancing of power grids through coordinating renewable energy production in accordance with real time demand (Machine Learning Algorithms). Commercially, the scalability of AI is important for Detributed Energy Resources (DER) integration, leading to greater flexibility and oversight of decentralized automation of energy production (Sehrawat et al., 2023; Machine Learning Algorithms; Cao et al., 2023a). AI-driven optimization improves the energy infrastructures adaptability to increasing demands and efficiency.

Ultimately, the strength of AI solutions is bolstered by the introduction of innovative predictive maintenance approaches which forecast failures to minimize service interruption in energy systems. Additionally, fault detection and diagnosis systems provide preemptive monitoring which improves the reliability of energy assets against disruption.

Fig. 3 Illustrates these key performance indicators and their role in evaluating AI applications in energy systems. It provides a visual representation of how accuracy, response time, scalability, and reliability contribute to optimizing energy management through AI-driven solutions.

In summary, the use of performance indicators will provide a methodical assessment of AI solutions in the energy sector to ensure greater efficiency and optimized use of resources with reduced environmental impacts. Future research could be directed towards the design of frameworks that support even greater assessment capability, considering additional performance indicators to enhance the sustainability and reliability of AI solutions in energy systems.

2.1.3. Economic analysis of AI integration in the energy sector

The application of artificial intelligence (AI) in the energy sector represents a major shift that could have significant repercussions on the economy. It raises critical questions regarding cost-benefit analyses, investment returns, and the long-term financial viability of implementing AI technologies in energy systems.

- **Cost-benefit analysis:** AI greatly contributes to increasing energy efficiency by improving the efficiency of production, transmission and use, by lowering operational costs and improving operational performance (Sehrawat et al., 2023; Bârã and Oprea, 2024). AI-predictive maintenance reduces both downtime and costs of maintenance by accurately predicting failures of equipment, and responding proactively with timing of required maintenance (Bârã and Oprea, 2024; Natgunanathan et al., 2023).

  From a market perspective, AI provides forecasting electricity prices to inform decisions by energy market participants that translate into cost savings and improved market positioning. Additionally, AI can aid in reducing imbalances and trading risks, improving overall stability and predictability of market operations (AI-driven predictive maintenance and optimization, 2024; Onimisi Dawodu et al., 2024).
- **Return on investment:** Investing in AI technologies such as digital twins and blockchain may represent a large initial purchase. However, the benefits these technologies provide through performance improvements and mitigating energy waste are substantial (Mittal et al., 2024; Bârã and Oprea, 2024). AI-based solutions in energy systems will improve the accuracy and efficiency of those energy systems, and therefore provide a stronger return on investment over time (AI-driven predictive maintenance and optimization, 2024).

  In addition, AI's applications will support the integration of renewable energy sources (RES), which are vital for sustainable development and long-term economic (Simankov et al., 2024). The ability of AI to facilitate the optimization of investments and to identify the best investments in renewable energy sources and renewable energy storage also supports the economic viability of energy projects (Mittal et al., 2024; Onimisi Dawodu et al., 2024).
- **Long-term financial viability:** AI contributes to the evolution of smarter and more responsive power systems, which are critical in balancing energy demand as it continues to grow around the world, while maintaining long-term economic viability (Bârã and Oprea, 2024). Furthermore, the application of AI to energy systems contributes to a transition to cleaner energy sometimes known as energy transitions—an increasing regulatory demand or clause guaranteed to help maintain long-term efficiency and economic stability for the future (Sehrawat et al., 2023; Bârã and Oprea, 2024; Simankov et al., 2024).

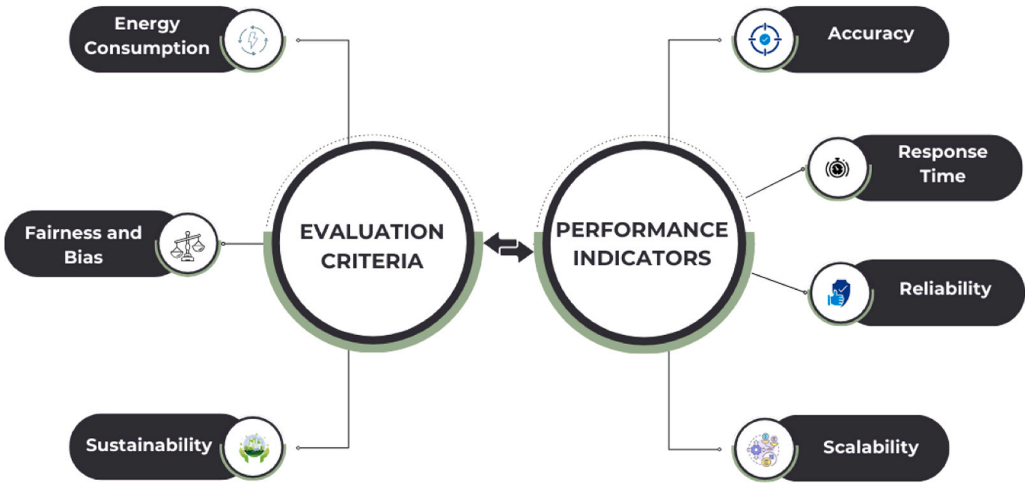

Fig. 3. Performance evaluation of AI solutions in energy systems: criteria and indicators.

2.2. Digital twins in the energy sector

Digital twin technology relates to the establishment of a virtual representation of a system, object, or physical process that is present in reality-so as to enable real-time monitoring, simulation and optimization Fig. 4. The integration of various advanced technologies into this system includes the Internet of Things (IoT), AI, machine learning, cloud computing, and edge computing, allowing them to collect and test data from the physical equivalent and thus provide insights for more strategic decision making and optimization of performance (Ferrigno, 2023; Digital Twins-Enabling Technologies Including, 2023; 'Digital Twin Understanding, 2023). Digital twins are dynamic and continuously updated with real-time data, enabling different scenarios to be simulated and predictive analyses to be carried out, which can be particularly useful in sectors such as industry, healthcare, automotive, energy and smart cities (Ferrigno, 2023; Jihyun Oh, 2023). The concept goes beyond simple data collection to include the interaction between people, processes and technologies to produce ideal results, as illustrated by Digital Twin of a Digital World (DTDW) framework, which integrates process Manning, experience mining, data mining and simulation for business process optimization (Sarnikar, 2023). In vehicle networks, digital twins facilitate task offloading and resource allocation by creating a state-of-the-art mirrored IT system, improving road safety and transport efficiency (Babbar, 2023). In addition, digital twins play a crucial role in the early stages of design by providing hybrid prototypes that combine digital and physical models, helping architects and designers to predict future design outcomes (Architectural hybrid physical-digital, 2023). Overall, digital twin technology represents a significant advance in the seamless integration of physical and virtual systems, stimulating innovation and efficiency in a variety of sectors (Exploration on the Application of Digital Twin Technology, 2023).

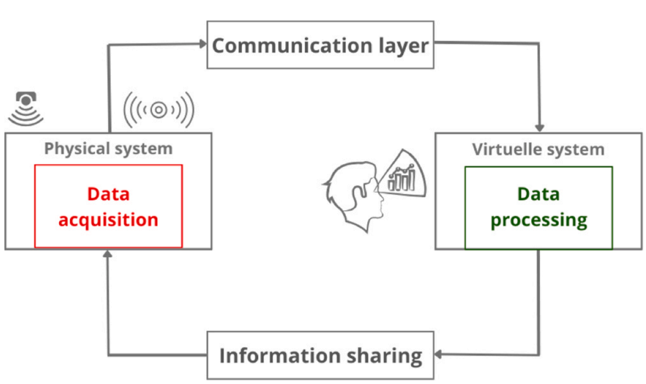

Fig. 4. Architecture of digital twin technology.

In the energy sector refer to the creation of a virtual replica of systems, processes or physical assets, enabling real-time monitoring, data analysis and simulation to optimize performance and decision-making. These technologies integrate various information technologies such as IoT, AI and machine learning to create a bi-directional data flow between physical and digital entities, enabling continuous updates and improvements (Ferrigno, 2023; Gupta Gourisetti et al., 2023; Cali et al., 2023). Digital twins can simulate the real world in cyberspace, including the virtualization of components, operations and system interactions, improving the efficiency, sustainability and reliability of energy systems (Cali et al., 2023; Schneider, 2023). They are particularly useful for managing energy consumption, optimizing operational processes and supporting green design initiatives aimed at reducing energy consumption and greenhouse gas emissions (Schneider, 2023). In the energy sector, digital twins have been applied to various fields such as power grid construction, power plant structure and electrical equipment management, providing detailed information for better asset management and operational efficiency (Fu et al., 2022). They also play a crucial role in renewable energy systems, improving real-time energy management and guaranteeing the stable operation of power grids (Chalal et al., 2023; Shen et al., 2022). Despite their potential, the practical deployment of digital twins in the energy sector faces challenges such as cost, regulatory compliance and the need for scalable, interoperable frameworks (Gupta Gourisetti et al., 2023). However, their ability to provide real-time data, simulate new assets and optimize existing ones makes them a transformative technology in the energy sector, capable of reducing downtime, extending asset life and improving overall system efficiency (Ahmad Shatiry et al., 2022; Stulov et al., 2023; Evtushenko and Isaev, 2023).

Fig. 5 illustrates the use of DT in various applications, demonstrating that DT play a crucial role throughout the lifecycle of solar systems, from design to management and innovation. In the design phase, they enable precise modeling of solar systems by integrating parameters such as panel orientation, tilt, and local climatic conditions. These models allow for the simulation and comparison of various configurations to optimize energy production while minimizing losses. Additionally, they facilitate economic assessments by predicting construction costs, return on investment, and environmental impacts, such as emissions avoided through installation (Jones et al., 2020). During the installation phase, digital twins provide detailed virtual planning by simulating real-world scenarios, including terrain conditions, physical constraints, and equipment failure risks. This helps identify and address potential issues, such as sizing errors or component incompatibilities, in advance.

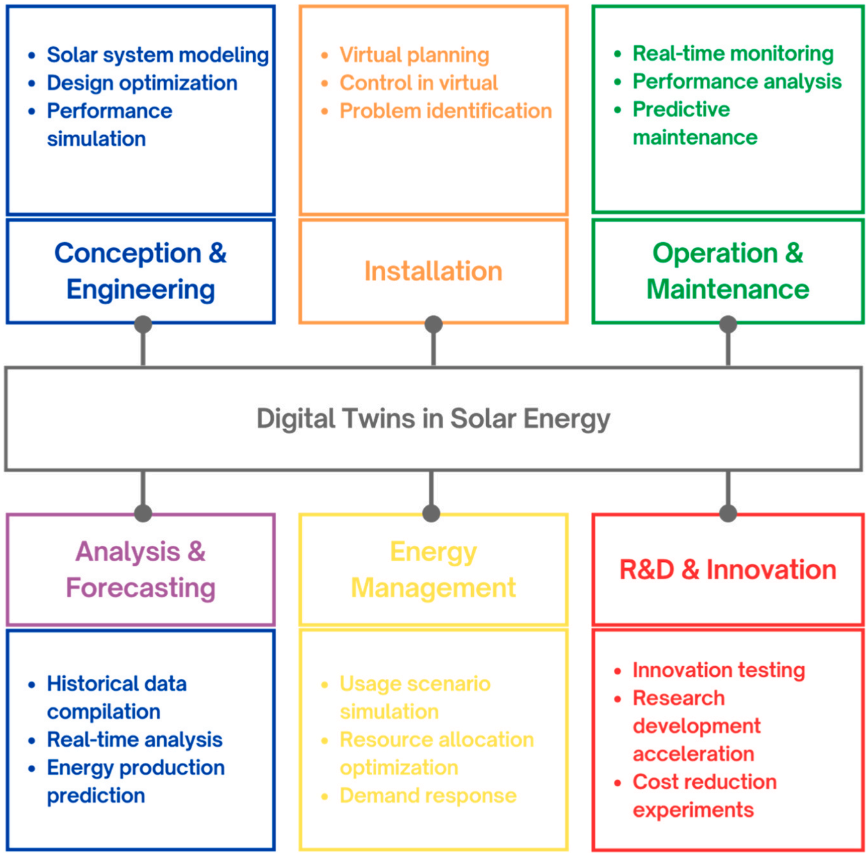

Fig. 5. Applications of digital twin technology in the energy sector.

