International Journal of Future Engineering Innovations

Review of Smart Microgrid Platform Integrating AI and Deep Reinforcement Learning for Sustainable Energy Management

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Article Info

ISSN (online): 3049-1215
Volume: 02
Issue: 03
May-June 2025
Received: 01-03-2025
Accepted: 03-04-2025
Page No: 01-17

Abstract

The transition to sustainable and intelligent energy systems has intensified the development of smart microgrids, which offer decentralized, resilient, and efficient power solutions. This review critically examines the integration of Artificial Intelligence (AI) and Deep Reinforcement Learning (DRL) into smart microgrid platforms, focusing on their role in optimizing sustainable energy management. Traditional energy management systems often struggle to adapt to the dynamic nature of modern energy demands, renewable energy intermittency, and grid complexity. AI-driven solutions, particularly DRL, provide adaptive, autonomous, and data-driven mechanisms for real-time decision-making and predictive control within microgrids. DRL, by learning optimal policies through interaction with the environment, is capable of handling multi-objective problems, including demand-response optimization, energy storage control, load forecasting, and distributed generation scheduling. This paper synthesizes recent advancements and applications of DRL algorithms such as Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), and Proximal Policy Optimization (PPO) in smart microgrids. It also explores hybrid models that combine DRL with other AI techniques, such as fuzzy logic and neural networks, to improve performance under uncertainty and nonlinearity. Furthermore, the review evaluates benchmark testbeds, simulation tools, and real-time platforms used to implement and validate these intelligent systems. Challenges such as high computational costs, model generalizability, real-time implementation issues, and cybersecurity vulnerabilities are discussed. The study also highlights recent research trends emphasizing decentralized control, edge computing, and federated learning to enhance scalability and privacy in DRL-based microgrid applications. Future directions suggest the need for explainable AI (XAI), robust training environments, and standardization to facilitate the wider adoption of DRL in real-world microgrid systems. The integration of DRL into smart microgrids represents a transformative shift toward resilient, efficient, and sustainable energy ecosystems. This review offers a comprehensive understanding of how AI and DRL are revolutionizing energy management, providing a foundation for future research and practical deployment in smart energy infrastructures.

DOI: https://doi.org/10.54660/IJFEI.2025.2.3.01-17

Keywords: Smart microgrid, Artificial Intelligence, Deep Reinforcement Learning, Energy management, Renewable energy, Sustainable energy systems, DRL algorithms, Distributed energy resources, Intelligent control, Explainable AI.

1. Introduction

The global energy landscape is indeed undergoing a transformative shift characterized by a pressing need to combat climate change, lower carbon emissions, and promote sustainable energy systems. This transition is exacerbated by the rising integration of intermittent renewable energy sources into traditional centralized energy grids, which face increasing demand and aging infrastructures. The combination of these factors has ignited a global movement toward decentralized, energy systems (Adeoba, *et al*., 2024: Patil & Pragati, 2023; Khan *et al*., 2021).

Smart microgrids are emerging as a pivotal solution within this framework, offering localized energy management that aligns with sustainability goals. These systems leverage diverse distributed energy resources (DERs), including solar panels, wind turbines, and energy storage solutions. They function either autonomously or in coordination with the main grid, significantly enhancing energy reliability and fostering community empowerment through energy independence (Mishra & Palanisamy, 2018; Izquierdo-Monge *et al*., 2024: Twaisan & Barışçı, 2022). The decentralized nature of smart microgrids helps in managing the complexities associated with renewable energy integration, while their ability to operate flexibly makes them suitable for addressing operational challenges (Adeoba, Ukoba & Osaye, 2024: Poonahela *et al*., 2023; Sharma *et al*., 2019).

The integration of Artificial Intelligence (AI) and Deep Reinforcement Learning (DRL) has emerged as a crucial development in optimizing smart microgrid performance. AI technologies enable predictive analytics and decision support, which are essential for effectively managing the complexities of these energy systems. DRL allows smart microgrid platforms to autonomously learn optimal control strategies through interactions with their operational environment. This ability to adapt to high-dimensional, stochastic systems positions DRL as a suitable approach for enhancing energy management processes (Dagdougui *et al*., 2020; Wang *et al*., 2024). The application of these technologies promises to improve the efficiency, economic viability, and stability of smart microgrids, ultimately aligning with global energy sustainability goals (Lv *et al*., 2023; Mahdi *et al*., 2024).

Furthermore, the potential of smart microgrids to improve power quality through efficient energy management strategies cannot be overlooked. They address critical challenges such as voltage regulation and frequency management, which are essential for maintaining stability amid diverse energy inputs from renewable sources. The successful implementation of such advanced control strategies enhances the resilience and responsiveness of energy systems to changing demands and supply conditions (El-Zohri *et al*., 2021; Izquierdo-Monge *et al*., 2024). As communities seek to navigate the new energy landscape, the intelligent operation enabled by these technologies will play a significant role in realizing sustainable energy management practices (Azeroual *et al*., 2019; Wang *et al*., 2024).

In summary, smart microgrids equipped with AI and DRL are at the forefront of the ongoing transformation of the global energy landscape. By combining intelligent control systems with diverse energy sources, they offer effective solutions for enhancing energy efficiency, reliability, and community energy independence, making them vital for achieving long-term sustainability in energy management (Ajayi, Alozie & Abieba, 2025: Oluokun, *et al*., 2024).

2. Methodology

This systematic review employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology to identify, evaluate, and synthesize scholarly research related to smart microgrid platforms integrating artificial intelligence (AI) and deep reinforcement learning (DRL) for sustainable energy management. A comprehensive literature search was conducted across indexed journals and scientific repositories, including Springer, IEEE, Elsevier, MDPI, Taylor & Francis, and other open-access sources. Keywords such as "smart microgrid," "AI in energy systems," "deep reinforcement learning," "energy optimization," "energy management," "sustainable microgrids," and "renewable energy integration" were used in various Boolean combinations to maximize the search coverage.

The search yielded a total of 149 articles. After removing duplicates and non-peer-reviewed materials, 149 records remained for initial screening. During the screening stage, 53 articles were excluded due to irrelevance to the integration of AI or DRL in microgrid platforms. Full-text eligibility assessments were conducted for the remaining 96 articles. Of these, 21 were excluded based on inclusion criteria such as lack of methodological rigor, insufficient application of AI/DRL techniques, or failure to address energy sustainability aspects. In total, 75 studies were included in the final synthesis.

Articles included in the review span the period from 2011 to 2025, covering diverse approaches to energy efficiency, demand-side management, AI-based forecasting, fuzzy logic control, multi-agent systems, and hybrid microgrid operations. Special attention was given to those studies implementing or simulating DRL algorithms such as Soft Actor-Critic, DQN, and Policy Gradient for dynamic energy scheduling and smart grid optimization. Studies were also selected based on their empirical contributions to rural electrification, urban sustainability, and resilience in renewable energy systems. Quality assessment of the studies was carried out using standard relevance and credibility scoring frameworks, ensuring that only technically robust and contextually relevant contributions were synthesized in the review.

