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].

In recent years, approaches towards energy transition and sustainable development have been ever-increasing due to the need for mitigating climate change issues and the efficient

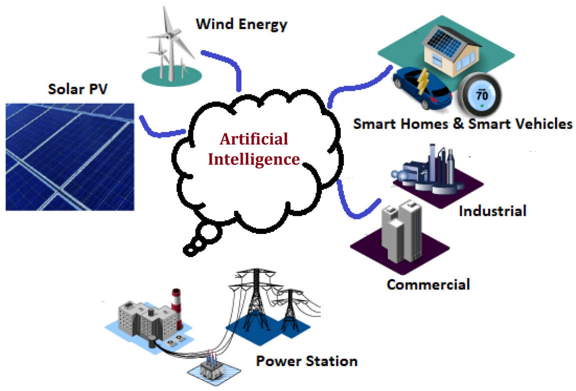

Fig. 1. AI and Distributed Energy Resources

utilization of existed energy resources. With this regard, state-of-the-art technologies and infrastructures along with active operation and control of different energy resources would become crucial.

Amongst all energy resources, microgrids are believed to be one of the highly potent resources to deal with the issues of electrical systems. In other words, active operation and control of MGs in which there exist different kinds of demands and energy resources would be beneficial not only for microgrid stakeholders in terms of cost-benefit efficiency but also for power system operators in terms of microgrid contribution to grid's flexibility. In order to unlock the active utilization of microgrid, cutting-edge technologies along with efficient infrastructure are a necessity. These technologies together in communication with the microgrid's energy resources are known as energy management systems. Energy management systems are intelligent automated systems that contribute to, for instance, lowering/shifting energy consumption in critical moments along with a reduction in the microgrid's costs. Although the utilization of energy management systems might consider other objectives such as CO2 emission reduction or self-sufficiency, they mostly employ optimization techniques either as single-objective or multi-objective approaches. Energy management systems can also enable either the bidirectional energy exchange with the network in grid-connected mode, or stand-alone operation of microgrid in islanded-mode. 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].

Microgrids contain a mixture of many distributed energy sources. These resources include wind turbines, energy storage systems, solar panels and generators. While microgrids offer many advantages, they also present several challenges, such as volatility, uncertainty and volatility in renewable energy sources, the need for energy management 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 various purposes, including energy management, load forecasting, renewable energy forecasting, fault detection and classification, and cyber-attack detection [10]. The use of many AI-based algorithms in microgrids has been discussed in the literature. These studies mostly focused on energy management between supply and demand, estimating the power produced from load and renewable energy sources, cyber security, which are important problems of today, fault detection and classification. 12] and demand-side management of energy [13], various uses of AI techniques in smart grids and power systems have been explored. Due to variables such as wind speed and solar radiation in renewable energy sources used in power systems, the balance between constantly changing generation power and time-varying demand power cannot always be achieved. However, it is impossible to achieve this balance by using AI in power systems. A review of various power system or smart grid parameters including energy management, load factor, demand response and fault detection has been presented in some papers [14].

In [9], which uses renewable energy sources, energy management in the system is carried out using artificial intelligence. The structure of the energy management system is also presented in the study. Artificial neural network is used to get rid of the limitations of centralized methods.

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.

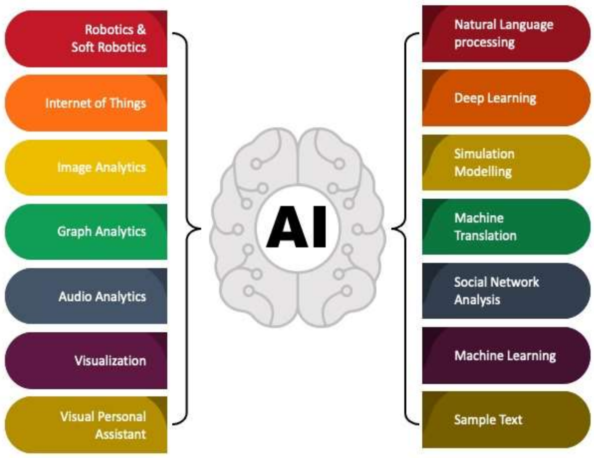

Fig. 2. Artificial Intelligence Applications

II. ARTIFICIAL INTELLIGENCE APPLICATIONS IN MICROGRIDS

In order for microgrids to be used efficiently, it is necessary to effectively control all components of dispersed energy sources in microgrids. Artificial intelligence technologies positively support microgrid organizations in many areas. Many artificial intelligence applications have been developed and continue to be developed.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].

