Artificial Intelligence Applications for Energy Management in Microgrid

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***Abstract* — Microgrids consist of distributed energy resources such as photovoltaic (PV) systems, wind energy conversion systems, energy storage devices and backup generators. Due to the intermittent nature of renewable energy resources, storage systems and energy management systems are required to achieve sustainable and reliable power. In microgrid systems, an energy management system is required to cover load power demand at any given time and to manage power flows throughout the entire microgrid. While microgrids offer many benefits, they contain various challenges such as energy management and control due to variable factors such as wind speed and solar irradiation. To overcome these challenges, Artificial Intelligence (AI) technologies have emerged as a promising approach to realize and optimize energy management in microgrid. In this article, AI technologies used in energy management system of the microgrids is reviewed and discussed in detail. Their abilities and limitations are explained.**

Keywords— Microgrids, Artificial Intelligence, Energy Management System, Renewable Energy

I. INTRODUCTION

Global warming and climate change is an important problem that the world is currently experiencing as a result of the use of conventional fossil source based energy resources [1]-[3]. In addition, the reserve of the fossil fuels is limited. As a result of the ongoing depletion of traditional energy resources and widespread concern over environmental pollution, there is currently a trend to rely on renewable resources rather than traditional resources [4].

To feed remote areas far from the main electrical grid, researchers therefore sought to integrate renewable resources together in isolated microgrids or to integrate them with the grid to improve reliability and stability. Integration of renewable energy sources has grown significantly in strategic significance to address energy issues. The integration of resources faces numerous issues and difficulties that must be resolved in order to lessen energy losses due to the diversity of renewable energy sources and the various factors that renewable energy resources depends on for power generation [6], [7]. In addition, irregular energy production characteristics of the renewable energy resources have led to a number of issues [5].

With the rise of renewable energy and decentralized power generation, microgrids have become an attractive solution for improving energy efficiency, resilience, and sustainability. Microgrids are small-scale localized power grids that can operate independently or in harmony with the main grid [8]. They typically include a mixture of distributed energy

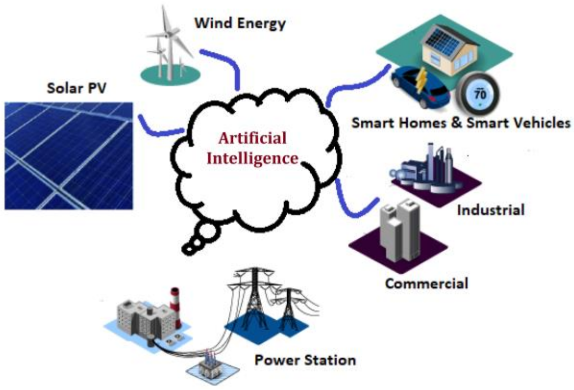

Fig. 1. AI and Distributed Energy Resources

resources (DERs), such as photovoltaic (PV) modules, wind turbines, energy storage systems and backup generators. While microgrids offer many benefits, they also pose several challenges, such as variability, uncertainty, and volatility of renewable energy sources, energy management requirement, and control complexity. The energy management requirement is one of the important challenges that has to be overcome to support the microgrid applications and integration of the renewable energy resources. Artificial Intelligence (AI) technologies have emerged as a promising approach to realize and optimize energy management in the microgrid [9]. An efficient energy management provided by AI in microgrids means making maximum use of the potential of renewable energy sources. Fig. 1 presents the combination of artificial intelligence and distributed resources in the microgrid.

The literature has discussed the use of various AI-based algorithms in microgrids for a variety of purposes, including energy management, load forecasting, renewable energy forecasting, fault detection and classification, and cyber-attack detection [10]. Besides, various uses of AI techniques in smart grids and power systems, including resilience of the power system [11], security and stability assessment [12], and demand-side management of energy [13] are examined. A review of various power system or smart grid parameters, including energy management, load factor, demand response, and fault detection, was presented in some papers [14].

In [9], the structure and combination of an energy management system based on artificial intelligence and renewable energy sources are presented. In order to overcome the limitations of existing centralized methods, a multi-agent system based decentralized control approach is estimated by using an artificial neural network [9].