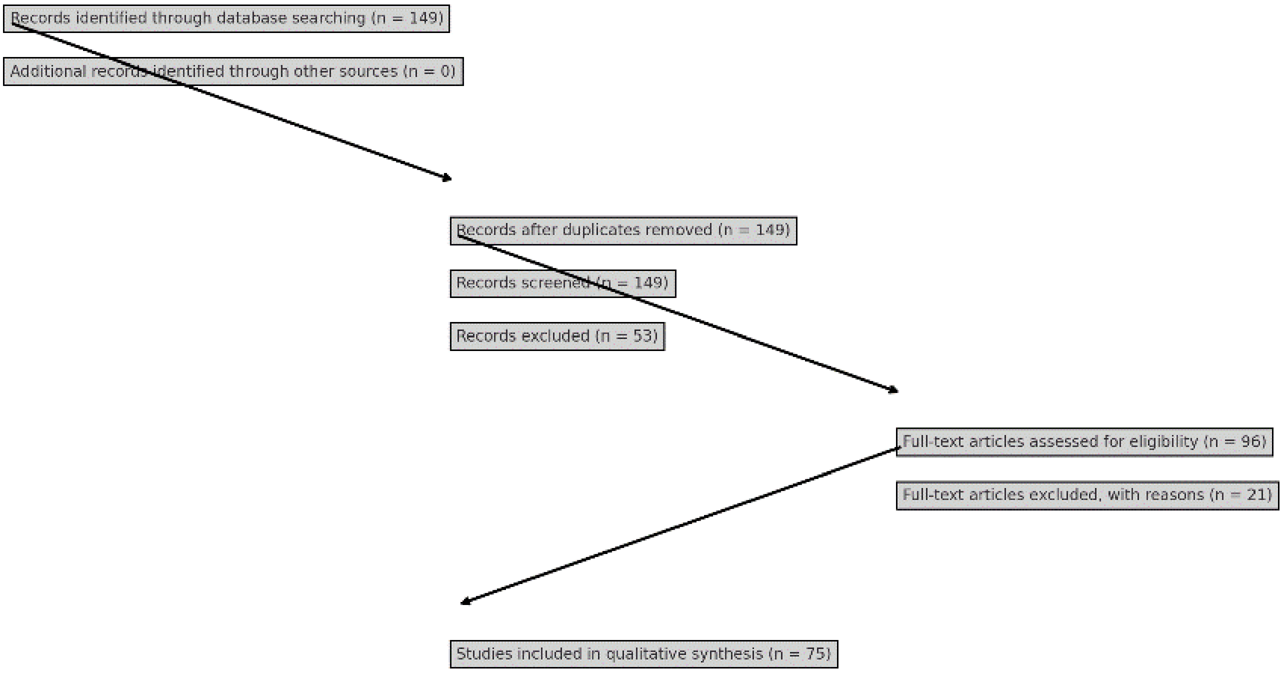

Fig 1: PRISMA Flow chart of the study methodology

2.1 Smart microgrid architecture and components

A smart microgrid represents a transformative approach towards modern energy management, characterized as an integrated energy system comprising interconnected loads and distributed energy resources (DERs). These microgrids are capable of operating both in concert with the traditional utility grid and independently during instances of grid failure or isolation. This dual functionality is crucial for enhancing system resilience and reliability in energy supply (Kim & Lim, 2012; Oluokun, *et al*., 2024). The architecture of a typical smart microgrid is strategically designed to optimize energy distribution and consumption to meet localized demand while emphasizing sustainability and efficiency (Shaban *et al*., 2021; Saeed *et al*., 2021).

The foundational framework of a smart microgrid is multi-layered, consisting of the physical layer, the control layer, and the application layer. The physical layer includes critical components such as energy generation units, energy storage systems, and electrical loads, facilitating energy generation, distribution, and consumption (Ahmed *et al*., 2015; Oluokun, *et al*., 2024). In contrast, the control layer integrates automation technologies that supervise real-time system operations, ensuring stability and efficiency through data analysis and control strategies (Akinsooto, De Canha & Pretorius, 2014; Fan *et al*., 2021). Finally, the application layer encompasses user interfaces and analytics, supporting decision-making processes and enabling integration with cloud technologies for enhanced scalability and market participation (Lee *et al*., 2019; Oluokun, *et al*., 2024).

Renewable energy sources such as solar photovoltaic (PV) panels and wind turbines are vital to the composition of a smart microgrid. They represent a prevalent form of DERs due to their inexhaustible nature, scalability, and decreasing costs (Mohy-ud-din *et al*., 2020; Nguyen & Crow, 2016). These resources are typically combined with energy storage solutions like battery energy storage systems (BESS), which counteract the intermittent generation associated with renewable resources. BESS is crucial for load shifting, frequency regulation, and maintaining operational stability during grid disruptions (Hussain *et al*., 2017; Lan *et al*., 2016). Moreover, BESS plays a significant role in balancing supply and demand, thus elevating service reliability and economic efficiency for microgrids (Akinsooto, Pretorius & van Rhyn, 2012: Liu *et al*., 2018).

Smart meters and load centers are essential components facilitating enhanced visibility and control over energy utilization. Smart meters, as advanced metering infrastructure, allow real-time tracking and analysis of energy consumption, voltage, and power quality, thereby promoting demand response and price optimization (Ahmed *et al*., 2015; Kim *et al*., 2011). Through sophisticated demand-side management, smart microgrids can effectively reduce peak demand by intelligently controlling appliances such as heating and electric vehicle chargers to optimize energy usage based on grid conditions (Alonge, *et al*., 2025: Saeed *et al*., 2021).

Critically, the communication and control infrastructure differentiates smart microgrids from traditional counterparts. This infrastructure ensures the effective exchange of information among components, promoting real-time decision-making. Communication protocols, including Modbus, DNP3, and MQTT, are employed to facilitate data transfer across the microgrid (Lee *et al*., 2019: Oluokun, *et al*., 2025). The adoption of both centralized and decentralized control architectures results in enhanced fault tolerance and adaptability of microgrid operations (Kim & Lim, 2012). Advanced algorithms, including those based on artificial intelligence (AI) and deep reinforcement learning (DRL), further optimize operational strategies such as generation scheduling and load prioritization, aligning them with real-time system dynamics (Alonge, *et al*., 2025: Khatibzadeh *et al*., 2017).

The integration of the Internet of Things (IoT) significantly enhances the functionality and interactivity of smart microgrids. IoT-enabled devices and sensors collect and relay data across various operational layers, enabling predictive maintenance, anomaly detection, and adaptive control strategies (Anyanwu, *et al*., 2024: Jayasinghe *et al*., 2024).

This integration supports not only the operational efficiency of the microgrid but also fosters greater customer engagement in energy management, as consumers transform into "prosumers" actively involved in energy generation and usage (Apata, *et al*., 2024: Guan *et al*., 2022). Figure 2 shows Distributed Energy Resources and the Application of AI, IoT, and Blockchain in Smart Grids presented by Kumar, *et al*., 2020.