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].

The basic approach to energy management problems would be based on optimization algorithms. This originates from the nature of the energy management since it is supposed to minimize or maximize an objective depending on the targets of microgrid's stakeholders as well as the method of asset management. There have been introduced many optimization techniques which could be employed correctly depending on the type of the problem. In general, the optimization techniques could be split into two main categories, convex and non-convex.

Depending on the characteristics of the problem, the type of optimization technique could be chosen correctly. In microgrid energy management, convex problems predominate or problems are defined in such a way that convex techniques (such as convex relaxation) could be used to solve them. This is because, in comparison to non-convex problems, convex problems provide better convergence. Due to the nature of the microgrid components, there may also be numerous uncertainties in microgrid operation. For instance, the intermittent renewable components such as wind turbines, photovoltaic units, and on the top of them, the unpredictable demand could create the mentioned uncertainties. These uncertainties, however, could be addressed by means of some well-known mathematical and statistical techniques during the definition of optimization problems for microgrid energy management. In order to analyze the impact of uncertainty of data, the following three types of optimization methods have been proposed: Deterministic optimization, stochastic optimization and robust optimization.

Although the deterministic approach for defining an optimization problem could be beneficial for comparing the results of the problem with other approaches, robust and stochastic optimization solutions are believed as the most effective techniques in energy management problems which are illustrated in details in the following subsections.

Deterministic issues are those in which each possible input results in a single output. The output power of wind turbines or photovoltaic systems, for instance, could be significantly impacted by variations in wind speed or solar radiation over time. Therefore, for different values of wind speed and solar radiation, the power generation of these renewable units would change. However, the power generation function of these renewable units could be defined deterministic meaning that, for any wind speed and solar radiation, the output power of wind and PV units are considered as certain values. This type of problem formulation would not take place in reality, however, there are some applications for deterministic approaches. Furthermore, this method could be beneficial when the aim is to have an idea about the overall operating points of the system in a certain condition.

In stochastic optimization, the problem of energy management could be presented by a statistical objective function. In this light, the uncertain parameters of the problem such as the output power of renewable energy units could be modeled as the well-known probability distribution functions. These distribution functions might be different due to the difference in the nature of renewable sources such as solar irradiation or wind power. They also might be different due to the uncertainties stemming from the stochastic behavior of consumers such as the behavior of EV owners and the pattern of charging their vehicles. However, all these uncertainties are can be considered as the most popular distribution functions since their sources mostly follow a predictable pattern.

The robust optimization method has been introduced and employed in many research as one of the most powerful approaches towards energy management in order to act as an alternative for modeling the problems with uncertain parameters. The robust optimization is employed when the energy management problems confront a limited amount of data but at the same time several uncertainties. In this optimization method, unlike the stochastic optimization with many possible scenarios, we consider only one scenario which means this optimization does not need any kind of probability distribution function. This scenario is assumed to be the worst case regarding the uncertain situations in the optimization procedure. In energy management problems, the worst-case scenario is the one that is believed to have the most severe outcome that happens in the real situation. In other words, in this method, it is assumed that the uncertain parameters are in their worst condition. This could help to have a realistic paradigm towards the occurring scenario and if possible, it could improve the results of the optimization in comparison with stochastic methods.

III. Energy Management IN MICROGRID

Energy management is defined as maximizing profits and minimizing expenses, as well as the rational and effective use of energy to increase competition. The aim of energy management is to ensure energy supply security and efficiency, increase the diversity in energy resources and the use of renewable energy sources, and reduce losses in electricity generation, transmission, distribution and use. Thanks to energy management in power systems, the energy produced in the distributed generation systems in the system is used effectively and efficiently. In addition, an effective energy management system should be used in microgrids to meet the demand continuously.