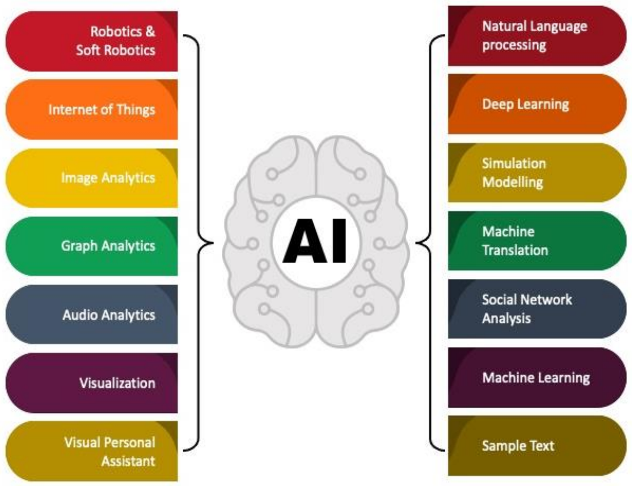

Fig. 2. Artificial Intelligence Applications

AI technologies in microgrids is promising, as more applications are developed and more research is conducted in this area. One of the main trends is the integration of AI and Blockchain technologies, which can enable the secure and transparent exchange of energy and data between microgrids and the main grid. This approach can also enable peer-to-peer energy trading and enable microgrid owners to monetize their excess energy. Another trend is the use of explainable AI, which can improve the interpretability and transparency of AI-based systems and increase their trustworthiness and reliability.

Besides, AI technologies are used for predictive analytics, optimization, control and monitoring and energy management in the microgrid [15]. In this article, artificial intelligence applications used in microgrids and energy management in microgrids using will be examined.

II. Artificial Intelligence Applications in Microgrids

AI technologies can be applied to various aspects of microgrid operation, such as prediction, optimization, control, and monitoring. These technologies, shown in Fig. 2, use machine learning (ML), deep learning (DL), and other AI algorithms to analyze large volumes of data generated by DERs, sensors, and other devices in the microgrid [16].

The followings are some of the AI technologies used in microgrid:

Predictive Analytics: Predictive analytics is a subset of data analytics that uses ML and other AI techniques to analyze historical data and predict future trends, patterns, and events. In microgrids, predictive analytics can be used to forecast the output of renewable energy sources, such as solar and wind power, based on weather forecasts, geographical location, seasonality, and other factors. This information can then be used to optimize microgrid operation and minimize the use of backup generators and other non-renewable sources [17].

Optimization: Optimization is the process of finding the best solution to a problem given specific constraints and objectives. In microgrids, optimization can be used to minimize energy costs, reduce carbon emissions, and improve the reliability and durability of DERs. Optimization algorithms can also be used to balance the supply and demand of energy in real-time, which is critical in microgrid operation [18].

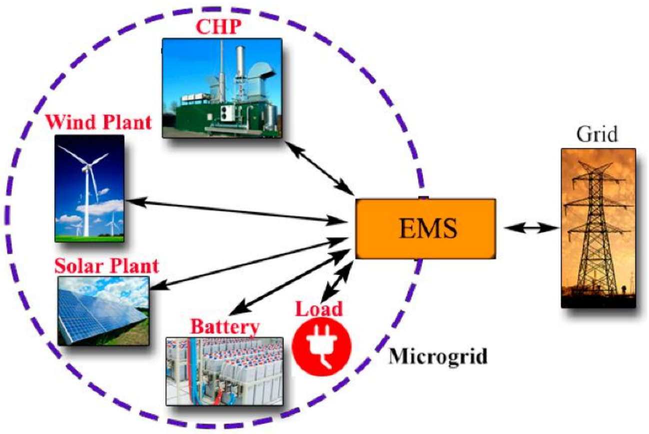

Fig. 3. Energy Management Systems(EMS) in Microgrid

Control: Control refers to the ability to manage and regulate the behavior of DERs and other devices in the microgrid. AI-based control systems can predict the energy demand and supply of the microgrid, and adjust the output of DERs accordingly. These systems can also detect and respond to emergencies, such as power outages, equipment failures, and natural disasters [19].

Monitoring: Monitoring refers to the process of tracking and analyzing the performance and health of the microgrid and its components. AI-based monitoring systems can detect anomalies, such as device malfunctions, cyber-attacks, and system failures, and trigger appropriate responses, such as preventive maintenance, shutdowns, and emergency backup [20].

