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Review

Review of Energy Management Systems in Microgrids

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Abstract: Microgrids usually employ distributed energy resources such as wind turbines, solar photovoltaic modules, etc. When multiple distributed generation resources with different features are used in microgrids, managing these resources becomes an important problem. The generated power of solar photovoltaic modules and wind turbines used in microgrids is constantly changing with solar irradiation and wind speed. Due to this impermanent and uncertain nature of renewable energy resources, generally, energy storage systems are employed in microgrid systems. To control the distributed energy resources and energy storage units and sustain the supply and demand balance within the microgrid and provide sustainable and reliable energy to the loads, energy management systems are used. Many methods are used to realize and optimize energy management in microgrids. This review article provides a comparative and critical analysis of the energy management systems used in microgrids. The energy management system can be tailored for different purposes, which are also discussed in detail. Additionally, various uncertainty measurement methods are summarized to manage the variability and intermittency of renewable energy sources and load demand. Finally, some thoughts about potential future directions and practical applications are given.

Keywords: microgrid; energy management system; renewable energy

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1. Introduction

One of the most efficient ways to produce energy is through fossil fuels, which include coal, oil, and natural gas. Recent scientific research demonstrates that these energy sources have detrimental effects on human health and the environment in addition to their economic effects [1–3]. Along with these effects, because of different reasons such as increasing energy demand, increasing energy prices, energy source dependency, etc., scientists are investigating alternate energy resources. Renewable energy resources and distributed generation have historically been used to try to meet the needs of reducing the negative effects of electrical energy production on the environment, meeting the ever-increasing demand for electrical energy, and improving the quality, reliability, and stability of power systems [4–6].

Increasing the capacity of electrical networks and extending transmission lines to feed farther-off electrical loads raise the costs of producing electrical energy as well as transmission–distribution losses due to the growing electricity demand [7]. Distributed generation which mostly employs renewable resources like solar and wind power is a good opportunity to solve these problems. Microgrids, which are small-size power grids, are also proposed for the same purpose. A microgrid can employ conventional and renewable distributed energy resources. Microgrids can supply energy to local-regional loads or the main power grid with these resources. Therefore, nearby loads can receive electrical energy from energy sources that are dispersed throughout a given area. They can also run in island mode (off-grid) or grid-connected (on-grid) mode. From these angles, microgrids provide many advantages for the future of power grids [8]. Microgrids containing renewable energy sources are used to reduce the annual electricity bill, energy purchased from the grid, and greenhouse gas emissions in the conventional power system. Microgrids can be used to increase the sustainability of electricity supply and minimize poverty in developing countries [9].

The large inertia moments of large power generators are crucial in suppressing oscillations in voltage and frequency that occur in traditional power systems. Compared to conventional generators, distributed generation units in microgrids are more unstable due to system oscillations in voltage and frequency because they are connected to the grid through power electronic converters [10]. To guarantee that microgrids run consistently, effectively, and in compliance with standards, a control system must be developed. Numerous problems, including voltage-frequency regulation, proper load sharing, synchronization with the main grid, control of the power flow between the microgrid and the main grid, and operating cost optimization, should be solved by this control system [11]. For the distributed energy resources that microgrids use as power sources to cooperate effectively, energy management is crucial.

Efficient, safe, and intelligent use of distributed energy resources among microgrid components is important for power quality and supply–demand balance in the system. This can be achieved by using energy management systems in microgrids. Numerous approaches, including multi-agent systems, model predictive control, artificial intelligence techniques, meta-heuristic-based methods, stochastic and robust programming-based methods, and classical method-based approaches, are used in microgrid energy management systems [12].

A new class of electricity sources that provides balanced electrical energy generated by clean and environmentally friendly energy resources is microgrid power systems. Microgrids are also called multiple energy source systems or hybrid renewable energy systems. Two of the cleanest methods of generating electrical energy are solar photovoltaic (PV) systems and wind turbines, which are both widely used globally. Hybridization of various energy sources aims to produce stable and sustainable electricity by providing maximum electricity generation capacity at the lowest possible cost for areas served by conventional electricity grids. Nevertheless, energy storage devices are required to guarantee energy sustainability because renewable energy resources are sporadic and dependent on weather [13]. To regulate the power flow between sources, loads, energy storage systems, and the main power grid with various characteristics within the microgrid, an energy management strategy, as illustrated in Figure 1, is necessary.

Microgrids combine energy storage systems, renewable energy sources, and the grid and can operate in island mode or grid-connected mode. Microgrids must have efficient energy management in place to guarantee maximum energy efficiency. However, integrating renewable energy resources is made more difficult by the stochastic nature of wind and solar energy [14]. Thus, among the difficulties in energy management and microgrid optimization are arranging unpredictable operating conditions of distributed generation and guaranteeing economical and adaptable operation with a variety of resources. The microgrid's energy management system carries out several tasks, including tracking, evaluating, and projecting power generation based on the features of distributed generation systems, load consumption, energy market prices, and meteorological conditions. Energy management systems can optimize the microgrid with the help of these features.

In the microgrid, if the power demand in the system is less than the power produced by resources, the excess power is stored in energy storage devices. If the demanded power is more than the produced power, the required power is met from energy storage devices, and in case of a connection to the grid, it will be drawn from the grid or transferred to the grid. To perform tasks such as determining the amount of power to be transferred, an effective energy management system must be established between the production, consumption, and storage systems. Thus, controllers can work in coordination with the demand from the load to achieve appropriate energy management [5].