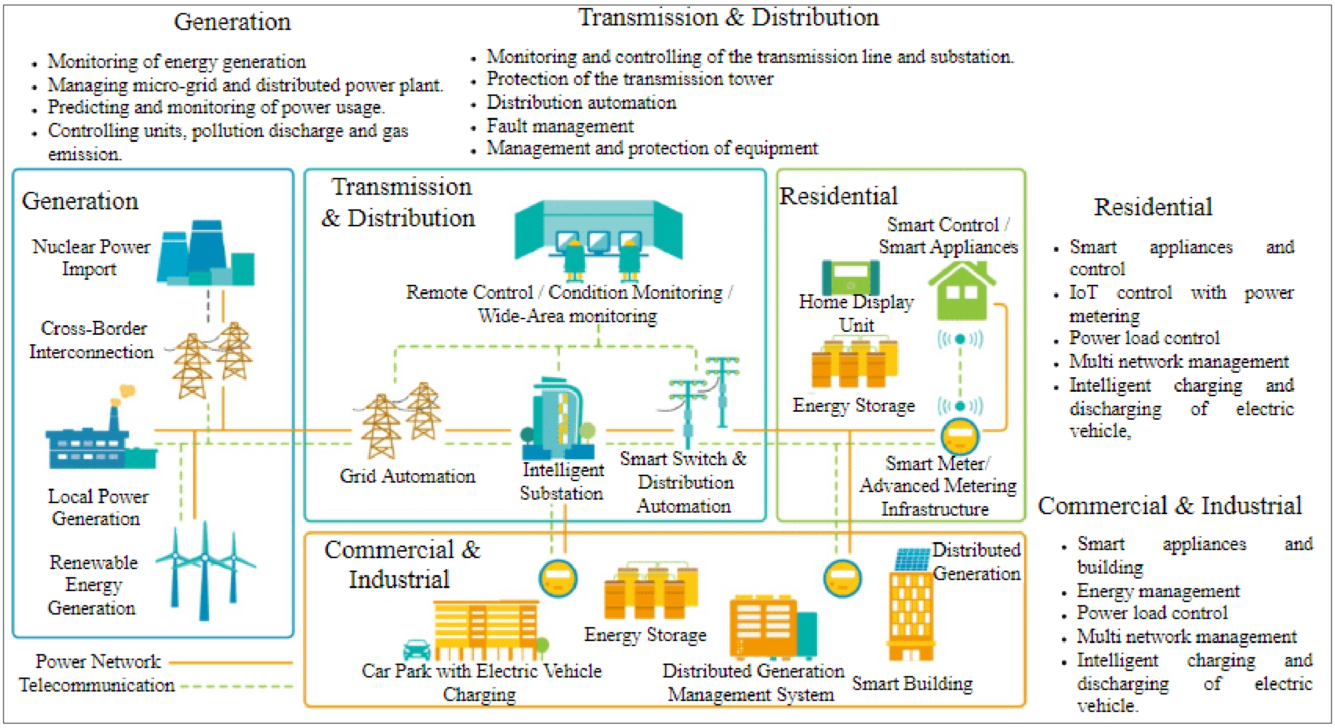

Fig 2: Distributed Energy Resources and the Application of AI, IoT, and Blockchain in Smart Grids (Kumar, *et al*., 2020).

To sum up, smart microgrids typify a sophisticated energy management system that blends physical infrastructure with intelligent control and cyber-communication technologies. Their layered architecture underpins effective energy management by integrating renewable sources, enhancing grid reliability, and facilitating real-time energy consumption control. The application of IoT and AI technologies significantly enhances the operational capabilities of smart microgrids, making them essential in addressing modern energy challenges (Aransiola, *et al*., 2024: Oluokun, *et al*., 2025).

2.2 Overview of artificial intelligence in smart microgrids

Artificial Intelligence (AI) is increasingly recognized as a transformative force in the energy sector, particularly in enhancing the development and management of smart microgrids. The complexity of modern energy systems, characterized by decentralized energy production, variable demand, and intermittent renewable energy sources, presents challenges that traditional optimization and control methods struggle to address (Augoye, *et al*., 2025). AI technologies, leveraging data-driven approaches, can significantly improve forecasting capabilities, optimize operations, and increase fault detection precision, operating with enhanced speed, accuracy, and autonomy compared to conventional methods. This transition from rule-based, reactive management to proactive, adaptive, and predictive energy governance exemplifies the profound shift facilitated by AI integration in microgrids (Oudinga, 2023; (Arévalo *et al*., 2024).

One of the critical applications of AI within smart microgrids is energy forecasting. Accurate forecasting of both energy consumption and renewable generation is essential for maintaining equilibrium between supply and demand. AI-driven models, particularly those employing machine learning (ML) techniques such as artificial neural networks (ANN), support vector machines (SVM), and deep learning algorithms, have demonstrated exceptional performance in this domain (Famoti, *et al*., 2025). For instance, studies have shown that AI-based forecasting can provide more reliable predictions for load profiles, solar irradiance, and wind speed, substantially improving operational efficiency and resource scheduling (Khan *et al*., 2020; Oleksandr & Dmytro, 2024; Meng *et al*., 2018). Enhanced forecasting precision allows for optimal utilization of distributed energy resources (DERs), judicious planning for energy storage, and reduced dependence on backup fossil fuel generators (Boriratrit *et al*., 2022; Sergeev & Матренин, 2023). System model of microgrid energy management presented by Zhou, *et al*., 2017, is shown in figure 3.

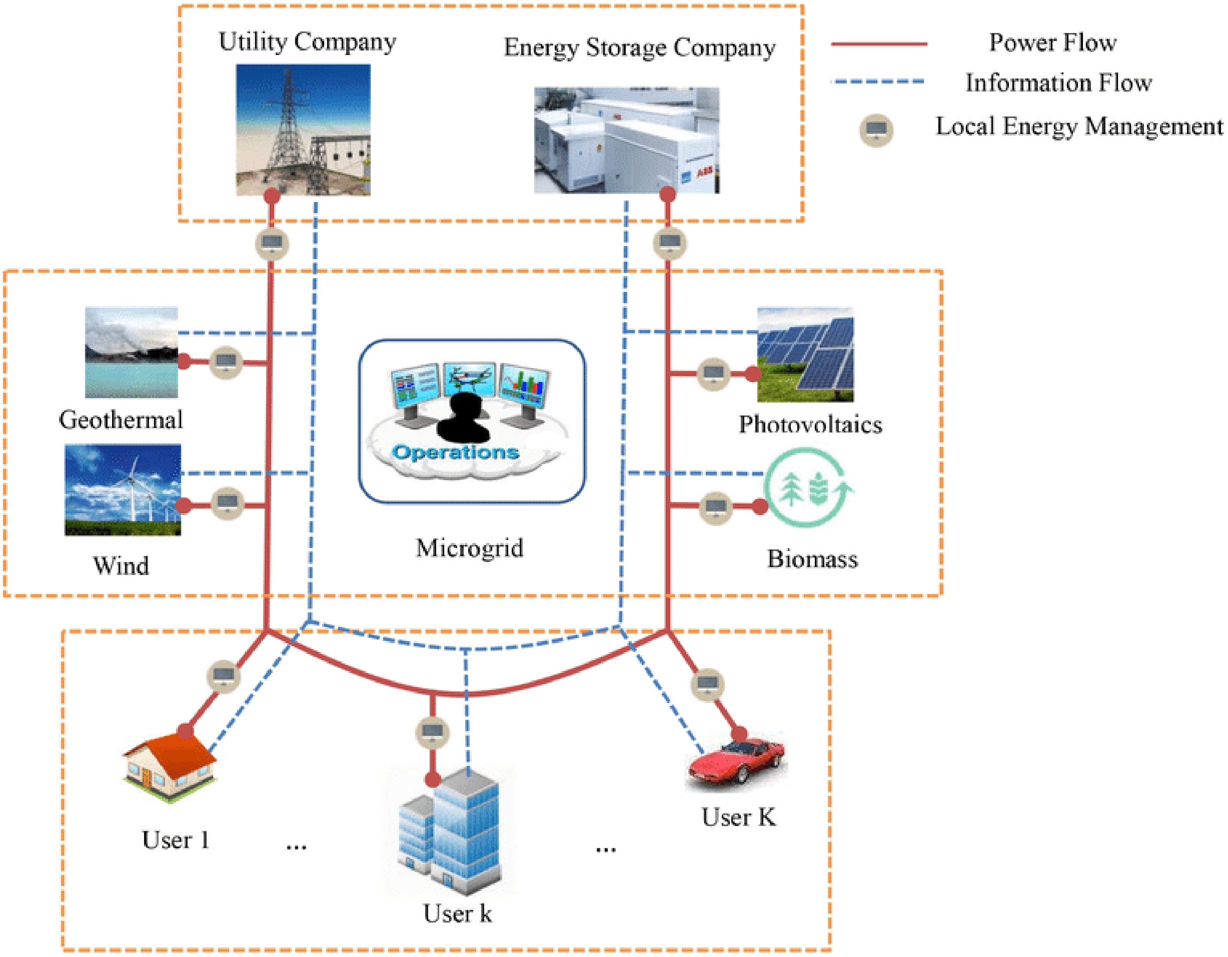

Fig 3: System model of microgrid energy management (Zhou, *et al*., 2017).