III. AI for Energy Management

There may be multiple distributed energy sources used in power systems. As the next generation of electricity sources that produce reliable and clean electricity, microgrid power systems—also known as hybrid renewable energy systems or systems that use multiple energy sources—are gaining popularity. The cleanest energy conversion technologies among renewable energy sources are PV modules and wind turbines. Both are widely utilized throughout the world. While ensuring maximum electricity generation capacity at the most affordable price for areas served by traditional electricity grids, hybridization of various energy sources aims to provide sustainable and stable electricity in remote areas. Renewable energy sources' sporadic nature and reliance on metrological conditions, however, could be problematic. Energy storage systems are incorporated into microgrid systems as a remedy for these issues. As a result, energy storage systems are increasingly crucial to microgrids. As shown in Figure 3, an energy management system (EMS) is also necessary to regulate power flows throughout the entire microgrid.

Microgrids are a new type of energy structure and management system that combines distributed renewable energy sources that are off-grid or connected to the grid, energy storage technologies, and other distributed energy sources. To ensure the best possible energy use in microgrids, efficient energy management is necessary. The stochastic nature of solar and wind energy, however, makes the integration of renewable energy sources more challenging. Organizing the unpredictable working conditions of distributed generation and providing affordable and flexible operation with a variety of resources is one of the challenges in energy management and microgrid optimization. For the microgrid to use these distributed energy resources optimally, safely, and reliably, an energy management system is required. An energy management system in a microgrid keeps track of, analyzes, and forecasts power generation, load consumption, energy market prices, and meteorological factors from distributed generation systems. These attributes aid energy management systems in maximizing the effectiveness of the microgrid.

In the microgrid, excess power is stored in energy storage devices if the system's demand for power is less than the amount generated by renewable energy sources, and the system's required power is supplied by energy storage devices with battery charge and discharge control if the system's demand for power is greater than the amount generated by renewable energy sources. As a result, a strong energy management system is required between the consumption and storage systems. In order to achieve an appropriate level of energy management, the controllers can cooperate with the load's demand.

Energy management systems with traditional methods, meta-heuristic approaches, artificial intelligence methods, stochastic (variable) and strong programming approaches, model prediction control-based energy management systems, and energy management systems for microgrids are all examples of such systems.

Heuristics and metaheuristics are used in a wide range of engineering disciplines, such as transportation, communications, power systems, product distribution, and microgrid energy management, to solve complex and non-differentiable optimization problems [21]. Particle swarm optimization (PSO) and genetic algorithms (GA) stand out as two popular meta-heuristic methods used in energy management systems of microgrids because of their parallel computing capabilities. The cost of battery degradation in an energy storage system and the economically efficient load distribution of a remote microgrid are the main topics of a study that developed a multi-purpose energy management system [22]. In this study, rule-based real-time processing and genetic algorithm day-ahead scheduling are discussed. In [23], an ideal energy management system based on PSO was created for the microgrid's grid-connected and off-grid island modes. Maximizing energy trade profits with the grid and reducing operation and maintenance costs are the main goals of off-grid islanded and grid-connected modes. The results demonstrate that this method outperforms the genetic algorithm in terms of computation time and the global optimum solution. There are additional approaches, such as differential evolution [24], gray wolf optimization (GWO) [25], ant colony optimization (ACO) [26], etc., in addition to the two well-known approaches of energy management systems, genetic algorithms, and PSO methods.

Energy management stands out as a crucial issue in microgrids when considering the technical and financial aspects of operation. Creating the proper models and parameters for model-based energy management systems is necessary to improve the system's performance in microgrids. As a result, this method cannot be transferred or scaled, which leads to high development costs. However, microgrid uncertainties can result in parameter redesign, which sharply raises maintenance costs [27].

Learning representations of nearly optimal control schemes in the microgrid from its operational data is one of the model-free or data-driven methods. Utilizing learning-based techniques can decrease reliance on an explicit system model, increase the scalability of the energy management system, and lower costs.

In [28], an AI-based data-driven stochastic energy management for isolated microgrids was suggested by considering the reactive power cost and DERs' capacity for reactive power. In this study, the uncertainties in the output power of the RESs to be used in the stochastic programming formulation were modelled using the generative adversarial network (GAN), a data-driven technique for scenario generation. Using GANs to ensure optimal energy management in a microgrid was covered in [29]. This study looked into the impact of data integrity attacks on the microgrids' central control, which can lead to severe blackouts and load shedding.