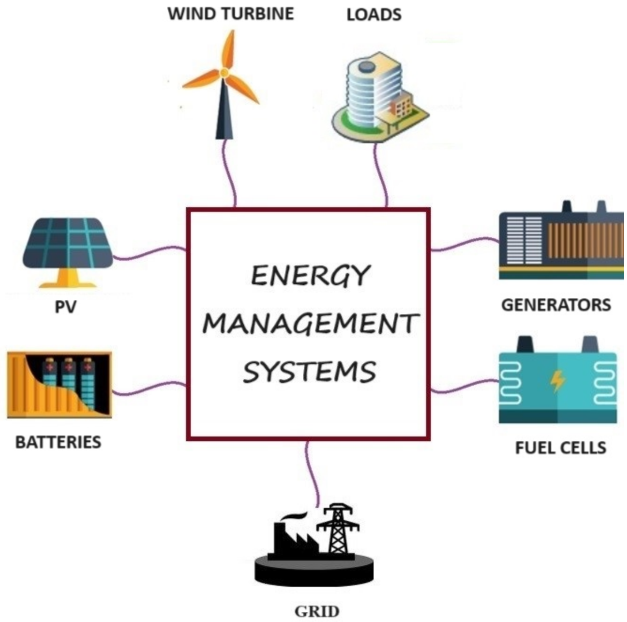

Figure 1. Energy management in microgrid units.

For energy-efficient operation, energy management systems are crucial in the utility, industrial, commercial, and residential sectors. Energy management systems aim to minimize greenhouse gas emissions, optimize distributed energy resource planning, and reduce energy consumption. Monitoring and data analysis are made easier for energy management systems by their integration with a human-to-machine interface (HMI) and supervisory, control, and data acquisition (SCADA) system. It includes the weather forecast, load demand, power output from generation resources, and the current price of energy. The energy management systems make use of this data to maximize system performance at the distribution, transmission, and generating ends. Most microgrid energy management systems examined in the literature have centralized supervisory control architecture. However, because distributed energy resources are becoming more and more integrated into the power system, the centralized architecture is confronted with challenges related to high computational time, limited system scalability, and high instability in the event of failures. For this reason, a decentralized supervisory control architecture has gained more attention from researchers recently. The requirement for a constant two-way communication link between microgrid components and their synchronization, however, raises the cost of the system. Furthermore, it is necessary to optimize the cost of these communication systems' upgrades [15].

Energy management in microgrids is very important in real-world applications in utilities, industrial, commercial, and residential sectors for efficient energy operation. By using these energy management systems in daily life, they aim to optimize distributed generation resource planning, reduce energy consumption, and minimize greenhouse gas emissions. These systems aim to operate the microgrid at maximum efficiency by monitoring the power output of generation resources, weather forecasts, load demand, and real-time energy prices. The cost of deployment and data rate are the main factors influencing the choice of communication technologies for microgrids in remote, residential, and rural areas. WiFi, Bluetooth, Z-wave, and Zigbee are used as communication technologies in such microgrids. Passive optical networks, 3G, and 4G technologies are also used in microgrids used in public services. These communication technologies are used by routers at distributed energy resource and load ends to communicate with the local controller and microgrid central controller. Arduinos and Rasberry PI are two examples of inexpensive embedded systems that can be used to implement local controllers. These technologies are designed to collect information from smart meters and monitoring sensors and carry out local control operations to protect consumer privacy. Data from SCADA, HMI, and local controllers are used by the microgrid central controller to drive energy management operations. The primary criteria used to choose the best solution approaches for these energy management operations are computational time complexity and convergence to the optimal solution based on merits [16].

The constant change of wind speed and solar irradiation values in renewable energy sources used in microgrids negatively affects system security and increases energy costs. The stochastic behavior of renewable energies, especially wind and solar, increases the need to find the optimum operation of the microgrid. The optimal operation of a typical microgrid aims to simultaneously minimize operating costs and accompanying emission pollutants over the daily planning horizon. By managing these energy resources in microgrids, it is aimed to increase the reliability and stability of the system while maintaining the balance between supply and demand [17].

This article provides an overview of microgrid energy management systems, outlining both their benefits and drawbacks. To control the unpredictability and erratic nature of renewable energy resources and load demand, a summary of different uncertainty measurement techniques is provided. A literature review and an investigation of the application of energy management techniques with varying goals in microgrids are also provided. Lastly, some thoughts about potential future directions and practical applications are given.

2. Energy Management Systems in Microgrids

A new energy structure called a microgrid combines energy storage systems, renewable and other energy resources, loads, and the power grid. Microgrids must have efficient energy management in place to guarantee maximum energy efficiency. However, integrating renewable energy resources has made it more difficult because of the stochastic nature of these resources. Thus, ensuring economical and flexible operation with a range of resources and arranging unpredictable operating conditions of distributed generation are among the challenges in energy management and microgrid optimization. An energy management system is essential for making the best use of these distributed energy resources in a microgrid in a way that is coordinated, safe, smart, and dependable. A microgrid's energy management system can monitor, analyze, and forecast power generation from distributed generation systems, load consumption, energy market prices, and meteorological factors, among other things. Energy management systems can optimize the microgrid with the help of these features [18].

In a microgrid, energy management systems are control software that allocates power output among distributed generation units and finds the most cost-effective way to feed the load. This is done by taking into account safety, reliability, and power quality. In general, a microgrid energy management system needs to coordinate various distributed generation sources, each with its constraints, to provide energy in a sustainable, reliable, environmentally friendly, and cost-effective manner. Energy management systems receive multiple inputs and then act on the available information to achieve the goals set by the microgrid owner. Figure 2 provides an illustrative overview of a microgrid energy management system.

Energy management is facilitated using energy storage systems in microgrids. Energy management enables the realization of scenarios such as storing excess power in energy storage devices if the power demanded by the system is less than the power produced by renewable energy resources, and meeting the required power from energy storage devices if the power demanded exceeds the power produced by renewable energy resources. Between the production, consumption, and storage system and the control of battery charging and discharge, an effective energy management system is needed. Controllers can thus collaborate with the load's demand to achieve appropriate energy management. Different approaches applied to energy management systems in microgrids are shown in Figure 3. Classical method-based energy management systems, energy management systems based on meta-heuristic approaches, energy management systems based on artificial intelligence methods, energy management systems based on stochastic (variable) and powerful programming approaches, energy management systems based on model predictive control, and multi-agent energy management systems are used in energy management system applications in microgrids [16].