Furthermore, these tools optimize logistical routes and installation schedules, thereby reducing costs associated with delays or human errors (Semeraro et al., 2021).

Once the systems are operational, digital twins enable real-time monitoring through connected sensors that collect data on temperature, energy output, component wear, and dust accumulation on panels. This information is analyzed to quickly detect anomalies, enabling predictive maintenance. Such an approach extends equipment lifespan while reducing costs associated with unplanned interventions (The Role of Digital Twins in Energy Transition, 2024). At the same time, their analytical capabilities support accurate energy production forecasts by integrating historical and real-time data, including weather predictions. These insights help to adjust energy management strategies to ensure grid stability (Jones et al., 2020).

Digital twins also play a key role in energy management by simulating various usage scenarios to optimize resource allocation. For instance, they enable efficient responses to periods of high energy demand without disrupting grid balance. They also identify areas of overproduction or underutilization, allowing managers to adjust supply strategies and minimize losses (Singh et al., 2021). Finally, in research and development, digital twins accelerate innovation by enabling the testing of concepts and prototypes in a virtual environment before physical implementation. For example, automated panel-cleaning technologies can be simulated and optimized to maximize efficiency, significantly reducing development costs and timelines while validating technological assumptions with high precision (The Role of Digital Twins in Energy Transition, 2024).

2.3. Human-machine interaction in AI-powered energy systems

The relationship between humans and machines is key to the progression of intelligent energy systems, especially with the inclusion of artificial intelligence (AI) and digitization. This relationship affects decision-making directly, the performance of intelligent energy systems, and the utilization of advanced technologies such as digital twins and cyber-physical systems. AI enables more effective grid stability and supports political and economic decisions by performing complex tasks such as electricity price forecasting and optimizing energy consumption strategies (Bârã and Oprea, 2024; The Role of Digital Twins in Energy Transition, 2024). Digital twins allows for sophisticated simulation of energy systems, allowing simulations to be assessed prior to implementation in the real world, and supporting long-term control and monitoring (do Amaral et al., 2023). Furthermore, the set of all digitizing changes to energy systems lead to a more coordinated decision-making process, using principles of multi-agent platforms, while also supporting the use of integrated optimization algorithms that allow for advanced energy management strategies (Digital technologies for netzero energy).

The incorporation of emerging technologies, in particular cyber-physical systems, remains a major task as the link between the digital artifacts – the sensor, the app, and the computing system – and the physical aspects is incomplete, thus preventing the full attainment of the potential of digital (Digital technologies for netzero energy; Jones et al., 2020; Semeraro et al., 2021). The advancement of this human-machine interaction is paramount to enhancing the efficiency, sustainability and resilience of contemporary energy systems, and ushering the optimized and intelligent energy transition forward.

2.4. Related reviews

A more recent literature review on the application of digital twins (DT) in the solar energy field has demonstrated various methodological approaches, application contexts, and challenges. Boolean searching, with the parameters "Digital Twin", "Energy", and "Review", yielded not less than 14 articles for an in-depth analysis Table 1. Digital twins are capable of supporting optimized complex processes under Industry 4.0, improving operational effectiveness in the reduction of energy costs by predictive maintenance (Angelova et al., 2024). The computing model allows simulation of various scenarios to eliminate potential failures and stabilize the grid (Ismail et al., 2024). However, even if they are chiefly deployed in built infrastructures, the benefits they confer on the improvement of energy efficiency and the reduction of emissions are faced with similar challenges encountered in solar power systems. Furthermore, other barriers like capital costs and security risks such as data privacy and cyberattack could hinder adults' widespread adoption (Evtushenko and Isaev, 2023). There were only 4.81 % of studies that directly look into the applications of DT within solar energy, pointing to some loopholes in harmonization of validation mechanisms and unification of standard digital model presentations (Ismail et al., 2024; Machado et al., 2023). Furthermore, problems concerning quality and quantity of data for integration into sophisticated environments remain a considerable challenge (Heluany and Gkioulos, 2023; El Zein and Gebresenbet, 2024). These studies justify a growing body of research interested in unlocking the actual potentials of DT within the solar energy sector.

3. Research method

The PRISMA methodology used in this SLR is generally acknowledged to beamong the best tools to prepare reviews. This particular section elaborates on the originality of this methodology and its application.

For conducting this SLR, PRISMA was selected for the packaging of the review process and improving its transparency and reproducibility. These strengths make it mandatory for behind-setting research and policy development in the energy sphere. In this SLR, PRISMA served to explore the applications of digital twins in solar power plants. In this respect, the methodology allowed a sweeping examination of scientific literature inclusive of diverse perspectives from relevant articles Fig. 6.

The first step was to find relevant literature on the application of digital twins in energy. Searches were done in many reputed databases like Springer, ScienceDirect, IEEE Explore, and IEEE Access to obtain the most relevant publications. Special care has been paid towards constructing precise queries so as to secure maximum coverage of the subject Table 2. This phase in itself yielded a compilation of 117 articles, paying much emphasis in this stage on title and article categories to enable a better synthesis based on the best articles found.

After accumulating an initial corpus of 117 potentially relevant articles, we undertook a thorough selection process guided by careful consideration of each reference based upon strict eligibility criteria. First, we reviewed each of the article titles, abstracts, and keywords; thus, rejecting those that were unrelated to our topic, duplicative, or otherwise in serious methodological shortcoming. This pre-review stage brought the number of articles down to 77, which were deemed relevant for more in-depth analysis. Next, we systematically reviewed the full contents of these 77 articles with regards to the quality of research methodologies employed, the strength of data collected, and the relevance of results obtained related to the current topic of study. Methodologies, quality of the data collected, and the robustness of the authors analysis were rated highly during the critical appraisal. Only works meeting the benchmarks of excellence were accepted for further consideration.

Finally, we carried out a final cross-check of the references cited in the selected articles, to ensure that we had not omitted any key publications from our corpus. This iterative process enabled us to achieve a high level of confidence in the representativeness and quality of our final sample.

Having collected the corpus, from the 77 identified articles, we continued to the most important phase of the detailed and meticulous extraction of the latest and most important claims, the application of the specific eligibility criteria, necessary to isolate the papers most likely to address our research question on the use of the digital twin in the energy field. To guide our selection process, we first defined a narrow scope of inclusion criteria Table 3.

Only publications that responded to these strict criteria were selected for further analysis. For all the retained publications, we performed a rigorous review of the full text, systematically summarizing the following: research objectives; methods; key findings; conclusions and reported implications of the digital twins application to the solar industry.

Special attention was given to the establishment of the technologies, architectures and algorithms applied to the digital twins, as well as the quantified operational, economic and environmental benefits. The main challenges and the identified limitations were recorded to provide a comprehensive view of the issues related to the adoption of this innovative technology in solar power plants. Hence, this process of data extraction and synthesis is paramount to enhance our understanding of the practice of digital twins in energy, as well as to evaluate and appraise the quality and trustworthiness of the results provided by the scientific literature. In the end, after filtering the publications based on the set of quality criteria, only 42 articles kept as the basis of this SLR on digital twins. A statistical analysis of the 42 articles used for this SLR. It details the number of articles stemming from each database, the distribution of articles by year and the quartiles. We notice that a majority of these papers are in the top quartiles of the different databases, meaning that a large percentage of the articles belong to the Q1 and Q2 categories. The fact that we primarily rely on articles that are highly ranked in their class supports the quality and relevance of the sources used. We can observe in Fig. 7 where the selected articles are positioned in terms of quartiles. We represent a snapshot of the dispersion of the publications used in this SLR.

Fig. 8 shows the 42 articles selected from each corresponding database.In Fig. 9, the geographic distribution of the selected articles being located and produced is shown. It is worth noting that the world's scientists have felt the need to contribute to the development of the CCS research area. Yet China, is the leading countries in this field of research. This may demonstrate the importance of the work done in China for this field and its weight for CCS knowledge accumulation, management, and extension.

In addition, Fig. 9, shows that the amount of scientific works carried out by China in the digital twin sub-field is by far the among the 28 countries with which China is compared. A word cloud created from the abstracts of the selected articles is presented in Fig. 10, showing that all the articles deal with digital twin technologies and, at the same time, its relevance to a wide range of services and applications.

4. Results and discussion

4.1. Distribution of articles analyzed by category

In Fig. 11, the analysis reveals how the selected articles are distributed among various key applications, with each segment representing the percentage of coverage within the research. The Table 4 describes the use of AI and digital twins in these categories.

Through digital twins and advanced technologies, energy systems from different sectors are experiencing transformation. Such microgrids enable optimization in the management of renewable resources, maturity of flexible decentralized systems, and local energy management. By complementing digital twins with real-time monitoring, precise demand forecasting and operational optimization is possible with enormous resilience and efficiency. Additionally, reinforcement learning and cloud computing enhance their capacity to adapt to fluctuations in energy demand (Li et al., 2023a; Yuan and Xie, 2023; Cao et al., 2023a; Li and Tan, 2023; Bazmohammadi et al., 2022; Xu and Gong, 2023; Li et al., 2023b; Gao and Huang, 2023; Espín-Sarzosa et al., 2023). Concurrently, predictions of solar irradiance and energy consumption are pivotal for

Table 1
Summary of reviews in Digital Twins in energy.

Paper	Year	Research Method	Journal	Focus	keywords
Angelova et al. (2024)	2024	SLR	Energies	Photovoltaic systems: energy efficiency, forecasting, reduction of operating and maintenance costs.	Industry 4.0 Digital twin(DT) Review Photovoltaic installations Renewable energies
Tahmasebinia et al. (2023)	2023	LR	Applied Sciences	Building energy management: energy optimization, environmental monitoring, efficiency assessment.	Digital twin Building energy management Machine learning Energy modeling
Ismail et al. (2024)	2024	SLR	Energy Strategy Reviews	Energy supply: predictive maintenance, grid optimization, integration of renewable and non-renewable energy, infrastructure challenges, and grid instability.	Digital twins. Electrical power supply system Energy management. Energy supply industry renewable and non-renewable energy sources
El Zein and Gebresenbet (2024)	2024	LR	Energies	Ingress of digital technologies, cost-and-security-related challenges, and synergies for sustainable energy transition and resilient infrastructure.	Blockchain Digital technologies Renewable energy Security Sustainability
Kumari et al. (2023)	2023	SLR	Energies	Microgrids: operational efficiency optimization, simulation, control, security, and resilience in distributed energy systems.	Digital twin Microgrid Point of common coupling Smart city
Mohammadi Moghadam et al. (2021)	2021	Survey	Intelligent & Fuzzy Systems	Energy systems: wind turbines, solar panels, electronic power converters, and embedded electrical systems, alongside an overview of emerging technologies (AI, IoT, 5 G).	Digital Twin (DT) Artificial Intelligence (AI) Ship power system Big data Internet of Things (IoT)
Bortolini et al. (2022)	2022	LR	Energies	Energy efficiency of buildings: design optimization, person comfort, management of operations and maintenance, and simulation of energy consumption.	Digital twin Energy efficiency Occupants comfort Energy performance Buildings
Lamagna et al. (2021)	2021	LR	International Journal of Energy Production and Management	Big data management, real-time measurements, continuous communication, and challenges of investment and data center infrastructure.	Barriers Digital twin Energy systems Modelling Real-time analyses
Digital Twins for Wind Energy Conversion Systems (2024)	2021	LR	Processes	Digital twin-based modeling of wind energy conversion system components, with an emphasis on fidelity versus computational load.	Digital twins Wind energy Wind turbines Industry 4.0 Direct-drive Permanent magnet synchronous generator
Ghenai et al. (2022)	2022	LR	Sustainable Energy Technologies and Assessments	In-depth examination of the application of digital twins across the entire energy value chain, with specialization towards the reduction of energy consumption and improvement of energy systems' efficiency.	Digital twin Energy Renewable energy Energy supply Energy demand Energy storage Digitalization Energy forecasting Energy optimization Energy management
Onile et al. (2021)	2021	LR	Energy Reports	Review of intelligent recommendation systems and digital twins to improve energy consumer behavior and promote energy efficiency and discuss challenges in adopting demand management solutions.	Recommender systems Demand side management Energy efficiency Digital twins Innovative energy services
Yu et al. (2022)	2022	LR	Renewable and Sustainable Energy Reviews	Examine energy digital twin technology, with an emphasis on developing a multidimensional classification framework and proposing applications towards resource management, optimization, and industrial and local site emissions reductions.	Digital twin Industry 4.0 Energy engineering Sustainable energy Renewable energy Process systems engineering
Sifat et al. (2023)	2023	LR	Energy and AI	Investigating the power grid digital twin concept with real-time assessment, loss detection, connection issues, and predicting future states of the grid with cybersecurity bundled in through blockchain.	Electric digital twin grid Online analysis of grid Cloud platform of grid Real-time grid analysis Self-healing Cybersecurity