In conjunction with forecasting, AI plays a pivotal role in optimizing microgrid operations. Various AI-powered optimization methods, including genetic algorithms and particle swarm optimization, are deployed to address the multifaceted challenges inherent in microgrid management, such as economic dispatch and load shifting (Nishok & Rajathi, 2023; Shukla *et al*., 2024). Advanced techniques like reinforcement learning (RL) and deep reinforcement learning (DRL) further demonstrate their capability to develop optimal control strategies through continuous learning and adaptation without relying on static models (Agupugo *et al*., 2024; Pandey *et al*., 2024). The dynamic and often unpredictable environments characteristic of high renewable energy penetration necessitates such responsive and flexible AI systems, enabling improved decision-making under uncertainty (Novikov & Khamitov, 2024).

AI integration also significantly enhances fault detection and system reliability in microgrids. Traditional fault diagnosis mechanisms often rely on manual inspections and threshold-based methods that may fail to capture complex system behaviors swiftly. In contrast, AI-driven diagnostic systems can analyze vast amounts of data from various sources, including sensors and smart meters, to identify anomalies, diagnose faults, and predict failure events proactively (Arévalo *et al*., 2024; Shukla *et al*., 2024; Hayajneh *et al*., 2024). Employing techniques such as decision trees and Bayesian networks allows for nuanced understanding of operational issues, ultimately leading to less downtime and extended equipment longevity within microgrids (Oleksandr & Dmytro, 2024; Vanitha *et al*., 2024). Nakabi & Toivanen, 2021, peoposed the microgrid architecture as shown in figure 4.

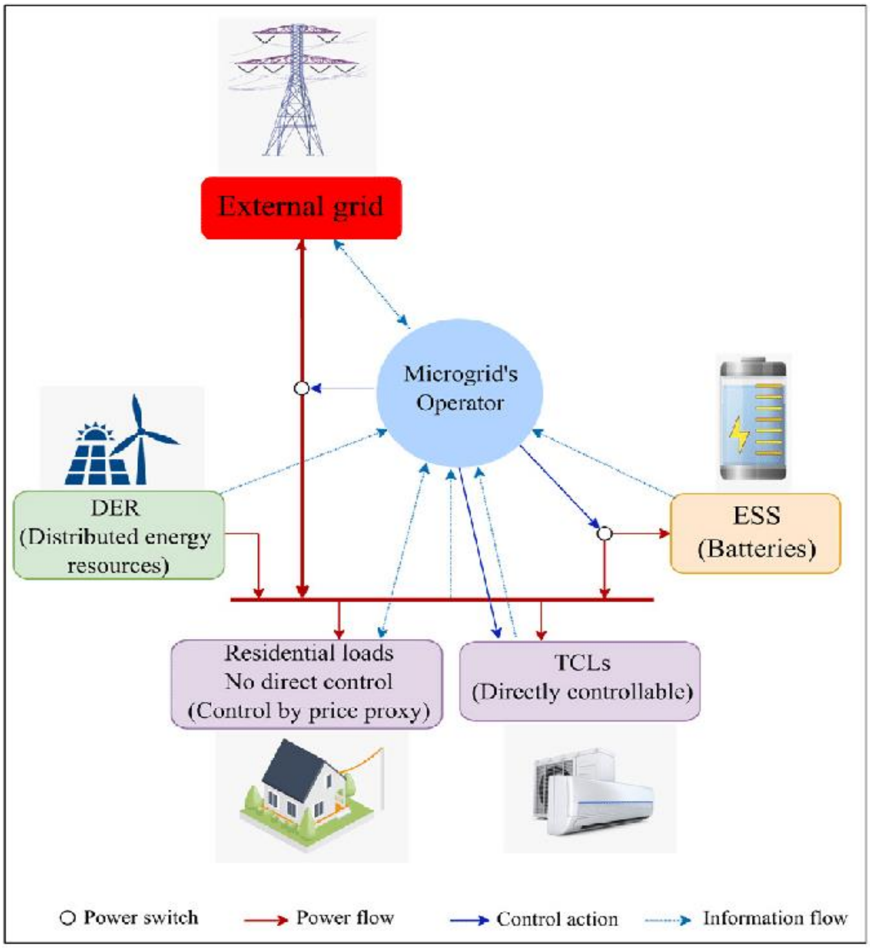

Fig 4: Microgrid architecture (Nakabi & Toivanen, 2021).

When comparing traditional control methods to AI-based strategies, the limitations of conventional approaches become evident. Traditional systems, like proportional-integral-derivative (PID) controllers, may require extensive manual tuning and struggle to accommodate rapid fluctuations typical of modern microgrids (Novikov & Khamitov, 2024; Lang, 2021). In contrast, AI systems offer a capacity for adaptability and scalability that enables them to learn and evolve with operational changes. They can assimilate diverse data sources, including predictive weather models and market behaviors, into a cohesive operational framework, fostering better coordination of DERs and improving demand-side management (Arévalo *et al.*, 2024; Pandey *et al.*, 2024; Vanitha *et al.*, 2024).

Ultimately, the benefits of AI-driven decision-making within smart microgrids are manifold, enhancing real-time adaptability to rapidly changing conditions and managing system complexities more efficiently. By applying AI for optimizing energy costs and revenues, systems can take advantage of dynamic pricing models and intelligent energy trading to maximize profitability (Benchikh *et al.*, 2024: Odunaiya, Soyombo & Ogunsola, 2021). Additionally, the effective management of renewable energy resources through AI minimizes reliance on fossil fuels, supporting environmental sustainability goals by significantly lowering greenhouse gas emissions (Lee & Kim, 2021; Mounter *et al.*, 2021). Moreover, AI facilitates user-centric energy systems, integrating consumer preferences into energy management strategies, thus encouraging sustainable behaviors (Vasina, 2023; Praveenraj *et al.*, 2024).

In summary, AI is redefining the operational landscape of smart microgrids by facilitating superior forecasting, optimizing resource management, and advancing fault detection methods. These capabilities yield significant operational, economic, and environmental benefits, establishing AI as an indispensable tool in the evolution of resilient and sustainable energy systems (Oladipo, Dienagha & Digitemie, 2025).

2.3 Deep reinforcement learning: concepts and relevance

Deep Reinforcement Learning (DRL) has emerged as a transformative branch of Artificial Intelligence (AI) with significant potential for applications in complex environments, particularly in smart microgrids. This convergence of reinforcement learning (RL) and deep learning (DL) techniques allows for the autonomous and efficient management of energy systems, which are often characterized by uncertainty and non-linearity. The foundational concepts of RL and DL establish the groundwork for understanding the functionality and advantages of DRL in sustainable energy management (Oladipo, Dienagha & Digitemie, 2025).