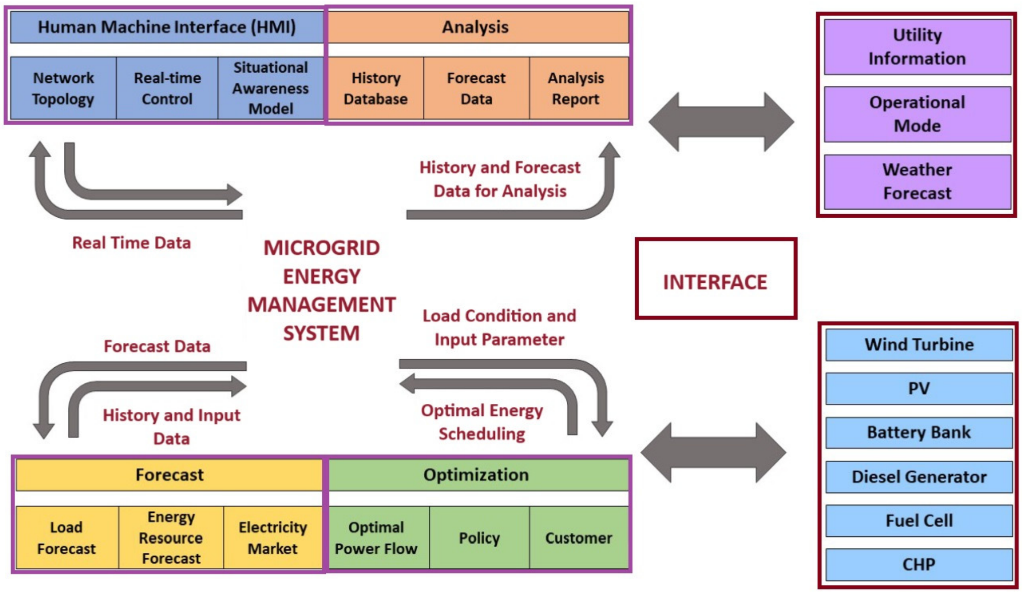

Figure 2. A diagrammatic summary of a microgrid energy management system.

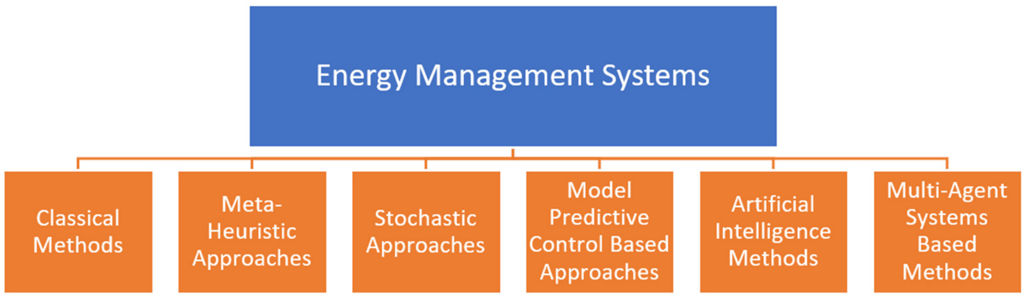

Figure 3. Different approaches are applied to energy management systems in a microgrid.

2.1. Classical Method-Based Energy Management Systems

The classical methods used in microgrid energy management are based on linear and non-linear programming techniques. Microgrid energy management systems employ centralized controller control architecture and linear or non-linear programming techniques, with an emphasis on microgrid energy resource optimization [19].

The rule-based and dynamic programming-based microgrid energy management techniques are among the classical methods. These techniques mostly concentrate on trading energy with the main grid and optimizing energy resources. Models of energy management based on a central rule are being developed for the microgrid operating in both the islanded and grid-connected modes. In terms of the microgrid system's voltage and frequency stability, a seamless transition between these two modes is guaranteed [20].

In research on microgrid control, where a controller manages voltage and frequency, dynamic modeling is necessary to evaluate how control algorithms affect the performance of individual microgrid components. Additionally, a dynamic model is useful in demonstrating regulatory compliance with specific standards, such as Institute of Electrical and

Electronics Engineer (IEEE) Standard 1547or local grid code. Software packages are typically used in dynamic modeling to either select pre-made component models or generate unique models from a diverse range of software packages.

2.2. Meta-Heuristic Approach-Based Energy Management Systems

To solve difficult nondifferentiable optimization problems, heuristics and meta-heuristics are applied in a variety of engineering domains, including communications, power systems, microgrid energy management systems, transportation, and power systems. Genetic algorithms and particle swarm optimization (PSO) techniques are two common metaheuristic approaches used in the development of microgrid energy management systems due to their parallel computing capabilities. Apart from the widely recognized PSO and genetic algorithm approaches for energy management systems, there exist novel approaches like Gray Wolf Optimization (GWO). Energy management in microgrids makes use of techniques like Ant Colony Optimization (ACO) [21], Bacterial Foraging Optimization (BFO) [22], Artificial Immune System (AIS) [23], Particle Swarm Optimization (PSO) [24], Genetic Algorithm (GA) [25], Artificial Bee Colony (ABC) [26], and Gray Wolf Optimization [27].

Various algorithms, such as GA and PSO, must be evaluated for computational complexity, scalability, and accuracy in real-world microgrid scenarios. As a result of this evaluation, problems are modeled with various dimensions in real-world optimization scenarios. The purpose of this is to estimate the scalability and adaptability of the proposed algorithm to unexpected changes.

2.3. Stochastic and Powerful Programming Approaches-Based Energy Management Systems

Energy management systems based on stochastic (variable) and powerful programming approaches use estimated values of electricity price, solar irradiation, wind speed, and load power. As a result, the overall operating cost, including the cost of energy trading with the grid and the operating cost, is minimized. This energy management approach is considered to deal with uncertainty by estimating variable parameters in the system through programming techniques. A controller is also used in the system to reduce fluctuations in the bus voltage and control the battery current. Stochastic programming models are being developed to optimize microgrid energy management that takes into account uncertainties such as wind speed, solar irradiation, and load demand in renewable energy resources [28–30].