In order to simplify the system's control, fuzzy logic controllers (FLCs) are used, especially in microgrids with numerous components and a variety of operating modes. The system prefers fuzzy logic controllers in particular because they do not require intricate mathematical modeling and are not dependent on the nonlinearity of the microgrid components. As a result, a comprehensive energy management system built on straightforward linguistic principles is created. [30] presents an energy management method based on fuzzy logic control for a fuel cell, batteries, and supercapacitors-based hybrid energy storage system and electric vehicles. This investigation was conducted on a test micronetwork. [31] suggests an energy management system based on fuzzy logic for the best control of the energy storage system in a residential microgrid. Studies on energy management system design should take into account low complexity, including input and rule numbers [32].

For energy management system of microgrids, handling uncertainty is a challenge. To address this issue, oversized batteries were used, which is not the best solution. Load and renewable energy resources like wind turbines and PV modules can be predicted using techniques like combining several artificial neural networks (ANN) with other techniques to handle uncertainties in energy management system. The main goals of energy management system -based studies using various ANN types are to reduce production costs, improve distributed energy sources utilization, and reduce emissions [33]. Online energy management systems are more advantageous because they can manage uncertainties by examining real-time data, which is important given the intermittent nature of renewable energy sources and the high stochasticity in market prices and loads. A model for energy and load management that is based on reinforcement learning (RL) and can be applied to each distributed energy source and customer has been developed [34]. The microgrid in the suggested model offers a framework for managing loads and energy while taking into account the stochastic entities' variability. In this framework, suppliers and customers are both rational, independent actors capable of adjusting to one another's actions. To assess the effectiveness of the distributed reinforcement learning method across the entire microgrid system—including distributed energy sources, customers, and the microgrid connected to the main grid to serve local customers—a set of performance measures is also proposed. The proposed model is examined in various configurations to examine how it functions and to confirm that it is effective for all system participants. Despite the fact that the study can infer a function from past data, conventional online techniques like model predictive control require a separate estimator. On the other hand, reinforcement learning (RL) techniques frequently struggle with slow training, complex constraints, and problems with the dimensionality of steady state and action spaces.

Both of these MPPT algorithms are implemented with a multi-agent system (MAS) in the energy management systems study suggested in [9], which is based on maximizing the energy extraction from renewable sources by operating in Maximum Power Point Tracking (MPPT) mode. Additionally, the management of the microgrid's energy storage is accomplished by using artificial neural networks controllers to optimize battery charge and discharge. The goal of the study is to provide a configurable and flexible control for various scenarios of any variation, as well as power balance in the microgrid. The multi-agent system is created using the Java Agent Development Framework (JADE), even though all system components are modeled in MATLAB/Simulink. To enable communication between the Simulink model and JADE in the design, the Multi-Agent Control (MACSIMJX) with Simulink with Jade extension program was used.

In another study, an ANN based EMS is proposed to control power in AC-DC hybrid distribution networks. The proposed ANN based EMS collects data such as distributed generation (DG), load demand and power supplied by state of charge (SoC) and selects the most appropriate operating mode. The proposed EMS controls each power converter in its optimum operating mode via the ANN already trained in grid-connected mode. To experimentally validate the proposed EMS, a small-scale hybrid AD/DC microgrid was fabricated and simulations and experiments were performed for each operating mode [35].

A summary of AI-based techniques for energy management systems in microgrid is given in Table I.

A study on microgrid optimization based on the PSO algorithm that can run a grid-connected or isolated microgrid was presented in [23]. The suggested approach considers the variations in load requirements for the microgrid and renewable energy resources, with suitable advance forecasts (available in advance of 24 hours) to account for these variations.

Using genetic algorithms, [36] proposed a control strategy for optimal energy management of a hybrid system. The system is made up of fuel cells, electrolyzer, generator, and renewable energy resources. The excess energy produced by renewable energy resources can be used to charge batteries or create hydrogen in an electrolyzer thanks to EMS that is optimized to reduce operating costs. Either the battery can be discharged or fuel cells can be used to supply the load that cannot be met by renewable energy sources.

A DC microgrid is designed in [37], which presents a case study to highlight multi-agent based control system for DC microgrids. The PV system, the wind turbine, the synchronous generator, the battery-based energy storage system, the critical DC load, and the non-critical DC load are the components of the designed microgrid. A distributed generation agent, a battery agent, a load agent, and a grid agent are all included in the proposed multi-agent- based controller. The results of the simulations run for various operating conditions confirm the multi-agent-based controller's effectiveness in terms of system stability and power quality at the common DC bus.

