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Review

The Brain Behind the Grid: A Comprehensive Review on Advanced Control Strategies for Smart Energy Management Systems

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Abstract

The integration of digital technologies is catalysing a fundamental transformation of modern energy systems, enhancing operational efficiency, adaptability, and sustainability. Despite significant progress, the existing literature often addresses digital innovations in isolation, with limited consideration of their synergistic potential within Advanced Energy Systems (AES). This paper presents a systematic review of key digital technologies—such as artificial intelligence, the Internet of Things, blockchain, and digital twins—employed in AES, providing a critical assessment of their individual functionalities, interdependencies, and collective contributions to the energy sector. The analysis highlights the capacity of integrated digital solutions to augment system intelligence, strengthen operational resilience, and increase flexibility across various layers of the energy infrastructure. In addressing persistent challenges—including demand-side variability, supply intermittency, and regulatory complexity—the coordinated implementation of these technologies enables real-time optimization, predictive maintenance, and data-informed decision-making. The findings demonstrate that the synergistic deployment of digital technologies not only enhances system performance but also contributes to measurable improvements in reliability, cost-effectiveness, and environmental sustainability. The review concludes that establishing a cohesive and interoperable digital ecosystem is essential for the development of future-ready energy systems that are robust, efficient, and responsive to the evolving dynamics of the global energy landscape.

Keywords: advanced energy systems; digital technologies integration; artificial intelligence; energy system resilience; predictive maintenance

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1. Introduction

Over the past two decades, there have been numerous significant blackouts reported in electric power systems globally, leading to considerable economic losses and underscoring the susceptibility of power networks to large-scale disturbances. These occurrences have significantly interrupted industrial activities, essential infrastructure, and public services, with financial losses frequently assessed in the millions to billions of dollars. Significant events such as the Spain and Portugal blackout of 2025 [1], Northeast blackout of 2003 in North America and the 2012 India blackout, which impacted more than 600 million individuals, highlight the profound consequences that can arise from failures in generation, transmission, or control systems. The rising intricacy and interconnectedness of

contemporary power systems, propelled by escalating demand and the incorporation of renewable energy sources including hydrogen production, storage, heighten the likelihood of such failures [2–6]. In response to the challenges posed by conventional power systems, including increasing demand, aging infrastructure, and the need for renewable energy integration, there has been a swift advancement in technologies such as Advanced Metering Infrastructure (AMI) and Bidirectional High-Speed Communication (BHC). These technologies facilitate immediate oversight and management, aiding the transition from centralized grids to more flexible and decentralized Smart Grids (SGs). This shift improves the efficiency of the grid, strengthens its resilience, and fosters better user engagement. An essential aspect of SGs is Demand Response (DR), which entails modifications in electricity consumption by users in reaction to price signals or incentive structures. Demand response has progressed from simple load reduction techniques to advanced, automated approaches that enhance grid stability and flexibility. It currently serves an essential function in handling peak demand, facilitating renewable integration, and enhancing overall system reliability [7]. Figure 1 illustrates a conceptual framework for a next-generation smart grid energy management system, integrating distributed energy resources, intelligent control strategies, and advanced communication infrastructure. It highlights the active role of both local and remote consumers in energy generation and demand response, enabling real-time optimization and enhancing grid flexibility, resilience, and sustainability.

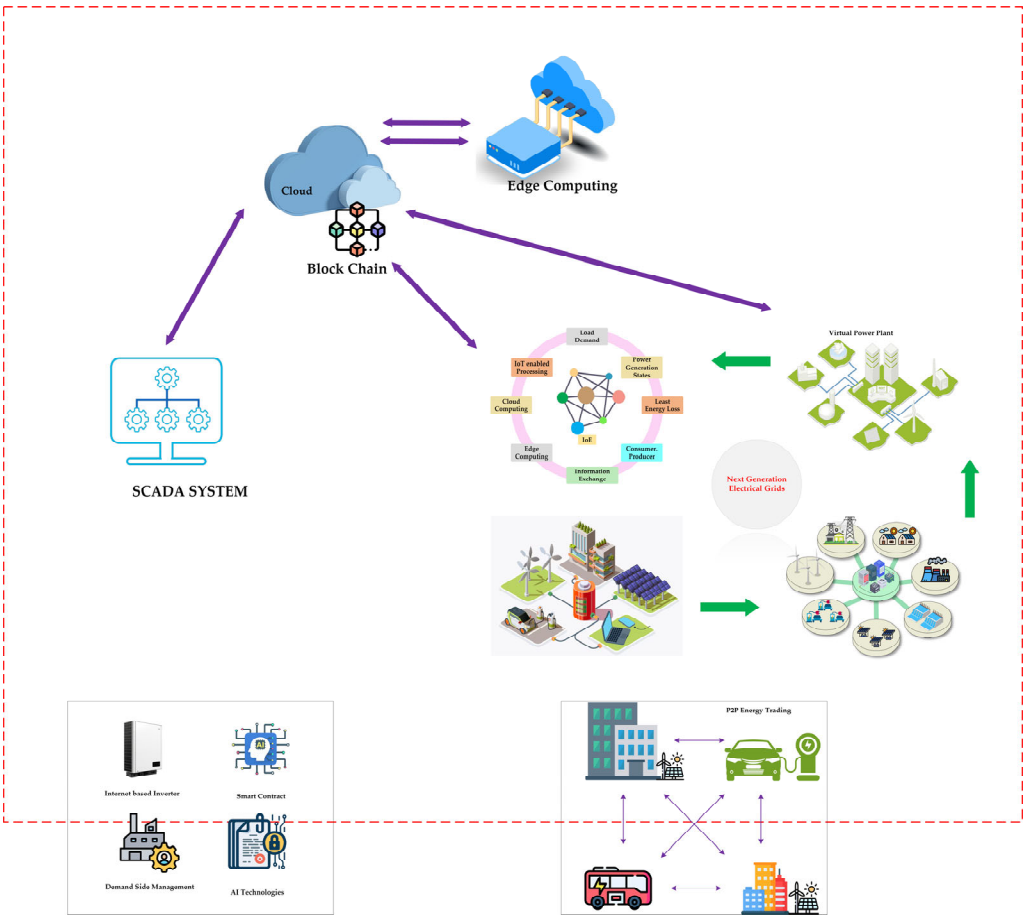

Figure 1. Conceptual framework for next-generation smart grid energy management system.

Furthermore, the utilization of Digital Twins (DTs) in SGs has received increasing attention, due to their ability to facilitate faster and more informed decision-making through complete and optimized system management [8]. Figure 2 illustrates the integration of smart grid infrastructure with advanced control technologies, emphasizing coordinated

energy flow, real-time monitoring, and intelligent decision-making. The architecture supports enhanced grid reliability, dynamic demand management, and efficient utilization of distributed energy resources.

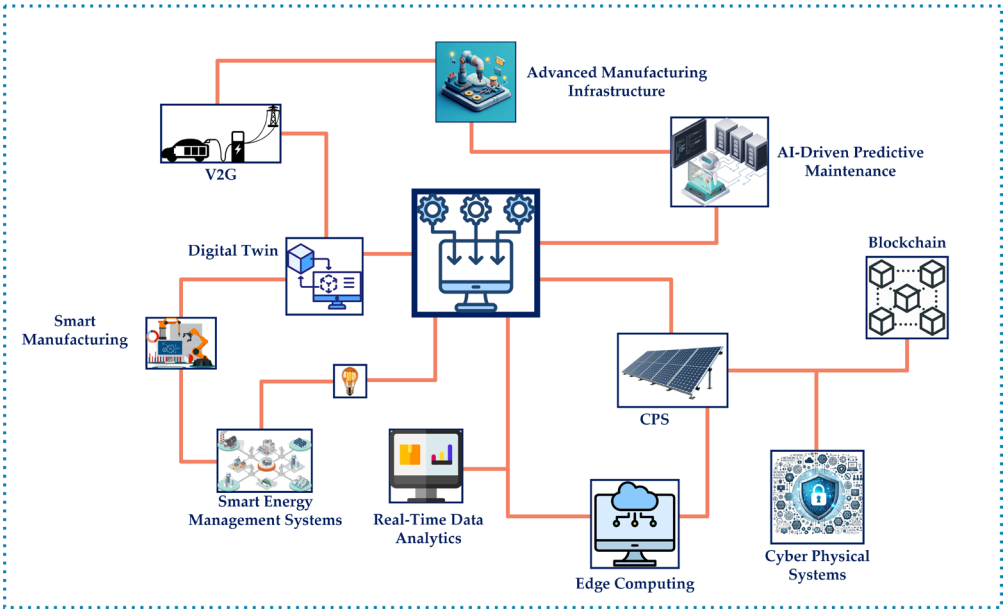

Figure 2. Integration of Smart grid with Advanced Control Technologies [9].

The energy sector is undergoing a significant transformation, driven by the dual objectives of decentralization and decarbonization, aimed at developing a cleaner, more flexible, and sustainable energy system. Digitalization is playing an increasingly important role in reshaping the energy sector, driven by the growing integration of digital technologies with traditional energy infrastructures. As the sector moves toward decentralization and decarbonization, the adoption of technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics is becoming vital for supporting these changes [10–12]. These digital tools enable real-time monitoring, predictive analysis, and more efficient management of energy systems, which enhance overall performance and operational flexibility. The convergence of digital and physical systems is particularly beneficial for optimizing the integration of renewable energy sources and Distributed Energy Resources (DERs), while also improving grid reliability and system resilience. This fusion is integral to the development of smart grids and Digital Twin models, both of which are essential to creating a more sustainable, flexible, and user-responsive energy infrastructure. Recent advancements in digital technologies, coupled with sophisticated control systems, are set to significantly transform the energy landscape. These innovations are driving the accelerated adoption of renewable and low-carbon energy sources, such as solar, wind, and energy storage solutions, while simultaneously enhancing system efficiency and flexibility [13]. Furthermore, the integration of advanced control systems helps optimize the balance between supply and demand, improves grid stability, and reduces energy losses. Together, these technological developments not only support the transition to a cleaner energy mix but also foster greater resilience and adaptability in energy systems, contributing to more sustainable and efficient operations across the sector [14]. Figure 3 illustrates the evolution of smart grid systems from the 1970s to the present and into the future. It highlights the transition from traditional centralized energy models to advanced, decentralized networks, driven by the integration of renewable energy sources, digital technologies, automation, and active consumer participation—enabling a more efficient, resilient, and sustainable energy ecosystem.

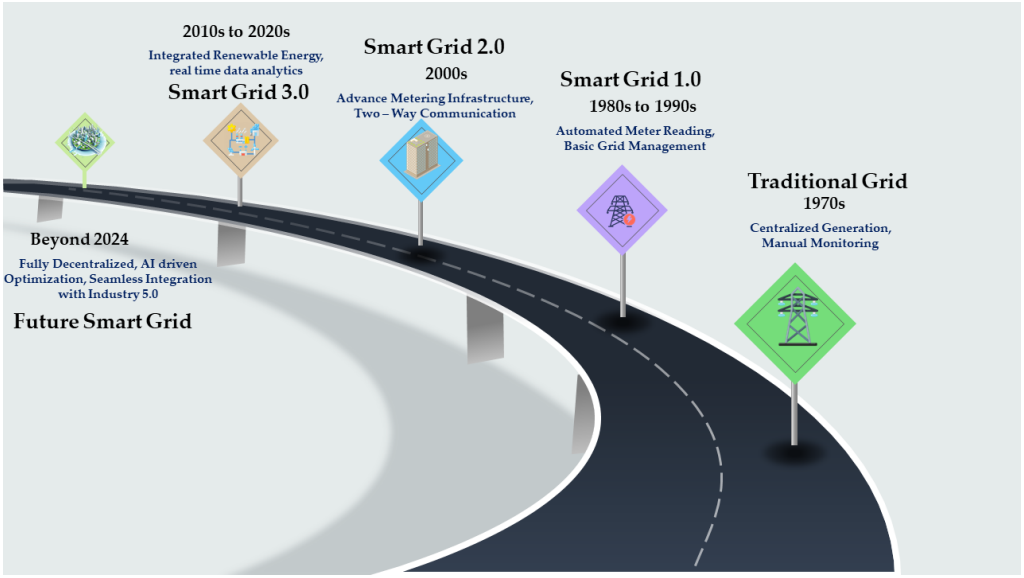

Figure 3. Evolution of smart grid system [15].

Digitalization has emerged as a pivotal enabler in the transition toward sustainable, efficient, and resilient energy systems. By facilitating real-time data acquisition, advanced analytics, and seamless communication across interconnected devices and infrastructures, digital technologies significantly enhance operational efficiency, reduce costs, and improve the adaptability of energy systems in response to evolving demands [16,17]. This paradigm shift aligns with global initiatives aimed at mitigating environmental impacts while promoting the development of energy infrastructures that are both technologically sophisticated and economically sustainable [18]. At the forefront of this transformation are Advanced Energy Systems (AES), which integrate innovative technologies such as smart grids, renewable energy sources (RESs), and intelligent Energy Management Systems (EMS). Unlike conventional fossil fuel-based systems, RESs are characterized by inherent intermittency due to daily and seasonal variations, posing challenges for maintaining grid stability and energy reliability. Nevertheless, the application of digital solutions has significantly improved the integration and management of RESs, thereby unlocking their full potential for large-scale deployment. The rising dependence on RESs is further driven by increasing global energy consumption, influenced by population growth, rapid urbanization, and industrial advancement [13]. In this context, digital technologies play a critical role in optimizing energy generation, distribution, and end-use consumption, thereby enhancing overall system performance and sustainability [19]. Furthermore, ongoing advancements in digital infrastructure and control methodologies are expected to accelerate the adoption of low-carbon energy solutions and redefine the operational dynamics of modern energy systems [20].

The integration of advanced digital technologies forms a comprehensive framework to address the challenges of Advanced Energy Systems. This synergy improves grid management, optimizes resource allocation, and enhances overall system resilience. Artificial Intelligence (AI) plays a key role in predicting fluctuations in energy demand through the analysis of historical consumption data, weather forecasts, and real-time grid inputs. This allows for timely adjustments in energy generation and distribution, particularly crucial for managing intermittent renewable energy sources such as solar and wind. The Internet of Things (IoT) further supports this process, with devices like smart meters and sensors providing continuous data streams from DERs. These devices enable real-time monitoring, which helps optimize resource usage and facilitates demand-side management, allowing

consumers to adjust their energy consumption based on grid conditions or pricing signals. Blockchain technology enhances the security and transparency of energy transactions by enabling decentralized peer-to-peer (P2P) energy trading. This allows prosumers to directly exchange excess energy, such as surplus solar power, without the need for traditional utility intermediaries. Digital Twin (DT) technology complements this ecosystem by creating virtual models of physical energy systems, allowing operators to simulate grid behavior, anticipate failures, and optimize maintenance schedules without affecting the actual infrastructure. For example, DTs can model the integration of renewable energy sources or evaluate the impact of new storage solutions, thus improving decision-making processes. Several real-world applications demonstrate the impact of these technologies. Google's DeepMind has optimized the cooling processes at power plants, leading to significant energy savings. Siemens uses predictive maintenance in wind turbines to reduce downtime, while IBM's platform assists in forecasting renewable energy output. Additionally, AutoGrid's automated energy trading system helps utilities optimize market operations, and WattTime enables consumers to choose cleaner energy, reducing carbon emissions [21]. Together, these technologies contribute to a more efficient, sustainable, and resilient energy system, supporting the transition to a decarbonized future while enhancing the reliability and flexibility of energy infrastructure [22,23].

The rapid evolution of digital technologies has significantly contributed to advancements in smart grids, renewable energy systems, and demand-side management. Several comprehensive review studies have examined the integration of digital technologies within Advanced Energy Systems. For example, the study examines the integration of energy-related fields with machine learning (ML) and artificial intelligence, assessing collaboration networks among authors, research themes, and principal publishing sources [24]. It also identifies existing research gaps and potential areas where ML techniques can be further applied to enhance energy system performance. Similarly, the review in [25] explores the role of big data (BD) and AI in energy management, detailing their applications and interconnections within the broader context of digital technologies. The study also outlines critical components and frameworks essential for the development of intelligent energy management systems. Furthermore, the work in [26] conducts an extensive bibliometric analysis to trace the progression and impact of AI technologies in the renewable energy sector, offering insights into research trends, influential publications, and thematic developments over time.

Figure 4 presents the quantitative benefits of Artificial Intelligence (AI), Big Data (BD), and Advanced Digital Technologies (ADT) in the context of smart grid systems. It demonstrates improvements in areas such as operational efficiency, forecasting accuracy, demand response, fault detection, and overall system reliability, highlighting the transformative impact of these technologies on modern energy management.

Figure 5 illustrates the application of smart grid technology integrated with energy management systems. It highlights the coordinated interaction between energy generation, storage, and consumption components, facilitated by real-time data monitoring, advanced control algorithms, and optimization techniques. This integration enables improved energy efficiency, enhanced grid reliability, and increased sustainability by dynamically balancing supply and demand while accommodating distributed energy resources and consumer participation.

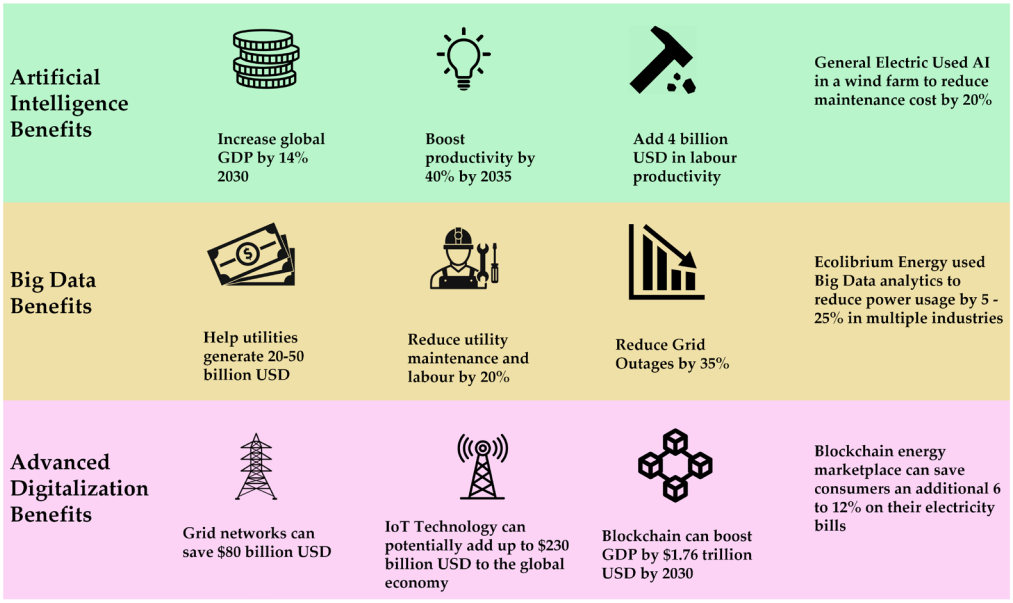

Figure 4. The quantitative benefits of AI, BD, and ADT [27–32].

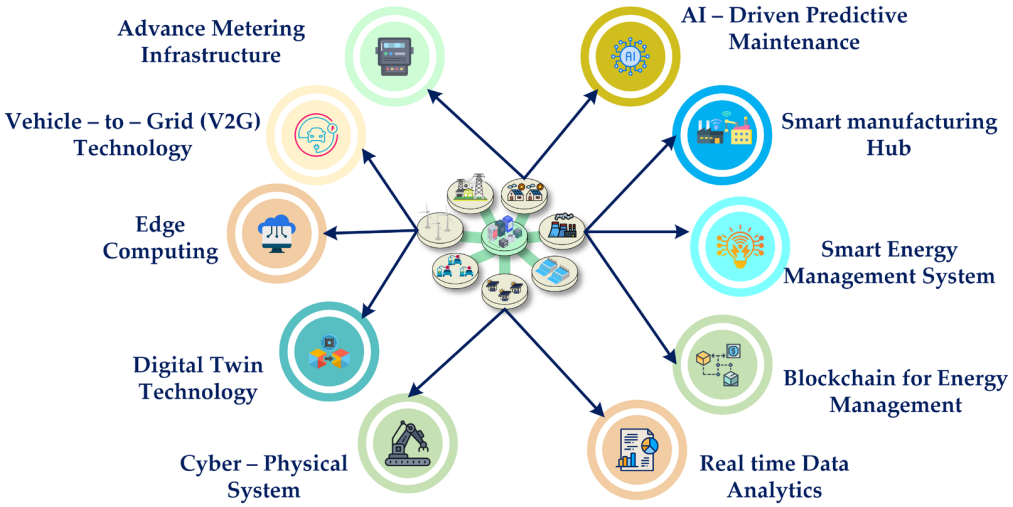

Figure 5. Application of smart grid with energy management systems [33].