Reinforcement learning encompasses a learning paradigm in which an agent interacts with an environment to maximize cumulative rewards. The key components of RL include the agent, environment, actions, states, rewards, and policies. As the agent observes its current state, it selects actions based on a particular policy and subsequently receives feedback in the form of rewards, which guide its learning process towards an optimal policy that yields maximum long-term rewards

(Hassan *et al*., 2022). The complexity of smart microgrid operations, which involve dynamic variables such as load demands and renewable energy availability, necessitates this iterative learning process to optimize energy management strategies.

Deep learning enhances this capability by employing deep neural networks that can automatically learn complex representations from large datasets. These neural networks are adept at approximating non-linear functions, making them suitable for high-dimensional pattern recognition and decision-making tasks (Chandrasekaran *et al*., 2020). Traditional RL methods can face challenges in scaling to accommodate the substantial state and action spaces present in energy systems; this limitation highlights the importance of integrating deep learning with RL to form DRL. The integration of these methodologies allows agents to derive optimal control policies in environments with extensive continuous state and action spaces, a critical requirement in smart microgrid applications (Jin *et al*., 2021).

Within the DRL framework, several components operate interdependently: the agent (equipped with a neural network), the environment (the microgrid system including energy resources and variables), the reward signal (which encourages or discourages actions), and the policy (the strategy for selecting actions based on state observations). DRL algorithms such as Deep Q-Networks (DQN) and Deep Deterministic Policy Gradient (DDPG) have showcased their effectiveness in this context. DQN leverages experience replay to maintain stability during learning by addressing the correlation of experiences (OuYang & Fan, 2023), while DDPG combines the strengths of policy gradient and Q-learning techniques, effectively managing continuous action spaces typical of energy control problems (Lin *et al*., 2023).

In smart microgrids, DRL is particularly valuable for facilitating intelligent decision-making under uncertainty. It has been applied successfully to various crucial tasks including but not limited to demand response, energy storage scheduling, and renewable energy integration (Nakabi & Toivanen, 2021). The Proximal Policy Optimization (PPO) algorithm, known for its robust and efficient sample convergence, exemplifies DRL's capability to facilitate decision-making in complex and dynamic environments characterized by fluctuating demands and stochastic resources (Xie *et al*., 2023). Moreover, actor-critic methods extend this adaptability by enabling simultaneous training of two networks—the actor and the critic—thereby stabilizing and enhancing policy learning processes.

The increasing need for advanced energy management strategies amid the variable nature of renewable energy sources underscores the relevance of DRL in smart microgrid applications. Unlike traditional control mechanisms that require explicit modeling, DRL learns optimal behaviors from experiences, allowing it to adapt to rapidly changing operational conditions inherent in modern energy systems (Afifi *et al*., 2024). Furthermore, the potential for multi-agent learning within DRL frameworks promotes cooperation between different entities—such as microgrid controllers and distributed energy resources—enhancing overall system performance amidst decentralized operations (Li *et al*., 2023).

In conclusion, the integration of Deep Reinforcement Learning into the operational frameworks of smart microgrids represents a significant advancement in achieving efficient and sustainable energy management. By coupling the trial-and-error learning approach of RL with the computational power of deep learning, DRL empowers systems to optimize energy production, storage, and consumption in real-time, ensuring resilience and efficiency. As the technology progresses, continued advancements in DRL methodologies will be crucial for addressing the evolving challenges faced by smart energy infrastructures.

2.4 Applications of DRL in smart microgrid energy management

The application of Deep Reinforcement Learning (DRL) in smart microgrid energy management has garnered significant attention in recent years due to its capacity to manage complex, high-dimensional, and dynamic systems typical of modern energy networks. Smart microgrids are characterized by decentralized energy production and fluctuating demand patterns, necessitating control mechanisms that are both intelligent and adaptive. DRL possesses self-learning and optimization abilities, which position it as an effective tool for achieving real-time, autonomous energy management solutions (Duc *et al*., 2024; Gautam, 2023; Zareein *et al*., 2022). Its implementation is evident across several key operational facets of microgrids, including demand response management, load balancing, energy storage control, renewable energy scheduling, and coordination of distributed generation, all of which are vital to enhancing reliability, efficiency, and sustainability in contemporary grid infrastructures (Zhao *et al*., 2020; Gomes *et al*., 2021; Ji *et al*., 2021).

One prominent application of DRL is in the domain of demand response (DR) and load balancing. Demand response strategies involve influencing consumer electricity consumption in response to price signals or grid conditions, especially during peak demand periods. Traditional methods, which are often based on pre-defined protocols or linear optimization techniques, fall short in accommodating the stochastic and non-linear characteristics of user preferences and load behaviors. In contrast, DRL innovatively learns optimal load-shifting strategies by interacting dynamically with its environment, allowing agents to adjust appliance schedules, curtail load during peak periods, and optimize energy use in tandem with renewable energy availability—all while ensuring user comfort (Mina-Casaran *et al*., 2021; Mohammadjafari *et al*., 2020). Moreover, DRL facilitates decentralized decision-making, whereby local agents representing distinct buildings or households autonomously develop strategies that enhance overall system stability and efficiency (Soares *et al*., 2018; Huang *et al*., 2020).

In the management of energy storage systems (ESS), DRL showcases formidable potential. Smart microgrids often deploy energy storage units, such as lithium-ion batteries, to mitigate the variability associated with renewable energy sources and provide backup power during outages. Effective management of these systems relies on precise control of charge and discharge cycles, which DRL algorithms such as Deep Deterministic Policy Gradient (DDPG) excel at optimizing (Li *et al*., 2024; Rui *et al*., 2019). These algorithms process real-time data, including battery state of charge, local electricity prices, renewable generation levels, and demand forecasts, enabling them to make informed, on-the-fly decisions about energy flow. Empirical studies have illustrated that DRL-optimized ESS can lead to substantial reductions in operational costs and improvements in energy autonomy (Zareein *et al*., 2022; Zhao *et al*., 2020; (Ji *et al*., 2021).

Renewable energy forecasting and scheduling represent yet another critical area enhanced by DRL. The intrinsic unpredictability of solar and wind resources complicates the alignment of generation with consumer demand. Advanced forecasting models help estimate the output of these resources; however, effective scheduling remains essential to maximize resource utilization. DRL agents leverage historical and real-time data, analyzing weather patterns, irradiance levels, and wind speed to craft optimized generation schedules. This capability entails managing when to deploy backup generators, optimize energy storage, and strategically sell excess electricity back to the grid, allowing for swift adaptability to unforeseen changes in environmental conditions (Rajamallaiah *et al*., 2024; Lu *et al*., 2022; Wang *et al*., 2018).

The coordination of distributed generation within smart microgrid structures is another complex challenge that DRL adeptly addresses. A typical microgrid consists of various distributed energy resources (DERs), such as solar panels and wind turbines. Efficiently managing the outputs from these diverse resources while adhering to both operational constraints and environmental objectives is a complicated multi-objective task. DRL can implement both centralized and decentralized strategies for coordination. In centralized setups, a singular agent oversees all DERs based on the overall grid condition, whereas decentralized approaches involve individual agents for each DER that concurrently share information to devise policies that enhance collective grid performance (Pan *et al*., 2024; Kandari *et al*., 2022; Ji *et al*., 2019). Such strategies mitigate the necessity for manual oversight and significantly enhance grid resilience.