TABLE I. LIMITATIONS OF AI-BASED TECHNIQUES IN MICROGRIDS

Ref.	Proposed method	Limitation
9	Multi-agent system	Voltage and frequency regulation are its two main weaknesses.
30	Fuzzy logic	There are limitations of not considering battery deterioration and not considering system losses.
31	Fuzzy logic	Battery degradation is not considered, battery is oversized to handle uncertainties.
32	Bee colony and ANN	There are limitations to consider voltage and frequency regulation and battery degradation.
33	Reinforcement learning and dynamic programming	Active and reactive power distributions have the limitation of dynamic state prediction, but also the limitation of not considering real-time implementation and coordination.
34	Imitation learning	There are limitations of not considering battery degradation, complex formulation, not considering system losses. An important limitation is that microgrids only consider the economic aspect.
35	Artificial neural network	There is a limitation of voltage and frequency regulation as well as not taking into account battery degradation.

By using a distributed energy management model, [38] proposed an energy management model for a smart microgrid based on game theory. In this plan, the microgrid decides on a course of action to maximize its advantages in terms of cost and effective use of energy.

[39] presents a study on determining the elements that different authors use to describe cloud-based architectures and making sure that supervised learning is effective in microgrid cluster environments. For instance, it was necessary to set up the energy management system using cloud computing and machine learning, update and run microgrid simulations, use real-time simulation platforms, connect to a virtual server for microgrid control, and connect to a virtual server for microgrid control. In this paper, a scalable and autonomous cloud-based architecture is presented that enables power generation forecasting, energy consumption forecasting, and a

TABLE II. AI-BASED METHODS USED IN MICROGRID

Ref.	**Proposed Method**	**Type of MG**	**Energy Management and Control Application**
23	Particle Swarm Algorithm	AC	The strategy is based on a regrouping PSO created with a one-hour time step over a day's worth of scheduling, taking into account anticipated renewable energy generation and electrical load requirements.
36	Genetic Algorithms	Hybrid	Control of autonomous hybrid renewable electricity systems with hydrogen storage is optimized by genetic algorithms.
37	Multi Agent	DC	A multi-agent based controller and energy management system design for DC microgrid is proposed. Network agent, battery agent, load agent and distributed generation agent are designed in energy storage system supported energy management system design.
38	Game Theory	AC	Timing is used in a non-cooperative game theory algorithm for distributed energy management. Multi-leader multi-follower game theory is employed. It uses a multi-leader, multi-follower game theory to choose the best course of action for reducing the cost of supplying customers' energy needs.
39	Machine Learning (Cloud-based)	Hybrid	It uses machine learning techniques. It offers a scalable and autonomous cloud-based machine learning architecture that provides power generation forecasting, energy consumption forecasting, and a real-time energy management system.
40	Deep Learning (Convolutional Neural Network-CNN)	Hybrid	It is founded on the ideas of moving horizon control and real-time forecasting. In order to provide dynamic forecasting of future renewable profiles and electricity prices, the proposed method entails the development of a hybrid deep learning model.

real-time energy management system using machine learning techniques based on scenario analysis and taking into account.

An online energy management system is presented in Ref. [40] with the intention of lowering electricity costs without compromising the ability to generate enough electricity to meet demand. For the proposed method to provide dynamic prediction of future renewable profiles and electricity prices, a hybrid deep learning model based on the concepts of real-time forecasting and moving horizon control is developed. A fixed-price scenario is evaluated by the corresponding average gap, compared to the ideal limits of online and offline solutions.

IV. CONCLUSION

In this study, AI technologies used in EMS algorithms were reviewed and discussed. It is clear that the AI technologies offer good alternatives to realize effective energy management in microgrids. As a result, different resources in the microgrid system will be able to continue to be used together and by maintaining the demand-supply balance.

AI technologies have the potential to revolutionize the way that microgrids operate and enable the widespread adoption of renewable energy sources. The use of Machine Learning, Deep Learning, and other AI algorithms can improve predictive analytics, optimization, control, and monitoring of microgrids, and enable real-time decision-making and better utilization of available resources. While AI technologies offer many benefits, they also pose several challenges, such as data quality, privacy, and interpretability. Future research and development should address these challenges and develop new approaches and solutions that enable the widespread adoption of AI technologies in microgrids.

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