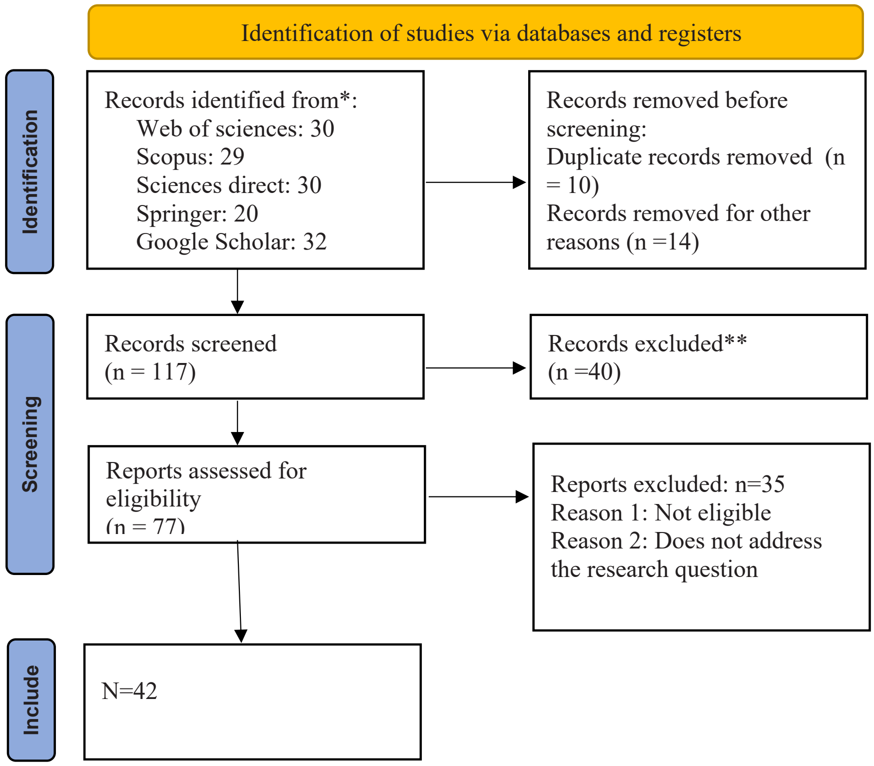

Fig. 6. PRISMA methodology.

Table 2
Utilized Queries and Time Ranges.

Request	"digital twins" AND "energy" AND " artificial intelligence"
Period	Between 2021 and now 2024

Table 3
Inclusion Criteria.

Inclusion Criteria	Scientific rigor
	Data reliability Ranked journals Relevance to our research questions

optimizing photovoltaic systems and smart grids. The model's ability to forecast changes in raw consumption and generation from photovoltaic systems on short notice is dependent on neural networks, ConvLSTM, Boltzmann networks, and other machine-learning models, which increases the robustness and flexibility of complex systems, like agrivoltaic farms and urban settings (Sehrawat et al., 2023; Bâră and Oprea, 2024; Simankov et al., 2024; Idrissi Kaitouni et al., 2024; Nie et al., 2023; Ebrahimi et al., 2024; Meng and Wang, 2023; You and Zhu, 2023; Yassin et al., 2023; İlker Aya c et al., 2023; Zohdi, 2021).Predictive maintenance backed by AI and digital twins allows intelligent usage for proactive equipment management, failure anticipation, and servicing optimization enforced by various features extended to projection. The redevelopment is used for lifetime extension, improved reliability, and reduced operational costs. Capabilities additionally coupled with cloud platforms allow for advanced diagnostics and additional scalability for

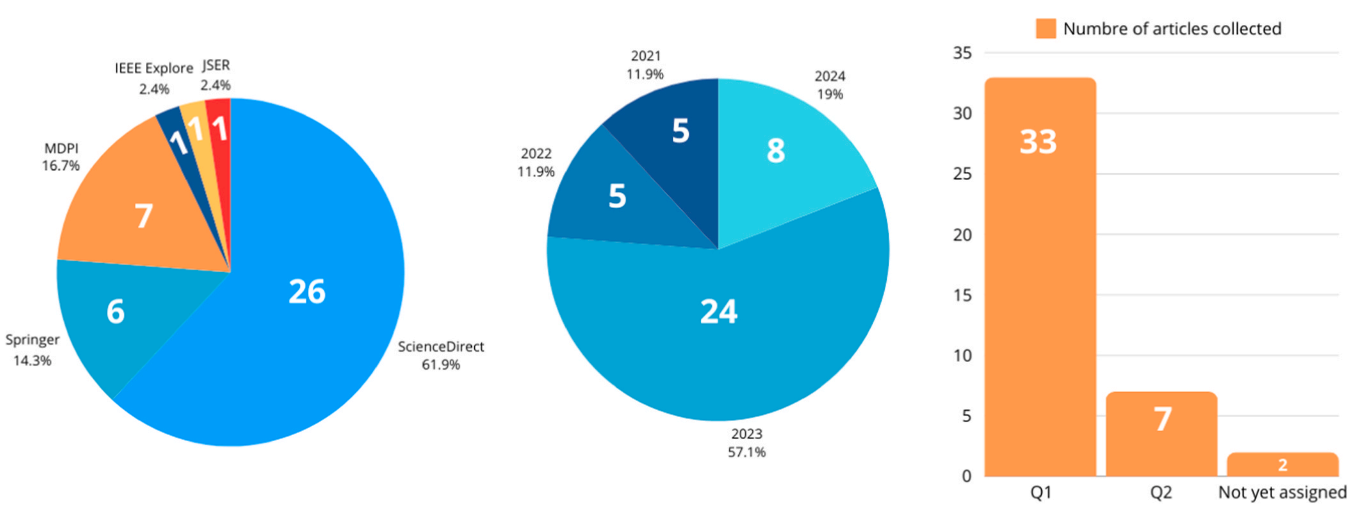

Fig. 7. Articles analysis: Sources, Years, and Quartiles.

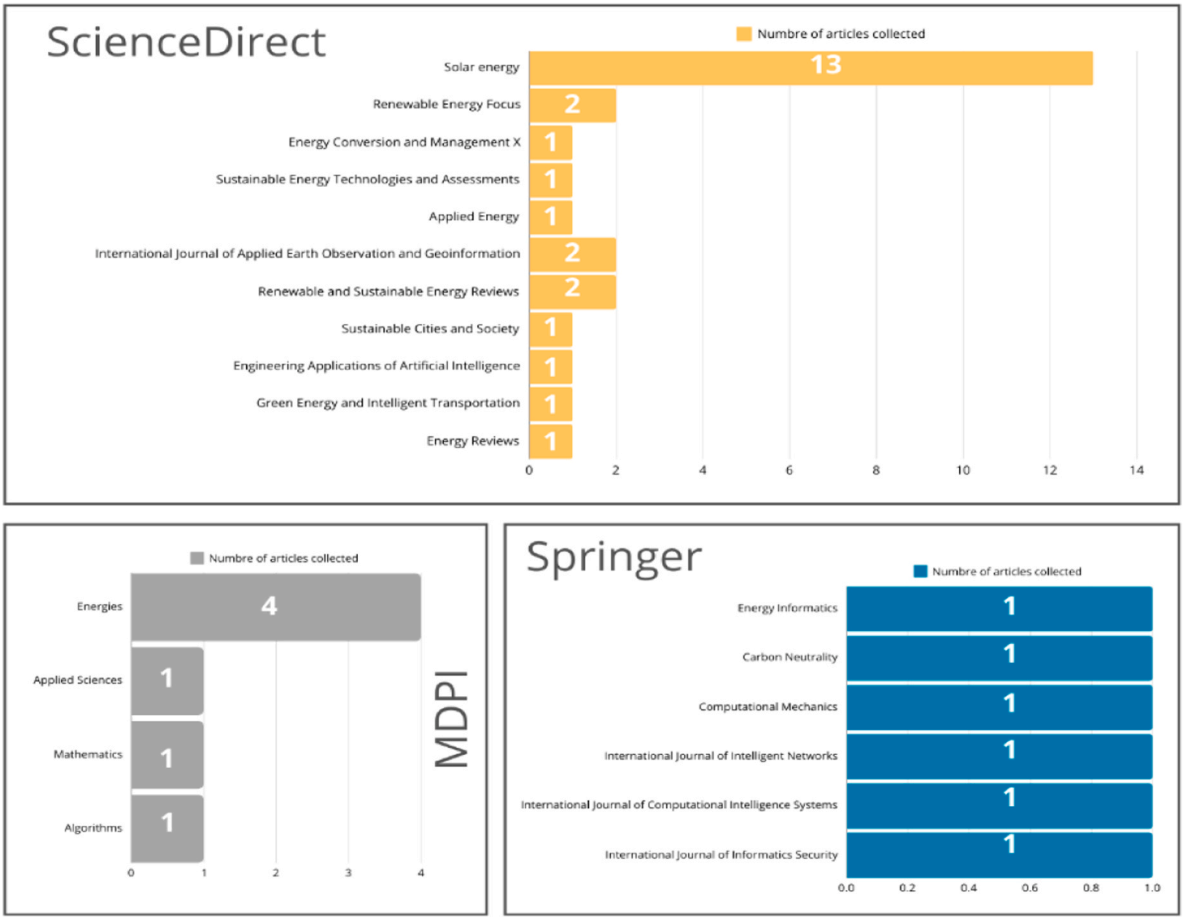

Fig. 8. Journals by collected source.

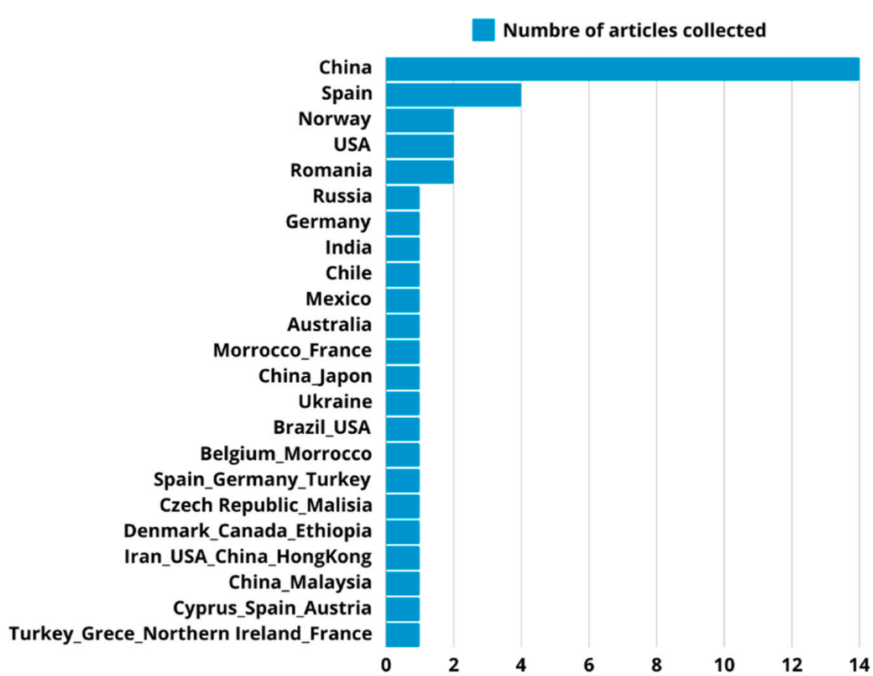

Fig. 9. Number of articles collected in different countries.