Numerous case studies and simulation experiments corroborate the effectiveness of DRL in smart microgrid management. For example, a study demonstrated that a DRL agent managing a hybrid energy system—comprising a solar PV unit, a diesel generator, and a battery storage setup—could reduce fuel consumption by over 30% compared to conventional control methods without sacrificing reliability or increasing emissions (Xiao *et al*., 2018; Zhu *et al*., 2018). Additionally, the application of Proximal Policy Optimization (PPO) in residential microgrid systems, where agents optimized battery usage based on variable pricing, has resulted in decreased energy costs and peak demand charges (Ji *et al*., 2021; Huang *et al*., 2020). Research on integrating electric vehicles (EVs) with microgrids using DRL methods has also highlighted scheduling efficiencies that minimize costs while maximizing renewable energy utilization (Pan *et al*., 2024; Wang *et al*., 2018).

Simulation platforms such as MATLAB/Simulink, EnergyPlus, and GridLAB-D have been crucial for modeling and evaluating DRL approaches in microgrid energy management, encompassing various operational conditions and user behaviors (Soares *et al*., 2018; Zhu *et al*., 2018). The results consistently indicate that DRL approaches not only outperform traditional model-based and rule-based controls, but they also enhance adaptability, efficiency, and long-term sustainability of energy management practices (Wang *et al*., 2019; Nayak, 2020). However, challenges remain, particularly concerning the training durations, convergence stability, and data requirements inherent to DRL algorithms. Recent advances in transfer learning and federated learning, alongside explainable AI techniques, are helping to overcome these barriers, increasing the potential for broader adoption of DRL methods within the microgrid landscape (Kandari *et al*., 2022; Huang *et al*., 2020; Wu *et al*., 2024).

In conclusion, Deep Reinforcement Learning presents a robust array of methodologies for confronting the complex challenges associated with energy management in modern smart microgrids. By facilitating autonomous and optimized strategies across demand response, storage management, scheduling, and generation coordination, DRL fosters enhanced efficiencies and sustainability (Onukwulu, *et al*., 2025). The growing body of supportive case studies and simulations evidences its utility in refining energy systems, propelling the field toward a more decentralized and low-carbon energy future.

2.5 Hybrid ai models for enhanced microgrid performance

Hybrid Artificial Intelligence (AI) models have emerged as critical components in the management of smart microgrid energy systems, leveraging the combined strengths of Deep Reinforcement Learning (DRL), fuzzy logic, traditional artificial neural networks (ANNs), and optimization algorithms. These hybrid models are tailored to meet the complex demands of energy management in microgrids characterized by real-time operation, uncertainty, and multifaceted dynamics. The integration of these AI methodologies facilitates efficient decision-making, enhances interpretability, and improves the overall performance and reliability of microgrid operations (Islam & Othman, 2024; Lin *et al*., 2023).

One significant advantage of incorporating fuzzy logic into DRL frameworks is its effectiveness in handling uncertainty, especially in environments with ambiguous or incomplete data. Fuzzy logic systems can abstract human-like reasoning through rules, providing valuable preprocessing input to DRL agents, which enhances the speed and accuracy of learning while offering a degree of explainability (Madhu, 2020; (Faal *et al*., 2023;. For instance, in scenarios where renewable generation fluctuates unexpectedly, fuzzy inference systems can classify these variations, guiding DRL agents toward more informed and robust decision-making (Sahoo & Kishore, 2020). The synergy between fuzzy logic and DRL not only streamlines operations but also helps maintain system coherence during unpredictable load conditions (Madhu, 2020; Kusmantoro, 2021).

Integrating traditional ANNs into these hybrid models further reinforces microgrid performance by enhancing capabilities for prediction, classification, and pattern recognition. Although DRL primarily utilizes deep neural networks to learn policies and approximate values, ANNs can independently project energy demand, environmental variables, and price signals (Islam & Othman, 2024; Sumarmad *et al*., 2022). This approach allows the DRL component to make more informed decisions, such as adjusting battery schedules or shifting loads based on predicted trends Lin *et al*., 2023; Upadhyay *et al*., 2024). Consequently, such integration fosters a data-efficient environment that is resilient to uncertainties and enhances the functionality of microgrid systems (Islam & Othman, 2024; Mughees *et al*., 2023).

The deployment of optimization algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) within hybrid AI frameworks significantly contributes to refining decision-making processes in microgrids. These algorithms excel in optimizing complex problems across multidimensional spaces, which traditional optimization methods may struggle to address. When synergized with DRL, these algorithms can be utilized for initializing policy formation or tuning action selections, thereby ensuring adaptive and optimal control of distributed energy resources (DERs) (Lin *et al*., 2023; Ahmed *et al*., 2025). For example, genetic algorithms can seed optimal policies that guide DRL agents, facilitating coordination amid competing objectives such as cost, emissions, and system reliability (Sumarmad *et al*., 2022; Mitkari *et al*., 2024).

The robustness of hybrid AI models is particularly evident under conditions of uncertainty and variability characteristic of modern microgrids, where challenges such as intermittent renewable energy, fluctuating user behaviors, and unpredictable energy prices prevail (Faal *et al*., 2023; Sahoo & Kishore, 2020). Pure DRL models alone often struggle with stability and convergence in such scenarios. However, hybrid approaches mitigate potential drawbacks by incorporating structured guidance through fuzzy logic or predictive models, thus facilitating smoother learning processes and reducing risks associated with suboptimal actions during training (Madhu, 2020; Mughees *et al*., 2023).

The need for rapid decision-making in real-time operations further elevates the utility of hybrid AI systems. These systems can compartmentalize responsibilities, assigning immediate operational tasks to simpler rule-based or predictive models while positioning DRL components to refine long-term strategies. This modular characteristic not only reduces computational load but also amplifies responsiveness to dynamic conditions within the microgrid Al-Sakkaf *et al*., 2019: Lin *et al*., 2023). Furthermore, the flexibility of hybrid models enhances scalability and maintainability, enabling upgrades or replacements of individual elements without disrupting the entire system framework (Sumarmad *et al*., 2022; Upadhyay *et al*., 2024).

Empirical applications of hybrid AI models illustrate their effectiveness in advancing energy management practices. Pilots involving DRL-fuzzy models for load shedding demonstrated the capacity to maintain stability and minimize operational disruptions during emergencies, surpassing conventional models in performance (Islam & Othman, 2024; Al-Sakkaf *et al*., 2019). Moreover, studies incorporating ANNs into DRL systems for residential energy management achieved significant cost reductions while bolstering efficiency without compromising user comfort Sumarmad *et al*., 2022; Sahoo & Kishore, 2020). When managing multi-agent systems, hybrid frameworks supporting energy trading across interconnected microgrids promote equitable resource distribution and economic efficiency, effectively facilitating cooperation under set market constraints (Arwa & Folly, 2020; Mughees *et al*., 2023).

In conclusion, hybrid AI models signify a transformative advancement in smart microgrid energy management by synergizing the adaptive learning capabilities of DRL with complementary techniques such as fuzzy logic, traditional neural networks, and optimization algorithms. These models adeptly navigate the complexities intrinsic to contemporary energy systems, demonstrating resilience under uncertainty and adhering to real-time operational constraints (Islam & Othman, 2024; Lin *et al*., 2023; Sumarmad *et al*., 2022; Mitkari *et al*., 2024). As the necessity for intelligent, autonomous energy systems continues to escalate, the role of hybrid AI models will undoubtedly be pivotal in redefining future microgrid architectures that are not only efficient but also sustainable and responsive.