A microgrid, as one of the potential solutions to the future smart grids, usually confronts the lack of power generation. This is due to the variability and intermittency both from generation and demand sides. Energy management methods have been believed as one of the solutions to this issue. The most important target of energy management is to find the optimal operation point of different kinds of energy resources in order to supply the requested demand constantly and efficiently. It should be mentioned that the main objective of these studies is reducing consumption costs while taking advantage of the microgrids' flexible capacity for the provision of energy and flexibility services. However, there might be various approaches and tools towards this target. The approaches toward the control and operation of microgrid resources as well as dispatchable loads are known as microgrid management methods. This management method could be deployed by having an agreement between the microgrid operator and the microgrid's members/stakeholders. The microgrid energy management could be defined in three perspectives: decentralized energy management, centralized energy management and distributed energy management.

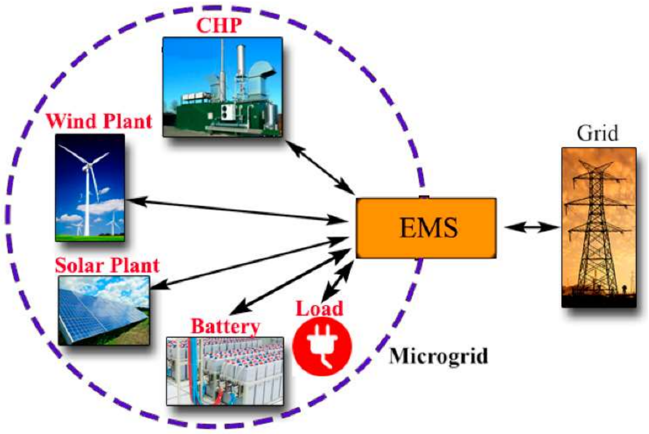

Fig. 3.Energy Management Systems(EMS) in Microgrid

In decentralized energy management, the control and operation of flexible energy resourcess located at the microgrid have more degree of freedom. This means the flexible energy resources's adjustability in this management method helps more to meet the preferences of the stakeholders/consumers. In centralized energy management, however, a central controller decides how the flexible energy resources and generation units should be operated. It has to be mentioned that in both centralized and decentralized management methods, the technical constraints of the microgrid must be taken into account. The most important constraint would be the balance between load and production within the microgrid. Distributed energy management as another management method in microgrids is presented in the literature as well. In microgrid, seek the best management method for their own objectives taking into account the overall goal of the energy management regarding energy management considerations. Having mentioned the above approaches, the energy management problems generally aim at scheduling the operation of generation units, storage systems, and even controllable loads in the microgrid.

One of the most important objectives of energy management is reducing the total operation cost of microgrids' components. This operational cost includes, for instance, the fuel cost, cost of purchasing energy from the grid, degradation cost of battery energy storages, etc. The cost reduction in an microgrid energy management could be over different time spans from real time to daily, monthly, or even yearly periods. However, energy management sometimes might be defined for real-time operation. In this case, the real-time operational cost of microgrid is the objective of the problem.

One of the important targets of energy management in microgrid is self-sufficiency. A microgrid is selfsufficient when there is a balance between the generation and consumption within the microgrid. In other words, the power produced by the microgrid's resources could fulfill its demand over a period of time. This objective becomes pivotal mostly when an islanding situation is predictable since, in that case, the microgrid becomes disconnected from the grid and the stability of the microgrid becomes critical. The energy managemen with an objective of selfsufficiency could be tackled by reducing the peak demand, load shedding as well as discharging the storage-based flexible resources. In this way, based on the level of emergency, the energy management should define a priority for the utilization of fast-response flexibility of microgrids. As traditional power systems experience a rapid and comprehensive transition to smart, local and decentralized systems, the concept of resilience services to cover all system-related issues is also an important topic. In this context, microgrids as local energy systems are believed to be an appropriate choice to provide local and system-wide flexibility.

Energy management can be defined as algorithms that ensure the economic, reliable and sustainable operation of microgrids. The algorithm analyzes variables such as the capacities of the units within the micro-grid, system constraints, user demands, electricity prices, according to the determined objective function, and tries to determine the optimum operating points and ensures the optimum operation of the network. Many different management strategies can be designed from production planning to energy saving, from reactive power support to frequency regulation, from security to cost optimization, from ensuring energy balance to applying demand-side management algorithms. Artificial intelligence methods are used for energy management in microgrids.