Optimal operation of the microgrid and optimization of investment costs can also be achieved through energy management and variable programming methods. Scenario creation methods are used for microgrid scenarios and the probabilities of these scenarios occurring, and problems caused by disruptions or malfunctions in the main grid or microgrid. The goal is to reduce the anticipated running costs as much as possible. These costs include load shedding and the running costs of renewable energy resources like solar, wind, and battery systems.

2.4. Model Predictive Control-Based Energy Management Systems

Model predictive control-based energy management systems aim to predict the microgrid's controllable load to implement an effective energy management strategy. The system performs better in terms of fewer power outages, a lower maximum demand, and an improved load factor because of its predictive control capability [31]. Energy trading with the main grid, optimizing the use of renewable energy resources, battery and electrical vehicle management, and other measures to guarantee system stability and profitability are all part of the microgrid's economic operation.

Optimal control schemes in the microgrid are learned from data, making them stand out as model-independent or data-driven calculations. By using learning-based techniques, and having an open system model, it is possible to reduce resistance, increase the scalability of the energy management system, and reduce costs. To release accurate models and permissions for a microgrid, model-based energy management systems depend on domain expertise. This means that while this method produces high improvement rates, it is neither scalable nor transferable. However, improvements in microgrids might force a redesign that results in noticeably higher maintenance costs [32,33].

2.5. Artificial Intelligence Methods-Based Energy Management Systems

In the microgrid, situations that affect power quality such as controller gains, frequency deviation, sudden drops in current, and voltage deviation occur. The difficulty in adjusting many parameters in these complex systems can be overcome with artificial intelligence techniques such as fuzzy logic, artificial neural networks, machine learning, deep learning, and game theory [34]. The fundamental thing about fuzzy logic is that, unlike classical logic systems, it aims to model uncertain modes of reasoning that play a notable role in people's rational decision-making in an environment of uncertainty and ambiguity. This ability refers to performing energy management with the ability to derive an approximate answer to a question that is uncertain, incomplete, or not completely reliable [35].

To accurately ensure the reliability of artificial intelligence systems used in energy management systems in microgrids, real-world scenarios and real failure modes need to be studied. The quality and variability of data used in artificial intelligence methods directly affect the performance and reliability of energy management systems. As a result, gathering data is necessary to demonstrate the dependability of artificial intelligence, and statistics are crucial in guiding the selection of relevant data. Following the acquisition of artificial intelligence reliability data, reliability predictions, statistical modeling, and analysis offer an overview of anticipated reliability in upcoming scenarios. Additionally, reliability tests and demonstrations can be used to pinpoint the root causes of reliability problems, allowing artificial intelligence system designers to make improvements that will increase reliability. Although it can be difficult, identifying the reasons behind artificial intelligence reliability failures offers opportunities for statistical reliability research.

2.6. Multi-Agent System-Based Energy Management Systems

Multi-agent systems are comprised of agents that collaborate to solve problems that an individual agent finds difficult or ineffective to solve on its own. These agents use their skills and knowledge to work together in a coordinated manner to solve these problems. Multi-agent systems consisting of many agents are applied to microgrids as an energy management strategy [36]. The agent is the fundamental component of an agent-based energy management system. It can be a real or virtual entity. Virtual agents are software algorithms that coordinate system components, whereas physical agents in applications are micro-resources and controllable loads. An agent possesses the capacity to act within the system and alter it through its actions. Depending on how big it is, a microgrid may have a lot of agents.

Multi-agent systems can be understood as an assembly of intelligent and self-governing entities, referred to as agents, which essentially develop within a perceivable and manipulable environment. Other than the agent itself, this environment can be regarded as anything. Depending on how they are set up, these agents can be somewhat autonomous due to their intelligence. Multi-agent systems in energy management applications are made up of different agents interacting in a particular setting. Agents can perceive changes in their surroundings and use reasoning to determine the best course of action. In the field of Electrical and Electronics Engineering, multi-agent systems find application in diverse problem areas, including but not limited to diagnostics, distributed control, modeling and simulation, protection, and maintenance planning [37].

Compared to traditional analytical control techniques, multi-agent systems offer many benefits [38,39]. In today's grid, the classical control techniques used in SCADA systems are not entirely functional [40]. Nonetheless, the control system needs to function well as a large-scale and flawed system in a smart grid with thousands of controllable devices. In multi-agent systems, agents see the world locally and possess a restricted amount of knowledge. Although agents only need to know about their immediate neighbors, more agents need to communicate with each other to work more functionally and cooperate with other agents [41]. In this way, more advantages are provided by choosing multi-agent systems for microgrid energy management. However, if the amount and costs of data to be transmitted in the system are desired, the communication of agents can be limited to the microgrid they belong to and their neighboring agents.

3. Energy Management Systems Applications in Microgrids

Microgrids contribute to low carbon emissions by increasing the diversity in energy production as well as the efficiency in energy consumption. In these systems, important issues such as energy management, adjustment of energy supply according to demand, efficient use of energy, and protection of power quality are addressed. Therefore, effective energy management in microgrids is extremely important for the reliability, sustainability, and economy of the system.

Energy management goals and practices in a microgrid depend on the user's preferences. Targets are influenced by factors such as geographic location, installed equipment, types of loads to be supplied, grid energy tariff structures, government regulations, and energy storage and generation options on the microgrid. Due to the modular and highly customizable nature of a microgrid, each microgrid has a unique set of goals. In general, the main purpose of a microgrid is to reduce operating costs by maximizing the savings of a microgrid through renewable energy and minimizing generation costs. As presented in Figure 4, microgrid energy management applications are carried out with targets such as environment, capital and operating costs, and energy storage costs.