competing infrastructure sizes51], (Yassin et al., 2023; Castilla et al., 2024; Wang et al., 2022; Kavousi-Fard et al., 2024; [85]; Fan and Li, 2023). Cybersecurity is involved with enabling protection of smart grids and energy infrastructure. Enabling proactive anomaly detection, continuous monitoring, and reinforcement against cyber-treats is performed through anomalies obviously mitigated by scaling AI solutions

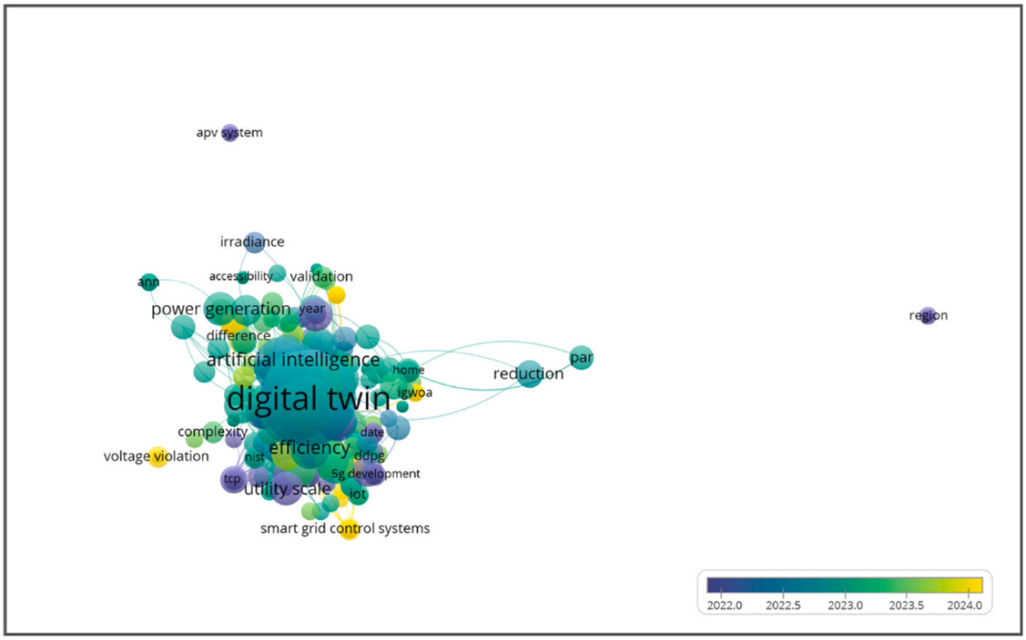

Fig. 10. Frequently occurring words in the reviewed literature.

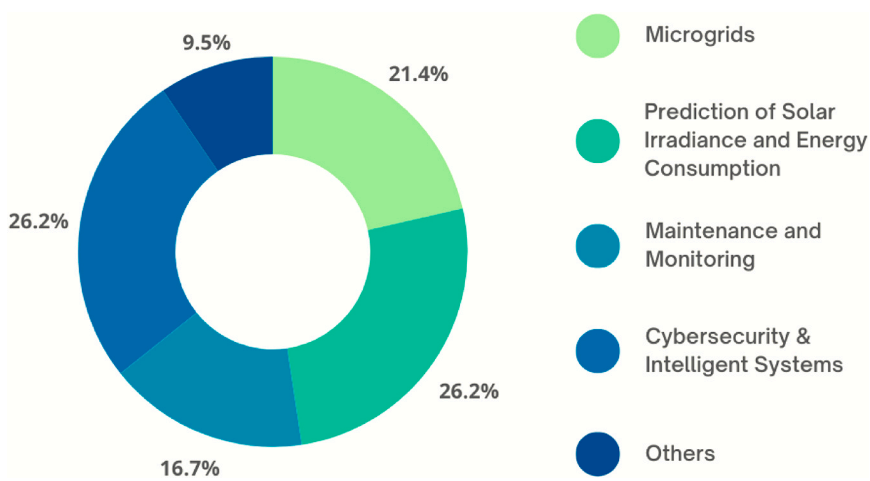

Fig. 11. Distribution of articles analyzed by category.

such as deep learning and infrastructure-centralized cyber-physical digital twins (Starkey et al., 2022; Bayer and Pruckner, 2023; Wang and Liu, 2024; Artetxe et al., 2023; Livera et al., 2022; Fara et al., 2021; Yalçin et al., 2023; Ji and Niu, 2024; Cao et al., 2023b; Bai et al., 2021; Jeddoub et al., 2023). Cutting-edge technologies mix AI and digital twins to generate benefits regarding the flow of energy, increase efficiency in decision-making processes, and utilize resources. The systems can employ reinforcement learning and various nature-based techniques to develop new energy and planning solutions, while IoT-based real--time monitoring with cloud computing enables smarter energy management in the urban and industrial contexts. The progression of this basic integration of digital twins and AI clearly positions them as fundamental enablers in enabling a sustainable, efficient, and resilient energy transition, thus addressing issues faced by modern energy infrastructures.

4.2. Methods for developing digital twins

The Fig. 12 illustrate the modeling side of digital twins indicates several technologies and modeling approaches that make them fastidious. AI and machine learning-based optimizations of solar energy forecasting and management rely on regression models and dynamic solar farm management (K.A. and Berlanga). Time series analysis and deep learning techniques use anomaly detection, predictive failure management, and autoencoders and recurrent neural networks to predict anomalies in processes. These sorts would improve solar farm reliability by pinpointing abnormalities (K. A. and Berlanga; Sehrawat et al., 2023) Monte Carlo simulations and other stochastic simulation and optimization methods model uncertainties in the solar energy systems and optimize resource utilization under changing conditions to guide decision-making processes for energy systems (Kavousi-Fard et al., 2024). IoT and big data integration guarantee constant real-time monitoring and optimization, where large data sets from solar panels and the rest of the equipment would be analyzed and would in turn favor performance and maintenance schedules (Gao and Huang, 2023).

Moreover, to accurately convey energy infrastructure, physical modeling with real-time updates is very important, with CAD and physical simulations aiding industrial system optimization (Teng et al.,

Table 4
Applications of AI and digital twins in various categories.

Categories	Utilization of Digital Twins and AI	References
Microgrids	• Optimized management of renewable resources • Integration with renewable energy sources, storage systems, and dynamic loads. • Real-time monitoring, accurate demand forecasting, and operational optimization through digital twins. • Demand-response management systems to balance grid loads and avoid overloads during peak demand periods.	(Li et al., 2023a; Yuan and Xie, 2023; Cao et al., 2023a; Li and Tan, 2023; Bazmohammadi et al., 2022; Xu and Gong, 2023; Li et al., 2023b; Gao and Huang, 2023; Espín-Sarzosa et al., 2023)
Prediction of Solar Irradiance and Energy Consumption	• Forecasting solar irradiance and energy consumption to maximize renewable energy production and efficiently meet demand. • Advanced models and machine learning algorithms, to enhance forecasting accuracy. • Optimization of solar production in complex environments. • Proactive management of reactive power to stabilize production and mitigate disturbances.	(Sehrawat et al., 2023; Bâră and Oprea, 2024; Simankov et al., 2024; Idrissi Kaitouni et al., 2024; Nie et al., 2023; Ebrahimi et al., 2024; Meng and Wang, 2023; You and Zhu, 2023; Yassin et al., 2023; İlker Aya c et al., 2023; Zohdi, 2021)
Maintenance and Monitoring	• Predictive maintenance using AI to anticipate failures and optimize servicing intervals. • Real-time diagnostics to enhance system reliability and reduce operational costs.	(Semeraro et al., 2021; Yassin et al., 2023; Castilla et al., 2024; Wang et al., 2022; Kavousi-Fard et al., 2024; [85]; Fan and Li, 2023)
Cybersecurity & Intelligent Systems	• Proactive anomaly detection. • Robust cybersecurity protocols to secure modern energy infrastructures.	(Starkey et al., 2022; Bayer and Pruckner, 2023; Wang and Liu, 2024; Artetxe et al., 2023; Livera et al., 2022; Fara et al., 2021; Yalçin et al., 2023; Ji and Niu, 2024; Cao et al., 2023b; Bai et al., 2021; Jeddoub et al., 2023)
Others	—	(do Amaral et al., 2023; Heluany and Gkioulos, 2023; Wang et al., 2022; Kavousi-Fard et al., 2024)

2021). Hybrid modeling methods merge real-time data and physical modeling, leveraging powerful computational architectures such as FPGAs and cloud computing to dynamically manage energy systems for microgrids (Bazmohammadi et al., 2022). Lastly, photogrammetry techniques, aided by drones and thermal cameras, provide detailed 3D modeling of solar panels for hotspots and crack inspections, optimizing maintenance schedules for large-scale installations (Starkey et al., 2022).

4.3. Global synthesis of article analyses

The summary results regarding our detailed and extensive evaluation of 42 selected articles that focus on the implication of digital twin technology and artificial intelligence in the energy sector appear in Table 5. This table provides the analysis total summary which summarizes the main objectives pursued in each study, the limitations that the authors pointed out, the methodologies they employed in achieving their purposes, and key results achieved. The organizer is aimed to understand how these technologies are used in the energy domain, their impact, and yet-to-be-met challenges.

4.4. Most used algorithms

The research articles we have analyzed represent a mixed collection of algorithms and their applications pertaining to IoT-enabled smart solar networks, which includes solar irradiance forecasting and anomaly detection. Fig. 13 synthesizes the main ideas and results of these studies, grouping similar algorithms and their applications to provide a coherent overview.

The digital twins of solar systems are therefore the amalgam of advanced methodologies and technologies that seek to optimize performance and energy management. In other words, it's a creation of data-driven models through techniques like AI, machine learning, IoT, and Big Data to make use of these platforms, be it smart grids, predictive solar irradiance forecasting, or others (Nie et al., 2023), [85]. The time series analysis and deep learning approaches leverage convolutional and recurrent networks to improve reliability via anomaly detection and predictive failure management in solar farms [85]. The stochastic optimization and Monte Carlo simulations tackle uncertainties while resource integration into smart grids (Cao et al., 2023b). Because of the respected capacity of IoT and Big Data about real-time monitoring and adaptive optimization concerning solar systems (Cao et al., 2023a). Physical modeling by CAD is augmented with computerized AI and blockchain to facilitate real-time updates and test/refine without directly intervening in reality (Natgunanathan et al., 2023). Hybrid models built in micro-grids with the control focused on FPGAs, GPUs, and more comparatively cloud-computing achieve real-time synchrony and optimally integrate renewable resources (Gao and Huang, 2023). Similarly, through photogrammetry using drones and thermal camera technologies, panel-centric patterns can also be monitored in great detail when monitoring large installations for maintenance optimization (Starkey et al., 2022). The qualifications pointedly show that these innovations are getting digital twins to show great potential for energy efficiency and low operational costs and sustainability as solar and energy systems (Heluany et Gkioulos, 2024).

The algorithms used in digital twins provide numerous advantages and limitations that could vary from one application to another. Stacking Regressor, for example, improves the accuracy of solar irradiance forecasting by using satellite data but at high computational costs. The Genetic Algorithm (GA) finds solar panel parameters that would minimize costs but suffers reduced efficiency with increasingly large search spaces. CNN provides 92 percent accuracy for classification of images like defective solar panels but requires massive amounts of data and computational resources. RL reduces collision rates in autonomous driving by 30 % in dynamic environments but depends highly on reward functions. SVMs yield high precision in solar power output prediction but suffer with larger and more complex datasets. The ANN-INC method increases a solar plant's efficiency under specific conditions, while such algorithms as XGB outperform most by speed and accuracy for unbalanced forecasting, even being affectively unexplainable. Anomaly detection techniques like ABOD and LSTMs variants proficiently spot outliers in the data but can be sensitive to input perturbations. LSTM works well for sequences, while Random Forest (RF) is reliable in modeling solar output prediction but have challenges in interpreting the result. Finally, models like ANNs or WSOA perform well in optimizing renewable systems and solving complex problems but require detailed tuning and are often infrastructure-heavy. Thus, the choice of algorithm, in the end, will depend on project-specific requirements and available resources.