Figure 6 illustrates the comparative volume of peer-reviewed publications related to digital technologies applied in advanced energy systems, retrieved from four prominent academic databases: IEEE Xplore, ScienceDirect, Taylor & Francis, and Wiley. The dataset was compiled following a rigorous and systematic search protocol, employing the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure methodological transparency, reproducibility, and comprehensiveness. The data were collected through a structured and systematic search protocol, using a combination of relevant keywords and Boolean operators, including but not limited to: "digital technologies", "smart grids", "advanced energy systems", "Internet of Things (IoT)", "artificial intelligence (AI)", "blockchain", and "digital twins". The search was limited to journal articles and conference proceedings published between 2014 to 2024, with further filters applied to ensure alignment with the scope of energy systems and digital innovation. Among the databases, IEEE Xplore contained the largest number of relevant publications, reflecting its strong focus on engineering, automation, and information and communication technologies (ICTs). ScienceDirect followed closely, contributing significantly from multidisciplinary domains such as energy systems engineering, data science, and environmental

technology. Taylor & Francis and Wiley demonstrated a moderate yet valuable contribution, particularly in journals focused on energy policy, digital transformation, and applied engineering. Notably, MDPI, although a rapidly growing open-access publisher with increasing visibility in the energy and digital domains, presented a smaller collection—approximately 200 publications—matching the defined inclusion criteria. This relatively modest representation may reflect the publisher's more recent focus on this research domain or the influence of the specific search parameters and filters applied during the systematic review process. The publication distribution across databases underscores the expanding academic interest in digitalization within energy systems and reflects the global research community's response to technological challenges and opportunities associated with Sustainable Development Goal 7 (SDG 7)—which emphasizes universal access to affordable, reliable, sustainable, and modern energy. This analysis also aids in identifying key knowledge repositories and may inform future literature review strategies and database selection for researchers in the field.

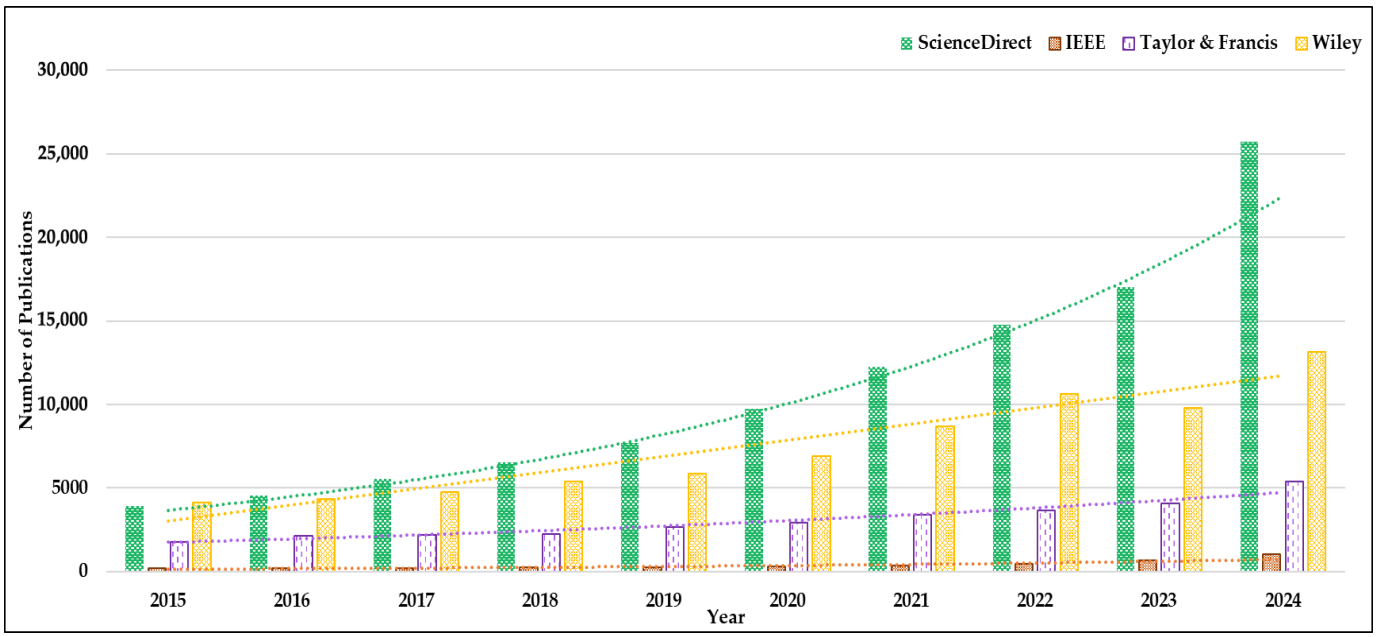

Figure 6. Number of publications on digital technologies in advanced energy systems in IEEE, ScienceDirect, Taylor & Francis, and Wiley.

A review of existing literature shows that most previous research has primarily focused on the development, application, and unique features of specific digital technologies in the energy sector. These studies frequently emphasize bibliometric assessments or the standalone deployment of technologies such as Artificial Intelligence, the Internet of Things, Blockchain, or Digital Twins. However, limited attention has been given to a comprehensive evaluation that examines the interrelationships and collective impact of these technologies within Advanced Energy Systems. To address this gap, the present study undertakes a systematic review of four closely interconnected digital technologies—AI, IoT, Blockchain, and DT—in the context of AES.

This work aims to rigorously synthesize the existing literature on the implementation and integration of four key digital technologies—Artificial Intelligence, the Internet of Things (IoT), Blockchain, and Digital Twins —in Advanced Energy Systems. This study adopts a systematic review methodology to examine the interrelationships among these technologies and to identify critical opportunities for their integrated application. Additionally, it assesses their collective potential to advance the intelligence, sustainability, and

resilience of contemporary energy infrastructures. The paper provides strategic insights focused on assisting policymakers, industry stakeholders, and the academic community, so enhancing informed decision-making and promoting successful management of digital transformation in the energy sector. This work also aligns with the objectives of the United Nations Sustainable Development Goals (SDGs), particularly SDG 7: Affordable and Clean Energy, which aims to ensure universal access to reliable, sustainable, and modern energy services. The advancement of renewable energy technologies, decentralized generation, and smart grid infrastructures examined herein directly supports this goal by promoting the development of energy systems characterized by enhanced efficiency, resilience, and environmental sustainability.

The manuscript is systematically organized to present a comprehensive analysis of advancements and future directions in advanced energy systems. Section 2 offers a critical review of state-of-the-art control strategies and enabling technologies pivotal for intelligent energy management within smart grid infrastructures. Section 3 examines the integration of renewable energy sources, highlighting emerging opportunities and strategic pathways to enhance system flexibility, resilience, and sustainability. Section 4 provides an in-depth exploration of the evolution and application of Digital Twin technology in smart grid contexts, emphasizing its impact on real-time monitoring, predictive analytics, and operational optimization. Section 5 addresses the prevailing challenges and delineates future research directions essential for the continued development of smart grid systems, underscoring the importance of interdisciplinary collaboration and innovation. The Conclusions synthesizes the key findings and delivers practical recommendations aimed at guiding researchers, policymakers, and industry stakeholders in advancing the digital transformation of energy systems.

2. Advanced Control Strategies and Technologies for Smart Energy Management

Microgrids necessitate advanced energy management systems to enhance the operation and real-time control of distributed energy resources, thereby ensuring stability and performance. In the last ten years, many optimization strategies have been investigated, encompassing mathematical techniques, metaheuristic methods, and sophisticated learning algorithms, with a strong emphasis on minimizing operational expenses and improving real-time control. A variety of studies have explored microgrid energy management systems from multiple viewpoints. For example, [34] examines energy management and control systems (EMCS) in building applications, focusing on the integration of thermal energy supply and electrical power generation, while noting that optimization methods are mainly rooted in mathematical and metaheuristic approaches. A critical analysis of microgrid control methods is presented in [35], while EMS for DC microgrids is comprehensively reviewed in [36,37]. In particular, ref. [37] offers a more extensive overview of optimization techniques, while Al-Ismail [36] conducts a critical examination of EMCS methods. Investigations such as [38–42] explore deeper into EMCS for microgrids, covering a range of classifications and subjects. In the design of a microgrid, it is essential to meticulously evaluate various operational aspects to guarantee its effectiveness and performance, as shown in Figure 7. These aspects encompass elements such as energy management, load prioritization, fault handling, and grid interaction strategies, each of which plays a crucial role in enhancing the overall performance and adaptability of the microgrid system. Figure 7 provides an overview of the fundamental components and operation of a microgrid. Also, it illustrates the integration of distributed energy resources, energy storage systems, control units, and loads within a localized network capable of operating both in grid-connected and islanded modes.

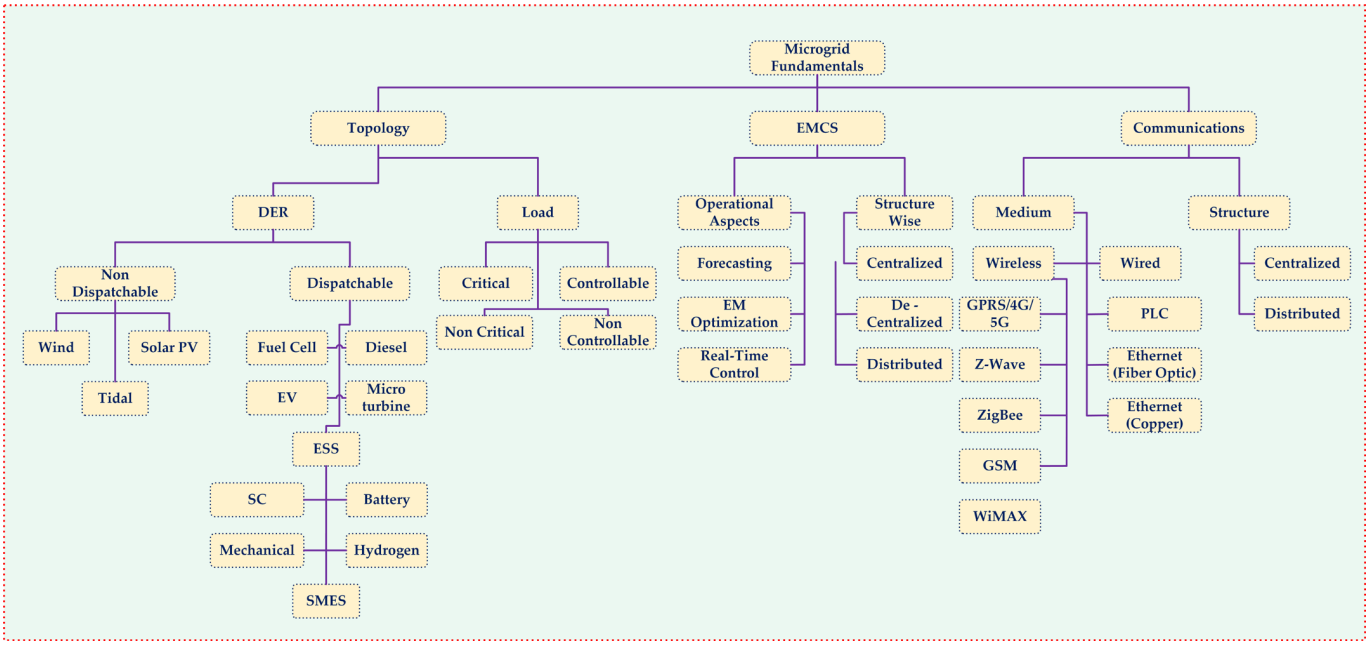

Figure 7. Overview of microgrid fundamentals.

An Energy Management and Control System (EMCS) serves as a crucial element within a microgrid, largely due to the distributed and dynamic characteristics of its energy resources. The EMCS functions as the central control unit of the microgrid, overseeing the optimal management of energy generation, storage, and consumption to achieve diverse goals including cost reduction, load balancing, emission minimization, and system stability, all while adhering to established system constraints. The implementation of the system can take various forms, including centralized, decentralized, or distributed computational approaches, which are determined by the size, complexity, and architecture of the microgrid. One of the essential responsibilities of an EMCS is to enhance the utilization of various DERs, including renewable energy sources, energy storage systems, and controllable loads. The optimization process focuses on the efficient allocation of resources, aiming to minimize operational costs, enhance energy efficiency, and ensure the stability and reliability of the microgrid. This optimization is generally accomplished using sophisticated algorithms, such as mathematical programming, metaheuristic techniques, and real-time control strategies, specifically designed to tackle the challenges presented by renewable intermittency, varying loads, and system dynamics. Furthermore, in addition to optimization, the EMCS must guarantee that the outcomes of these calculations are successfully implemented within the physical microgrid system. The EMCS generates optimum operation setpoints, which are then converted into executable instructions for the microgrid's components via a real-time control system. The real-time control system plays a crucial role in ensuring system stability, particularly when addressing dynamic fluctuations in energy generation, load demand, and external disturbances. This necessitates swift communication, accurate control systems, and strong decision-making frameworks to guarantee seamless functioning across diverse conditions. The operational flow of the majority of EMCS systems can be categorized into three essential stages. Initially, forecasting is conducted to anticipate energy demand, renewable energy production, and other essential factors like weather patterns or electricity costs. Precise forecasting is essential since it supplies the necessary data for the optimization process. Secondly, the optimization phase employs the projected data to identify the most effective operational setpoints for energy generation, storage, and consumption. This phase may utilize methods such as model predictive control (MPC), algorithms based on machine learning, or metaheuristic strategies like genetic algorithms

to address intricate optimization challenges in real time. Ultimately, the real-time control phase executes the optimized setpoints, making dynamic adjustments to the operation of distributed energy resources, energy storage systems, and loads to ensure the microgrid performs as intended.

An EMCS facilitates the incorporation of sophisticated functionalities, including demand response initiatives, wherein users modify their energy consumption based on immediate pricing signals or grid circumstances. Furthermore, the EMCS has the capability to manage several microgrids or engage with the primary grid, facilitating seamless energy transfer and maintaining grid stability. The importance of interoperability cannot be overstated in contemporary energy systems, where microgrids are progressively recognized as fundamental components of expansive smart grid ecosystems. To address the inherent uncertainties in renewable energy generation and varying load profiles, EMCS systems are progressively integrating advanced technologies, including machine learning, artificial intelligence, and edge computing. These technologies improve the system's capacity for predictive and adaptive decision-making, facilitating proactive energy management. Additionally, the integration of real-time data acquisition and communication systems, such as IoT-based sensors and smart meters, is vital for facilitating uninterrupted data flow, which is crucial for accurate forecasting, optimization, and control.

In the architecture of power systems control, control techniques can be classified into three main categories: centralized, decentralized, and distributed control approaches, as depicted in Figure 8. It outlines the primary functions of energy management systems (EMS), including real-time monitoring, load forecasting, demand response, optimization of energy generation and consumption, and fault detection. These functions collectively enable efficient energy utilization, cost reduction, and enhanced reliability within power systems. Centralized Control: In this framework, a central controller, usually referred to as the Microgrid Central Controller (MGCC), oversees and regulates the functioning of all components within the system. The central controller collects data, including frequency and voltage, from all units and issues control commands based on that information. This method guarantees effective resource coordination; however, it necessitates significant communication between the central controller and all units involved. The significant dependence on communication infrastructure renders centralized control unfeasible for microgrids that cover extensive geographical regions or distances. Moreover, any delays or failures in communication can undermine the reliability and responsiveness of the system. Figure 9 illustrates a centralized control structure, where a central controller manages and coordinates all connected energy resources and loads. This architecture enables unified decision-making, streamlined communication, and optimized system performance, but may face challenges related to scalability and single points of failure.

Decentralized Control: Unlike centralized control, decentralized control designates a local controller for each unit. Each controller functions autonomously, depending exclusively on localized data, including frequency and voltage, to inform its decision-making process. In certain instances, restricted communication with adjacent units is allowed. Decentralized control offers advantages in reducing communication needs and enhancing system resilience; however, it faces challenges in attaining global optimization because of insufficient coordination among units. The lack of comprehensive information across the system can result in instability or less-than-ideal functioning, especially in interconnected microgrids where the actions of individual units affect the overall performance. Figure 10 depicts a decentralized control structure in which multiple local controllers independently manage distributed energy resources and loads. This approach enhances system scalability, flexibility, and resilience by reducing reliance on a single central controller and enabling autonomous operation within localized areas.

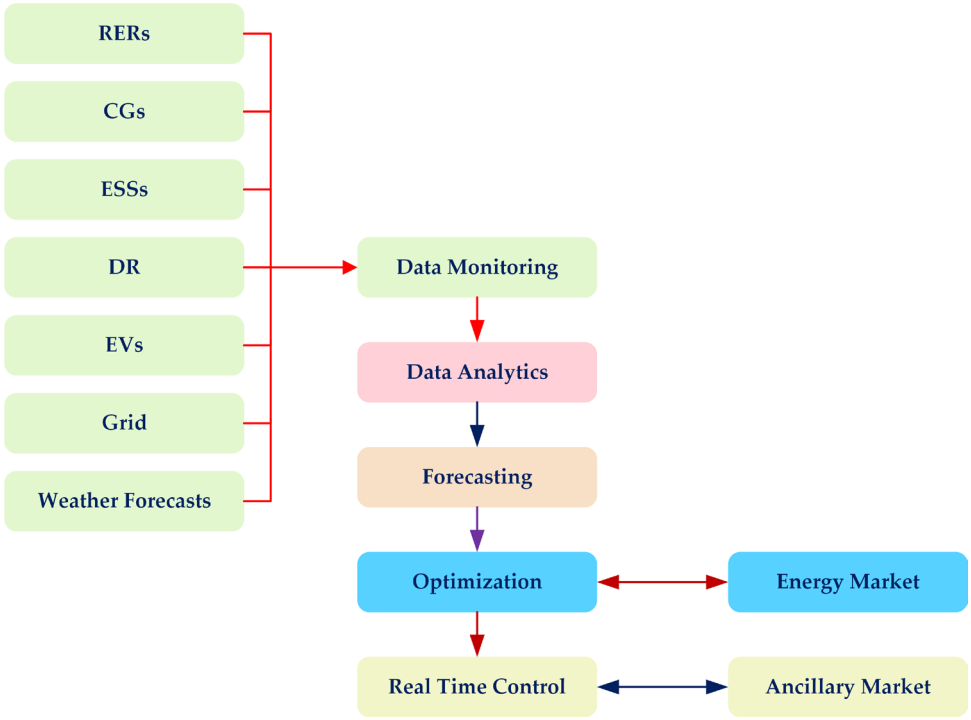

Figure 8. Functions of energy management systems [38].

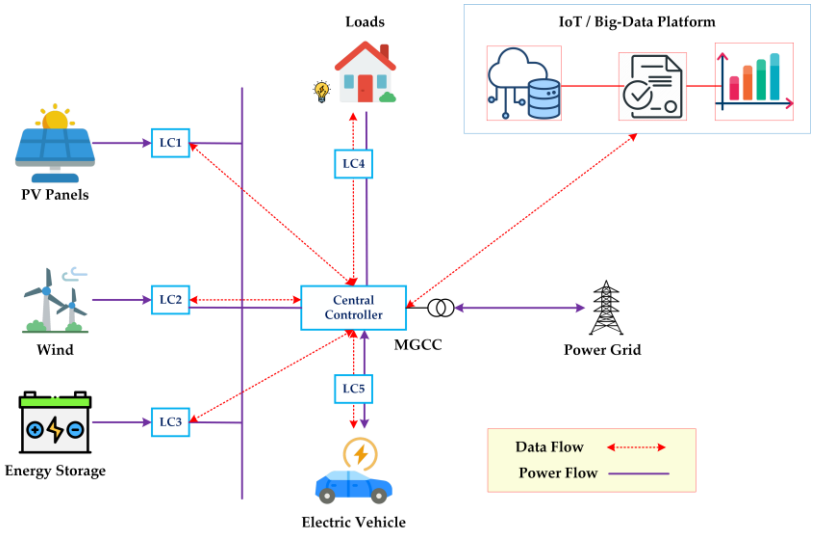

Figure 9. Centralized control structure.

A distributed control or hierarchical control scheme is introduced as a compromise to address the limitations of both centralized and decentralized approaches. Distributed control combines elements of centralized and decentralized systems, enabling a degree of centralization while preserving local autonomy. This method involves each unit functioning according to its local controller, making use of the information available in its immediate environment, including frequency and voltage. However, in contrast to completely decentralized control, units share information with adjacent controllers through two-way communication links. This collaborative communication facilitates coordinated decision-making throughout the system while maintaining the confidentiality of individual units, as sensitive information is not disseminated universally. Distributed control improves system stability, scalability, and fault tolerance, rendering it especially appropriate for contemporary microgrids where flexibility and efficiency are essential [41]. Figure 11 illus-

trates a hierarchical control structure that combines centralized and decentralized control approaches. It features multiple control layers—typically primary, secondary, and tertiary levels—each responsible for specific functions such as local regulation, coordination among subsystems, and overall system optimization, enabling efficient and reliable management of complex energy networks.

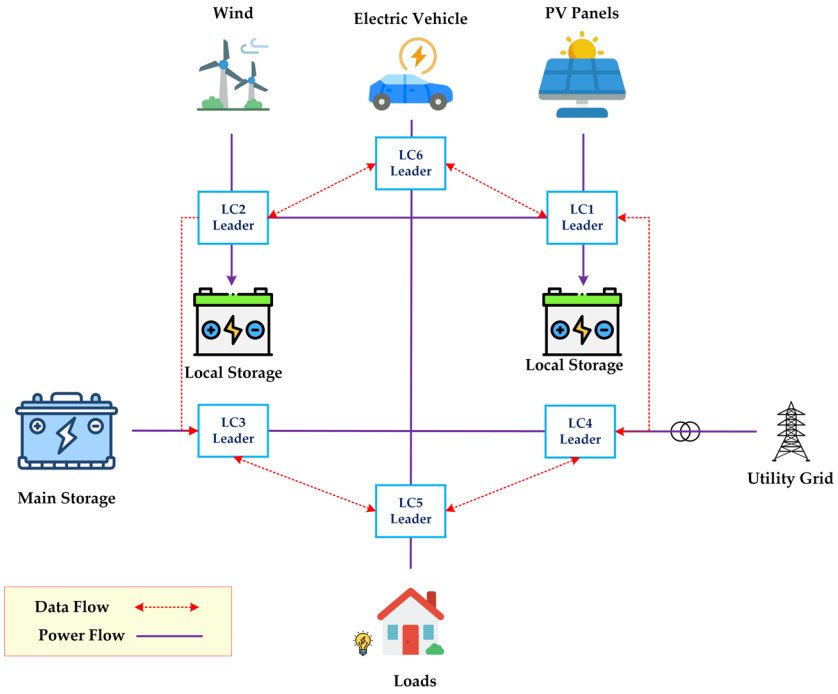

Figure 10. Decentralized control structure.