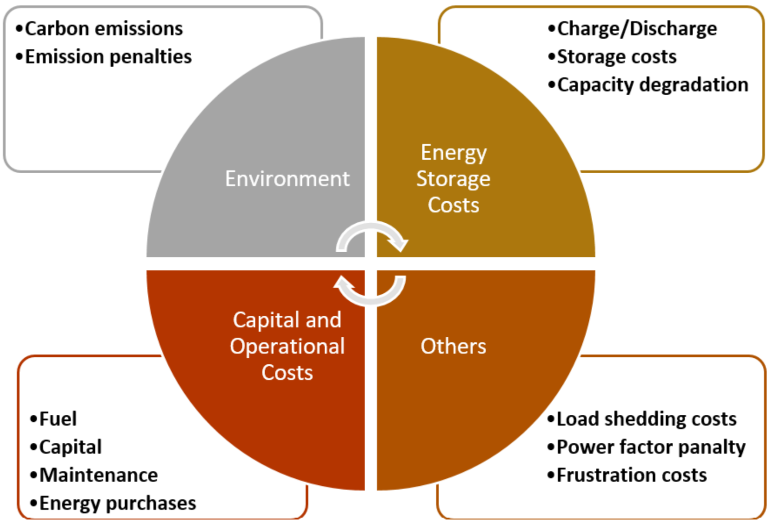

Figure 4. Microgrid energy management objectives.

Ref. [42] designed a centralized control system for energy management in an interconnected microgrid based on the concept of flexibility for the end users. It was possible to attain an ideal economic dispatch by employing quadratic programming. This grid was integrated with a photovoltaic system. A modified IEEE 33-node grid was used to test the algorithm.

A mixed-mode microgrid energy management system with power sharing, continuous run, and on/off base was proposed by [43]. The power-sharing mode allows for power trading with the main grid, but the fuel cell must always operate in continuous run mode. Both modes are solved using linear programming, an optimization technique. In contrast, a mixed-integer linear programming solution approach is used to solve the on/off mode, maximizing the microgrid's performance concerning the fuel cell, energy storage system, and the on/off connection status of the main grid. The microgrid's operational requirements are taken into consideration when determining the size of the energy storage system.

By using a solar desalination system, an energy management system for a hybrid AC/DC microgrid in a remote community was investigated [44]. The proposed optimization algorithm uses mixed-integer non-linear programming as the foundation for its goal function, which minimizes daily operating costs.

A proposal for a mixed-integer nonlinear energy management model of an isolated three-phase unbalanced microgrid can be found in [45]. The designed system reduces fuel consumption, system costs, and reactive power penalty costs. Energy storage systems, transmission lines, and transformer mathematical models were developed. Two successive stages of a mixed-integer nonlinear-based unit commitment model and optimal power flow model form the developed model.

Ref. [46] studied how to parametrize the uncertainty of solar and wind energy generation in a microgrid using mixed-integer linear programming to manage energy in the microgrid. Two levels of optimization are accomplished. The selection of the parametrization scheme comes first, followed by operational decisions that take market price variation and storage system disposition into account.

A multi-timescale-based energy management system was presented by [47]. Two factors are taken into account in the optimization problem: dynamic compensation in real time and daily static programming. The optimal load flows in a mixed-integer quadratic programming method are used to solve this, and data on solar irradiation and wind speed and direction are used to forecast the batteries' load state.

Ref. [48] studied distributed energy management for networked microgrids embedded in modern distribution systems using mixed-integer linear programming. An alternating direction method of the multiplier-based distributed framework was developed for the scheduling of networked microgrids embedded in contemporary distribution systems by iteratively adjusting nodal price signals, taking into account the diverse ownership of microgrids, distributed energy resources that interface directly with utilities, and responsive loads. A contemporary distribution system made up of numerous networked microgrids, dispersed energy resources that communicate directly with utilities, and responsive loads is used to validate the suggested approach using numerical simulation results.

A summary of classical method-based energy management systems applications in microgrids is given in Table 1.

In Ref. [49], a two-layer energy management system was showcased for distant microgrids. An innovative scheduling algorithm that takes battery lifetime into account was put forth, and it should lower microgrid operating costs. The technique was based on goal programming, which gives varying weights to the cost of using batteries and fuel. Findings indicated that extending the battery life could lower the microgrid's overall operating costs despite an increase in fuel consumption. Over relatively large variations in battery costs for this case study, a wide range of weights proved effective in lowering the operational cost. Despite the analysis being restricted to lead-acid batteries, the technique is sufficiently universal to be applied to other kinds of batteries.

To minimize the expenses associated with managing distributed energy resources, [50] proposed the use of memory-based genetic algorithms to optimize power management in grid-connected microgrids. The proposed method outperforms genetic algorithms and particle swarm optimization with a constriction factor and an inertia factor.

A study on microgrid optimization using the particle swarm algorithm, which can run an isolated or connected microgrid, was presented by [51]. The suggested method takes into account the variations in the microgrid's load demands and renewable resource supply, and it provides suitable advance (24 h) forecasts to mitigate these variations.

Ref. [52] suggested a system subject to demand, wind energy, electric vehicle costs, and electricity prices. In the optimization procedure of this investigation, the gray wolf algorithm is employed. The microgrid system's timing and operation are optimized utilizing this enhanced algorithm. Reduced general operating costs are a result of the system. Efficient management of the grid's integration of energy storage technologies, demand response programs, renewable energy sources, and other emerging technologies results in this cost reduction.

Table 1. Classical method-based energy management systems applications.

Ref.	Proposed Method	Energy Management Application
[42]	Quadratic programming	Quadratic programming was used to achieve the best possible economic distribution.
[43]	Linear programming	The problem is resolved by applying a mixed-integer linear programming solution technique, which optimizes the microgrid's performance concerning the fuel cell's on/off connection, energy storage system, and main grid conditions.
[44]	Non-linear programming	Mixed-integer nonlinear programming forms the basis of the objective function of the suggested optimization algorithm, which minimizes daily operating costs.
[45]	Mixed-integer nonlinear programming	Designed with mixed-integer non-linear base unit commitment and optimal power flow models, the system reduces fuel consumption, system expenses, and reactive power penalty costs.
[46]	Mixed-integer linear programming	Optimizes the system with operational decisions that take into account market price variation and storage system layout.
[47]	Mixed-integer quadratic programming	Optimum load flow was achieved by considering real-time dynamic balancing and daily static scheduling.
[48]	Mixed-integer linear programming	It is aimed at distributed energy management for modern distribution systems embedded in networked microgrids. By iteratively adjusting the node price signals, the alternative direction method of the multiplier-based distributed framework is developed.