2.6 Tools, testbeds, and simulation platforms

The development, testing, and deployment of smart microgrid platforms incorporating Artificial Intelligence (AI) and Deep Reinforcement Learning (DRL) necessitate effective simulation environments and testing frameworks. These tools are essential for modeling intricate energy systems and validating intelligent algorithms significantly before deployment into real-world scenarios, given the substantial costs and risks involved with live experimentation in microgrids (Shafiullah *et al*., 2022; De *et al*., 2019). Simulation platforms facilitate the prototyping of control strategies and play a critical role in refining them to enhance safety and efficiency.

Various platforms have gained prominence, including MATLAB/Simulink, OpenAI Gym, GridLAB-D, and EnergyPlus, each providing unique capabilities that form a comprehensive ecosystem for AI advancement in microgrid research (Shafiullah *et al*., 2022; Wan *et al*., 2024; Hong *et al*., 2014). For instance, MATLAB/Simulink, a widely used tool in microgrid modeling, provides a user-friendly environment that supports the detailed simulation of power systems. Its Simscape Electrical toolbox empowers users to create high-fidelity models of distributed generation, energy storage, and power electronics that are crucial for developing intelligent algorithms for energy management (Dayalan & Rathinam, 2021: Ukoba, *et al*., 2024). The integration of DRL with MATLAB/Simulink allows researchers to customize, train, and validate DRL agents in a dynamic environment, enabling sophisticated control strategies such as voltage regulation and optimal resource dispatch (Palma--Behnke *et al*., 2011: Touma *et al*., 2021).

In contrast, OpenAI Gym provides a standardized framework for developing and benchmarking reinforcement learning algorithms, making it versatile for researchers who wish to implement energy system operations through DRL while leveraging popular machine learning libraries like TensorFlow and PyTorch (Amrouni, 2021). Although it lacks the intricate physical modeling capabilities seen in platforms like MATLAB/Simulink, its modular design fosters extensive experimentation with varied DRL techniques, enhancing its utility for comparative research (Allen & Monks, 2020).

GridLAB-D, developed by the U.S. Department of Energy, offers a specialized environment for simulating power distribution networks and is adept at incorporating the dynamic interactions of renewable energy sources and load variations (Nunna & Doolla, 2011). When combined with AI/DRL algorithms, GridLAB-D offers a powerful platform to examine intelligent decision-making under practical constraints such as voltage drop and economic dispatch strategies. The open-source nature of GridLAB-D provides researchers the flexibility to customize simulations to suit their specific requirements while ensuring alignment with regulatory standards (Shafiullah *et al*., 2022; Ding *et al*., 2019).

EnergyPlus serves as another crucial tool in this landscape, particularly concerning the interaction between building energy systems and the power grid (Mina-Casaran *et al*., 2021). It excels in simulating the intricate building-level dynamics affecting demand-side management strategies, which are integral to the operation of smart microgrids.

Coupled with AI agents, EnergyPlus can facilitate innovative demand response solutions and enable detailed load forecasting through co-simulation tools like the Building Controls Virtual Test Bed (BCVTB) (Gilda *et al*., 2018).

The transition from simulated environments to real-world applications often necessitates hardware-in-the-loop (HIL) testing systems, which facilitate the integration of physical devices with real-time simulation environments. HIL testing is essential for assessing the performance of DRL strategies under genuine operational conditions, providing critical insights into how algorithms interact with physical components across various scenarios (Alyahya *et al*., 2025). These setups, often employing simulators like OPAL-RT or dSPACE, allow researchers and practitioners to ensure robustness and safety before deployment, thus bridging the pivotal gap between simulation and implementational practice (Li & Ye, 2022).

Moreover, the evaluation of AI strategies within microgrid management is supported by a variety of metrics (De *et al*., 2019; Chauhan & Chauhan, 2017). These metrics aid researchers in identifying the efficacy of their proposed methods, such as peak demand reduction and energy efficiency, while ensuring comparability across studies by using standardized test cases. The consistency of benchmarks, such as the IEEE 33-bus and 69-bus distribution networks, further enhances the validity of results obtained across different research efforts, facilitating the broader adoption of AI-driven strategies (Boqtob *et al*., 2022; Palma--Behnke *et al*., 2011).

In summary, the evolution of smart microgrids integrating AI and DRL heavily depends on the robust ecosystems provided by advanced simulation platforms and frameworks. MATLAB/Simulink, OpenAI Gym, GridLAB-D, and EnergyPlus uniquely address diverse modeling needs of microgrid research, offering researchers tools to validate and optimize intelligent control strategies effectively. HIL testing acts as the crucial step connecting theoretical models to practical implementations, while rigorous evaluation methodologies solidify the reliability of findings in advancing sustainable energy systems.

2.7 Challenges and Limitations

The integration of Artificial Intelligence (AI) and Deep Reinforcement Learning (DRL) into smart microgrid platforms presents significant promise for enhancing sustainable energy management. The advanced algorithms inherent to DRL enable the optimization of energy dispatch, load management, and resource allocation, transforming traditional microgrid operations into more efficient and responsive systems (Oudinga, 2023), (Hassan *et al*., 2022). However, despite the considerable potential benefits, several challenges hinder the effective adoption and deployment of DRL in actual microgrid environments.

A primary limitation of DRL approaches in smart microgrids is their computational complexity and the extensive training times associated with developing effective control policies. DRL models, particularly those that leverage deep neural networks, require substantial computational resources, including high-performance graphical processing units (GPUs) and large memory capacity to manage their high-dimensional state and action spaces (Pu *et al*., 2021; Hassan *et al*., 2022). The stochastic nature of energy systems, along with factors such as load fluctuations and renewable energy variability, complicates the training process further, necessitating thousands to millions of interactions for the agent to converge upon optimal strategies (Sinsel *et al*., 2020). This prolonged learning phase may be impractical for environments where rapid deployment is critical, making it difficult for DRL methods to be implemented in real-time scenarios without incurring significant delays or performance degradation (Rathor & Saxena, 2020).

Real-time implementation of DRL in microgrids poses additional challenges concerning latency and responsiveness. While DRL systems can eventually arrive at effective decision-making policies, executing these decisions within the strict timeframes common in energy management is often problematic (Hassan *et al*., 2022). Decisions such as switching energy sources, regulating inverter operations, or responding to sudden demand changes must essentially be instantaneous, often within milliseconds or seconds. The computational burden of processing these deep neural network models can introduce unacceptable latency, necessitating a careful balance between the need for swift operational responses and the complexities inherent in DRL computations (Rajitha & Ram, 2024). Furthermore, the need for continuous retraining and policy updates based on incoming data exacerbates the challenges associated with real-time applications, demanding constant computational capability that may be unattainable for some microgrid configurations (Divya *et al*., 2022).

Another critical hurdle is the scalability and generalizability of DRL systems. Often, DRL models are tailored to specific configurations, which limits their effectiveness when applied to microgrids with distinct operational priorities and characteristics (Beg *et al*., 2023), Divya *et al*., 2022). For instance, a model optimized for a residential microgrid may fail to perform adequately in a large commercial setting due to differences in energy use patterns, resource availability, and regulatory environments. This limitation necessitates periodic retraining whenever the operational context shifts, an undertaking that can be resource-intensive and time-consuming (Mishra & Palanisamy, 2018). As microgrid systems continue to evolve and expand, the increasing complexity of state and action spaces poses significant learning stability and convergence challenges (Lv *et al*., 2023).