IV. 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.

Genetic algorithms and PSO are used as energy management approaches in microgrids. In addition to these energy management system approaches, Gray Wolf Optimization (GWO) [24,25] and Ant Colony Optimization (ACO) [26] are also used in energy management systems in microgrids. It mimics the social and hunting behavior of gray wolves. Gray Wolf Optimization (GWO), a meta-heuristic optimization algorithm developed with the help of ant colonies, and Ant Colony Optimization (ACO), a technique inspired by the methods of finding the shortest path between ant colonies' food sources and their nests by releasing pheromones, are important optimization approaches used in energy management.

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].

Energy management is also carried out by using learning-based techniques such as machine learning and deep learning in the microgrid. Microgrids, using learning-based techniques, optimize control schemes in the energy management they perform, but also realize energy efficiency by using a dataset based on predictions and real data. The use of learning-based techniques can increase the scalability of the energy management system and reduce costs. However, it also has limitations such as reduced system security.

In [28], artificial intelligence-based data-driven stochastic energy management is proposed for isolated microgrids considering the reactive power capacity of distributed energy sources. In this study, uncertainties in the output power of renewable energy sources are modeled using generative adversarial network (GAN), a data-driven technique for scenario generation. The use of GANs to achieve optimum energy management in a microgrid is discussed in [29]. This study examined the impact of data integrity attacks on centralized control of microgrids, which can lead to severe power outages 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.

It is implemented with a multi-agent system (MAS) in the energy management systems study proposed in [9], which is based on maximizing the energy obtained from renewable sources by using MPPT algorithms operating in Maximum Power Point Tracking mode. In the study, the energy storage system is controlled by using artificial neural network controllers. In this way, battery charge and discharge are optimized. In the study, it is aimed to provide power balance in the microgrid. Providing this balance with a flexible control is one of the advantages of the study. All components in the designed micronetwork are modeled in MATLAB/Simulink. Agents are created on the system using the multi-agent system Java Tool Development Framework (JADE). The information exchange and communication information between the created agents are designed in JADE. In this design, MACSIMJX program was used as the program that provides the relationship and communication between JADE and MATLAB. In this way, it is ensured that the microgrid designed in MATLAB and the agents designed in JADE work together.

An ANN-based EMS has been proposed in a study to control power in AC-DC hybrid distribution networks. ANN-based energy management is carried out to select the most appropriate operating mode for the power system by collecting data such as distributed generation (DG) power, load demand and the state of charge (SoC) of the battery in the energy storage system. In the proposed energy management, it is important to control each power converter in its optimum operating mode, using an already trained ANN in grid connected mode. In the study, hybrid AC/DC microgrid was designed and simulations were performed for each operating mode to test and verify the efficiency of energy management. The simulation results are reported and discussed[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.

In [37], DC microgrid was designed and energy control studies were carried out for the designed microgrid. In order to ensure power quality and supply-demand balance in the system, energy management is carried out by using multi-agent system (MAS) and artificial intelligence-based algorithms. In addition, a fully decentralized control approach based on a multi-agent system is designed. In the designed microgrid, there are photovaltaic panels, wind turbine, energy storage system including Lithium-ion battery, critical and non-critical DC loads, network. Distributed generation agent, battery agent, load agent and network agent also make up the multi-agent system. These agents in the multi-agent system communicate with each other and receive information such as power, voltage, current, charge level between the units and perform the tasks defined for them. The control unit and energy management unit have been tested on the DC microgrid system designed in MATLAB. Control of DC connection voltage of the system, energy management, stability, power quality etc. The performances of the control and management algorithms to be designed according to other performance criteria are reported.

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.

TABLE II. AI-BASED METHODS USED IN TYPES OF 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.

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 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.

V. CONCLUSION

In this study, artificial intelligence technologies used in the energy management system algorithms of distributed energy sources in microgrids are examined and discussed. It is clear that artificial intelligence technologies offer good alternatives to realize efficient energy management in microgrids. Since microgrids require different sources to work efficiently together, a good energy management can be realized by using artificial intelligence methods. In this context, many studies on microgrids are examined and advantages and disadvantages are also discussed. The effects of artificial intelligence applications on energy management in the microgrid have been researched and discussed. As a result, different sources in the microgrid system will be able to continue to be used together and maintaining the supply-demand 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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