Ref. [53] presented an adaptive modified particle swarm algorithm approach based on the hybridization of chaotic particle swarm algorithm and fuzzy self-adaptive particle swarm algorithm to optimize the multi-objective energy management system model of a grid-connected microgrid. The objective is to lower the operating costs and emissions of microgrids. The developed algorithm outperforms fuzzy self-adaptive and chaotic particle swarm algorithms.

A novel approach to optimizing an interconnected microgrid was introduced by [54]. It combines a fuzzy logic expert system with a meta-heuristic grey wolf optimization. With this approach, the costs of the power plants as well as the emissions from fossil fuel sources are kept to a minimum. By taking into account the batteries' optimal capacity and minimizing the use of fossil fuels, this strategy lowers microgrid costs.

In a stand-alone microgrid, ref. [55] introduced a genetic algorithm-based technique for determining the best location for renewable energy generation and batteries. The suggested multi-objectives include energy disposal and a decrease in life cycle and operational expenses. To optimize the microgrid, the optimization takes into account variations in wind and solar irradiation and extracts data from a load profile.

A summary of meta-heuristic approach-based energy management systems applications in microgrids is given in Table 2.

Table 2. Meta-heuristic approach-based energy management systems applications.

Ref.	Proposed Method	Energy Management Application
[49]	Genetic algorithms	Genetic algorithms were used to provide energy supply options through the use of diesel generators and demonstrated reduced operating costs of the microgrid.
[50]	Genetic algorithms	Power management is implemented to reduce the operating costs of distributed energy resources.
[51]	Particle swarm algorithm	It takes into account changes in the microgrid's load demands and renewable resource supply and provides appropriate advance (24 h) forecasts to mitigate these changes.
[52]	Grey wolf optimization	The algorithm is used to optimize the timing and operation of the microgrid system. Thanks to the system, general operating costs are reduced.
[53]	Fuzzy self-adaptive particle swarm algorithm	The algorithm, developed to reduce microgrid operating costs, realizes the multi-purpose energy management system of a grid-connected microgrid.
[54]	Grey wolf optimization	With a new approach to optimizing an interconnected microgrid, both the costs of the power plants and emissions from fossil fuel sources were kept to a minimum.
[55]	Genetic algorithms	It takes into account changes in wind and radiation sources and extracts data from a load profile to optimize the microgrid to save energy and reduce operating expenses.

An energy management model for a microgrid that takes into account supply and demand uncertainty is presented [56]. The study also takes into account uncertainties in solar and wind energy production and energy demand. The Nuclear Energy Research Center in Taiwan tested it on a real grid with stochastic programming. In the first stage, battery capacity was optimized. In the second, an ideal microgrid operating strategy was evaluated.

A multi-objective stochastic technique was employed by the author to present a hybrid microgrid optimization system in [57]. The objective function of this study was applied at various microgrid stages to minimize system losses and lower the operating costs of renewable resources. The feeding systems' overall operating costs and losses were weighted and used to formulate the problem. Mixed-integer linear programming was utilized to solve the problem, and the IEEE 37 node distribution system was used to test the proposed approach.

A hybrid grid-connected community microgrid architecture is also advised for agricultural purposes [58]. To reduce the cost of the irrigation system, pumped storage unit, and energy trading costs with the main grid, the author suggested a stochastic coordination framework. The wholesale electricity price and the uncertainties associated with wind power are modeled using the point estimated method.

An optimization technique for a two-stage interconnected grid was presented by [59]. The first stage uses a conventional generator, and the second stage uses hourly marketing to ensure that the conventional and distributed generation is dispatched economically. This combination enables the Lyapunov optimization method to be used to manage uncertainty in renewable generation.

In Ref. [60], a novel approach to energy management for a thermal and electrical multi-energy microgrid is proposed. Industrial, commercial, and residential agencies optimize their energy trading strategies at the bottom level, while energy planning and pricing strategies are optimized at the top level. For computational tractability, an analogous single-level mixed integer linear program reformulation is then derived. The day-ahead and intraday energy market strategies are coordinated using an adaptive stochastic optimization approach.

A summary of stochastic and powerful programming-based energy management systems applications in microgrids is given in Table 3.

Table 3. Stochastic and powerful programming-based energy management systems applications.

Ref.	Proposed Method	Energy Management Application
[56]	Stochastic programming	Considering the uncertainties in solar and wind energy production and energy demand, an energy management model for a microgrid that takes into account supply and demand uncertainty is presented.
[57]	Multi-objective stochastic	The objective function applied at various stages of the microgrid reduces the operating costs of renewable resources by minimizing system losses.
[58]	Stochastic coordination framework	An application was developed to reduce the system cost, pumped storage unit, and energy trading costs with the main grid, and wholesale electricity price and wind energy uncertainties were modeled using the estimation method.
[59]	Lyapunov optimization method	Using hourly marketing techniques, it was possible to dispatch conventional and distributed generation economically while also managing the uncertainty associated with renewable generation.
[60]	Stochastic optimization	In a multi-energy microgrid, the strategies developed in the day-ahead and intraday energy markets are coordinated using an adaptive stochastic optimization approach.

A model predictive control approach was introduced by [61] to manage a mixed-generation microgrid that combines distributed and renewable sources. The goal of the model is to lower the expenses and limitations associated with energy demand and generation.

Ref. [62] introduced an energy management system based on a control algorithm to manage distributed generation, energy storage systems, and microgrids made up of supply grids and various loads. TCP/IP-based control and communication was introduced as a solution to the transition problem between solar system generation and storage systems.

In Ref. [63], an application to operate a hybrid system with solar energy and battery storage was presented. Batteries were used to store grid power during off-peak hours and provide power to customers during peak demand hours.

Ref. [64] used model predictive control to maximize the daily performance of the diesel–wind–PV hybrid system. A method was defined that combines the system with forecast data on temperature, wind speed, solar irradiance, and daily load.