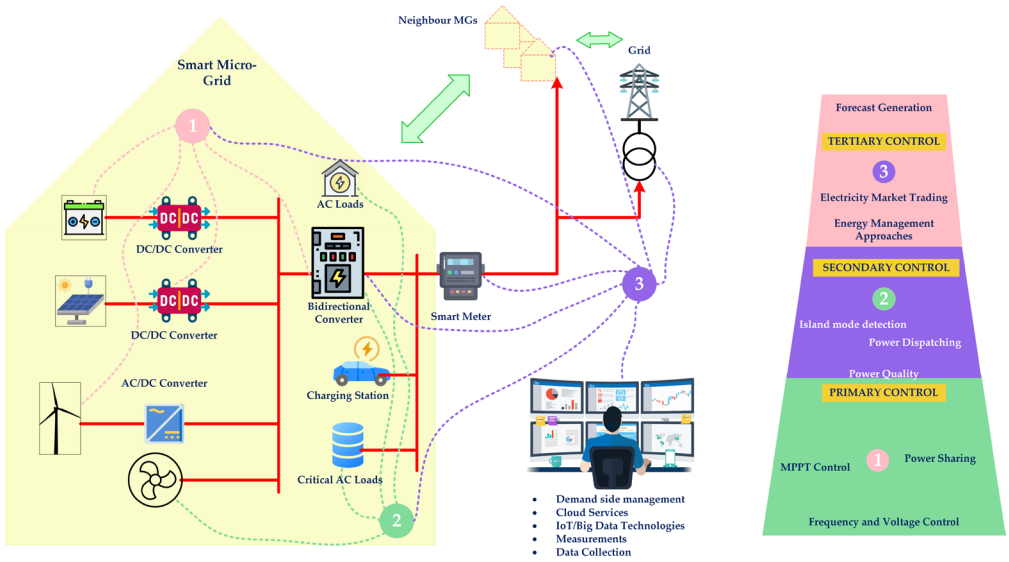

Figure 11. Hierarchical control structure.

Distributed Energy Resources (DER) signify a ground-breaking method for updating energy infrastructure through the decentralization of power generation, which improves the resilience, efficiency, and adaptability of energy grids. compared to conventional energy systems that depend significantly on large, centralized power plants situated at a distance from consumers, distributed energy resource systems emphasize the generation of power nearer to the consumption point. Technologies such as solar photovoltaic (PV) panels, wind turbines, battery energy storage systems, and electric vehicles are essential

components of distributed energy resources, facilitating localized energy generation and usage. Strategic positioning of DER systems in proximity to consumers leads to a notable reduction in energy transmission losses, thereby enhancing overall efficiency. This closeness facilitates immediate adjustments to supply and demand within the community, reducing pressure on centralized grid systems and improving overall reliability [43]. Furthermore, incorporating DER technologies can enhance recovery speed during outages, as these systems are capable of supplying power to essential loads even when the main grid experiences disruptions. The environmental advantages of distributed energy resources are significant, as these technologies frequently utilize renewable energy sources such as solar and wind. This approach not only minimizes greenhouse gas emissions but also supports international objectives aimed at addressing climate change and moving towards a more sustainable energy future [44]. Moreover, DER systems enable consumers to achieve energy independence, facilitating the production of their own electricity and, in certain instances, the ability to sell surplus power back to the grid via net metering programs. The democratization of energy represents a paradigm shift from traditional, centralized energy systems toward more decentralized models that actively engage consumers in energy generation, management, and decision-making processes. The extensive use of DERs—including rooftop photovoltaics, domestic battery storage, and demand response technologies—facilitates direct participation of people and communities in the energy market. This involvement can lead to enhanced energy independence and possible financial savings for consumers [45]. By leveraging advanced control systems and communication technologies, distributed energy resources can engage in demand response initiatives, contributing to the optimization of energy consumption during peak demand times. For example, energy storage systems can be charged during periods of low demand and low costs, then discharged during times of high demand to ease grid pressure and lower energy expenses. In a similar way, electric vehicles serve as mobile storage units, thereby increasing the flexibility of the grid. The increasing adoption of DER technologies is transforming the conventional centralized energy model into a decentralized and dynamic network. This development is essential for addressing the issues related to the incorporation of renewable energy sources, handling variable energy demands, and maintaining grid stability amidst rising electrification and digitization. The integration of technological advancements with a focus on consumer needs is propelling the shift towards a more sustainable, resilient, and adaptable energy ecosystem, setting the foundation for the energy grids of the future.

Various utility companies are increasingly adopting microgrids as a strategic approach to incorporate local DERs, such as solar PV systems, wind turbines, and energy storage systems, into their energy distribution networks. By doing so, they can offer consumers access to sustainable, reliable, and low-cost energy options. Microgrids not only enhance energy resilience by operating independently during grid outages but also support the transition to greener energy systems by reducing reliance on fossil fuels. This integration helps utilities balance supply and demand more effectively, optimize energy efficiency, and lower operational costs while empowering consumers with localized and environmentally friendly energy solutions [46]. The growing integration of Distributed Energy Resources in power systems has notably enhanced the responsibilities of Distribution System Operators (DSOs) in maintaining the stability, reliability, and efficiency of distribution grids. The changing roles of distribution system operators (DSOs) involve overseeing the incorporation of distributed energy resources, such as distributed generation, demand-side response, and energy storage systems, into the current power grid framework [47]. The emergence of distributed energy resources has introduced both challenges and opportunities for distribution system operators, who are now essential in utilizing decentralized flexibilities to improve grid performance and services for end customers. In this new paradigm, a crucial role of

DSOs is to leverage distributed flexibilities to enhance the efficiency of distribution networks, thereby reducing the necessity for expensive grid reinforcements. DSOs can reduce grid congestion, enhance operational planning, and facilitate the dependable integration of renewable energy sources by controlling the bidirectional power flows and variability created by DERs. This transition necessitates that distribution system operators evolve from their conventional responsibilities of network planning, maintenance, and managing supply interruptions, into proactive system operators who oversee real-time grid dynamics and encourage the active involvement of distributed energy resources. Distribution system operators have the capability to acquire flexibility services from network users, including voltage support and congestion management, to postpone infrastructure investments and address engaging grid operational issues. Alongside managing local flexibility, distribution system operators can offer reactive power support to transmission system operators (TSOs), promoting a more cohesive strategy for maintaining grid stability across various system levels. To further facilitate participation in specialized markets, DSOs and TSOs can work together to standardize flexibility service market offerings. The offerings encompass the definition of technical requirements for services like voltage control and local congestion management, managed by distribution system operators, whereas transmission system operators maintain responsibility for frequency-related ancillary services [48]. The evolving role of distribution system operators as active system managers highlights the necessity of a conducive regulatory environment to fully realize the benefits of distributed energy resource integration. This framework aims to empower distribution system operators to embrace cutting-edge grid management techniques, acquire flexibility services, and engage in productive collaboration with transmission system operators to ensure a stable and efficient power system. With the ongoing increase in DER adoption, distribution system operators will play a crucial role in maintaining the efficient and sustainable functioning of contemporary distribution networks. Figure 12 presents a schematic diagram of a distributed energy resource management system (DERMS). The diagram illustrates the coordination of various distributed energy resources, including generation units, storage devices, and controllable loads, through a centralized platform that enables real-time monitoring, control, and optimization to enhance grid stability and efficiency.

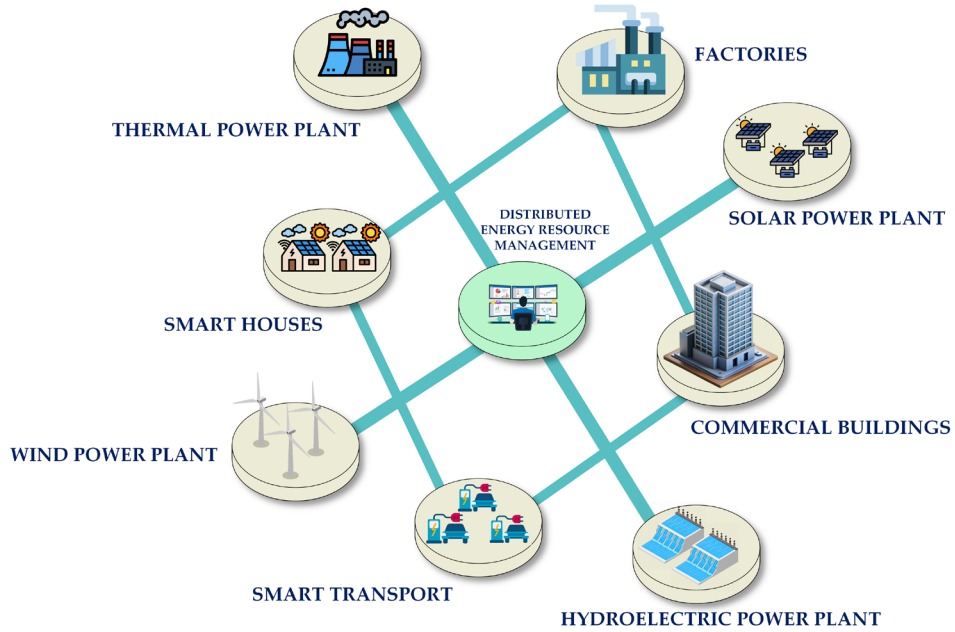

Figure 12. Schematic diagram of distributed energy resource management system.

The integration of Distributed Energy Resources (DERs) in power systems represents a transformative approach that brings about substantial changes in various dimensions: physical, market, and operational decentralization. This multifaceted transformation holds the promise of improving the adaptability, effectiveness, and sustainability of energy systems, simultaneously fostering greater empowerment among consumers. Nonetheless, it presents a range of challenges that necessitate creative solutions and teamwork.

Physical decentralization involves the geographical distribution of power generation by utilizing small—and medium-sized energy resources, including solar panels, wind turbines, and battery storage systems, which are directly linked to low- or medium-voltage distribution grids. This method minimizes transmission losses, enhances reliability, and facilitates the incorporation of renewable energy sources nearer to the consumption point. Decentralizing energy production leads to a decrease in reliance on large, centralized power plants, while also providing communities with the chance to embrace cleaner and more resilient energy solutions. Nonetheless, it presents difficulties for the conventional grid infrastructure, including the management of bidirectional power flows, ensuring grid stability in the face of renewable intermittency, and the need to enhance distribution networks to support various distributed energy resource technologies [49,50].

Market decentralization emphasizes the development of innovative trading and clearing mechanisms that support the secure, efficient, and user-friendly integration of distributed energy resources and data. This encompasses novel concepts such as peer-to-peer (P2P) energy trading, enabling consumers and prosumers to engage in direct energy transactions within local communities, thereby establishing localized energy markets. Market decentralization enables end-users to engage actively in energy markets, promoting enhanced transparency, competition, and financial inclusion. Blockchain technology and smart contracts are progressively utilized to facilitate secure and automated transactions within these decentralized markets. Nonetheless, the implementation of these mechanisms encounters obstacles, such as the need to create equitable and transparent pricing structures, safeguarding data privacy and cybersecurity, and tackling regulatory hurdles that could impede the establishment of decentralized market platforms [51].

Operational decentralization emerges through the participation of various energy managers, including Distributed Energy Resource Management Systems (DERMS), Virtual Power Plants (VPPs), and Local Energy Communities, which work together to manage the operation of Distributed Energy Resources (DERs) in order to align local energy supply with demand. The role of these managers is essential in enhancing the performance of decentralized energy systems through the facilitation of dynamic interactions among distributed generation, storage, and consumption. For instance, DERMS and VPPs have the capability to aggregate and oversee a variety of distributed energy resources, delivering essential grid services like frequency regulation, peak shaving, and demand response. Furthermore, Local Energy Communities have the potential to improve energy self-sufficiency while still ensuring connections to the main grid for backup support. Nonetheless, operational decentralization presents a unique array of challenges, such as the necessity for sophisticated algorithms and real-time data management systems, collaboration among various stakeholders, and the smooth integration with current grid architectures [52–54].

The complex and multifaceted aspects of decentralization—encompassing physical, market, and operational realms—represent a significant and complex transformation journey within the energy sector. This transformation necessitates tackling several significant challenges, including ensuring the interoperability of various DER technologies, managing the extensive real-time data produced by decentralized systems, and creating regulatory frameworks that promote equitable access to decentralized markets while encouraging the adoption of renewable energy. Despite the significant operational savings and envi-

ronmental advantages that DERs and decentralized systems may provide in the long run, their initial investment costs may be rather expensive, which raises concerns about their economic feasibility.

Figure 13 illustrates the infrastructure development required for integrating emerging DERs within a microgrid. It highlights key components such as advanced communication networks, control systems, energy storage, and renewable generation units, emphasizing their roles in enabling efficient, flexible, and reliable microgrid operation. Several significant problems in decentralized energy systems emerge from the integration of DERs and their effects on grid operations and energy markets. The challenges encompass addressing the unpredictability of renewable energy generation, as the variable characteristics of solar and wind power can result in erratic energy outputs, necessitating advanced forecasting and management tools to ensure grid stability. A significant concern is the necessity to reduce high and variable energy prices for consumers, leading to the creation of economical energy storage solutions, adaptive pricing strategies, and effective market systems to stabilize costs and maintain affordability [55]. Furthermore, overseeing real-time discrepancies between energy supply and demand is a multifaceted challenge that requires strong control algorithms, demand response initiatives, and the implementation of virtual power plants (VPPs) or distributed energy resource management systems (DERMS) to effectively align energy generation with consumption. The issue of preventing grid instability and ensuring high power quality is increasingly critical as renewable energy sources become more prevalent. This necessitates significant investments in modernizing the grid, enhancing power electronics, and providing ancillary services such as frequency and voltage regulation [56]. Furthermore, addressing the challenges of distribution grid congestion and facilitating grid enhancements, all while securing profitability for emerging participants in energy markets, presents a distinct economic aspect. Innovative approaches like peer-to-peer energy trading, the aggregation of distributed energy resources for market engagement, and the establishment of local energy communities have the potential to generate new revenue opportunities while reducing pressure on the grid. To fully realize the potential of decentralized energy systems, it is crucial to address these challenges in a comprehensive manner, ensuring a reliable, resilient, and affordable energy future [57].

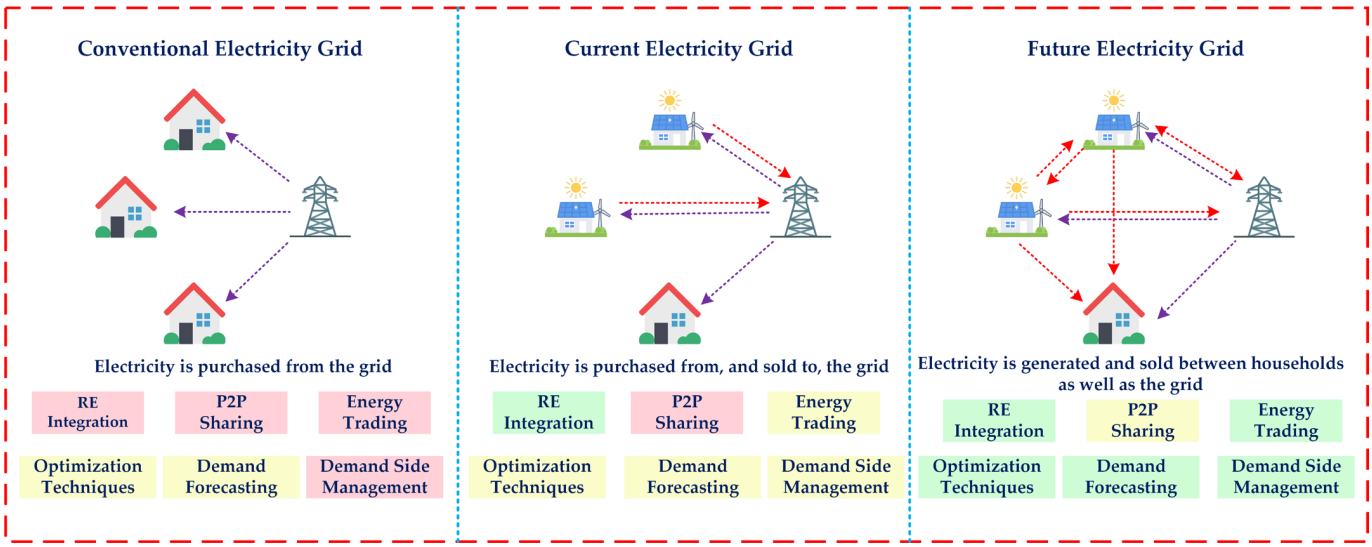

Figure 13. Infrastructure development for emerging DER in microgrid.

The choice of an Energy Management (EM) strategy is essential for maintaining the reliable and stable functioning of a microgrid (MG) system. The selection of a particular method is contingent upon the attributes of the system, including its topology, operational

modes, and structure. Nonetheless, choosing one method does not inherently undermine the validity of alternative approaches; rather, the key factors are the specific constraints being examined and the established goals of the control strategy, which guide the selection of the most suitable technique for the particular application.

A successful EM strategy should consider various essential elements, such as:

1. The unpredictable characteristics of control parameters.
2. Initial expenses and the longevity of components.
3. The existence of distributed energy resources (DERs).
4. The dependable and secure functioning of the microgrid system.

The implementation of an EM control strategy necessitates the categorization of the MG system into various operational levels, with each level coordinating with the others. The levels encompass power generation sources that employ techniques such as Maximum Power Point Tracking (MPPT) to end-users including both local consumers and those farther away, such as neighbouring microgrid consumers. In contemporary systems, intelligent components are incorporated into every source and microgrid system. Advancements in Information and Communication Technologies (ICTs) enable these components to communicate and cooperate with remarkable efficiency. Modern inverters, for instance, are capable of employing a range of control strategies, including the regulation of source power, the facilitation of grid interconnectivity, and the coordination with other microgrids. Moreover, these inverters are capable of supporting extensive microgrid systems, allowing for data clustering and promoting electricity exchange. Through internet connectivity, inverters have the capability to archive historical data in cloud servers, thereby enhancing long-term monitoring and system analysis. Nonetheless, a notable challenge persists: the main goal for numerous inverters is to provide a continuous power supply to users, frequently overlooking considerations like the longevity of battery storage systems or the expense of electricity. To tackle this gap, it is essential to create an EM control strategy that: analyses fluctuations in electricity pricing, reduces the frequency of battery charge and discharge cycles to extend battery lifespan, and enhances overall profitability of the system by decreasing electricity expenses. The primary objective is to develop a sophisticated and anticipatory control strategy that can enhance the functionality of DERs in the microgrid environment. This strategy needs to tackle various constraints and objective functions at the same time to guarantee efficient energy use, lower operational costs, and longer component lifespans, ultimately improving the overall stability, profitability, and sustainability of the MG system. Figure 14 illustrates the three key stages of energy management and control strategies: forecasting, energy management optimization, and real-time control. The forecasting stage involves predicting energy demand and generation based on historical data and external factors. The optimization stage focuses on developing optimal schedules and resource allocations to balance supply and demand efficiently. Finally, the real-time control stage executes control actions to adjust system operations dynamically, ensuring stability, reliability, and efficient performance of the energy system.

Table 1 provides a comprehensive comparative analysis of different optimization approaches applied in energy management systems. The evaluation criteria include computational complexity, scalability to large or distributed systems, accuracy in achieving optimal solutions, flexibility to adapt to changing operational conditions, and compatibility with various energy system architectures. By systematically comparing these factors, the table offers insights into the advantages and limitations of each method, thereby assisting researchers and practitioners in selecting the most suitable optimization strategy for specific energy management challenges.

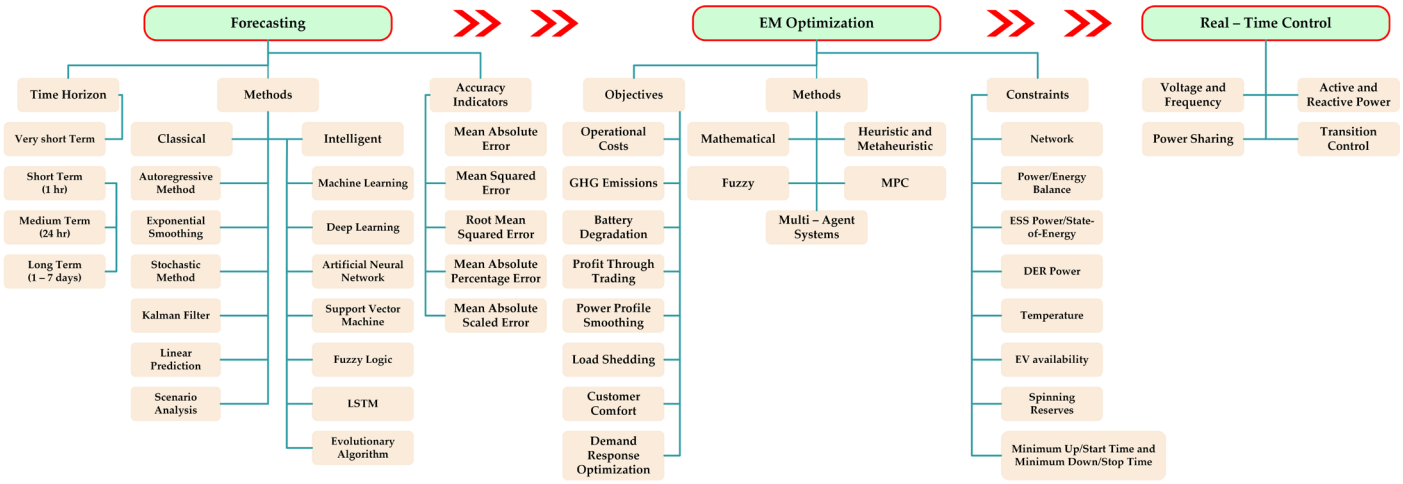

Figure 14. Three stages of energy management and control strategies [58].