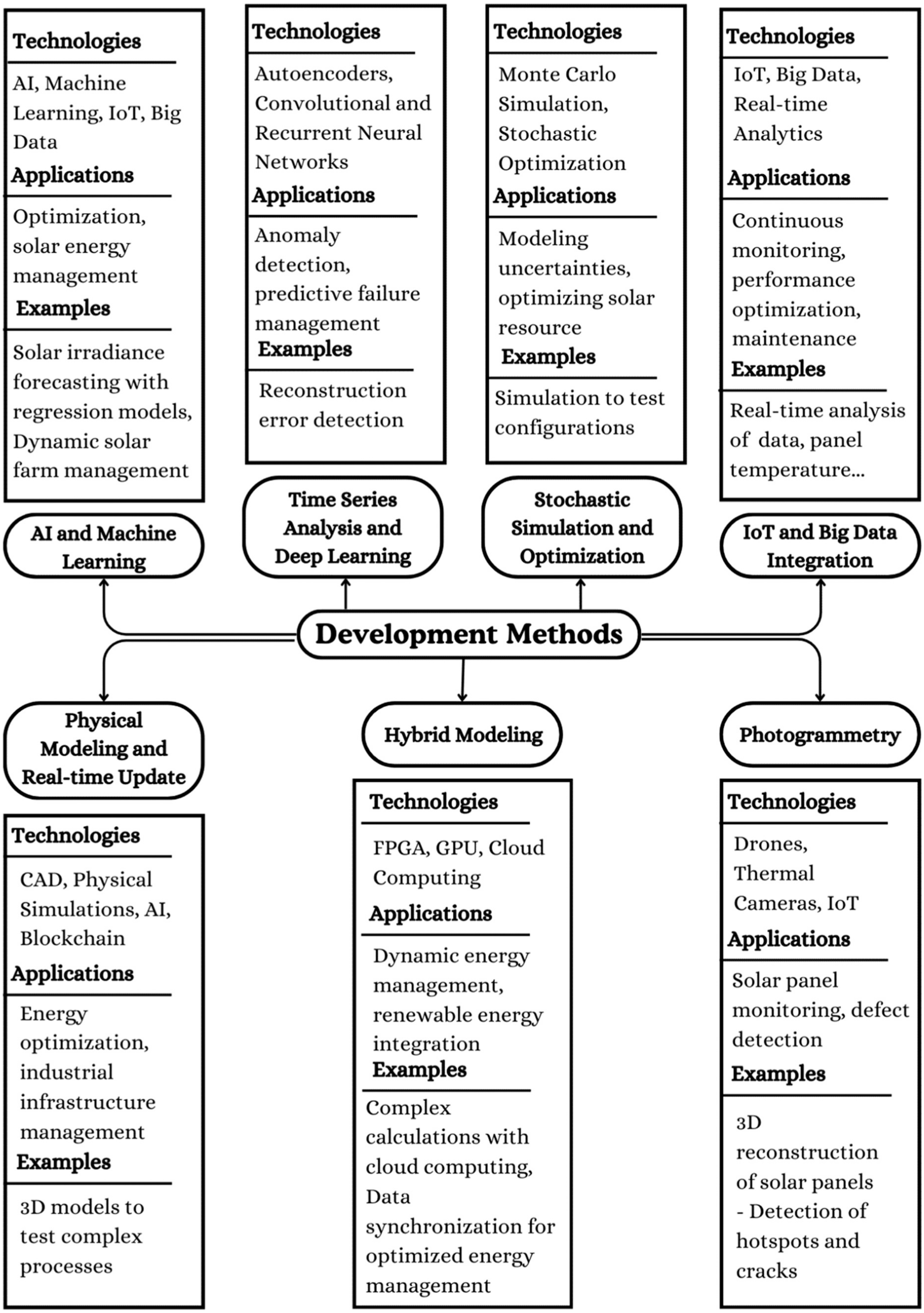

Fig. 12. Overview of development techniques and applications for solar digital twins.

Table 5
Results synthesis.

Author	Country	Year	Methods used	Limits	Results	Objectives
Zohdi (2021)	USA	2021	Use a reduced-order model of Maxwell's equations and genomics-inspired machine learning for solar energy optimization.	Simplified panel configurations and lack of experimental validation	Presents a computational framework for optimizing agrophotovoltaic systems using bifacial panels.	Optimizing solar energy in complex agrophotovoltaic systems with bifacial panels
(Espín-Sarzosa et al., 2023).	Chili	2023	Develops a digital twin for small productive processes in microgrids with real data tuning.	Focuses on one type of process, lacks variable work hours consideration.	Improved energy management and reduced costs in microgrids using digital twins.	Enhance energy management of small productive processes in microgrids.
Gao and Huang (2023)	China	2023	Uses a stochastic approach and optimization algorithms for managing loads in microgrids.	Limited by network constraints and precise load forecasting issues.	Efficient management of generation, batteries, and loads in microgrids under uncertainties.	Develop an efficient energy management system for microgrids with stochastic loads.
(Sehrawat et al., 2023).	India	2023.	Uses an 8-stacked cross-validated regression model to predict solar irradiance.	Challenges with integration, cost, and unpredictability of energy production.	High accuracy predictions of solar irradiance across different climatic zones.	Accurately predict solar irradiance using machine learning techniques.
İlker Aya c et al., 2023	Türkiye, Greece. Northern Ireland, France	2023.	Uses a linear regression algorithm to monitor photovoltaic systems and optimize maintenance.	Relies solely on solar panel data, requiring additional equipment.	Developed a real-time monitoring system that detects issues like shading and defects.	Optimize maintenance schedules and reduce workload for photovoltaic systems.
(Yalçin et al., 2023).	Spain, Germany, Turkey	2023	Uses machine learning techniques to monitor and detect faults in photovoltaic plants.	Challenges with non-linear behaviors of DC-DC converters.	Enhanced maintenance efficiency with 98.3 % accuracy in fault detection.	Optimize operation and maintenance of solar plants through digital twins.
(Li et al., 2023b).	China	2023	Uses the Grey Wolf algorithm to optimize demand response in microgrids.	Constraints related to storage systems and managing demand response programs.	Reduced operational costs and optimized energy production from tidal and solar units.	Optimize energy management in microgrids by integrating renewable energy.
(Teng et al., 2021).	Czech Republic, Malaysia	2021	Applies optimization techniques like Taguchi and genetic algorithms for industrial energy savings.	Energy consumption variability and incomplete adoption of Industry 4.0 technologies.	Developed infrastructures to improve energy efficiency in industrial systems.	Enhance industrial energy efficiency by standardizing data infrastructures.
(Cao et al., 2023a).	china	2023	Uses an intrusion detection system to secure hybrid AC-DC microgrids.	Does not explicitly discuss limitations in fault detection for large solar energy systems.	Effective detection of cyberattacks and optimization of energy management in microgrids.	Ensure reliability and security of hybrid microgrids while reducing operational costs.
(Fara et al., 2021).	Romania	2021.	Numerical modeling of an off-grid photovoltaic pumping system optimized by AI.	Dependency on specific meteorological data and simplified modeling.	Optimized photovoltaic pumping for irrigation in Romania using AI and maximum power point tracking.	Model and optimize a photovoltaic pumping system for irrigation
(Xu and Gong, 2023).	china	2023	Uses a pigeon-inspired algorithm to optimize energy management in urban microgrids.	Constraints related to storage system capacities and energy exchanges with the grid.	Improved energy efficiency and cost reduction in islanded and non-islanded microgrids.	Optimize energy costs and improve urban microgrid management.
Wang and Liu (2024)	China.	2024	Uses the IGWOA algorithm to optimize industrial energy consumption.	Challenges with renewable energy adoption and existing electrical infrastructure.	26.2 % reduction in energy costs with faster stabilization times in urban grids.	Optimize urban energy consumption and manage prices using digital twins.
(Li et al., 2023a).	China	2023	Uses neural networks to address energy management challenges in fog computing.	Challenges with the geographic distance of fog computing services and load management.	Reduced electricity costs and improved microgrid management with cloud and fog systems.	Improve energy management in microgrids with digital twins and neural networks.
(Bazmohammadi et al., 2022).	Denmark, Canada, Ethiopia	2021	Uses AI algorithms on FPGAs to solve complex energy models.	Complexity in continuously updating digital twin models.	Improved microgrid performance with continuous learning solutions.	Optimize microgrid management using digital twin and AI technologies.
(Artetxe et al., 2023).	Spain	2023	Uses the DDPG algorithm to improve maximum power point tracking in solar systems.	Issues with oscillations around the maximum power point in traditional methods.	Significant increase in total power output and reduction in stabilization time.	Optimize the efficiency of maximum power point tracking in photovoltaic systems.
Bârã and Oprea (2024)	Romania	2024	Uses multiple machine learning algorithms to predict imbalances in the electricity market.	Does not consider external factors like COVID−19 or conflicts.	Significant improvement in predicting electrical imbalances and reducing associated costs.	Accurately predict electricity imbalances by combining LSTM networks with classification techniques.
Livera et al. (2022)	Cyprus, Spain, Austria	2022	Develops a cloud-based platform for real-time monitoring of photovoltaic power plants.	Lack of standardization in digital twin monitoring methods.	Validation of digital twin accuracy for performance modeling and fault diagnosis.	Improve monitoring and maintenance of photovoltaic systems using digital twins.
(Idrissi Kaitouni et al., 2024).	Morocco, France	2024	Combines model-based and data-based methods for fault detection in photovoltaic systems.	Challenges with integrating urban photovoltaic systems into digital platforms.	Early detection of anomalies and improved performance of urban photovoltaic systems.	Improve monitoring and maintenance of urban solar systems through a digital twin framework.

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Table 5 (*continued*)