Microgrids are now a viable option for integrating distributed generation to provide remote communities with energy, so it is critical to control and manage them well. The three control levels of a DC microgrid operating in isolated mode are designed and simulated in [65]. A model predictive control-based energy management system with real-time measurement feedback is also suggested. This system ensures power flow distribution and optimal energy dispatch at the lowest possible cost while prolonging the life of the energy storage system. Disturbances generated in the lower control levels can be responded to by the energy management system. The effectiveness of the microgrid is examined and contrasted under two conditions: one in which it has no energy management system and the other in which it has one in response to variations in irradiation and electricity demand.

Analyzing the power and operating costs provided by each production unit allows to evaluate whether the battery's state of charge and power balance are maintained.

A summary of model predictive control-based energy management systems applications in microgrids is given in Table 4.

Table 4. Model predictive control-based energy management systems applications.

Ref.	Proposed Method	Energy Management Application
[61]	Model predictive energy management	By managing the microgrid, it is aimed at reducing expenses and limitations related to energy demand and production.
[62]	TCP/IP-based control and communication	It provides communication between photovoltaic system generation and storage systems to solve the energy management problem.
[63]	Model-based energy management	In a hybrid system, an energy management system that provides supply/demand balance was implemented with an energy storage system.
[64]	Model-based energy management	The application was developed to maximize the daily performance of distributed generation.
[65]	Model predictive energy management	This system ensures power flow distribution and optimum energy distribution at the lowest possible cost while extending the life of the energy storage system. Analyzing the power provided by each production unit, the operating cost and the charge state of the battery allows the evaluation of the fulfillment of the power balance.

A two-stage AI-based energy management in an isolated microgrid is proposed in [66] to find the optimal day-ahead distribution. With the efficient management of microgrid power sources, including diesel generators, battery energy storage systems, and intermittent renewable energy resources, the deployment aims to minimize expected operating costs, reactive power costs, spinning reserve, and load-shedding. To model the uncertainties in the output power of renewable energy resources to be used in the formulation of stochastic programming, generative adversarial networks were utilized to generate scenarios based on data.

Ref. [67] used models with two different recurrent neural network architectures (RNN), long short-term memory (LSTM) and gated recurrent unit (GRU) to predict wind speed and solar irradiance at a designated location for the establishment of microgrids. The models improved the prediction accuracy of the models. While data on extreme weather events such as wind were taken into account to increase the data, it was trained using meteorological data obtained from meteorological stations and energy management was carried out in the system.

Fuzzy logic controllers are used to streamline system control, especially in microgrids that have several different operating modes and components. Because fuzzy logic controllers do not require complex mathematical modeling or rely on the nonlinearity of the microgrid's parts, the system specifically favors them. This leads to the creation of an all-encompassing energy management system based on simple linguistic concepts. Ref. [68] describes a fuzzy logic control-based energy management technique for electric cars and hybrid energy storage systems that use fuel cells, batteries, and supercapacitors. This study was carried out on a test microgrid. For optimal control of the energy storage system in a residential microgrid, Ref. [69] proposes an energy management system based on fuzzy logic. Research on the design of energy management systems ought to consider low complexity, encompassing both input and rule numbers [70].

An energy management system for a connected microgrid utilizing fuzzy logic based on the Mamdani algorithm was introduced by [71]. Making decisions regarding the management of the energy flow in the microgrid model—which is made up of energy storage components and renewable energy sources—is the primary goal. A scheme that combines genetic algorithms and fuzzy logic was used to realize the optimization.

A challenge for microgrid energy management systems is managing uncertainty. This issue was resolved by using oversized batteries, which is not the best solution. Load and renewable energy resources, like wind turbines and PV modules, can be predicted using techniques like combining multiple artificial neural networks with other techniques to manage uncertainties in the energy management system. Research has attempted to reduce production costs, improve the utilization of distributed energy sources, and reduce emissions by employing various kinds of artificial neural networks in studies based on energy management systems [72].

Online energy management systems have an advantage over offline ones because they can manage uncertainties by looking at real-time data, which is particularly useful given the intermittent nature of renewable energy resources and the highly stochastic nature of market prices and loads. Every distributed energy source and customer can now benefit from the application of an energy and load management model based on reinforcement learning [73].

A program based on incentive-based demand response was proposed by Nnamdi and Xiaohua [74] for the operations of grid-connected microgrids. The grid-connected operational mode of a microgrid was examined using the game theory-based demand response program. The findings indicate that when the grid operator's distributed generation benefit is maximized at the price of minimizing fuel/transaction costs, lower costs could be obtained in the microgrid.

In Ref. [75], a new deep learning-based prediction model for microgrid operation is proposed, considering renewable energy resources, load, and day-ahead price uncertainties. To overcome demand-side uncertainties, a program was developed to provide participants with optimal incentive rate strategies, as different customers have different attitudes toward paid incentives. In this program, reasonable incentive rates are determined according to customers' bid/offer data by using ranking points to determine the clustering structure.

A summary of artificial intelligence methods-based energy management systems applications in microgrids is given in Table 5.

In Ref. [76], energy management during a grid outage in microgrids—each with two photovoltaic and wind generators in addition to local load—was examined. To lower generation costs brought on by the randomness of the load and the intermittent nature of the solar capacity, a multi-agent-based energy management system based on the differential evolution algorithm in the Java Tool Development Framework (JADE) was employed. The best solution was selected by considering critical loads, and this system also took grid price fluctuations into account.

Energy management systems are also designed for microgrids containing homes and buildings [77]. Distributed generation management and coordination of demand response are part of the energy management system optimization process. The main purpose of the cost function is to meet the customer's energy and heat demands while reducing operating expenses. The Hypertext (HTPP) communication protocol forms the basis of the communication platform of agents.

For DC microgrids, energy management systems using artificial intelligence-based algorithms and multi-agent systems to ensure supply-demand balance and power quality in the system can be used [78]. Additionally, a fully decentralized control approach based on multi-agent systems can also be applied. In Ref. [78], a microgrid design including photovoltaic modules, a wind turbine, a lithium-ion battery energy storage system, critical and non-critical DC loads, and a grid is proposed, and energy management of this microgrid system is obtained by using a multi-agent-based control structure. Distributed generation agents, battery agents, load agents, and grid agents are further components of the multi-agent system. These agents communicate with one another, share data (like power, voltage, current, and charge level) between the units, and complete the tasks that have been delegated to them in the multi-agent system.