Table 1. Comparative analysis of optimization approaches for energy management systems [59,60].

Control Approach	Application	Advantages	Disadvantages
Model predictive control [61–63]	1. Reliable for power sharing between MG and the utility grid 2. Hybrid AC/DC coupled MG	1. Robust against uncertainty. 2. Power smoothing. 3. Multiple control objective and constraint functions are implemented for the same control strategy. 4. Optimal control.	1. Requiring the use of advanced ICTs. 2. Control parameters information should be defined in advance.
Adaptive droop [64,65]	1. Hybrid system of RESs 2. Parallel DC/DC converter 3. Heavy loading conditions	1. The different operation modes eliminate the overload conditions between generator unites, storage devices, and utility grid. 2. Minimizing circulating current.	1. Difficult to select the proper voltage levels. 2. Generating interconnection resistances between the installed converter and requiring information about the DC bus. 3. Control parameters should be known in advance.
Artificial neural networks [66,67]	1. Distributed power generation units 2. Multiple MG system interconnection	1. The approach can control, optimize, and identify the system's parameters in online or offline applications. 2. Solve problems with nonlinear data approaches in large-scale systems in MG. 3. Solve the system's stability and fault tolerance via self-learning and prediction.	1. Complexity of the model structure. 2. Experimental interpretation of the model is difficult (black boxes). 3. Difficult to determine the best network structure in case of adding or raising units from the MG topology. 4. Possibility only on stable system structure.
Distributed cooperation control [68–70]	1. The control is optimal for DC-MG system 2. Improving voltage levels for DC-MG	1. Flexible, robust, and, extensible. 2. Optimal coordination control and improved voltage profile.	1. Less security for the communication system. 2. Frequency response nature cannot be visualized.
Conventional droop [71,72]	1. Reliable for DC-MG 2. Linear loads 3. Inductive transmission lines	1. Easy implementation for the primary control.	1. Voltage regulation is not ensured. 2. The voltage drops across the bus resistance, causing a current sharing degradation. 3. Active and reactive power bandwidth variation of the controllers affects the voltage and frequency controls.
FL based control [73,74]	1. Reliable for primary control 2. Voltage and frequency regulation	1. Improved voltage and frequency regulation and power sharing for multiple MG.	1. Requiring a high processing unit. 2. Errors methods adopted for the participation function and time-consuming process.

Table 1. *Cont.*

Control Approach	Application	Advantages	Disadvantages
Multi-agent-based control [75–77]	1. Distributed power generation units 2. Multiple MG system interconnection	1. The group of agents can address larger problems than any individual is capable to do in MG system. 2. Redundancy and economies of large scale. 3. The ability to meet global constraints. 4. Flexibility to work in uncertain environments under unforeseen conditions [78].	1. Potential for conflicts; need for increased agent sophistication. 2. Short term benefits may not outweigh organization construction costs for the installed MG systems. 3. Requiring a high connectivity between agents and the LC. 4. The agent should operate at the same parameters of the other agents, especially for voltage and frequency regulation.
Mixed integer linear programming [79–81]	1. Control for a stand-alone MG 2. Optimal programming for hybrid MG	1. Linear programming (LP) is a fast way to solve the problems and the linear constraints result in a convex feasible region, being guaranteed in many cases to obtain the global optimum solution.	1. Reliability and economic stochastical analysis. 2. Limited capabilities for applications with not differentiable and/or continuous objective functions.
Mixed integer non-linear programming [82]	1. The control is optimal for hybrid AC/DC MG	1. It uses simple operations to solve complex problems. 2. It can obtain more than one optimal solution to choose from, which is an advantage over the MILP formulation.	1. High number of iterations (high computational effort).
Dynamic programming (DP)	-	1. It can split the problem into subproblems, optimizing each subproblem and therefore solving sequential problems.	1. Complex implementation due to high number of recursive functions.
Genetic algorithms (GA)	-	1. Population-based evolutionary algorithms that include operations such as crossover, mutation, and selection to find the optimal solution. 2. Adequate convergence speed. Widely used in many fields.	1. Crossover and mutation parameters, and population and stopping criterial parameters must be set.
Particle swarm optimization (PSO)	-	1. Good performance in scattering and optimization problems.	1. High computational complexities.

Table 1. *Cont.*

Control Approach	Application	Advantages	Disadvantages
Artificial bee colony	-	1. Robust population-based algorithm simple to implement. 2. Adequate convergence speed.	1. Complex formulation.
Artificial Fish Swarm	-	1. Few parameters. 2. Fast convergence. 3. High accuracy 4. Flexibility.	1. Same advantages of GA but without its disadvantages (crossover and mutation).
Bacterial foraging algorithm	-	1. Size and non-linearity of the problem does not affect much. 2. Converge to the optimal solution where analytical methods do not converge.	1. Large and complex search space.

2.1. Communication Technologies

In microgrid systems, a robust and effective data communication system is crucial for maintaining uninterrupted and fast operations. The selection of a communication system is influenced by the configuration of the system, the protocols involved, and various other considerations including control objectives, complexity of implementation, and associated costs.

2.1.1. Technologies for Communication in Microgrids

The existing literature emphasizes the importance of both wired and wireless communication technologies in facilitating effective communication among microgrid components. The choice of a particular technology is shaped by various factors, including data rate, communication distance, quality of service (QoS), reliability, and power consumption.

2.1.2. Wired Communication Technologies

Technologies such as Ethernet, Communication for power lines, and fiber optics provide enhanced data transmission rates and improved reliability, rendering them ideal for essential and secure applications. Nonetheless, these technologies frequently entail elevated installation expenses because of the requirement for comprehensive cabling and infrastructure.

2.1.3. Wireless Communication Technologies

Various technologies, including ZigBee, Z-Wave, Global System for Mobile Communications (GSM), General Packet Radio Service (GPRS), and WiMAX/Wi-Fi, offer a cost-effective alternative to traditional wired networks. Although these technologies offer reduced deployment costs, they encounter obstacles like reduced data transmission rates and problems with signal interference.

2.1.4. Internet Protocols (IP) in Microgrids

A range of internet protocols (IP) has been introduced in the literature to facilitate communication within microgrids. These protocols enable the exchange and synchronization of data in microgrid operations:

1. The Network Timing Protocol (NTP) guarantees accurate time synchronization.
2. Transmission Control Protocol (TCP) and User Datagram Protocol (UDP) play significant roles in facilitating data communication within microgrid systems.

The Modbus protocol was implemented in [83] to facilitate the exchange of data between Programmable Logic Controllers (PLCs). The discussion covered two variations of Modbus: Modbus Remote Terminal Unit (RTU) and Modbus TCP/IP. Modbus TCP/IP integrates Modbus RTU with a TCP interface, functioning over Ethernet, and is widely employed in industrial networking.

2.1.5. Standards for Wired Communication in Microgrids

In the realm of serial transmission, commonly utilized wired communication standards include RS-232, RS-422, and RS-485. These standards can be effectively implemented over various physical links, including fiber optics and Ethernet [84]. Within this group:

- RS-485 is widely utilized in energy management for DC microgrid systems because it effectively supports numerous devices across extended distances.

Alongside industrial communication standards, open protocols such as Konnex (KNX) have become increasingly popular, particularly in the realm of building automation. KNX has been employed for energy management in both commercial and residential buildings, frequently alongside Modbus serial RS-485 to improve functionality. For instance, ref. [85] explores the combination of KNX and Modbus in the context of energy management for

smart buildings. Hence, microgrid communication technology selection requires a cost-benefit analysis of performance needs. Wired technologies excel in scenarios that demand high reliability and data rates, whereas wireless technologies offer flexibility and cost benefits for operations that are less critical. Furthermore, the incorporation of standardized protocols such as Modbus serial RS-485 and KNX facilitates smooth communication and improves energy management in microgrid systems, applicable to both industrial and residential settings. In this context, the Smart Grid Architecture Model (SGAM) serves as a comprehensive reference framework for the systematic evaluation of communication technologies within smart grid systems. By delineating five interoperability layers—component, communication, information, function, and business—across distinct domains, SGAM enables a structured analysis of protocol applicability and integration. This facilitates the alignment of communication solutions with technical and operational grid requirements, ensuring scalability, interoperability, and coherence across heterogeneous infrastructures. Table 2 summarizes the key parameters of various grid communication technologies used in smart grid systems. It includes metrics such as data transmission speed, latency, coverage range, reliability, security features, and cost. This comparison provides an overview of the strengths and limitations of each technology, facilitating informed decisions for selecting appropriate communication solutions tailored to specific grid applications.

Table 2. Grid communication technologies parameters [86–88].

	Technology	Data Rate	Cover Range	Applications
Wired	Broadband PLC	Up to 300 Mbps	Up to 1500 m	Smart grid, HAN
	Narrowband PLC	10–500 Kbps	Up to 3 km	Smart grid, HAN
	Ethernet	Up to 100 Gbps	Up to 100 m	SCADA, backbone Communication
	Fiber optics	Up to 100 Gbps	Up to 100 km	SCADA, HAN
Wireless	GSM	Up to 14.4 kbps	1–10 km	AMI, HAN, BAN, IAN
	GPRS	Up to 170 Kbps	1–10 km	AMI, HAN, BAN, IAN
	WiMAX	Up to 75 Mbps	Up to 50 km	AMI, Mobile workforce management
	Z-wave	40–250 Kbps	30 m point-point, Unlimited with mesh	AMI, HAN, BAN, IAN
	ZigBee	250 kbps	100+ m	AMI, HAN

Abbreviations: HAN—home area network, SCADA—supervisory control and data acquisition, AMI—advanced metering infrastructure, BAN—business area network, IAN—industry area network.

Figure 15 outlines the future research directions for intelligent energy management systems (ISMs). It highlights key areas such as the integration of advanced artificial intelligence techniques, improved data analytics, enhanced cybersecurity measures, development of adaptive control algorithms, and the incorporation of emerging technologies to address challenges related to scalability, interoperability, and sustainability in modern energy systems.

2.2. Modelling and Simulation Tools

Software such as MATLAB/Simulink and MATPOWER are notable for their adaptability and extensive use in various applications. MATLAB is a robust numerical computing environment and a fourth-generation programming language that facilitates interaction with multiple languages such as C, C++, C#, Java, Fortran, and Python, allowing for sophisticated simulations and control design. MATPOWER, a widely utilized open-source tool, is often used for simulating optimal power flows, employing techniques such as Monte Carlo simulations to evaluate microgrid performance. Furthermore, optimization tools like GAMS, which is a powerful platform for addressing linear, nonlinear, and mixed-integer programming challenges, have been employed to manage uncertainties in energy manage-

ment and enhance microgrid dimensioning. In a similar way, CPLEX, an optimization tool rooted in the C programming language, facilitates integration with other languages such as C++, Java, and Python, thereby serving as a significant asset for energy management solutions. In the realm of microgrid simulation and modeling, tools such as Simulink and PSCAD/EMTDC have been widely utilized for power control and energy management. These programs facilitate comprehensive examination of system dynamics and control strategies. Specialized software such as HOMER, HOGA (or its updated version, iHOGA), and HYBRID2 is tailored for hybrid energy systems. The tools concentrate on enhancing the functionality and energy management of renewable energy systems, rendering them appropriate for hybrid microgrid setups. This varied collection of tools highlights the significance of choosing the appropriate platform tailored to the unique needs of microgrid simulation, optimization, and energy management operations. The Table 3 presents a comprehensive overview of well-known simulation tools utilized for microgrid analysis, emphasizing their functionalities and applications in energy management and system optimization.

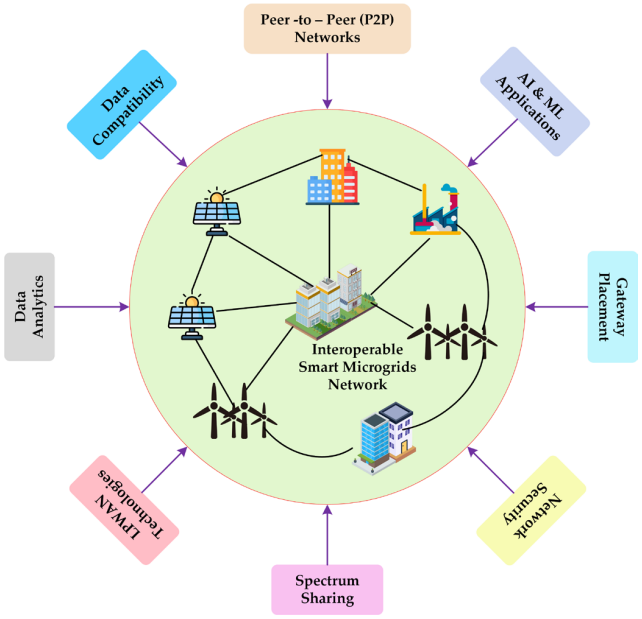

Figure 15. Future research directions for ISMs [59].

Table 3. Tools and simulation software for energy management and system optimization [60].

References	Tools	Characteristics
[89]	PSCAD/EMTDC	Simulation software power systems, power electronics, HVDC, FACTS, and control system.
[90–92]	MATLAB/Simulink MATPOWER	Matrix based programming language used by engineers in power systems, power electronics, telecommunications, and control, among others. Compatible with other programming languages (C++, Java, and fortran).
[78,93]	GAMS (GAMS Development Corp., Fairfax, VA, USA)	High level language for mathematical optimization of mixed integer linear and nonlinear.
[94–98]	TRNSYS (Thermal Energy System Specialists, LLC, Madison, WI, USA), HOMER, HOGA	Simulation software to model hybrid systems of energy generation. Hybrid Optimization by Genetic Algorithms.
[99,100]	RSCAD (RTDS Technologies Inc., Winnipeg, MA, Canada) JADE (Jade, Christchurch, New Zealand)	Real time simulator for power systems.
[101,102]	JADE	Java environment platform for multi-agents.
[103–106]	HOMER	Simulation software to model hybrid systems of energy generation.
[107]	CPLEX (IBM, Armonk, NY, USA)	Optimization software compatible with C, C++, Java, and Python languages.
[108–111]	DIgSILENT	Digital Simulation and Electrical Network Calculation Program
[112–114]	ETAP	Electrical Transient Analyzer Program

2.3. Energy Management Strategies Analysis

Depending on the control mechanisms and goal functions used, different control frameworks create issues in different ways. While many energy management strategies have been examined in existing literature, there is a notable scarcity of those that focus specifically on DC microgrid systems intended for residential use. Widely utilized energy management strategies encompass linear programming-based systems, artificial intelligence-driven solutions, and integrated hardware and software tools, including SCADA and HOMER. The selection of a strategy frequently hinges on the configuration of the system (e.g., PV, wind, fuel cell, storage systems) and the specific control objectives, including the optimization of energy consumption, the minimization of operational expenses, or the enhancement of system reliability. In the context of DC microgrid systems, a summary of several analogous systems found in the literature is presented in Table 4, which emphasizes their element characterizations and associated energy management strategies. It is crucial to recognize that no individual EMS approach can completely satisfy all system demands, given the diverse goals and limitations inherent in various microgrid configurations. Consequently, hybrid methods that integrate various approaches are frequently employed within an EMS to effectively tackle a range of operational challenges. Table 4 presents further specifications for the microgrid systems previously examined in the literature. This encompasses specifics regarding element characterization, including the various types of distributed energy resources, storage technologies, and loads, as well as the diverse energy management strategies employed. This detailed examination underscores the variety in system configurations and control methodologies, illustrating how EMS strategies are customized to address the specific needs of each microgrid system. LabVIEW, developed by National Instruments and listed in Table 4, is widely used for monitoring, control, and data acquisition in renewable energy systems. Its compatibility with embedded hardware makes it suitable for applications such as PV monitoring and hybrid system management.

Table 4. Analysis of EMS strategies with element characterization.

Intelligent EMS Based on SCADA System (MATLAB/Simulink Integrated with Modbus and Konnex)			
System Element	**Type**	**Capacity**	**Objective**
PV Panels	Monocrystalline	5 kW	MPPT
Battery	Li-ion	0.5 kWh	Charging/discharging
Load		9 kW	Reveals daily consumption
EMS with fuzzy control for a DC microgrid system [72] (MATLAB/Simulink, LabVIEW, Rs-485/Zigbee tools)			
PV panels	Monocrystalline	5 kW	MPPT
Wind Turbine	AWV 1500	1.5 kW	MPPT
Battery	Li-ion	1.5 kWh	SOC
Load		6.5 kW	
DC bus voltage		380 V (±20 V)	
EMS for islanded microgrid based on rule-based power flow control [54] (PSCAD simulation tool)			
PV panels	Monocrystalline	30 kW	MPPT
Wind Turbine		3 kW	MPPT
Battery	Li-ion Lead Acid	800 Ah	SOC
Load	(10 kW + 15 kW)	25 kW	
EMS for residential microgrid system based on NN and MILP [66] (Neural network and Mixed integer linear programming algorithm)			
PV panels		6 kW	MPPT
Battery	Li-ion	5.8 kWh	SOC

Table 4. *Cont.*

Intelligent EMS Based on SCADA System (MATLAB/Simulink Integrated with Modbus and Konnex)			
EMS for real time laboratory control based on feedback & PI cascade control [107] (MATLAB/Simulink integrated with RT-LAB tool)			
PV panels		260 W	MPPT
Wind Turbine	PMSG	260 W	Speed/torque
Battery	Lead acid	10 Ah	SOC
DC bus voltage		20 V	
Intelligent EMS with linear programming based multi-objective optimization [108] (Artificial neural network and Fuzzy logic controller)			
PV panels		20 kW	Cost minimization
Wind Turbine		25 kW	Cost minimization
Battery	Lead acid	15 kWh	SOC
Fuel cell		15 kW	Cost minimization
EMS with multi-agent system [109] (MATLAB/Simulink tool)			
PV panels	Titan S-60	100 kW	MPPT
Wind Turbine	PMSG	200 kW	MPPT
Battery	Lead acid	300 kWh	SOC
Load		Load	

3. Opportunities and Future Directions in Renewable Energy—Integration

The widespread adoption and integration of Distributed Energy Resources (DERs) have been notably shaped by various overarching trends commonly known as the 3Ds—decarbonization, digitalization, and decentralization. The observed trends signify the fundamental elements of moving towards a more sustainable, efficient, and resilient energy system. In combination with these trends, progress in energy technology, such as the creation of new devices, cutting-edge systems, and unique operational methods, has enabled a smooth and transformative fusion of energy systems with Information and Communication Technologies (ICTs). This integration has proven crucial for facilitating the real-time management, optimization, and operation of decentralized energy systems. This integration prominently features blockchain technology, which has surfaced as a transformative instrument for decentralized energy systems. Blockchain provides several essential features that are vital for the effective and secure operation of these systems, such as privacy, security, transparency, reliability, interoperability, and flexibility. The features address numerous challenges related to the decentralized functioning of energy systems, including fostering trust among stakeholders, facilitating peer-to-peer energy trading, overseeing distributed transactions, and ensuring a tamper-proof record of energy exchanges. Through the enhancement of these capabilities, blockchain has emerged as a crucial facilitator of decentralized energy systems, bolstering their scalability and reliability within intricate energy markets [115].

A key technological element of this energy-ICT convergence is Advanced Metering Infrastructures (AMIs). AMIs have become essential to energy-focused ICTs, significantly improving communication, data collection, and resource management in decentralized systems. Advanced Metering Infrastructures facilitate immediate, two-way communication between energy users and providers, a crucial element for maintaining equilibrium between supply and demand in systems characterized by significant Distributed Energy Resource integration. They possess the ability to measure and store electricity-related data with high temporal resolution, offering the detailed insights required for energy optimization and forecasting. Additionally, AMIs work harmoniously with various ICT-based solutions, including blockchain, facilitating innovative features like remote monitoring, automated control, and secure energy transactions. The capabilities of AMIs position them as essential

for the efficient and effective management of distributed energy resources. Alongside their operational advantages, AMIs are essential for enabling the remote oversight of distributed energy resources, including solar PV systems, wind turbines, and energy storage units. These systems enable grid operators and energy market participants to oversee and manage energy flows, enhance resource distribution, and adapt swiftly to evolving grid conditions. This capability enhances grid stability and supports the participation of distributed energy resources in energy markets, allowing small-scale energy producers to engage as active market participants. The integration of AMIs with blockchain technology guarantees that operations are secure, reliable, and resistant to tampering, thereby boosting trust and transparency in decentralized energy systems [116,117].

The implementation of ICT-based solutions, including AMIs and blockchain, has significantly transformed power system operations. The implementation of these technologies facilitates a more effective management and oversight of energy resources, leading to increased grid flexibility, lower operational costs, and improved reliability of energy supply. Moreover, they advocate for the incorporation of distributed energy resources as essential generation assets within energy markets, guaranteeing that these resources are both technically integrated into the grid and economically sustainable. This underscores the significance of blockchain and ICTs as vital instruments for addressing the challenges associated with energy transition. The influence of ICT-based solutions on the development of energy systems is anticipated to become increasingly significant. As energy markets progress, these technologies will foster innovation and facilitate the emergence of new business models, including peer-to-peer energy trading, virtual power plants, and local energy communities. Their efforts will contribute to the overarching objectives of decarbonization by enabling the incorporation of renewable energy sources into the grid. Improving the efficiency, security, and transparency of decentralized energy systems is crucial. The integration of blockchain and AMIs will be pivotal in establishing a more resilient, consumer-focused, and sustainable energy ecosystem [118].