Moreover, issues related to data privacy and cybersecurity further compound the difficulties associated with deploying DRL in smart microgrids. The application of DRL typically hinges on collecting vast amounts of sensitive data regarding user energy consumption and operational conditions (Beg *et al*., 2023). This raises important concerns regarding unauthorized access and potential data misuse, particularly in distributed settings where IoT devices are prevalent. Cybersecurity challenges such as data interception and adversarial attacks are critical, given the essential nature of energy infrastructure (Oudinga, 2023). Consequently, robust measures, including encryption and secure communication protocols, must be incorporated into DRL applications to mitigate these risks without sacrificing system performance (Azeroual *et al*., 2020).

The complexity of achieving explainability and interpretability within DRL models presents further practical challenges. DRL systems often operate as "black boxes," obscuring the rationale behind their decision-making processes. This lack of transparency can hinder trust among users and operators, particularly in critical applications where understanding the basis of operational decisions is paramount. Furthermore, the absence of industry standards for implementing DRL systems within energy networks leads to fragmentation, complicating collaboration and inhibiting widespread adoption (Sharma *et al*., 2019).

In conclusion, while the integration of Deep Reinforcement Learning into smart microgrid platforms offers innovative pathways for sustainable energy management, numerous obstacles remain, including high computational demands, real-time operational constraints, issues surrounding scalability and generalizability, cybersecurity concerns, and the pressing need for explainable AI systems. Addressing these multifaceted challenges requires concerted efforts across technical, operational, and regulatory domains, ensuring that the transformative potential of DRL in energy systems is fully realized.

2.8 Emerging trends and future directions

The ongoing evolution of smart microgrid systems is marked by significant advancements in the integration of Artificial Intelligence (AI) and Deep Reinforcement Learning (DRL), addressing the increasing complexities of modern power systems while enhancing efficiency, scalability, and reliability. This technological advancement is crucial as energy demands become more dynamic and decentralized, driven by a pressing need for secure and sustainable energy solutions. One major trend emphasizes the transition from centralized DRL architectures to decentralized and multi-agent systems. This shift allows various agents to operate independently while collaborating on shared objectives, enhancing resilience against system failures and optimizing the management of distributed energy resources (DERs) (Nakabi & Toivanen, 2021; Darshi *et al*., 2023;, Darshi *et al*., 2023).

Decentralized DRL approaches facilitate better adaptive responses in real-time microgrid operations, which is particularly important given the variability and unpredictability of renewable energy sources. For instance, the deployment of cooperative reinforcement learning in multi-agent systems has shown effectiveness in enhancing operational coordination and energy trading among microgrids (Xi *et al*., 2021), Gao *et al*., 2020). Such systems allow agents to share learning experiences and improve their local policies, making them adept at managing energy loads and scheduling within more complex environments, ultimately translating to greater overall system efficiency (Fan *et al*., 2022: Onukwulu, *et al*., 2024).

Parallel to advancements in decentralized learning, the rise of edge computing and federated learning frameworks represents a paradigm shift in the processing of data and training of models within smart grid environments. Traditional DRL methods, heavily reliant on centralized data aggregation, can introduce latency and raise concerns regarding cybersecurity and data privacy due to the vast amounts of information transmitted to cloud infrastructures. Edge computing mitigates these concerns by allowing local data processing at the point of collection, facilitating quicker decision-making (Xi *et al*., 2021). Federated learning further enhances this model by enabling decentralized training of DRL algorithms without the need to transmit sensitive information, aligning with evolving data governance frameworks (Hu *et al*., 2022).

Moreover, the importance of Explainable AI (XAI) is increasingly recognized in the context of smart microgrids. As DRL models become more sophisticated, ensuring that stakeholders can interpret and trust these decision-making processes is vital. XAI techniques can offer insights into the rationale behind automated decisions made by AI systems, which is particularly critical in operations that directly impact energy dispatch, load prioritization, and overall grid stability (Lin *et al*., 2023; Hassan *et al*., 2022). Greater transparency facilitates stakeholder engagement and assists regulatory bodies in evaluating the acceptability of automated systems in critical infrastructures.

Supporting this technological evolution is the pressing need for cohesive policy frameworks, regulatory alignment, and standardization. Despite the advancements in DRL and AI capabilities, the adoption of these systems often falters due to ambiguities and inconsistencies in regulations. Comprehensive policies addressing automation levels, data privacy standards, and cybersecurity measures are essential to promote the widespread deployment of AI in microgrid management. Moreover, the establishment of standardized communication protocols and performance specifications would enable interoperability among various technologies and vendors (Nakabi & Toivanen, 2021; Afifi *et al*., 2024; Upadhyay *et al*., 2024).

Finally, as a forward-looking perspective, the integration of hybrid models that synthesize DRL with optimization strategies, as well as the application of transfer learning, presents promising avenues for future research (Dai, 2023). These approaches aim to bolster the adaptability of DRL systems in novel environments while enhancing their capacity to respond intelligently to dynamic changes within the grid landscape. In conclusion, the convergence of these emerging trends builds a robust foundation for the next generation of intelligent microgrid systems, intimately connected to global objectives for sustainability and energy justice.

3. Conclusion

The integration of Artificial Intelligence and Deep Reinforcement Learning into smart microgrid platforms represents a significant advancement in the pursuit of sustainable energy management. This review has examined the architecture, components, and technological enablers that define modern smart microgrids, alongside a detailed exploration of how AI, and particularly DRL, contributes to optimizing their performance. By addressing key functions such as demand response, energy storage management, renewable energy scheduling, and distributed generation coordination, DRL demonstrates an exceptional ability to adapt to the dynamic, uncertain, and nonlinear nature of energy systems. Its capacity to learn from experience and make real-time, data-driven decisions positions it as a transformative tool in the ongoing evolution of decentralized and intelligent energy networks.

The findings reveal that DRL, when combined with other AI techniques such as fuzzy logic, neural networks, and optimization algorithms, can significantly improve the operational efficiency, resilience, and sustainability of smart microgrids. Hybrid AI models offer enhanced performance under uncertainty and real-time constraints, while simulation platforms and hardware-in-the-loop testing environments support the safe development and validation of these intelligent systems. Despite its advantages, the adoption of DRL is still challenged by factors such as computational complexity, scalability, real-time implementation limitations, and data privacy concerns. These barriers must be addressed to enable the seamless integration of AI-driven intelligence into real-world energy infrastructures.

The contributions of DRL to sustainable energy management are particularly noteworthy in how they enable localized, autonomous control and foster greater flexibility in integrating renewable energy resources. DRL supports long-term optimization strategies that reduce energy costs, improve grid stability, and promote cleaner energy consumption patterns. It allows microgrids to respond dynamically to external factors such as price fluctuations, weather conditions, and load variability, ultimately contributing to a more resilient and environmentally responsible energy landscape.

To realize the full potential of DRL in smart microgrids, there is a pressing need for interdisciplinary research that bridges the gap between energy engineering, computer science, policy, and social sciences. Collaborative efforts among academia, industry, and government are essential to address technical limitations, develop robust regulatory frameworks, and promote standards that ensure interoperability, security, and transparency. Strategic deployment strategies that include real-world pilots, policy support, and public engagement will be key to accelerating the adoption of these intelligent systems. As energy systems become increasingly complex and distributed, the synergy between AI and smart microgrids offers a path toward a more sustainable, efficient, and inclusive energy future.

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