Author	Country	Year	Methods used	Limits	Results	Objectives
(Machado et al., 2023)	Norway	2023	Uses a seven-step systematic review approach for analyzing digital twin technologies in the energy sector.	Lack of detailed technical discussions on digital twin architecture and security.	Highlights the importance of digital twins in energy management, with gaps in security being a key issue.	Provide a comprehensive review of digital twin applications in energy and address their challenges.
Fan and Li (2023)	china,Japon	2023	Proposes a three-layer fog computing model for optimizing energy management in renewable grids using the Whale Optimization Algorithm.	Does not explicitly address challenges or limitations of the proposed model.	Improved energy management performance and latency reduction compared to other algorithms.	Optimize energy management in renewable grids with a focus on reducing latency through fog computing.
(do Amaral et al., 2023).	Brazil, USA	2023	Uses a systematic literature review to explore digital twins in energy systems using the CIMO-Logic framework.	Challenges in data noise management and continuous model validation for energy digital twins.	Identified significant growth in publications related to energy systems, especially in energy production and telecommunications.	Review the benefits and challenges of energy digital twins and identify future research opportunities.
(Jeddoub et al., 2023).	belgium, Morocco	2023	Systematic literature review and online survey to explore urban digital twin applications and definitions.	Limited participation from industry and municipal authorities in the survey, affecting findings.	Uncovered diverse definitions of urban digital twins, emphasizing the need for data integration standards.	Clarify urban digital twin definitions and propose a classification method based on data maturity.
(Yassin et al., 2023).	Norway	2023	Systematic review of digital twin technologies in power systems, focusing on communication, security, and integration with IoT and machine learning.	Challenges in implementing digital twins due to complexity and lack of standardization.	Provides an overview of digital twin applications in power networks, with a focus on monitoring and optimization.	Review digital twin technologies in power systems, focusing on future research directions and network security.
K. A. and Berlanga.	Spain	2021	Uses an autoencoder-based digital twin model for anomaly detection in photovoltaic solar farms.	Lack of meteorological data and the use of univariate series limits the analysis.	High accuracy in detecting anomalies, with an area under the curve (AUC) of 0.97.	Develop a digital twin for detecting anomalies in photovoltaic systems using deep learning.
(Starkey et al., 2022).	UK	2022	Develops a digital twin for photovoltaic systems, focusing on defect detection via drones and statistical methods.	Challenges with image quality and data capture during drone inspections of solar assets.	Proof-of-concept for automating inspections in large-scale solar farms with high accuracy.	Create a cost-effective digital twin process for fault detection in utility-scale solar plants.
(Yuan and Xie, 2023).	China	2023	Uses reinforcement learning (RL) and digital twin technologies to optimize load planning in smart microgrids.	Does not address multi-neighborhood or transformer optimization challenges.	Significant reduction in electricity costs and improved load planning efficiency.	Develop a load planning solution for smart microgrids using reinforcement learning and digital twins.
You and Zhu (2023)	China	2023	Combines Modified Mutual Information and a Factorized Conditional Restricted Boltzmann Machine to predict short-term electric load.	Challenges with forecasting due to random and non-linear user behavior.	Achieved significantly higher prediction accuracy compared to conventional methods.	Improve short-term load prediction accuracy using advanced machine learning techniques.
(Heluany and Gkioulos, 2023).	Spain, Brazil	2023	Uses a combination of phenomenological modeling and adaptive neuro-fuzzy inference systems (ANFIS) for dynamic modeling of Fresnel solar collectors.	High computational load and challenges with real-time optimization techniques.	Successfully developed a dynamic model for optimizing Fresnel solar collectors in a digital twin framework.	Develop a digital twin to optimize the operation of Fresnel solar collectors through dynamic modeling.
(Tariq et al., 2022).	Mexico	2022	Uses multivariate regression and multilayer perceptron artificial neural network (MLP-ANN) to develop a digital twin of a solar chimney.	Sensitivity to building characteristics and internal heat production affects performance.	Improved air changes per hour from 71 % to 87 % through geometric optimization.	Develop a digital twin for solar chimneys to optimize geometric dimensions and energy efficiency.
Bai et al. (2021)	China.	2021	Uses a hybrid model combining data-driven and mechanistic approaches to model energy consumption in solar vehicles.	Challenges with real-time updates and high-fidelity modeling.	Achieved a prediction error of less than 5.17 % in energy consumption for solar vehicles.	Optimize energy consumption and component operation in solar vehicles using digital twin technology.
Kavousi-Fard et al. (2024)	Iran, les États-Unis,la Chine.	2024	Integrates Monte Carlo simulation, Bayesian inference, and fault tree analysis for reliability analysis of renewable energy systems.	Challenges with adopting advanced digital twin technology due to energy efficiency and security concerns.	Enhanced monitoring and reliability of renewable energy systems using digital twin technology.	Improve reliability, management, and maintenance of renewable energy systems with digital twin technology.
Meng and Wang (2023)	China	2023	Uses the White Shark Optimization Algorithm and a probabilistic model to predict short-term load in smart grids.	Model sensitivity to uncertainties in input data like solar irradiation.	High accuracy in predicting solar energy production per hour using real data.	Develop a scalable model for short-term load prediction in solar smart grids using digital twins.
Cao et al. (2023b)	China	2023	Uses a neural network model to predict hydrogen production and optimize photovoltaic systems for electric bus transportation.	Challenges with data heterogeneity and low data reuse in digitized energy systems.	Reduced depreciation of photovoltaic panels and rooftop batteries, achieving net-zero energy consumption.	Optimize energy systems for net-zero energy transition using digital technologies.
Natgunanathan et al. (2023)	Australia	2023	Uses machine learning models such as SVR, LSSVR, Random Forest, and LSTM to predict energy production in microgrids.	Difficulty determining the best model for different percentiles, limiting the understanding of prediction accuracy.	Random Forest outperformed other models with fast training times and high accuracy for microgrid digital twins.	Develop a web-based digital twin for accurate energy production prediction in microgrids using AI models.

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Table 5 (*continued*)

Author	Country	Year	Methods used	Limits	Results	Objectives
Wang et al. (2022)	China.	2022	Proposes a four-layer network architecture for advanced battery management in digital twins.	Challenges with data interoperability and the migration of digital twin models to other platforms.	Improved battery management and consumer demand optimization using real-time data analysis.	Explore digital twin applications in energy storage systems and address challenges in data management and interoperability.
Simankov et al. (2024)	Russia	2024	Uses a hybrid model combining exponential smoothing, decision trees, and LSTMs to predict renewable energy production.	Limited consideration of seasonal fluctuations due to lack of long-term data.	Developed accurate forecasts for solar and wind energy systems using AI techniques.	Optimize energy systems through accurate forecasting and operational planning using AI.
Castilla et al. (2024)	Spain	2024	Uses a NARX neural network model to predict system dynamics in solar collector arrays.	Overfitting risks in certain model configurations, limiting improvements in performance.	Accurate predictions of system behavior, enhancing operation and control of solar collectors.	Develop a digital twin for solar collectors to optimize system control and reduce carbon emissions in buildings.
Ebrahimi et al. (2024)	USA	2024	Introduces the Delta-Q approach for Volt-VAR control in solar inverters to stabilize voltage without additional hardware.	Traditional Volt-VAR techniques fail to manage voltage violations under high solar penetration.	Improved grid stability by reducing voltage fluctuations in photovoltaic systems.	Improve power quality and integration of solar energy in grids by introducing the Delta-Q approach.
Nie et al. (2023)	China, Malysia	2023	Uses ILPSO to optimize the scheduling of demand-sensitive devices in smart homes, integrating real-time energy pricing in a digital twin.	High costs and complexity of demand-sensitive devices, as well as security concerns.	Reduced energy costs and improved user satisfaction by optimizing demand-responsive devices.	Optimize energy management in smart homes and landscapes through advanced scheduling algorithms and renewable energy integration.
Li and Tan (2023)	China	2023	Applies the Whale Optimization Algorithm (WOA) in a digital twin framework to optimize energy management in smart cities.	Model sensitivity to uncertain inputs like solar irradiation and wind patterns limits accuracy.	Reduced energy costs and improved voltage stability compared to other algorithms like PSO and DEA.	Optimize energy management in smart cities using digital twins and WOA for integrating solar and wind energy.
Ji and Niu (2024)	China	2024	Combines K-Nearest Neighbors (K-NN) and Artificial Neural Networks (ANN) to predict solar irradiance and detect cyber-attacks in smart grids.	Dependence on meteorological data quality and lack of sufficient cyber-attack datasets for training.	Improved accuracy in detecting cyber-attacks in smart grid systems using a hybrid deep learning approach.	Enhance cybersecurity and predict solar irradiance in smart grid control systems using hybrid AI techniques.
Bayer and Pruckner (2023)	Germany	2023.	Uses discrete simulation with digital twins for modeling local energy systems, integrating smart meters, photovoltaics, and batteries.	Issues with low correlation coefficients in some profiles, and challenges with matrix combinations in control unit configurations.	Reduced grid load and increased energy self-sufficiency in local energy systems through optimized photovoltaic deployment.	Model and optimize local energy systems by integrating digital twins to assess the impact of high photovoltaic penetration.

4.5. Data integrity, collection methods, and processing techniques

The implementation of sophisticated data collection and processing techniques greatly contributes to energy efficiency, specifically in industrial applications. Optimization of these processes can include multiple techniques, such as the use of external data loggers for optimizing processes live (Teng et al., 2021). External data loggers are typically paired with advanced process controllers (APC) to minimize overall energy. Furthermore, enterprise level strategies that incorporate statistical data from governmental reports and technical audits (Gupta Gourisetti et al., 2023) have been developed to estimate the potential for energy savings across industries. In addition, IoT-based strategies to facilitate data collection within processing plants and utilities have been proposed to further optimize energy management (Cao et al., 2023b). Due to the enjoyments of employing "real-time" data and performance indicators (Cao et al., 2023a), industries are able to discover energy saving opportunities to improve performance. Moreover, other comparative analysis strategies such as (Gutierrez-Rojas et al., 2023) developing the potential for the energy savings in refrigeration systems as well as machine scheduling optimization with multi-attribute data (Cao et al., 2023b).

Enhance the overall energy efficiency. Data collection is also performed by the use of programmable logic controllers (PLC) and human-machine interfaces (HMI) for monitoring essential energy performance metrics (Hashmi et al., 2024). Finally, it is critical to pursue a holistic approach to data collection that treats the entire energy value chain for the enhancement of energy management (Fan and Li, 2023). In conclusion, the combination of these data analytics methodologies will be the key to industrial energy savings, and future research may be able to improve these existing techniques through the use of rapidly emerging technologies such as artificial intelligence and machine learning.

4.6. Case study

The complete IoT-enabled intelligent solar network system involves working on several interconnected domains such as physical layer, models, operating systems, standards, protocols, and architecture. The body integrates IoT devices, back office systems, and workflows and describes their configuration and design on Solar Energy Systems, the implementation procedure as well as performance while identifying the issues in real-time deployments. A linear regression algorithm investigates climatic and PV system performance metrics, modeling the relations among the predicting variables-climatic and technical factors-and the performance metrics for solar panels. Another real-time diagnostic algorithm illustrated by a Fig. 14 applies climatic data-light intensity, ambient temperature, humidity, wind-and panel-specific parameters-surface temperature, and maximum current and voltage-to detect signs of dust accumulation, shading, panel defects, or short circuits. It gives immediate alerts, graphical representations of performance, and estimates of the long-term losses in efficiency. The system operates on three-layered software architecture and relies on using

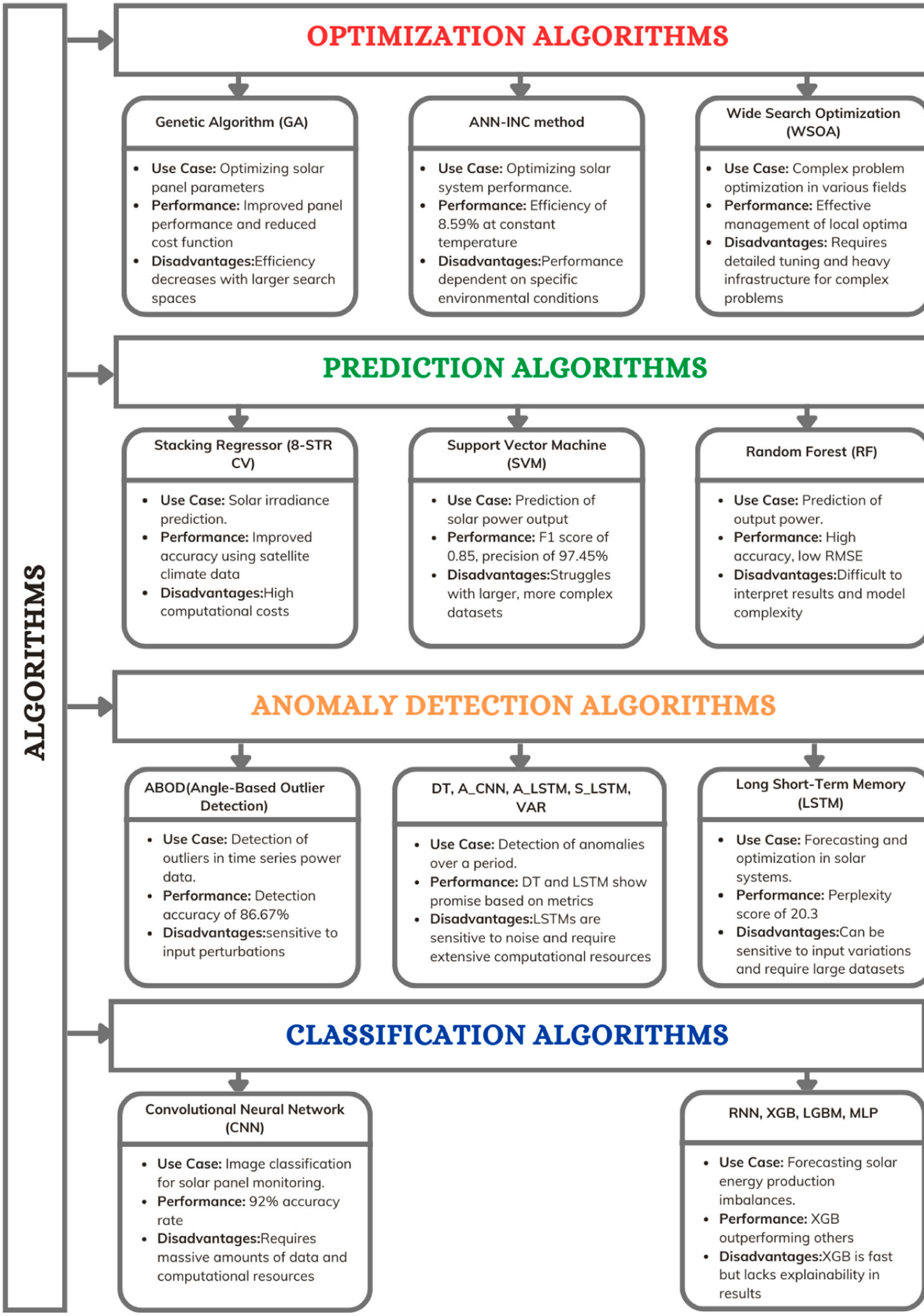

Fig. 13. Analysis of algorithms in digital twin solar energy systems: use cases, performance, and disadvantages.