Blockchain technology offers a revolutionary solution to tackle the challenges associated with DERs, providing numerous advantages that improve system efficiency, security, and collaboration. Blockchain fundamentally establishes a reliable, clear, and secure setting, allowing different participants—like prosumers, consumers, utilities, and energy market operators—to engage directly within a peer-to-peer (P2P) structure. The establishment of this trust is essential for energy, data, and financial transactions, as it reduces disputes, improves accountability, and protects sensitive information. The ability of blockchain technology to facilitate quicker and more efficient operations within decentralized systems stands out as a significant benefit. By utilizing smart contracts—self-executing agreements with established parameters—blockchain streamlines processes like energy trading, billing, and demand response. This minimizes delays, decreases transaction costs, and streamlines the coordination of distributed energy resources, facilitating more efficient operations throughout the system. Moreover, the decentralized and distributed characteristics of blockchain make it particularly suitable for the integration of distributed energy resources, as it corresponds with the core principles of decentralization in power systems. The integration of blockchain with various energy-related technologies and frameworks is noteworthy, encompassing smart grids, peer-to-peer energy trading, virtual power plants, and the Internet of Things.

1. In smart grids, the implementation of blockchain technology significantly bolsters operational security and resilience. It achieves this by guaranteeing that grid data remains immutable and readily auditable, which in turn enhances grid stability and coordination [119,120].

2. In the realm of peer-to-peer (P2P) energy trading, blockchain facilitates direct transactions between prosumers and consumers, removing intermediaries and promoting the establishment of local energy markets. This allows participants to engage in the buying and selling of electricity in a more efficient and transparent manner [121–124].
3. In the context of virtual power plants (VPP), blockchain plays a crucial role in the aggregation and coordination of distributed energy resources. This technology ensures that assets such as solar panels, wind turbines, and batteries can work together to deliver essential grid services, including frequency regulation and load balancing [125–128].
4. The integration of IoT with blockchain facilitates secure and instantaneous communication among interconnected devices, including smart meters, sensors, and distributed energy resources. This integration facilitates enhanced monitoring, data sharing, and optimization of distributed energy resources, resulting in superior system performance [129,130].

Furthermore, blockchain facilitates a unified integration of technical, market, and financial systems by offering a shared platform that promotes interoperability among various technologies and participants. This integration enables distributed energy resources to engage in energy markets, enhancing grid stability and offering value-added services including ancillary services, demand-side management, and energy negotiation. Blockchain provides consumers with increased control over their energy usage and transactions, promotes transparency in pricing, and opens up new market opportunities for participation. Figure 16 illustrates a blockchain-driven decentralized energy distribution network, showcasing the application of blockchain technology to enable secure, transparent, and tamper-proof peer-to-peer energy transactions. The network facilitates direct interaction between distributed energy resources and consumers, eliminating the need for centralized intermediaries. This approach enhances system efficiency, promotes energy trading autonomy, and improves trust and traceability within the energy ecosystem.

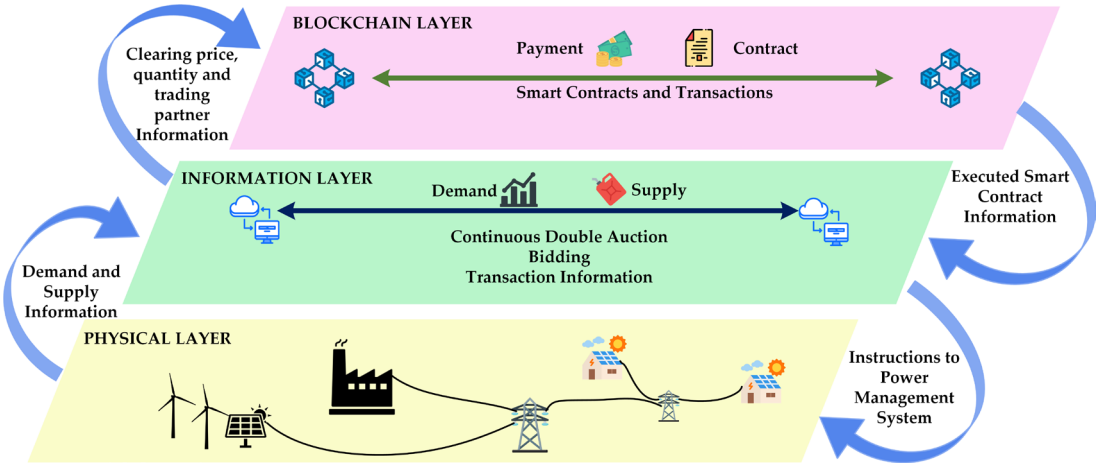

Figure 16. A blockchain-driven decentralized energy distribution network.

Figure 17 illustrates the integration of blockchain technology within smart grid systems, underscoring its capability to facilitate secure, decentralized data exchange and energy transactions among diverse stakeholders, including energy producers, consumers, and system operators. It highlights blockchain's contribution to enhancing transparency, data integrity, and auditability through immutable ledger records, while enabling the automation of contractual agreements via smart contracts. This integration supports improved

grid security, operational efficiency, and stakeholder empowerment, thereby advancing the development of a more resilient and trustworthy energy infrastructure.

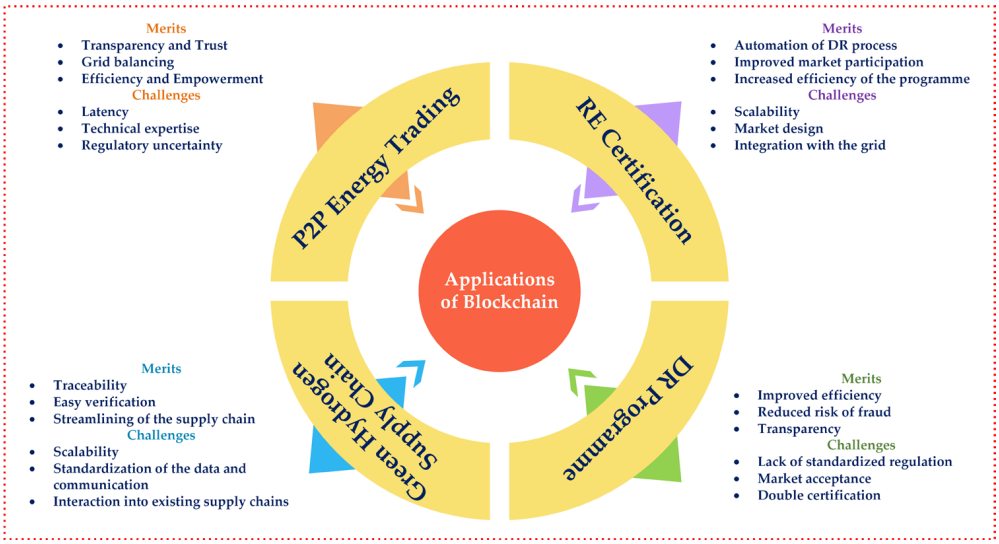

Figure 17. Application of blockchain technology in smart grid system.

3.1. Smart Contract Systems

Smart contracts are essential components of modern blockchain systems, acting as self-executing scripts created in programming languages, primarily Solidity, that autonomously carry out predetermined actions with a level of immutability, transparency, and security that is notably high. As detailed by various authors [131–133], these contracts function as auto-executable scripts that verify and enforce specific conditions, similar to contractual clauses found in traditional agreements. Without any outside interference, the appropriate activities are initiated and carried out when the specified circumstances are fulfilled. In a way similar to Distributed Ledger Technology (DLT), smart contracts facilitate the removal of intermediaries across multiple applications, leading to a notable decrease in transaction costs and promoting the efficient execution of low-value transactions. A smart contract is fundamentally a code segment that is deployed and stored on a blockchain, functioning autonomously within the blockchain ecosystem without the supervision of a central authority. Rather than depending on conventional legal terminology, smart contracts articulate and retain conditions and events like values, deadlines, or transaction data [134,135], facilitating the smooth execution of actions once the specified parameters are met. According to various authors [136], smart contracts excel in scenarios where agreements can be reduced to straightforward "if-then" conditions, as these can be seamlessly converted into computer code. This level of efficiency facilitates automated execution while guaranteeing reliability and precision across diverse applications. Figure 18, adapted from [137], presents the life cycle of a smart contract, emphasizing its organized phases from inception to execution. It depicts the life cycle of a smart contract, outlining its key stages from creation and deployment to execution and termination. It illustrates processes including contract coding, validation, deployment on a blockchain platform, automated execution upon predefined conditions, monitoring, and eventual completion or termination. This life cycle highlights the role of smart contracts in enabling autonomous, transparent, and enforceable agreements within decentralized systems.

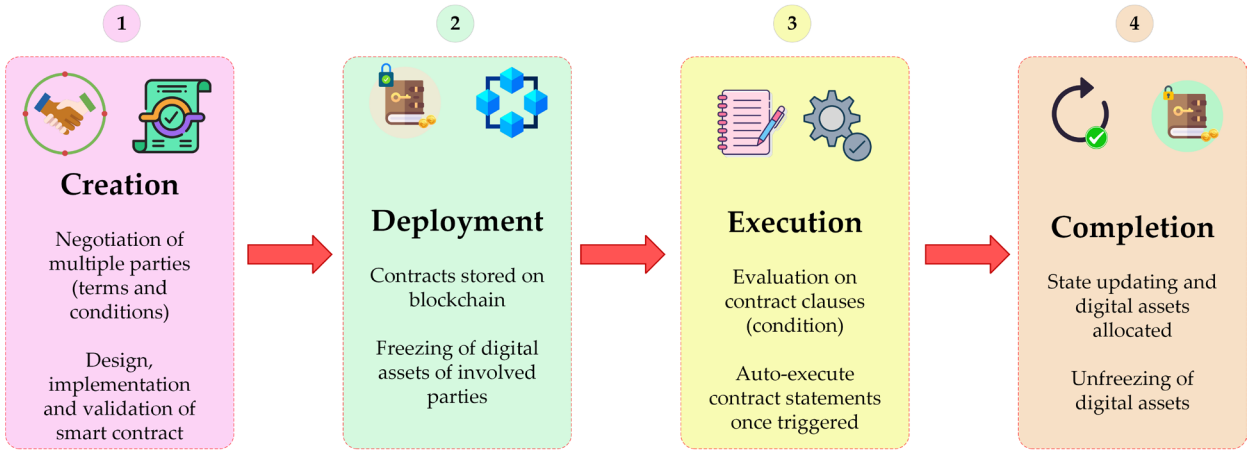

Figure 18. Life cycle of smart contract.

3.2. Advanced Metering Infrastructure (AMI)

Advanced Metering Infrastructure (AMI) signifies a crucial technological development for modern energy systems, facilitating two-way communication among utility companies, consumers, prosumers, and energy producers via smart meters. In contrast to conventional energy meters, smart meters equipped with advanced metering infrastructure not only quantify energy consumption but also gather comprehensive data related to energy usage. This data fulfils various functions, including billing, control, troubleshooting, and monitoring, and is usually kept in centralized storage systems or cloud platforms. Nonetheless, reliance on centralized data storage systems presents various challenges, such as the possibility of data manipulation, privacy violations (for instance, the exposure of identities, contact details, energy consumption, and usage patterns), scalability concerns, and potential delays in response times. The identified limitations decrease confidence in AMI systems, leading to reluctance among generators and consumers to completely adopt these infrastructures. In response to these challenges, numerous investigations have examined the incorporation of blockchain technology within AMI systems. The decentralized, immutable, and secure framework of blockchain presents a compelling approach to address the vulnerabilities found in conventional AMI configurations [138–142].

3.3. Blockchain-Based Access Control with Smart Contracts [138]

An efficient, safe, and blockchain-based access control approach was suggested, with smart contracts built on the Ethereum platform serving as a trusted intermediary for distributed permission management [143]. Deployed on Ropsten, an Ethereum test network, the solution showcased enhancements in security, flexibility, and efficiency at a minimal cost, positioning it as a promising strategy to mitigate cyber-attacks in smart grids. The contribution of this study is notably important for enhancing the security of distributed energy resources linked to advanced metering infrastructure systems.

3.3.1. Resiliency and Security in Smart Grids Using Blockchain [139]

The study introduces a blockchain model incorporating smart contracts aimed at improving the resiliency and security of smart grids. Smart contracts function as intermediaries between consumers and prosumers, optimizing processes and minimizing expenses. Upon establishing a connection to the blockchain, smart meters transmit records to create timestamped blocks that can be validated at a later stage. Charges for consumers are determined by the records maintained in the blockchain ledger. Nonetheless, the restricted technical discourse within the study has hindered its advancement.

3.3.2. Energy Trading and Governance for Local Energy Communities (LECs) [140]

Plaza et al. introduced a system in which smart metering infrastructure functions as a secure platform for the trading of energy data and the governance of communities. An energy exchange mechanism utilizing blockchain technology was proposed for members of local energy communities with photovoltaic generation. This method enables safe peer-to-peer energy trading among community members, all while maintaining clear governance practices.

3.3.3. Decentralized Smart Grid Model Incorporating Demand-Side Management [141]

This model emphasizes the decentralization of smart grids through the application of blockchain technology, aiming to establish an automated and decentralized energy grid. Each node in the system functions autonomously, free from centralized oversight. The blockchain records energy consumption data gathered from smart meters, whereas smart contracts authenticate agreements, compute incentives or penalties, and uphold supply-demand balancing regulations. This method offers enhanced adaptability and effectiveness for managing demand-side operations.

3.3.4. Privacy-Preserving Energy Scheduling for ESCOs [142]

This study presents the PPES model, focusing on the privacy issues linked to centralized energy service companies (ESCOs). The model safeguards financial and behavioral data through the use of blockchain and smart contracts, facilitating secure energy scheduling in distributed markets. A distributed optimization approach breaks down the model into separate problems that are addressed using consensus algorithms and smart contracts. The methodology was confirmed through case studies that included various energy buses, demonstrating its dependability for systems integrated with distributed energy resources.

In addition to the specific studies referenced, blockchain has advanced considerably in addressing wider issues within AMI systems. The areas of application include:

1. Integrating IoT with blockchain technology enables a secure and efficient method for data exchange and real-time monitoring within energy systems.
2. Enhancements in Privacy and Security: Addressing risks associated with centralized data storage through the decentralization of data management and the encryption of sensitive information.
3. Energy Trading Interfaces: Evolving AMI into a robust platform for peer-to-peer energy trading and ensuring transparent transactions.
4. Smart Metering and Management: Utilizing blockchain technology for automated energy management, secure metering, and enhanced system transparency.
5. Integrating blockchain technology with artificial intelligence to facilitate sophisticated data analysis and self-sufficient operations in energy management within smart cities.

Integrating blockchain technology into AMI systems can lead to improvements in security, privacy, scalability, and efficiency within energy systems. The progress made presently sets the foundation for a more robust, transparent, and consumer-focused energy landscape, enhancing trust among participants and speeding up the integration of distributed energy resources in decentralized energy markets. Figure 19 illustrates the architecture of Advanced Metering Infrastructure (AMI), highlighting its key components such as smart meters, communication networks, data management systems, and utility control centers. It demonstrates how AMI enables two-way communication between utilities and consumers, facilitating real-time monitoring, accurate billing, demand response, and enhanced grid management capabilities.

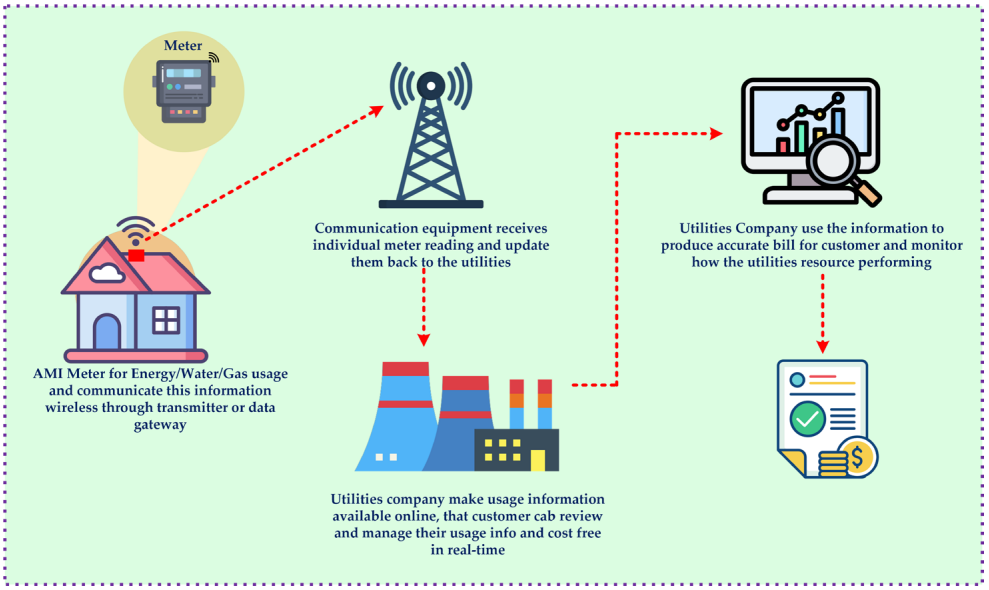

Figure 19. Advanced metering infrastructure (AMI).

3.4. Smart Electric Vehicles Charging Systems

Electric vehicles (EVs) are becoming increasingly important in the shift towards sustainable and decentralized energy systems [144]. Electric vehicles are transforming the landscape of energy distribution, storage, and trade by functioning as both consumers and providers of energy. Beyond their essential role in transportation, electric vehicles enhance the stability and efficiency of the energy grid by acting as mobile energy storage systems [134]. By examining scenarios like Vehicle-to-Vehicle (V2V), Vehicle-to-Grid (V2G), and Grid-to-Vehicle (G2V) interactions, electric vehicles (EVs) enable two-way energy flows. This capability supports the integration of renewable energy and provides essential grid-supporting services, including demand response. Nonetheless, these opportunities are accompanied by technological and operational hurdles, especially in terms of regular two-way communications, short-range mobility interactions, and the necessity for secure data exchange [145]. The challenges presented have highlighted the potential of blockchain technology, which offers decentralized, transparent, and secure solutions to improve the management and integration of electric vehicles.

Blockchain technology presents a ground breaking method for addressing issues related to the integration and management of electric vehicles (EVs) in energy ecosystems [143,146–149]. The decentralized architecture guarantees tamper-proof data exchange, secure transaction validation, and transparent mechanisms for energy trading. Major applications involve the implementation of smart contracts for EV charging powered by renewable energy, facilitating automated and efficient energy distribution while enhancing profitability for aggregators [146]. Blockchain improves payment systems and data validation via decentralized applications, promoting interoperability and scalability. By using blockchain technology, privacy-focused solutions may optimize the selection of charging stations according to energy costs and distance while also masking user data [147]. Furthermore, blockchain facilitates secure operations for electric vehicle charging, incorporating authentication and scheduling via smart contracts, while frameworks based on game theory enhance resource allocation in private charging stations using cryptocurrency payments. Licensed energy systems enhance the efficiency of energy distribution for EV charging and discharging by utilizing consensus mechanisms and incentive schemes [149]. In addition to charging infrastructure, blockchain is essential for optimizing smart energy scheduling, managing battery systems, and facilitating the integration of electric vehicles

into virtual power plants (VPPs). This enables secure energy trading, facilitates real-time data exchange, and supports predictive maintenance for EV batteries, enhancing performance and prolonging lifespan [150]. The introduction of cryptocurrency-based incentives for peer-to-peer (P2P) energy trading through blockchain technology significantly enhances market efficiency. The combination of artificial intelligence (AI) and blockchain facilitates enhanced optimization of charging schedules and energy pricing, setting the stage for smart cities where electric vehicles (EVs) play a crucial role in urban energy systems. Moreover, blockchain technology empowers electric vehicles to engage actively in decentralized energy markets, facilitating dynamic pricing and optimizing energy distribution [151].

Although it holds significant promise, numerous obstacles need to be overcome to facilitate the broad implementation of blockchain within electric vehicle ecosystems. Challenges such as scalability issues, energy-intensive consensus mechanisms, interoperability with existing infrastructure, and the necessity for effective incentivization models present considerable obstacles. The complexity is heightened by regulatory and legal concerns, such as data privacy and liability frameworks, in addition to the significant costs and technical expertise necessary for implementation. Addressing these challenges by implementing energy-efficient consensus mechanisms, establishing standardized protocols, and developing clear regulatory guidelines is essential. Through ongoing exploration and innovation, blockchain is set to transform the integration of electric vehicles, promoting sustainable, resilient, and intelligent energy systems. Figure 20 illustrates a blockchain-based smart electric vehicle (EV) charging system, integrating blockchain technology to enable secure, transparent, and automated energy transactions between EV users and charging infrastructure. The system facilitates decentralized authentication, real-time data exchange, dynamic pricing, and smart contract-based billing. This approach enhances trust, efficiency, and interoperability in EV charging networks, supporting the broader adoption of electric mobility within smart grid ecosystems.