Table 5. Artificial intelligence methods-based energy management systems applications.

Ref.	Proposed Method	Energy Management Application
[66]	Generative adversarial network	It aims at managing uncertainties in the output power of renewable energy sources with a data-driven, artificial intelligence-based energy management strategy for isolated microgrids.
[67]	Deep learning	Models with two different recurrent neural network architectures (RNN), long short-term memory (LSTM) and gated recurrent unit (GRU) were used to predict wind speed and solar irradiance.
[68]	Fuzzy logic controllers	An application has been developed for energy management in microgrids with multiple operating modes.
[69]	Fuzzy logic controllers	For the best possible control of the energy storage system in a residential microgrid, a fuzzy logic controller-based energy management system is suggested.
[72]	Artificial neural networks	Energy management system-based studies aim to reduce production costs, increase the use of distributed energy resources, and reduce emissions.
[73]	Reinforcement learning	It manages uncertainties by looking at real-time data with online energy management systems.
[74]	Game theory	Fuel/transaction costs are minimized, and the grid operator's distributed generation benefit is maximized at its price.
[75]	Deep learning	To overcome demand-side uncertainties, a program was developed to provide participants with optimal incentive rate strategies, as different customers have different attitudes toward paid incentives.

Energy management systems based on multi-agent systems can also optimize energy from renewable resources by employing Maximum Power Point Tracking (MPPT) algorithms. An artificial neural network controller can be used to control the energy storage system in addition to the multi-agent system-based energy management system. This maximizes the charge and discharge of batteries [79]. The goal of the study is to balance the power within the microgrid. This study offers a flexible control to achieve this balance. MATLAB/Simulink is used to model all components of the designed microgrid. JADE is used to create agents for multi-agent systems on the system and design the communication and information sharing between the generated agents. The program, called MACSIMJX, facilitates the relationship and communication between JADE and MATLAB in this design. This ensures that the agents designed in JADE and the microgrid designed in MATLAB cooperate.

In Ref. [80], an energy management system based on multiple agents is used. This system takes into account various load models and energy from distributed energy resources. They proposed a cutting-edge method that inspires customers to participate. Using JADE programming, this proposal was validated on interconnected grids. The management system provides customers with an attractive benefit-cost ratio and reduces peak consumption.

Ref. [81] introduced a multi-agent hybrid energy management system that combines the best features of decentralized and centralized approaches to optimize the economic operation of the microgrid. A novel simulation platform for energy management systems was developed and implemented in the C++ programming language, based on the client-server architecture.

In Ref. [82], an intelligent and sustainable energy management system for a microgrid based on a multi-agent system is examined. The system is designed to address issues brought on by the intermittent availability of renewable energy resources. Furthermore, the system optimizes the utilization of available AC and/or DC renewable energy sources by leveraging load flexibility and the complementarity of renewable resources. An evaluation of this proposed multi-agent framework is conducted through a co-simulation for a microgrid linked to the main grid, utilizing the MATLAB and JADE platforms.

A summary of multi-agent energy management systems applications in microgrids is given in Table 6.

Table 6. Multi-agent system-based energy management systems.

Ref.	Proposed Method	Energy Management Application
[76]	Multi-agent management with differential evolution algorithm	Production costs were decreased by using a multi-agent management system based on JADE's differential evolution algorithm.
[77]	Multi-agent-based energy management	By applying energy management system optimization between distributed generation management and coordination of demand response, it aimed at reducing operating expenses.
[78]	Multi-agent with MATLAB	Multi-agent systems are used in the designed DC microgrid to guarantee power quality and supply-demand balance.
[79]	Multi-agent with JADE	It is based on optimizing the energy obtained from renewable sources using MPPT algorithms. JADE was used to design communication and information shared between the created agents.
[80]	Multi-agent with JADE	Taking into account various load models and energy from distributed energy resources, the application provides customers with an attractive benefit-cost ratio and reduces peak consumption.
[81]	Multi-agent and based on the client-server architecture	The microgrid's economic performance was enhanced by developing a client-server architecture-based simulation platform for energy management systems.
[82]	Multi-agent with MATLAB and JADE	The application, which maximizes load flexibility and the use of renewable resources, was developed using MATLAB and JADE platforms.

4. Conclusions

In this article, a review of energy management systems and energy management system applications in developed microgrids is presented. A comprehensive and critical analysis of energy management strategies and solution approaches has been carried out. Optimizing system reliability, energy planning, and operation in microgrids that can operate both on the island and on the grid is the main goal of the energy management system for sustainable development. Therefore, a microgrid energy management system is a multi-purpose issue that addresses financial, environmental, and technical concerns.

Although there are many methods to perform energy management in microgrids, artificial intelligence technologies have become popular recently and have great potential in the future. Artificial intelligence technologies hold great promise for transforming microgrid operations and facilitating the broad integration of renewable energy resources. In addition to enabling real-time decision-making and better resource utilization, the application of machine learning, deep learning, and other artificial intelligence algorithms can enhance predictive analytics, optimization, control, and monitoring of microgrids. Although artificial intelligence technologies have many advantages, they also present many difficulties, including interpretability, privacy, and data quality. To facilitate the broad adoption of artificial intelligence technologies in microgrids, future research and development should address these issues and provide fresh strategies and solutions.

Energy management techniques are chosen for the best possible operation of microgrids due to their applicability and traceability. The types of purposes of microgrid energy management systems depend on various factors, such as the way they operate, decentralized or centralized operation, economic considerations, and the variable and intermittent nature of renewable energy sources. They also take into account the environmental impact of traditional generators, battery health, distributed generation integration, system reliability and losses, and customer privacy. A comprehensive approach is still needed to manage customer privacy concerns and ensure a secure and reliable communication system, especially in decentralized operations. Additionally, the reliability analysis of microgrid systems for remote and island applications should be studied comprehensively. These potential areas need to be comprehensively addressed to ensure that microgrids operate as energy-efficiently as possible.

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