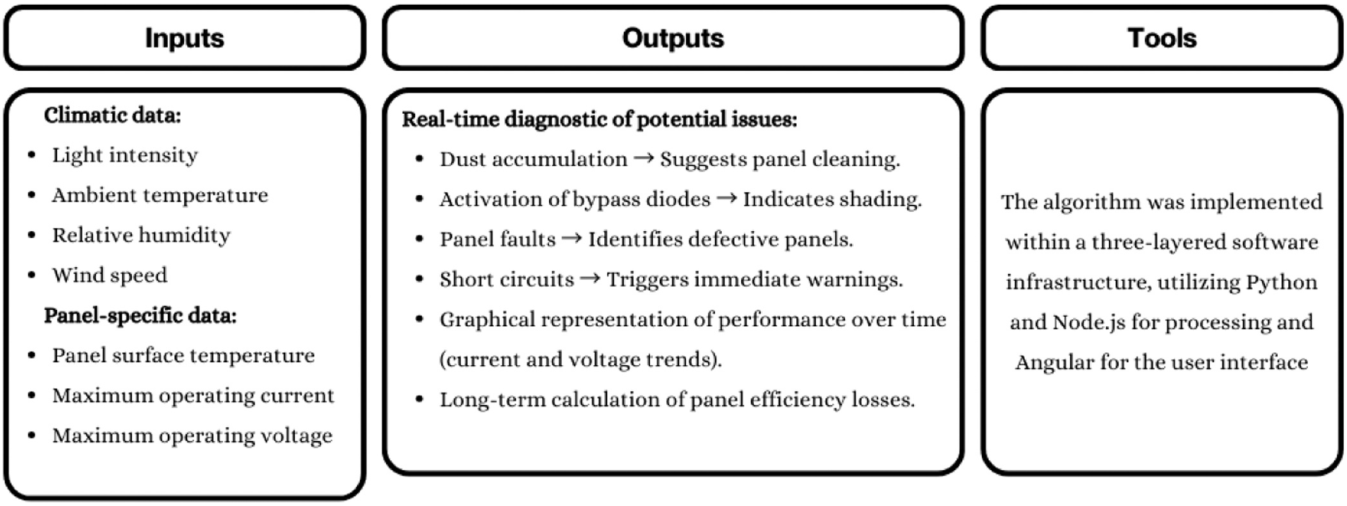

Fig. 14. Overview of inputs, outputs, and tools used in the algorithm for smart maintenance of photovoltaic systems.

Python and Node.js for data processing, while Angular is specifically used for the user interface making it a robust tool for solar panel monitoring and optimization (İlker Aya c et al., 2023).

A different research paper regarding successful uses of artificial intelligence (AI) in the energy sector shows the positive results AI can generate in support of efficiency and energy system management. For example, AI has been applied to improve forecasting of electricity demand, which better enables matching of energy production to distributed consumption, lowering costs, and improving reliability of the grid. AI also enables further adoption of innovative applications, such as digital twins, which can be used to simulate and evaluate the performance of energy systems before actual implementation, enabling better management of energy resources and improved decision making (do Amaral et al., 2023; Bârã and Oprea, 2024).

The scalability of AI solutions in this field is also evident in their dependance to scale complex networks and support the energy transition to new sustainable and resilience solutions as they evolve. This flexibility and scalability support energy management and the challenges of integrating renewables and reducing carbon emissions on a larger scale ($author1$ et al., 54]</id>). These examples show how AI applications are working successfully within the energy sector now, but also the large potential for further development and responsiveness to future challenges.

4.7. Current challenges in AI and digital twin adoption in the energy sector

4.7.1. Technical and implementation challenges

The use of digital twin and artificial intelligence technologies within the energy sector is a significant advancement in improving performance and energy efficiency. Still, their widespread uses encounter significant challenges, mainly around high costs and the complexity of integrating them into existing systems. The use of digital twins requires the purchase of high-accuracy sensors and sophisticated processing devices needed for real-time data collection and processing (Teng et al., 2021). This need is accompanied by the need of niche software and platforms that can aggregate and process a massive amount of data from multiple sources (Sehrawat et al., 2023; Nie et al., 2023). Similarly, the proper use of DTs will place a burden on advanced processing resources including cloud computing and edge computing that may be essential but adds substantial cost to a project's operations (Xu and Gong, 2023). Also, the long-term reliability and accuracy of DTs depend on ongoing maintenance and updates of software and hardware that also adds to the cost ('A survey on artificial intelligence assurance, 2024).

In addition to economic concerns, deploying digital twins into existing energy systems also poses an adoption challenge because of the heterogeneity of technologies and equipment in use. Many operations still utilize legacy technology, often undermining the operations of a digital twin solution, and are not compatible with today's modern applications, making it more complicated to interconnect and increasing overall adaptability (Heluany and Gkioulos, 2023). In addition, it is necessary to have a stable and reliable communication network for the real-time transmission of data between digital twins and assets (Idrissi Kaitouni et al., 2024). Nonetheless, the development of such infrastructure will involve an additional capital outlay which would hinder further implementation of these technologies as well (Heluany and Gkioulos, 2023; Bai et al., 2021). Overall, while, digital twins/AI have considerable transformative potential for the energy sector, these two major challenges constrain adoption; the cost and technical challenges are both significant. A solution to facilitate the deployment of these technologies would be optimally merging solutions with appropriate additional updates that are economically reasonable.

4.7.2. Data-related challenges

The integration and utilization of artificial intelligence and digital twin technologies will raise a number of data challenges which may impede their effective implementation. These challenges are primarily related to data acquisition, processing, security, and interoperability, which are critical factors to successfully deploy AI- and DT-based systems in energy applications.

A major issue that energy systems face is the acquisition of large, heterogeneous data streams from multiple sources including sensors, text data, and data derived from the web. These data tend to come in a variety of formats, including tables, figures, and natural language, thus further complicating the processing stream, especially when integrating data (Cao et al., 2023b). Supplementing this issue are data acquisition systems that do not capture all the data needed, thus creating even more difficulty in collecting complete and dependable datasets that are necessary for AI and DT applications (Teng et al., 2021).

Ensuring data accuracy, completeness, and consistency is still a major challenge, as measurements taken by sensors may be noisy, incomplete, or affected by numerous uncertainties. Inconsistency in data can adversely impact decision-making and predictive models, leading to unreliable outputs (Yassin et al., 2023). Data quality is an important factor for the efficacy of data-driven models, as data with poor quality can lead to inaccurate forecasts and poor decision-making processes (Teng et al., 2021). Furthermore, another significant challenge is data integration and fusion from various sources, especially as we move toward heterogeneous and inconsistent datasets and cloud computing environments. The lack of standardized data integration formats and interoperability mechanisms complicates data integration (Cao et al., 2023b). One important example of the problem is the integration of smart meter data with geospatial data; the efficient development of digital twins relies on this. It is an example where such integration rarely takes place at present (Bayer and Pruckner, 2023).

To address these data-related challenges, it is essential to have new ways to improve data acquisition and its integrity and to promote interoperability across energy systems. Without these, AI and DT technologies will be limited in their application in the energy sector.

4.7.3. Cybersecurity and system vulnerabilities

The combination of Artificial Intelligence (AI) and Digital Twin (DT) technologies in the energy sector presents opportunities and challenges from an intersection of cybersecurity and system vulnerabilities. These multifaceted challenges associated with the interplay between physical and cyber systems demand scrutiny to guarantee the safety and resilience of digital energy systems.

Current energy devices are complex systems that can take advantage of the interaction between physical and cyber systems, which can create vulnerabilities for the energy supply, especially due to the risks inherent in the methods to create a cyber-physical Digital Twin (CPDT) model (Alvarez-Alvarado et al., 2024). CPDT is important in the modeling and execution of smart grids, but the feasibility of its implementation can raise security risks (Cali et al., 2023). A CPDT must capture both data from the physical system as well as the computing platform. This can expose digital energy platforms to additional cybersecurity breaches. As a result, the complexity introduced by the CPDT model can compromise smart grids and expose systems to high vulnerability (Ji and Niu, 2024).

Intrusion Detection Systems (IDS), conventionally employed to provide protection for networks, are limited when it comes to managing the asymmetric nature of data sets in Smart Grid Control Systems (SGCS) (Ji and Niu, 2024). Efficient cyber threat detection becomes more difficult because of the ever-changing approaches to attack and the vulnerabilities created as a result. A deep learning framework may help overcome the challenges of data management and cyber threat detection (Lamagna et al., 2021).The heterogeneity of data is also a notable obstacle. Energy systems are frequently composed of varied data sources, which may not communicate or be easily integrated. Such variety can impact the performance of communicating and processing data over systems, resulting in possible gaps for attackers to take advantage of. The inclusion of data from different sources, like sensors, smart meters, and geospatial data makes these data sources even more vulnerable and makes implementing secure and efficient systems even more difficult (Digital technologies for netzero energy).

Finally, real-time monitoring and threat management pose another major problem. The challenge of rapidly detecting anomalies or cyber-attacks in such expansive and interconnected systems is nuanced, in part due to system complexities, data heterogeneity, and the capabilities of monitoring systems to efficiently process data across an entire system. These complexities place additional challenges on monitoring systems that need to operate in real-time for security and continuity of services (Sifat et al., 2023; Ji and Niu, 2024).

To summarize, incorporating AI and Digital Twins into the energy sector presents various cybersecurity challenges. However, the cyber vulnerabilities posed by complexity, data heterogeneity, and monitoring systems must be actively managed to avoid threats to the security and the availability of energy infrastructures.

4.7.4. Regulatory and ethical challenges

The energy sector is facing considerable regulatory and ethical issues associated with the adoption of Artificial Intelligence (AI) and Digital Twin (DT) technologies requiring significant consideration for responsible adoption. From a regulatory point of view, the main challenge is data privacy and data security. For instance, the implementation of these technologies include processing large amounts of sensitive data, and newer technologies such as blockchain are being proposed to ensure secure and transparent data processing (Teng et al., 2021). However, these new technologies have drawbacks that include but are not limited to higher energy usage of blockchain technology, and the potential for delayed data processing from transactions on a blockchain, which raise concerns about the usefulness of a blockchain in large scale energy networks (Kavousi-Fard et al., 2024). In addition, the lack of standardized protocols for data interchange and interoperability of systems also negatively impacts the adoption of DT. Therefore, common standards need to be introduced and standardized digital languages developed to enable interoperability amongst different systems and platforms, because without such standards, the adoption of DT becomes increasingly difficult in the energy sector.

In terms of ethical aspects, transparency and accountability of AI and DT systems are two fundamental ethical issues. Automated decisions made by AI/DT systems need to be transparent and explainable to build trust within the stakeholders. Accountability mechanisms also need to be in place to prevent biases in algorithmic reasoning in AI and DT, ensure technologies do not reinforce existing social inequities, or create a new set of difficult ethical issues (Kavousi-Fard et al., 2024; Tariq et al., 2022). Additionally, automation of work on ethical concerns is essential, particularly given the impacts of automation on jobs. Automation efficiencies and cost savings supported by AI and DT should be harnessed, but may develop job displacements. Thus, there is an urgent need to develop some retraining and upskilling methods to support workers and alleviate job loss impacts and promote an equitable transition in the energy sector (Teng et al., 2021; Heluany et Gkioulos, 2024).

These regulatory and ethical issues must be addressed to develop AI and DT technologies that are safe, equitable, and beneficial to society.