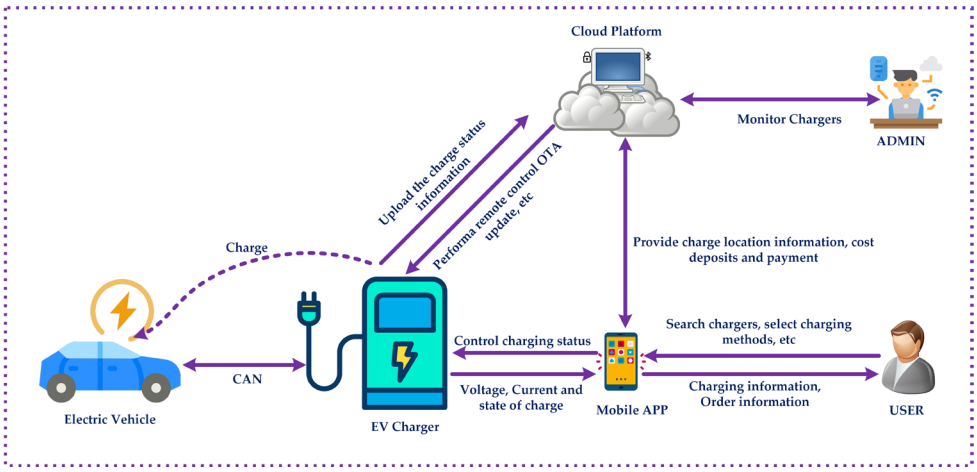

Figure 20. Blockchain based smart electric vehicle charger.

Figure 21 illustrates a blockchain-enabled energy trading and charging payment system for electric vehicles (EVs). The system facilitates peer-to-peer energy transactions and secure, automated payment processes between EV owners, charging stations, and energy providers. By leveraging smart contracts and decentralized ledgers, it ensures transparency, data integrity, and real-time settlement. This architecture supports efficient energy management, dynamic pricing, and greater user autonomy within the EV charging ecosystem.

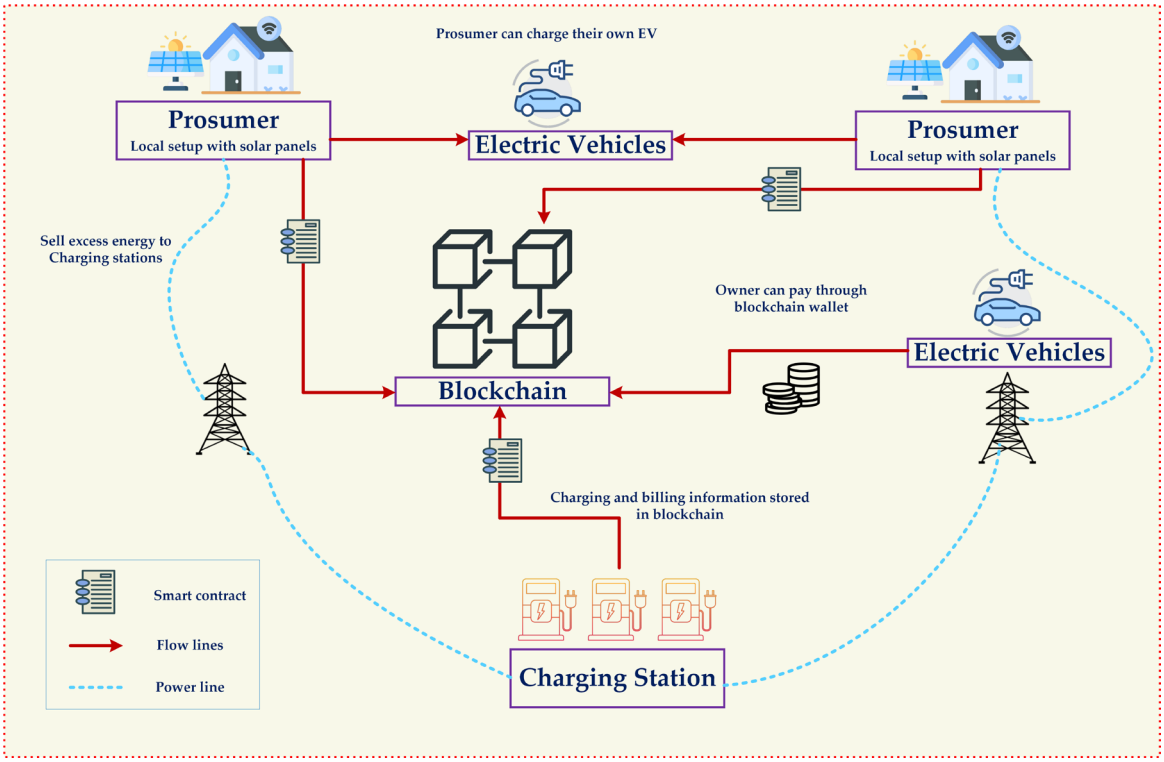

Figure 21. Blockchain enabled energy trading and charging payment system for electric vehicles.

3.5. Peer-to-Peer Energy Trading Systems

Peer-to-peer (P2P) energy trading represents a significant advancement in energy management, allowing prosumers—those who generate and utilize electricity—to exchange excess energy directly with one another. This model enables consumers to lower their electricity expenses while also engaging in the development of a more sustainable energy market through local renewable energy sourcing. Decentralizing electricity markets through P2P trading opens up new avenues for optimizing power systems and encourages innovative approaches to energy management. Blockchain technology has surfaced as a fundamental element for facilitating P2P energy trading [152,153]. The architecture is both decentralized and transparent, eliminating the necessity for intermediaries and guaranteeing secure, tamper-proof transactions. This innovative digital ledger system transforms energy markets by redistributing control from centralized utilities to individuals and microgrids [154]. This transition tackles significant challenges, including the phenomenon known as the "utility death spiral", in which the extensive adoption of rooftop photovoltaic (PV) systems reduces the demand for grid electricity, while peak demand stays constant, compelling utilities to increase their prices [155]. The integration of blockchain technology with batteries enhances energy storage efficiency, trading capabilities, and demand-response strategies, thereby reducing pressure on current infrastructure. Smart contracts facilitate the automation of the trading process within blockchain technology, allowing prosumers to directly sell surplus electricity to consumers at competitive rates. Individuals enjoy lower electricity expenses and enhanced oversight of their energy options, whereas those who both produce and consume energy achieve better returns compared to conventional feed-in tariffs. Dynamic auction markets significantly improve efficiency, enabling the trading of renewable electricity according to real-time supply and demand profiles. For instance, LO3 Energy effectively showcased auctions powered by blockchain technology, allowing consumers to indicate their highest price per kilowatt-hour, thereby facilitating transactions that are advantageous for all parties involved [156].

Beyond the financial benefits, blockchain significantly improves privacy and security for users by removing intermediaries and implementing strong data encryption measures. The capacity to align supply and demand instantaneously enhances the efficiency of energy distribution in microgrids and smart grids. Additionally, blockchain technology provides adaptability for emerging business models, fostering innovation and speeding up the shift towards a decentralized, low-carbon energy future. While blockchain holds significant potential, the implementation of P2P energy trading encounters many challenges. The challenge of scalability persists, with existing blockchain systems facing difficulties in managing the substantial transaction volumes associated with large-scale applications. The lack of interoperability among various blockchain networks presents a significant challenge, obstructing smooth integration across different platforms and geographical areas. Moreover, optimizing the performance of blockchain systems, such as transaction speed and energy consumption, is essential for their widespread deployment [139]. Although blockchain-enabled P2P energy trading remains in the proof-of-concept stage, its capacity to transform energy markets is clear. This innovation has the potential to tackle existing technological and regulatory challenges, positioning itself as a key element in the worldwide shift towards sustainable energy systems. It aims to lower costs, improve market efficiency, and enable consumers to engage actively in energy management. Figure 22 illustrates a blockchain-enabled peer-to-peer (P2P) energy trading system, where prosumers and consumers interact directly to buy and sell energy within a decentralized marketplace. It highlights the use of smart contracts for automating transactions, distributed ledgers for ensuring transparency and security, and real-time data exchange for market efficiency. This system promotes energy democratization, enhances grid flexibility, and supports the integration of distributed renewable energy sources.

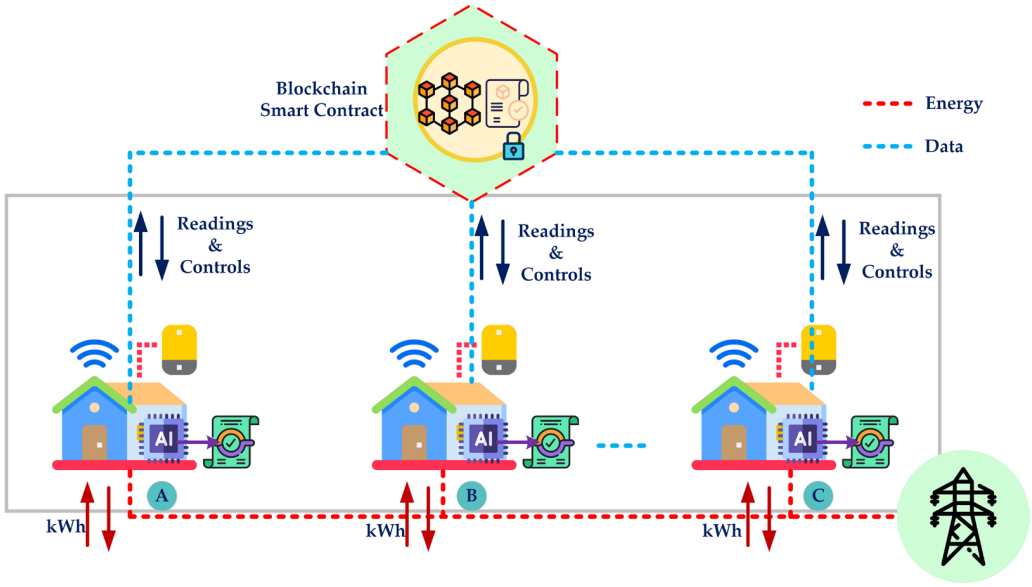

Figure 22. Blockchain enabled peer-to-peer energy trading systems.

Table 5 provides an overview of companies leveraging blockchain technologies for peer-to-peer (P2P) energy trading. It details each company's operational model, geographic region, underlying blockchain platform, and key features, such as the use of smart contracts, support for renewable energy sources, transaction transparency, and consumer engagement strategies. This analysis highlights the practical implementation of decentralized energy markets, showcasing how these companies are driving innovation in energy trading, improving market efficiency, and promoting prosumer participation in the evolving smart grid landscape.

Table 5. Companies utilizing blockchain technologies for P2P energy trading [157,158].

Company	Blockchain Platform	Country of Operation	Remarks
Green Power Exchange	Ethereum	USA, China	The Green Power Exchange Platform, powered by blockchain technology, simplifies and streamlines P2P energy trading.
Greeneum	Ethereum	USA, Singapore	Greeneum is a blockchain-powered marketplace that leverages smart contracts, artificial intelligence, and machine learning to establish a decentralized and sustainable energy trading platform for P2P transactions.
Electrify	Ethereum	USA, China, South Korea	ELECTRIFY has developed a decentralized energy marketplace powered by blockchain technology, enabling a robust P2P trading platform for seamless energy transactions.
Pylon Network	Private blockchain	Spain	Pylon Network develops a blockchain-based P2P energy trading platform, facilitating secure and efficient energy transactions among users.
Alliander	Ethereum	The Netherlands	Alliander introduced a blockchain-based renewable energy sharing token and has successfully piloted a P2P energy trading platform to enable decentralized energy transactions.
Dajie	NA	UK	Dajie enables P2P energy trading through an Internet of Things (IoT) device that functions as a blockchain node, facilitating decentralized energy transactions.
WePower	Ethereum	Spain	WePower operates a blockchain-based P2P energy trading platform and integrates artificial intelligence to forecast supply and demand, optimizing energy transactions within the marketplace.
Conjoule	NA	Germany	Conjoule's blockchain-enabled platform facilitates P2P energy trading between rooftop PV owners and public-sector or corporate buyers, creating a decentralized marketplace for renewable energy transactions.
Power Ledger	Ethereum	Australia	Power Ledger is a blockchain-based platform that enables P2P energy trading, allowing users to buy and sell surplus energy directly, enhancing transparency and efficiency in the energy market.
LO3 Energy (Exergy)	Private blockchain	USA	Exergy employs a revolutionary approach to localized energy marketplaces by utilizing blockchain technology, enabling decentralized and efficient energy trading within local communities.
Electron	Ethereum	UK	Electron leverages blockchain technology to transform the energy market, with a focus on supporting Peer-to-Peer (P2P) energy trading, enhancing transparency, efficiency, and decentralized energy exchanges.
Energo Labs	Qtum	China and Philippines	Energo Labs develops a blockchain-based Peer-to-Peer (P2P) platform tailored for distributed energy systems, with a particular focus on enhancing microgrid operations and enabling decentralized energy trading.
SunContract	Ethereum	Slovenia	SunContract utilizes blockchain technology to establish a decentralized Peer-to-Peer (P2P) electricity market, enabling direct energy transactions between producers and consumers.
Volt Markets	Ethereum	USA	Volt Markets enables Peer-to-Peer (P2P) energy trading and leverages blockchain technology to streamline the distribution, tracking, and trading of energy, ensuring transparency and efficiency in the process.
Verv	Ethereum	USA, China	VLUX combines deep learning artificial intelligence with blockchain to improve access to affordable, low carbon energy by enabling peers to trade.
Toomuch.energy	NA	Belgium and Austria	Toomuch.energy develops a Peer-to-Peer (P2P) energy trading platform tailored for corporate customers, enabling businesses to trade renewable energy directly with one another, enhancing sustainability and reducing energy costs.
Solar Bankers	Skyledger	Asia, Europe, and USA	Solar Bankers facilitates Peer-to-Peer (P2P) energy trading, enabling users to directly trade solar-generated electricity with one another, promoting a decentralized and sustainable energy market.

3.6. Virtual Power Plants

Virtual Power Plants (VPPs) represent a cutting-edge approach to addressing the complexities associated with the increasing integration of DERs into the power grid. By combining different energy resources, including solar panels, wind turbines, energy storage

systems, and flexible loads, virtual power plants form a cohesive, coordinated unit capable of engaging in electricity markets and delivering vital grid services similar to traditional power plants [159,160]. This capability facilitates the seamless integration of intermittent renewable energy sources, improving grid stability and allowing small-scale distributed energy resources to play an active role in electricity markets. VPPs play a vital role in enhancing the efficiency and adaptability of power systems, addressing challenges like demand response, energy storage, and load balancing, while facilitating the shift towards sustainable and decentralized energy generation [161–163]. The role of Virtual Power Plants (VPPs) in contemporary power systems is crucial and complex. Through the coordination of the output from multiple Distributed Energy Resources (DERs), Virtual Power Plants (VPPs) are essential in maintaining equilibrium between supply and demand, particularly in grids characterized by a significant integration of renewable energy sources like wind and solar [161]. This coordination enables VPPs to deliver essential ancillary services, including frequency regulation and voltage support, thus improving grid stability and reliability [162]. Furthermore, VPPs facilitate the involvement of small-scale distributed energy resources, such as residential solar panels and energy storage systems, in electricity markets. This expands market involvement and encourages heightened competition, potentially resulting in reduced energy expenses for consumers [163]. Additionally, within the framework of demand-side management, virtual power plants have the capability to consolidate flexible loads to deliver demand response services. This contributes to lowering peak demand and stabilizing the grid by adjusting or limiting energy use during times of high demand [164]. Therefore, VPPs play a crucial role in improving grid resilience, optimizing energy consumption, and accelerating the shift towards a sustainable, decentralized energy future.

The intricate systems that Virtual Power Plants (VPPs) coordinate make their management and pricing very difficult. The varied attributes of Distributed Energy Resources (DERs), the unpredictability of renewable energy production, and the ever-changing landscape of electricity markets contribute to a challenging decision-making environment [165]. Furthermore, the introduction of dynamic pricing, which causes electricity prices to vary in real-time according to supply and demand, adds another dimension of unpredictability and complexity to VPP operations [166]. These challenges necessitate advanced management and pricing strategies that can effectively navigate the complex and fluctuating dynamics of VPP systems. To address these challenges, various approaches have been suggested, with game-theoretic models, especially Stackelberg games, receiving considerable focus. Stackelberg game models effectively illustrate the hierarchical decision-making process that characterizes VPP operations [167]. In a conventional Stackelberg game model utilized for VPPs, the VPP operator takes on the position of the leader, making strategic choices related to pricing or resource distribution. The owners or consumers of distributed energy resources, in turn, respond as followers, modifying their actions according to the decisions made by the operator. This framework facilitates the modeling of strategic interactions among various stakeholders engaged in VPP operations, enhancing decision-making related to resource optimization, pricing strategies, and coordination among diverse DERs. Figure 23 provides an overview of various types of Virtual Power Plants (VPPs), illustrating their structure, functionalities, and roles within modern energy systems. It categorizes VPPs based on their control mechanisms, energy sources, and operational objectives—such as balancing supply and demand, integrating distributed energy resources, enhancing grid reliability, and participating in energy markets. It also emphasizes the flexibility, scalability, and economic value VPPs bring to decentralized power generation and smart grid environments.

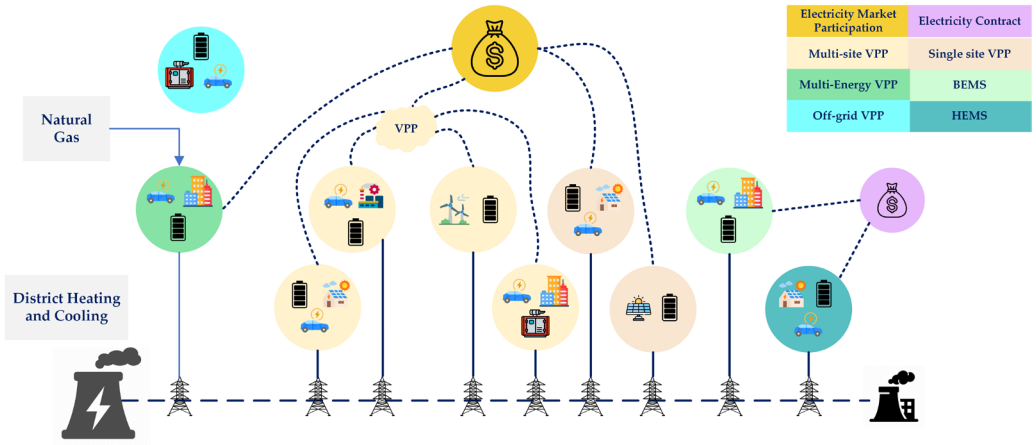

Figure 23. Overview of various VPPs.

Figure 24 illustrates the system model of a Virtual Power Plant (VPP) comprising multiple smart houses interconnected within a smart grid. Each smart house is equipped with distributed energy resources, including solar panels, battery storage, and smart appliances, contributing to the collective operation of the VPP. Advanced communication and control systems coordinate energy generation, consumption, and storage across all participating units to optimize grid performance, enhance energy efficiency, and enable real-time demand-response capabilities.

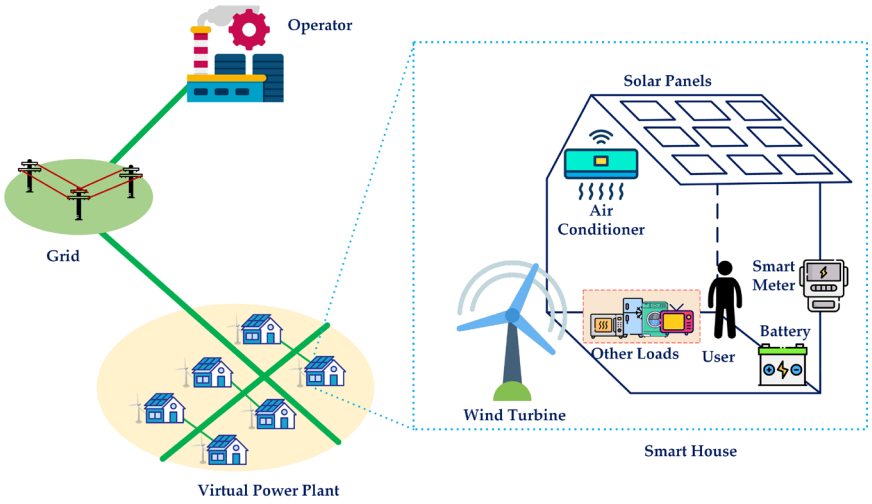

Figure 24. The system model of the virtual power plant that consists of multiple smart houses in the smart grid [126].

3.7. Home Energy Management Systems (HEMS)

Smart cities are emerging as a viable option for sustainable and effective urban development at a time of growing urbanization and rising energy needs. The incorporation of Home Energy Management Systems (HEMS) in modern urban landscapes is essential for facilitating the shift towards sustainable smart cities. This transition is driven by various elements, such as changing electricity prices, the emergence of intelligent homes, and the increasing availability of smart household devices, all of which together provide enhanced opportunities for optimizing the use of home appliances in a cost-effective manner. Promoting the use of renewable energy sources, such as solar panels and energy storage systems, HEMS integration effectively reduces environmental impact while providing practical benefits to individuals. Moreover, managing energy consumption can be achieved by modifying the operational schedules of household appliances to coincide with lower-cost

electricity periods, allowing consumers to significantly lower their electricity expenses. The implementation of HEMS has emerged as a crucial element in evolving energy communities into centers of innovation, resilience, and mindful energy usage. This method is crucial for moving towards more sustainable urban communities.

Home Energy Management Systems (HEMS) guarantee that renewable energy sources are completely used and not squandered by intelligently controlling energy consumption and storage. This allows for a more efficient alignment of renewable energy supply with demand. While renewable energy sources are generally viewed as non-dispatchable due to their variable production reliant on environmental conditions, the implementation of HEMS can help address the discrepancies between energy supply and demand. By utilizing real-time monitoring and control, HEMS enhances the functionality of Smart Homes (SHs) in smart cities, facilitating improved integration of renewable energy sources. Through the strategic management of energy consumption and storage, HEMS effectively utilizes surplus renewable energy during peak generation times, ensuring it is available for use during periods of low generation. This capability improves the effectiveness of renewable energy systems and decreases dependence on non-renewable backup power. The integration of HEMS within Smart Homes in urban areas can enhance grid stability, minimize energy waste, and decrease energy expenses, thereby supporting the sustainable advancement of city environments. The effective functioning of Smart Homes, along with the incorporation of renewable energy sources, enhances the utilization of clean energy and fosters a more robust and efficient energy framework in urban areas [168].

The rapid development of the smart home IoT sector has heightened security concerns, especially in the realm of information security, drawing significant attention from users of smart home technology. Conventional centralized security approaches in smart homes frequently encounter issues like significant system overhead, restricted scalability, and weaknesses in security management [169]. This has initiated the exploration of alternative solutions, and in 2009, blockchain technology (BT) surfaced as a possible transformative force. Due to its decentralized nature and immutability, BT provides a solid basis for building trust mechanisms in potentially distrustful contexts. The effectiveness of BT in enhancing security across various sectors, particularly in digital currency, lies in its ability to ensure the integrity and credibility of transactions through decentralized records. Furthermore, BT has demonstrated its worth in domains such as supply chain management, electronic contracts, and intellectual property protection through enhancements in transaction transparency, traceability, and security. In the realm of smart homes, BT presents potential solutions for addressing the network security issues commonly faced in IoT applications. The utilization of BT for enhancing access control and maintaining network integrity in smart homes presents a compelling solution. Integrating BT with IoT technology enables the development of smart home ecosystems that are more secure, transparent, and reliable [170]. At present, the BT models utilized in smart home security encompass public blockchains like Bitcoin, as well as consortium chains represented by Hyperledger Fabric. High degrees of security are provided by public blockchains, which are renowned for their decentralization and impenetrability. Nonetheless, there are obstacles concerning scalability, energy usage, and performance limitations when these are implemented in real-world situations. Conversely, consortium blockchains tackle certain drawbacks of public blockchains, including scalability and privacy issues, by providing a more regulated framework. Nonetheless, consortium chains continue to face challenges related to centralized management and the need for trust among participants. Researchers have analyzed and contrasted these blockchain models thoroughly to evaluate their appropriateness for smart home security. Mansouri et al. (2021) emphasized the importance of decentralization in public blockchains, which plays a crucial role in ensuring data security and trustworthiness.

Nonetheless, they highlighted the performance constraints and energy inefficiencies that public blockchains might face in practical applications, especially when accommodating extensive IoT systems such as smart homes [171]. In contrast, Zang et al. (2019) examined the benefits of consortium blockchains, highlighting their improved transaction efficiency and privacy safeguards. It was observed that consortium chains necessitate an elevated degree of trust among participants and continue to encounter scalability issues, which may affect their efficiency in extensive smart home networks [172]. Hence, the integration of blockchain technology within smart homes presents a significant opportunity to enhance security and privacy. However, it is crucial to tackle challenges concerning scalability, energy efficiency, and trust among users to unlock its full potential in IoT-enabled smart home settings. Figure 25 presents a comprehensive model of a blockchain-enabled Home Energy Management System (HEMS), showcasing the integration of DERs, smart appliances, IoT sensors, and advanced communication networks within a residential environment. The system utilizes blockchain technology to ensure secure, transparent, and decentralized management of energy data and transactions. Smart contracts automate energy trading, demand response, and device control based on predefined conditions, reducing reliance on centralized intermediaries. This architecture enhances user autonomy, improves energy efficiency, enables real-time monitoring, and builds trust among stakeholders by providing a tamper-proof and verifiable energy management process.

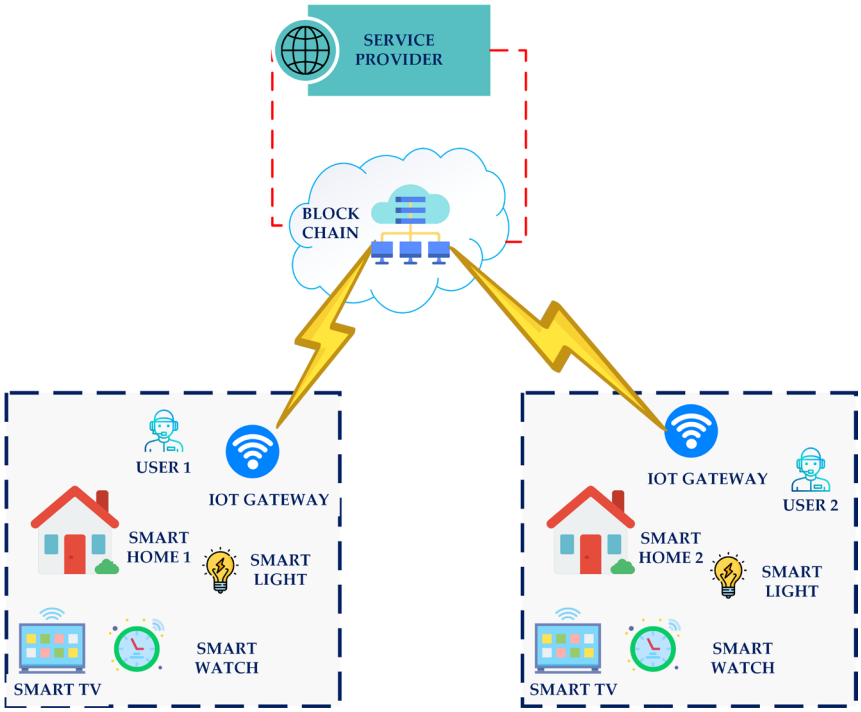

Figure 25. Blockchain enabled home energy management systems.

Table 6 presents a summary of existing research findings by various scholars on smart home energy management systems. It outlines key contributions, methodologies, technologies used, and the primary objectives of each study—such as energy efficiency improvement, demand-side management, renewable energy integration, and user behavior modeling. This comparative overview highlights current trends, challenges, and research gaps, providing valuable insights for future advancements in intelligent and sustainable residential energy management.

Table 6. Existing research findings by various researchers on smart home energy management [173].

References	Year	Research Topics	Technology	Findings
Dang [174]	2018	Data security technology	BT based smart home	The SHIB system demonstrates data privacy, trust access control, and good scalability. Compared with existing models, factors such as smart contracts, data privacy, token usage, policy updates, and misbehaviour judgment were considered.
Tchagna [175]	2022	Blockchain protected IoT data	Smart home architecture using blockchain	A comprehensive evaluation of the privacy, integrity, and accessibility of blockchain-based smart home architecture was conducted. Simulation results highlighted that the additional costs associated with this approach were independent of system protection and privacy, ensuring efficiency without compromising security.
Ammi et al. [176]	2021	Blockchain smart home system	The combination of Hyperledger structure and Hyperledger editor	A blockchain-based smart home system solution was proposed by mapping smart home attributes to the corresponding attributes of the Hyperledger framework.
Farooq et al. [177]	2022	Smart home network architecture	Intrusion detection based on private blockchain	In-depth research was conducted on the critical components and functionalities of the smart home network framework.
Menon et al. [178]	2023	Smart home communication network	Blockchain-based learning engine	A blockchain-based secure communication layer and a cloud-based data evaluation layer were implemented to ensure a secure and efficient smart home communication network.
Liao et al. [179]	2021	Blockchain and edge computing	Application of mobile edge computing-IoT system	The integration of blockchain and edge computing in IoT systems was explored to address challenges related to device security, data security, and forensic analysis.
Wang et al. [180]	2021	Efficient transaction verification for industrial IoT	Optimized Merkle tree structure	An optimized Merkle tree structure was proposed to enable efficient transaction verification within a trusted blockchain-enabled industrial IoT system.
Dhanaraj et al. [181]	2022	Probit Regressive Davis Mayer Kupyna Cryptographic Hash Blockchain	Blockchain and Kupyna cryptography	A novel blockchain technology was proposed to generate hash values for each data entry using Kupyna cryptography.
Zhang et al. [182]	2020	Blockchain-based systems and applications	The application of blockchain traceability technology	Blockchain-based systems and applications were summarized, with a particular focus on the application of blockchain traceability technology across various fields, highlighting its potential to enhance transparency, security, and accountability in industries such as supply chain management, healthcare, finance, and energy.
Singh et al. [183]	2021	Deep Block Scheme	The combination of blockchain and deep learning	A solution combining blockchain and deep learning was proposed to ensure the integrity, decentralization, and security of manufacturing data. This approach leverages blockchain's immutable ledger to provide secure, transparent data storage while utilizing deep learning algorithms to analyze and validate the data, enhancing system reliability and enabling advanced predictive analytics for better decision-making in manufacturing processes.
Ren et al. [184]	2019	Data storage and connection of smart homes	Identity-based proxy aggregation signature scheme	Data storage security was strengthened by introducing blockchain technology, which provides a decentralized and immutable ledger for data storage. This ensures that data cannot be tampered with or altered, enhancing its integrity and protecting it from unauthorized access or manipulation. Additionally, blockchain's transparency and auditability features allow for better tracking and verification of data transactions, further improving overall security.
Ren et al. [185]	2021	The Importance of edge computing in intelligent computing	The combination of blockchain and regenerative encoding	A hybrid approach was developed, combining edge network devices and cloud storage servers to create a global blockchain at the cloud service layer and a local blockchain at IoT terminals. Regenerative encoding enhances data storage reliability, while a mechanism for regular hash value verification ensures the integrity of stored data in the global blockchain.

Energy Management Systems (EMS) are experiencing notable progress, utilizing cutting-edge technologies like blockchain, virtual power plants (VPPs), peer-to-peer (P2P)

energy trading, home energy management systems (HEMS), electric energy vehicles (EEVs), information and communication technology (ICT), and advanced metering infrastructure (AMI). The implementation of blockchain technology is crucial for guaranteeing secure and transparent energy transactions. It facilitates decentralized energy systems, allowing prosumers to directly trade surplus energy, which in turn promotes the adoption of renewable energy and the development of local markets. Virtual power plants (VPPs) consolidate and oversee DERs, including solar panels, wind turbines, and battery storage, to optimize grid operations by balancing supply and demand, enhancing the integration of renewable energy, and improving grid reliability and stability. Peer-to-peer (P2P) energy trading enables individuals to engage in direct energy exchanges, reducing dependence on conventional utilities and fostering localized energy markets. This method not only broadens energy accessibility but also promotes more effective use of renewable energy resources. Home energy management systems (HEMS) leverage cutting-edge technologies such as artificial intelligence (AI) and the Internet of Things (IoT) to optimize energy consumption in households, improve energy efficiency, and lower costs through the automation of appliances, energy usage forecasting, and the integration of renewable energy sources. Electric vehicles (EVs) are becoming essential elements of energy management systems by facilitating vehicle-to-grid (V2G) technologies. These technologies allow EEVs to operate as mobile energy storage units, providing flexibility to the grid, assisting in peak shaving, and enhancing grid stability. Information and communication technology (ICT) acts as the foundation for real-time monitoring, control, and advanced analytics. Innovations such as 5G, IoT, and edge computing facilitate quicker and more effective energy management across diverse systems. Advanced metering infrastructure (AMI) enables bidirectional communication between utilities and consumers, enhancing capabilities such as demand response, dynamic pricing, real-time energy monitoring, and energy efficiency initiatives. AMI facilitates improved forecasting and management of energy demand for utilities, thereby boosting operational efficiency. The future of EMS is centered around enhanced integration and interoperability of technologies, utilizing AI-driven automation, strong communication networks, and predictive analytics to develop a unified, intelligent, and sustainable energy ecosystem. The recent developments will facilitate more intelligent energy systems, improve the integration of renewable energy sources, and aid in the shift towards a low-carbon economy, all while maintaining reliability, resilience, and economic efficiency.

4. Evolution and Role of Digital Twin Technology in Smart Grid Systems

Digital Twin (DT) technology, although formally articulated in the early 21st century, has its conceptual foundation rooted in much earlier engineering practices. A notable historical precursor was its implicit application during NASA's Apollo 13 mission in 1970, where engineers constructed a ground-based replica of the spacecraft to mirror its operational state in real time [186]. This allowed mission control to test and validate corrective procedures remotely, setting a precedent for what would later be defined as a digital twin system. Over time, the theoretical framework of DTs evolved through several key contributions. David Gelernter's *Mirror Worlds* (1991) introduced the idea of dynamic digital representations of real-world entities, updated through continuous data input [187]. In 2002, Michael Grieves formalized the concept within Product Lifecycle Management (PLM) through the "Mirrored Spaces Model", which illustrated the interaction between physical systems, their digital equivalents, and the flow of information between them. NASA subsequently adopted and refined this model into what is now formally recognized as the Digital Twin architecture in 2010 [188,189].

As technological capabilities in data acquisition, computational modeling, and communication networks have progressed, DTs have transitioned from conceptual models to

practical tools with broad industrial relevance. In the energy sector, particularly within smart grids, microgrids, and virtual power plants (VPPs), DTs have become essential components of digital infrastructure. They enable real-time simulation, system optimization, and predictive analysis by replicating the behavior of physical assets through continuous data streams obtained via smart sensors and advanced metering infrastructure (AMI). These dynamic models provide operators with critical insights into equipment performance, load distribution, and energy flows, allowing for improved reliability, efficient energy storage utilization, and rapid response to operational anomalies. In practical applications, DTs allow energy providers to model and analyze scenarios involving the integration of variable renewable energy sources—such as solar and wind—alongside traditional generation assets. They also facilitate demand forecasting, resilience planning, and assessment of potential disruptions, whether due to mechanical failures or cyber incidents [190–192]. Through simulation-based decision support, operators can test intervention strategies in a risk-free virtual environment, enabling more proactive and adaptive grid management [193].

However, the effective implementation of DTs is heavily dependent on the integration and governance of data. Many of the datasets required to simulate a physical system already exist within established organizational data storage systems. For example, maintenance logs, performance histories, and sensor readings may reside in siloed repositories managed under legacy governance frameworks. For the digital twin to accurately model system behavior—including the effect of altering maintenance schedules or equipment configurations—these existing datasets must be systematically integrated into the DT environment [194]. This integration demands a shift in mindset and practice, particularly for engineers and technicians who are accustomed to accessing data in a decentralized and ad hoc manner. These users may not typically consider the broader implications of data availability, consistency, and quality, nor the structured processes necessary for ensuring data reliability across digital platforms. To support a robust and functional DT, organizations must adopt comprehensive data governance strategies. These include identifying critical datasets, establishing centralized or federated data storage systems, defining access protocols, and implementing quality assurance measures. Poor-quality or redundant data must be identified and removed to prevent inaccuracies in simulation outcomes and system diagnostics. Moreover, as smart grids become more digitized and interconnected, the risk of cyber threats increases substantially. DTs play a crucial role in this domain by enabling the simulation of cyberattack scenarios and assessing system vulnerabilities. These capabilities support the continuous evaluation of cybersecurity strategies, ensuring that defensive mechanisms are current, effective, and responsive to evolving threats [195].

High-fidelity virtual models are essential to the functionality of Digital Twin (DT) systems, enabling critical capabilities such as monitoring, forecasting, optimization, and decision-making. These capabilities highlight the fundamental role of modeling and simulation in DT research. To support these functions, comprehensive modeling methodologies have emerged that represent both the physical and virtual aspects of systems. Modern approaches to DT modeling typically divide virtual models into four key dimensions: geometry, physics, behavior, and rules. This multidimensional framework offers a robust foundation for creating virtual representations that can closely mirror their physical counterparts and is widely regarded as a foundational approach in DT research. Building on this foundational framework, more advanced methodologies have been developed that expand the scope of virtual models. One such approach introduces a more detailed categorization of models, encompassing geometric models, physical models, capability models, behavioral models, and rule models. The inclusion of the capability model represents a significant innovation in this methodology, as it specifically focuses on defining and capturing the functional capabilities of physical entities. By articulating the performance

and competencies of these entities, the capability model enhances the depth of the digital representation, allowing for more accurate simulations and predictive analytics [196–200]. Figure 26 illustrates the development of Digital Twin (DT) technology from the 1960s to the present, highlighting key milestones and advancements. The timeline captures significant technological breakthroughs, conceptual evolutions, and applications across various industries, emphasizing the progressive enhancement of modeling accuracy, real-time data integration, and predictive capabilities. This historical overview underscores the growing importance of DTs in enabling advanced simulation, monitoring, and optimization within modern engineering and energy systems.

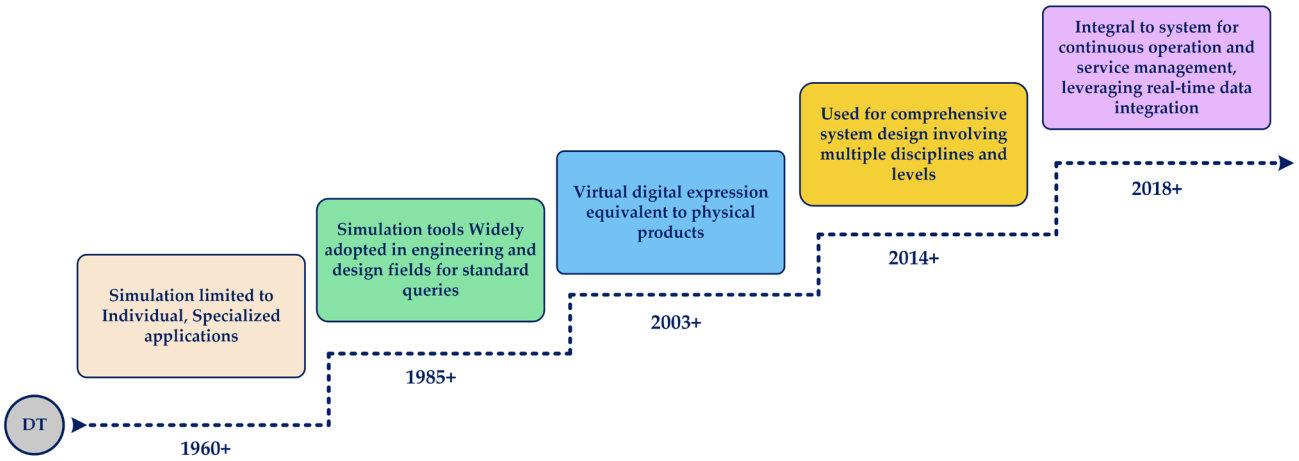

Figure 26. Development of Digital Twin (DT) technology from the 1960s to the present, highlighting major milestones [14,195].

Figure 27 presents a block diagram illustrating the process of developing a Digital Twin (DT) for a Smart Grid system. It highlights the continuous collection of real-time data from physical assets within the grid, gathered through strategically placed sensors. This data is then communicated to a digital platform, where it is used to construct a virtual representation, or "twin", of the physical infrastructure. The virtual twin allows for ongoing analysis, control, and feedback to the physical system, facilitating enhanced operational efficiency, predictive maintenance, and dynamic decision-making. Several leading companies, such as General Electric, Siemens, ABB, and Rolls-Royce, are at the forefront of creating digital twin models for various electrical components and systems. These efforts are aimed at improving grid reliability, optimizing energy distribution, and enabling proactive management of grid assets [201].

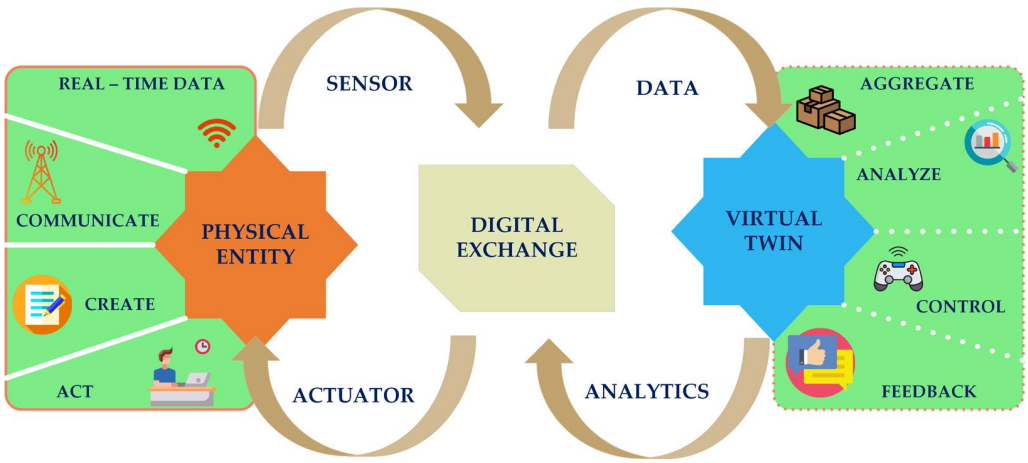

Figure 27. Digital twin concept [202].

Another notable advancement in DT modeling involves the introduction of the GHOST framework, which broadens the traditional model structure to include additional key elements such as geometric data, historical samples, object assemblies, snapshot collections, and topological constraints. This framework emphasizes the integration and management of diverse, multi-sourced data, addressing the complexity of managing large volumes of heterogeneous information typically found in DT systems. By incorporating these elements, the GHOST approach allows for more efficient handling of complex data and enhances the overall functionality of DTs in real-world applications. Alongside these specific modeling frameworks, two primary approaches dominate the field of DT modeling: model-driven and data-driven methodologies. Model-driven approaches focus on the fundamental physical mechanisms and processes governing the behavior of a system. These models aim to replicate the intricate dynamics of real-world entities, often requiring detailed knowledge of the underlying physical laws. While this approach provides an in-depth and accurate representation of physical systems, it can be computationally intensive and complex [203].