4.7.5. Environmental Impact

The integration of artificial intelligence (AI) and digital twin (DT) technologies has a significant environmental impact, particularly due to their negative aspects, making it a growing concern. One of the main challenges lies in the high energy consumption associated with AI models, especially deep learning models, which require substantial computing power.

This higher energy consumption results in carbon emissions, particularly when the source of energy used every day is from fossil fuels (Teng et al., 2021). Likewise, although Digital Twins are designed to optimize various operations, they too will require considerable computing resources for processing real-time data and performing the various simulations. That means that any energy intensive consumption for computational power may offset the environmental benefits that they may provide (do Amaral et al., 2023; Wang et al., 2022).

Furthermore, using AI and Digital Twins involves substantial infrastructure, with data centers and IoT devices involved in the process. The production and maintenance of this infrastructure can deplete resources and create electronic waste (İlker Aya c et al., 2023; Tariq et al., 2022). The environmental repercussions of the lifecycle of digital technologies, from manufacturing to disposal, also involves environmental concerns, such as raw material extraction, energy-intensive manufacturing, and the challenges of recycling electronic parts, which become components of the environmental footprint itself (Heluany et Gkioulos, 2024). Overall, the highlighted aspects require proper consideration of environmental impact before the emergence of AI and DT technologies ultimately develop even further and take up more space.

4.8. Discussion and remarks

Digital twin (DT) technology has developed itself into a transformative tool across multiple sectors by harnessing real-time data, artificial intelligence (AI), machine learning (ML), and deep learning (DL) to create virtual replicas of physical systems for better monitoring, analysis, and optimization (Gao and Huang, 2023; Teng et al., 2021). The original conception came through NASA, where DT developed itself into a versatile one to fore proactively and efficiently manage complex systems (Bazmohammadi et al., 2022). In turn, DTs formulate micro-grids (MG) to do real-time production, consumption, and storage of energy. They connect renewable resources, solving complex optimization problems and delivering solutions cost-effectively and sustainably through advanced energy management systems (EMS) and SCADA(Supervisory Control and Data Acquisition) systems (Gao and Huang, 2023; Espín-Sarzosa et al., 2023). Additionally, DT optimizes agrophotovoltaic (APV) solar parks using reduced-order control models and genomics-based machine learning (Zohdi, 2021), all while aligning operations across computing layers via Generic Digital Twin Architectures (GDTA) (İlker Aya c et al., 2023).

For photovoltaic systems, DTE will allow for predictive maintenance and remote diagnostics using IoT and ML algorithms for system assurance under varying weather conditions and scenario replication for upgrades (Fara et al., 2021; Yalçin et al., 2023). Urban energy systems, on the other hand, benefit from DT based on real-time monitoring, adaptive decision-making, and integration with EMS, enhancing responsiveness and resilience (Wang and Liu, 2024). A number of companies, for instance, General Electric, Siemens, and ABB showcase their potential in cost reduction and performance enhancement (Bazmohammadi et al., 2022). In positive energy districts and smart buildings, DTs optimize energy use and energy production based on ANN and other advanced optimization algorithms to create energy self-sufficiency and provide predictive maintenance (Li et al., 2023a; Sehrawat et al., 2023).

Furthermore, Industry 4.0 technologies, i.e. IoT, Cyber-Physical Systems, big data, increase the capacity of DTs for real-time data gathering and predictive diagnostics on residential heating-cooling systems and building management (do Amaral et al., 2023). The creation and updating of DTs use techniques such as IoT, laser scanning, and image-processing methods to ensure data fidelity and automation (Starkey et al., 2022). By simulating the complete lifecycle with feedback on interactive bases, a DT better parameterizes observation and potential model controls, greater efficiency and more rapid decision-making, along with more sustainable energy management and industrial applications (Wang et al., 2022). It also alters engineering and energy practices in ways that include but are not limited to benefits such as performance optimization, cost reduction, and sustainability across other disciplines.

The most effective utility of digital twins, therefore, across 42 papers examined in this study, is a hybrid one where rigorous modeling is complemented with intelligent real-time data usage. According to my vision of an ideal digital twin, a structured methodology incorporating various stages should provide guidelines Fig. 15.The procedure must start from detailed, modular modeling of the system such that each of its components is modeled independently and, subsequently, put together to develop an overall model. The model should represent an ideal state of the system; this can be considered the benchmark for its optimal performance. The simulated scenarios would be used depending on diverse conditions to evaluate how the system would act.Real-time data from the physical system being monitored is central to virtual modeling. This data enhances the virtual model and also provides a framework wherein the two are dynamically interlinked relating the real and ideal states of operation. In this way, it becomes very possible to detect anomalies and also foresee the probabilities of failure.

My ideal stance as regards a digital twin also revolves around a phase of deep investigations for anomalies found and a quest for root causes. Predictive simulations allow one to estimate the effect of multiple modifications into the system and virtually test solutions before they reach implementation; all such processes are absolutely amongst, I consider, the strongest capabilities of this technology.

An ideal digital twin should then also endorse a more proactive and well-informed approach in decision-making processes. A fix put on the physical system should emphasize solving a problem and must lead to constant improvement of performance with respect to cost and

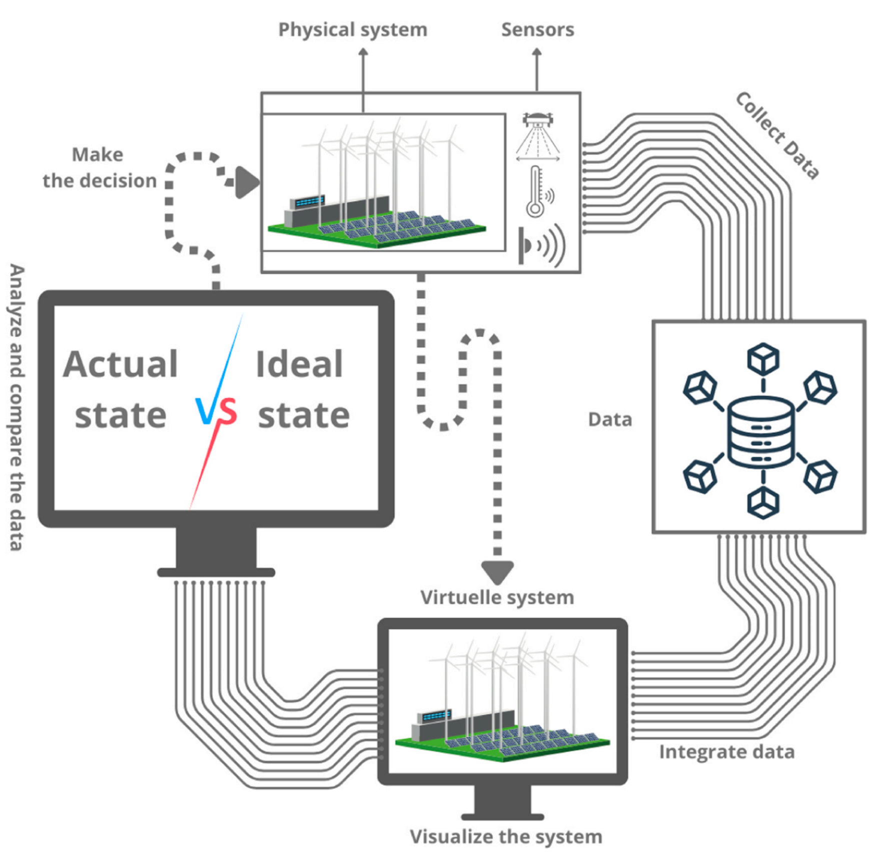

Fig. 15. The ideal proposition for a complete digital twin.

sustainability.

So, condensing this, my vision of the ideal digital twin is that of an intelligent and adaptable instrument, serving as a dynamic link between the two worlds of virtual and physical. It is a proactive and predictive device that transfers the management of complex systems into a process of cautious optimization.

5. Future perspectives

The future of real-time monitoring in the energy industry will occur through the use of Digital Twins and Artificial Intelligence this is a game changer, providing real-time monitoring, optimizing resources, and better decision-making for the energy sector. With their ability to model intricate energy systems and exploit real-time data, AI-DT will deliver bespoke solutions for energy generation, storage, and distribution, enhancing efficiency and sustainability in the sector. It is essential to pursue further work in multiple research directions to realize their potential (Cao et al., 2023b; Teng et al., 2021; Hashmi et al., 2024).

First, the development of advanced Machine Learning (ML) models integrated into energy Digital Twins (DT) is crucial for refining simulations and energy predictions, particularly in contexts where only limited data is available (Yu et al., 2022). Algorithms based on Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Regression Trees (RT) have shown promising performance, with ANN standing out due to its enhanced accuracy in predicting the output power of energy systems (Fara et al., 2021). Additionally, adopting classification frameworks for DT that account for attributes such as appearance, behavior, and connectivity could help identify and exploit less studied variants of these technologies, opening the way for new applications and improvements (Yu et al., 2022).

Furthermore, the integration of emerging technologies such as 5 G, the Internet of Things (IoT), and blockchain provides a significant lever for improving data communication, securing transactions, and managing distributed energy infrastructures. The optimization of real-time information flow enabled by these technologies enhances the resilience and flexibility of smart energy networks (Teng et al., 2021). Moreover, the implementation of modular and standardized solutions for DT design could reduce integration costs and improve scalability, facilitating their large-scale adoption (Li et al., 2023b; Ji and Niu, 2024).

Another major challenge lies in the need to establish robust security frameworks and standardized protocols to mitigate risks related to cybersecurity and data reliability. The adoption of appropriate policies that support both innovation and the implementation of secure solutions is essential for ensuring a reliable and sustainable energy transition (Ghenai et al., 2022). Meanwhile, the engagement of academic institutions, industry players, and policymakers in strengthened collaborations will help overcome the technological and economic barriers associated with integrating DT and AI in the energy sector (Bayer and Pruckner, 2023).

Finally, government incentives and public-private partnerships play a key role in accelerating the adoption of DT and AI. By pooling resources and expertise, these initiatives help alleviate the initial implementation costs and promote a faster, more efficient energy transition. In this context, the establishment of grants and tailored financing mechanisms would encourage the development of innovative solutions while ensuring an equitable and sustainable deployment of these technologies (Teng et al., 2021).

In summary, the combination of Artificial Intelligence and Digital Twins provides a distinctive opportunity to disrupt the energy space by making it more intelligent, efficient, and resilient. A unified approach to its challenges of standardization, security, costs, and policy/governance is necessitated to take full advantage of this transformational opportunity. Effective collaboration across researchers, industry practitioners, and policymakers will be critical in tackling the challenges that will lead to successful adoption of these technologies, and speed the path to a more sustainable and high-performance energy future.

6. Conclusion

This systematic review of the literature discusses the exciting and transformative power of Digital Twins (DT) and Artificial Intelligence in the energy industry. Through the review of 42 key studies on energy research, it was shown that AI-enabled DT models can improve energy management and predictive maintenance, and support decision making. These developments result in reduced downtime, greater accuracy of fault detection, reduced operational costs, and improved efficiencies in energy infrastructures Nevertheless, there are obstacles to the widespread uptake of Digital Twins in the energy industry; while the benefits are considerable, there are significant challenges associated with their implementation means considerable investment in physical infrastructure, software, and expertise. Furthermore, the intricacy of integrating with existing energy infrastructures as we know, these infrastructures are often old, poorly interoperable, and lack ease of interoperability, remain a considerable challenge, as do the complexities relate to cybersecurity, and the lack of standardisation complicating a greater rollout and acceptance of DT as a solution. It is important to foster interaction between researchers, industry, and policy makers in order to devise scalable, secure, and economically feasible DT solutions in response to the challenge presented by DT in the energy industry To this end, as this review suggests, greater focus of future research will need to be directed towards many of the topics mentioned herein. First, and most fundamentally, addressing the improvement of AI-based DT models to increase the reliability and accuracy of predictions and improve management.

By successfully addressing these hurdles, DT and AI technologies can advance the energy transition into smarter, more resilient, and sustainable systems. This study provides a useful guide for researchers, practitioners, and policymakers who want to develop a complete appreciation of the current challenges, opportunities, and future research needs of Digital Twins in energy contexts.

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

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

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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