In contrast, data-driven methods prioritize the use of input-output data to model and predict the behavior of physical processes, bypassing the need for a detailed understanding of the system's underlying mechanisms. This approach is particularly useful in situations where the physical processes are complex, poorly understood, or too difficult to model explicitly. Data-driven methods provide a more flexible and scalable solution for modeling systems, particularly when real-time data can be leveraged to inform predictions and system optimizations. Together, these modeling methodologies provide complementary approaches for creating accurate, dynamic, and functional digital twins. The integration of both model-driven and data-driven strategies ensures that Digital Twin systems can adapt to a wide range of applications, from highly controlled industrial environments to complex, data-rich scenarios. By combining these approaches, researchers and engineers can create more effective virtual models, enabling more advanced simulations, decision-making, and system optimizations across various industries.

Figure 28 provides a comprehensive overview of the various tools utilized for digital twin modeling, categorizing them according to their primary functionalities including simulation, data analytics, visualization, and system integration. It highlights key software platforms, development frameworks, and specialized applications that enable the creation, real-time updating, and management of digital twin models. By illustrating the capabilities and interoperability of these tools, it emphasizes their critical role in facilitating accurate virtual representations, predictive analytics, and decision-making processes across multiple industries such as manufacturing, energy, and smart infrastructure.

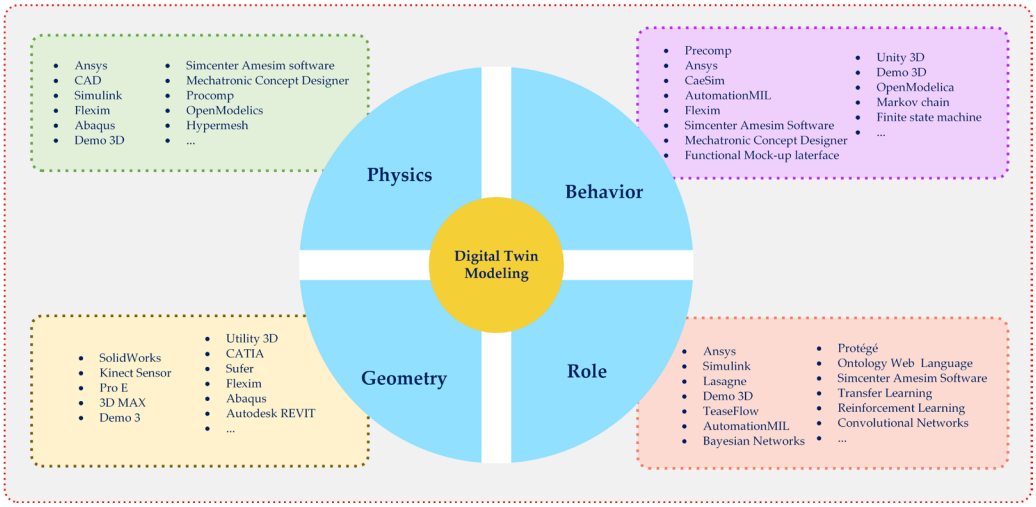

Figure 28. Tools for digital twin modelling [204,205].

5. Future Directions in Smart Grid Systems

The integration of advanced technologies such as artificial intelligence (AI), blockchain, and edge computing is revolutionizing smart grid energy management systems, driving improvements in operational efficiency, data security, and system responsiveness. AI plays a critical role in enabling intelligent energy forecasting, demand-side management, and automated control of distributed energy resources. By leveraging machine learning algorithms, smart grids can predict consumption patterns, optimize energy distribution, and quickly respond to fluctuations in supply and demand with minimal human intervention. Blockchain technology enhances the transparency and security of energy transactions within the smart grid ecosystem. Through its decentralized and tamper-proof ledger, blockchain supports secure peer-to-peer energy trading, accurate tracking of energy provenance (e.g., verifying whether electricity was sourced from renewables), and the implementation of automated agreements via smart contracts. This not only increases trust among stakeholders but also reduces the need for centralized authorities or intermediaries. Edge computing further supports smart grid efficiency by enabling real-time data processing at or near the point of generation or consumption—such as at smart meters, solar inverters, or electric vehicle charging stations. By reducing reliance on cloud-based servers, edge computing minimizes latency, enhances reliability, and ensures continuous grid operation even during connectivity disruptions. It also facilitates faster decision-making and localized control, which is vital for balancing loads and maintaining grid stability in increasingly decentralized energy networks. Collectively, these technologies form the backbone of next-generation smart grid systems. They support a more adaptive, resilient, and decentralized energy infrastructure capable of meeting growing demands for sustainability, cybersecurity, and operational agility. As energy systems become more complex and dynamic, the convergence of AI, blockchain, and edge computing will be essential to achieving efficient and intelligent grid management [206,207].

Figure 29 depicts the synergistic integration of Artificial Intelligence (AI), Blockchain technology, and Edge Computing within smart grid infrastructures. AI-driven analytics enable sophisticated forecasting and decision-making processes, blockchain provides a secure, immutable, and transparent ledger for decentralized transactions, and Edge Computing offers low-latency, distributed data processing at or near the data source. This convergence of advanced technologies enhances the operational intelligence, cybersecurity, scalability, and resilience of smart grids, facilitating more efficient and reliable energy management and distribution.

5.1. Collaborative Energy Innovations

The advancement of smart grid energy management systems increasingly relies on cross-sector collaboration to integrate emerging technologies such as artificial intelligence (AI), blockchain, and the Internet of Things (IoT). Future developments in this domain will depend heavily on strategic partnerships among stakeholders from various industries, including energy utilities, information and communication technology (ICT) firms, hardware manufacturers, software developers, and regulatory agencies. These alliances bring together complementary expertise—ranging from cybersecurity and data analytics to grid infrastructure and policy compliance—forming a foundation for the development of intelligent, secure, and adaptable energy networks. Looking ahead, collaborative innovation is expected to drive the broader adoption of AI-enabled demand forecasting models, decentralized energy control schemes, and real-time monitoring systems facilitated by IoT devices. For example, ICT firms can enhance the resilience of grid infrastructure through robust analytics and cybersecurity tools, while energy providers contribute domain-specific insights into operational requirements and regulatory frameworks. Blockchain technology,

integrated through multi-stakeholder cooperation, will likely support transparent energy trading systems, automated settlement mechanisms, and immutable records for energy provenance—enhancing trust and efficiency across the energy value chain. Furthermore, these partnerships enable the co-development of technologies such as edge-computing-enabled sensors and adaptive algorithms for load optimization, which are essential for dynamic and responsive grid operations. Emphasizing interoperability, standardization, and shared innovation across sectors will promote the scalability and replicability of smart grid solutions in diverse regulatory and geographic contexts. Strengthening such cooperative models will be essential to accelerating the digital transformation of energy systems, ultimately fostering grid infrastructures that are not only more intelligent and efficient but also resilient and environmentally sustainable [208].

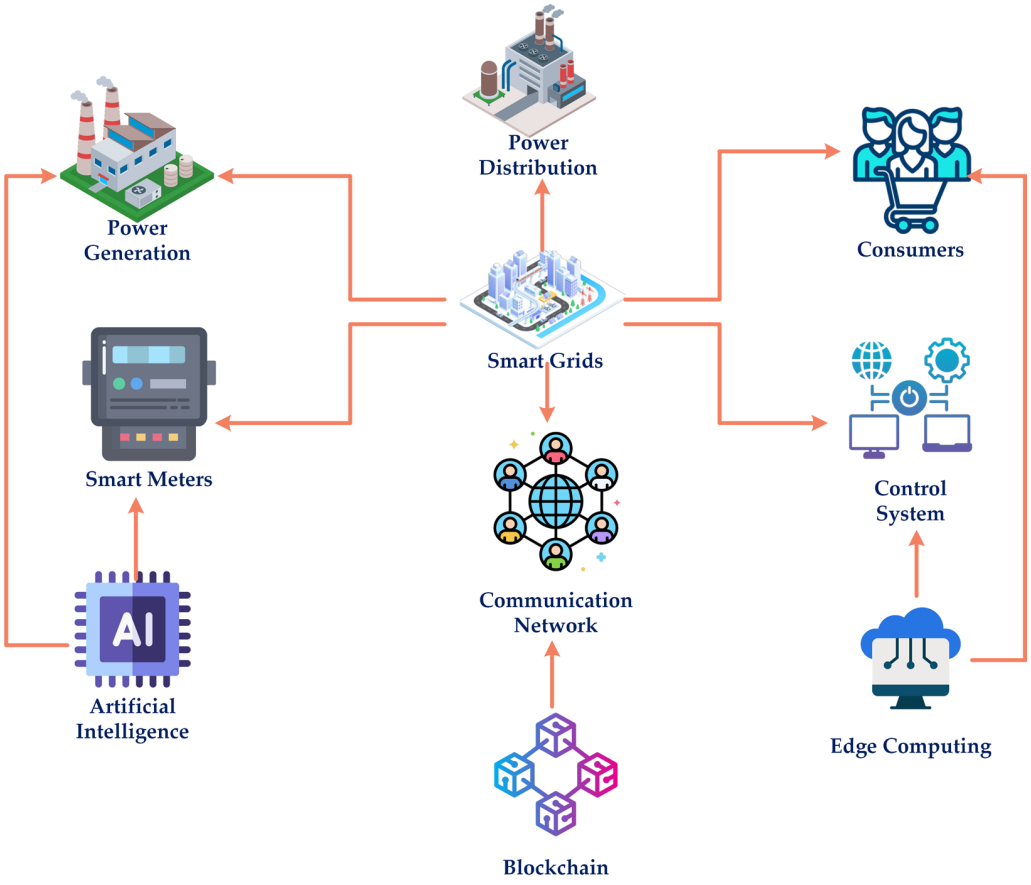

Figure 29. AI, Blockchain, and Edge Computing in Smart Grid Integration [207].

5.2. Enhancing Cyber-Physical Security in Smart Grids

The transformation of conventional power systems into smart grids has introduced significant advancements in operational efficiency, sustainability, and adaptability, driven by the integration of automation, sensor networks, and sophisticated communication technologies. However, this digital convergence also brings new layers of cyber-physical vulnerabilities. The increased interconnectivity and complexity of smart grid infrastructures expand the potential attack surface, elevating the risk of cyber intrusions, data breaches, and even physical damage to critical assets. Addressing these challenges requires comprehensive and integrated cybersecurity strategies that encompass both digital and physical dimensions. These strategies include ensuring data confidentiality and integrity, safeguarding critical infrastructure from unauthorized access, enhancing operator awareness through targeted training, and reinforcing communication networks and software systems against exploitation. Within this context, the Smart Grid Architecture Model (SGAM) provides a

valuable framework for mapping and analysing smart grid components, functions, communication protocols, and information flows across multiple interoperability layers. SGAM enables a systematic approach to identifying security requirements and aligning protective measures with functional and operational needs. Emerging solutions—such as AI-driven threat detection, blockchain-enabled authentication mechanisms, and adaptive security architectures—offer robust capabilities for enhancing system resilience and real-time response. In parallel, collaboration among utilities, cybersecurity experts, regulators, and technology developers remain critical for establishing standardized, interoperable, and future-ready security frameworks. Integrating security as a foundational design element, guided by structured models like SGAM, ensures the development of smart grids that are resilient, reliable, and secure in the face of evolving cyber-physical threats [209,210].

5.3. Leveraging Big Data Analytics in Smart Grids

Big data analytics is poised to become a cornerstone of next-generation smart grid systems, offering transformative potential in how energy networks are monitored, managed, and optimized. With the proliferation of data from smart meters, IoT sensors, and distributed energy resources, advanced analytics will enable utilities to gain real-time operational insights, support rapid decision-making, and improve system responsiveness. Key future developments include enhanced demand forecasting, enabling utilities to better balance supply and demand while minimizing peak loads. Big data will also support proactive maintenance strategies by identifying early signs of equipment failure, thereby reducing downtime and extending asset lifespans. As smart grids increasingly integrate variable renewable energy sources, analytics will help manage generation volatility and ensure grid stability. Cybersecurity will also benefit from real-time data analysis, with anomaly detection systems capable of identifying malicious activity before it disrupts operations. On the consumer side, data-driven insights into usage patterns will promote energy efficiency and informed decision-making. Additionally, big data will support strategic grid planning and market optimization, guiding infrastructure investments and enabling more dynamic pricing models. In summary, the integration of robust, scalable big data analytics platforms will be essential to building intelligent, secure, and adaptive energy systems that meet the demands of a rapidly evolving energy landscape [211,212].

5.4. Metaverse-Driven Smart Grid Innovation

The convergence of metaverse technologies with smart grid systems represents a novel and promising direction for the digital transformation of the energy sector. The metaverse—characterized by immersive, real-time, and interconnected virtual environments—offers new possibilities for enhancing grid design, simulation, monitoring, and stakeholder interaction. Future smart grids are expected to increasingly leverage these capabilities to create virtual replicas of physical grid infrastructure, known as digital twins, enabling real-time visualization, predictive analytics, and collaborative decision-making within a metaverse context. Immersive virtual platforms will allow operators, engineers, and policymakers to interact with complex grid environments in a shared, data-rich 3D space. This can significantly improve training, system diagnostics, and emergency response planning through scenario simulations and virtual testing. Moreover, integrating metaverse interfaces with AI and IoT systems will facilitate more intuitive and responsive control of distributed energy resources, enhancing grid agility and reliability. From a consumer perspective, the metaverse could also support interactive energy management tools, allowing users to visualize their consumption patterns, participate in virtual energy communities, and engage with decentralized energy markets in real-time. These developments will foster greater energy literacy, participation, and efficiency. As the technology matures, key research

challenges will include ensuring the interoperability of metaverse platforms with existing grid systems, securing virtual environments from cyber threats, and addressing the energy demands of metaverse infrastructure itself. Addressing these concerns will be critical for unlocking the full potential of metaverse-driven smart grid applications [213,214].

5.5. Investment in Research and Development

Innovation and global progress in smart grid energy management are increasingly underpinned by sustained investment in research and development (R&D), particularly in enabling technologies such as artificial intelligence (AI), the Internet of Things (IoT), renewable energy integration, and cybersecurity. These technological domains are essential to the transformation of conventional energy systems into intelligent, decentralized, and resilient smart grids. R&D not only fosters innovation in energy storage, grid automation, and real-time energy analytics but also facilitates the creation of high-value employment, enhanced system efficiency, and long-term competitiveness in the global energy market. Investments in R&D lead to tangible improvements in both energy products and operational processes. For instance, AI and IoT are being leveraged to optimize load forecasting, enable predictive maintenance of grid assets, and support real-time decision-making in energy distribution. Similarly, advanced cybersecurity research is critical to safeguarding grid infrastructure against digital threats, especially as grids become increasingly digitized and interconnected. The resources necessary to sustain this innovation ecosystem are often mobilized through collaborative frameworks involving public-private partnerships, academic-industry alliances, and government policy support. Governments play a key role by offering grants, subsidies, and tax incentives that reduce financial barriers and encourage long-term R&D initiatives. These incentives are particularly important in high-capital areas such as renewable energy integration and smart metering infrastructure, where the return on investment may be long-term and dependent on technological maturation. Furthermore, strategic alignment between public institutions and private sector stakeholders ensures that R&D priorities reflect both market needs and public policy goals—such as decarbonization, energy equity, and grid resilience. As a result, smart grid R&D not only advances technological innovation but also supports broader societal imperatives, including climate action, energy accessibility, and economic sustainability [215].

5.6. Encouraging Sustainable Practices

Smart grid technologies represent a critical advancement in the pursuit of sustainable, efficient, and resilient energy management systems. By leveraging digital infrastructure, automation, and advanced analytics, smart grids enable the seamless integration of renewable energy sources, improve overall energy efficiency, and reduce dependence on fossil fuels. These systems are designed to intelligently monitor and manage the flow of electricity from generation to consumption, offering a flexible and adaptive framework for modern energy needs. A core strength of smart grids lies in their ability to support real-time energy tracking, allowing utilities and consumers to gain detailed insights into consumption patterns, grid performance, and potential inefficiencies. This data-driven approach empowers operators to optimize energy distribution and enables consumers to make more informed decisions that contribute to overall system efficiency and sustainability. In addition, decentralized energy production—such as rooftop solar installations, local wind turbines, and microgrids—is supported through smart grid architecture. This decentralization not only enhances grid flexibility and resilience but also reduces transmission losses and improves energy access in remote areas. Smart grids also incorporate AI-driven predictive maintenance tools that monitor the health of grid infrastructure, anticipate failures, and schedule repairs proactively, thereby reducing downtime and extending

the lifespan of critical assets. These innovations contribute significantly to environmental impact reduction, as improved operational efficiency leads to lower greenhouse gas emissions and minimized resource waste. Smart grids also facilitate the integration of clean energy technologies and energy storage systems, which are essential for balancing intermittent renewable sources and maintaining grid stability. These advancements are directly aligned with the objectives of the United Nations Sustainable Development Goal 7 (SDG 7), which aims to guarantee universal access to affordable, reliable, sustainable, and modern energy. In conclusion, smart grids play a pivotal role in shaping a modern energy ecosystem that is eco-friendly, efficient, and resilient. By enabling smarter energy use, supporting decentralized production, and leveraging advanced digital technologies, smart grids are central to achieving global sustainability and energy transition goals [216].

6. Conclusions

This systematic review highlights the pressing need to transition from fragmented, technology-specific approaches toward a cohesive and integrated framework for the deployment of digital technologies in Advanced Energy Systems (AES). While individual technologies—such as Artificial Intelligence (AI), the Internet of Things (IoT), Blockchain, and Digital Twins—exhibit substantial potential, their combined and coordinated integration offers synergistic benefits far beyond isolated applications. This integrated digitalization strategy enables the creation of intelligent, adaptive, and resilient energy infrastructures capable of addressing the multifaceted technical, operational, and regulatory challenges confronting contemporary energy systems.

The findings of this review affirm that digital technologies enhance critical functionalities across the energy value chain, including real-time monitoring, predictive analytics, decentralized control, secure data exchange, and adaptive decision-making. These capabilities are vital in accommodating the intermittency of renewable energy sources, supporting decentralized generation and storage assets, reinforcing grid stability, and adapting to increasingly complex cybersecurity and market dynamics. When implemented strategically, digital solutions can significantly improve the efficiency, flexibility, and sustainability of energy production, transmission, and consumption—thereby contributing to global decarbonization targets and long-term energy resilience.

Despite these advantages, several persistent challenges must be addressed to realize the full benefits of digital integration. These include the lack of standardized interoperability protocols, fragmented regulatory frameworks, concerns over data governance and cybersecurity, legacy system incompatibilities, and limited cross-sectoral collaboration. Overcoming these barriers requires a structured, multi-stakeholder approach that aligns technical innovation with regulatory reform, institutional coordination, and societal acceptance.

To support practical advancements in the energy sector, this review offers the following key recommendations:

1. Develop and deploy interoperable digital platforms that enable seamless integration across diverse energy technologies and system layers.
2. Implement enabling policy and regulatory mechanisms that incentivize innovation while safeguarding ethical data use, security, and privacy.
3. Modernize legacy infrastructure and grid assets to support compatibility with advanced digital applications and decentralized energy models.
4. Invest in large-scale pilot projects and demonstration environments to assess the performance, scalability, and impact of integrated digital solutions under real-world conditions.
5. Strengthen digital literacy and workforce capacity-building efforts to ensure effective system adoption and user engagement across all levels of the energy value chain.

6. Encourage multi-sectoral collaboration between academia, industry, government, and civil society to align innovation with inclusive, sustainable development objectives.

Future research should prioritize the empirical validation of modular, scalable, and context-adaptable digital architectures that can be deployed across diverse energy environments. Furthermore, interdisciplinary investigations into the institutional, behavioral, and equity-related dimensions of digital energy transitions are essential to ensure that technological innovation translates into inclusive, just, and socially responsible outcomes.

In conclusion, the strategic integration of digital technologies within AES represents a pivotal pathway toward developing future-ready, low-carbon, and secure energy systems. By fostering interdisciplinary collaboration, aligning technical standards, and embedding digital innovation within broader sustainability frameworks particularly in support of SDG 7, the energy sector can fully leverage the transformative potential of digitalization. This convergence is not only key to enhancing system performance and resilience but also vital to accelerating the global transition toward a sustainable, equitable, and climate-resilient energy future.

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Abbreviations

The following abbreviations are used in this manuscript:

AES	Advanced Energy Systems
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ADT	Advanced Digital Technologies
BD	Big Data
DER	Distributed Energy Resource
DERMS	Distributed Energy Resource Management System
DR	Demand Response
DSO	Distribution System Operator
DT	Digital Twin
EM	Energy Management
EMCS	Energy Management and Control System
EMS	Energy Management System
EV	Electric Vehicle
FL	Fuzzy Logic
GAMS	General Algebraic Modeling System
GPRS	General Packet Radio Service
GSM	Global System for Mobile Communications
HAN	Home Area Network
HOGA/iHOGA	Hybrid Optimization by Genetic Algorithms
HVDC	High Voltage Direct Current
IAN	Industry Area Network
ICT	Information and Communication Technology
IoT	Internet of Things

IP	Internet Protocol
ISMs	Intelligent Energy Management Systems
JADE	Java Agent DEvelopment framework
KNX	Konnex
LEC	Local Energy Community
LP	Linear Programming
MG	Microgrid
MGCC	Microgrid Central Controller
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MPPT	Maximum Power Point Tracking
MPC	Model Predictive Control
NN	Neural Network
NTP	Network Time Protocol
P2P	Peer-to-Peer
PLC	Programmable Logic Controller
PPES	Privacy-Preserving Energy Scheduling
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSCAD	Power Systems Computer-Aided Design
PSO	Particle Swarm Optimization
SC	Supercapacitor
SCADA	Supervisory Control and Data Acquisition
TSO	Transmission System Operator
VPP	Virtual Power Plant
WiMAX	Worldwide Interoperability for Microwave Access

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