

Intelligent Control Techniques for Microgrid Systems

Mohamed Mohamed Khaleel^{1,2*}

¹Department of Aeronautical Engineering, Division of Automatic Control, College of Civil Aviation, Misrata, Libya

²Department of Research and Development, College of Civil Aviation, Misrata, Libya

¹lykhaleel@yahoo.co.uk



***Corresponding Author**

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ABSTRACT

Microgrids (MG) are complex systems that integrate distributed energy resources to provide reliable and efficient power to local loads. Due to the dynamic and uncertain nature of the MG environment, intelligent control techniques have become a popular solution to ensure optimal performance. This paper provides an overview of the recent advances in intelligent control techniques applied in MG, including neural networks, model predictive control, game theory, deep reinforcement learning, and Bayesian controllers. The paper also presents a discussion of the advantages and limitations of these techniques, highlighting the challenges associated with implementing them in MG systems. Finally, investigation of the existing literature on the performance of intelligent control techniques in MG systems is presented, providing insights into their effectiveness in improving the energy efficiency, stability, and reliability of MG systems.

INTRODUCTION

Recently, the world's population has grown significantly, leading to a substantial increase in energy consumption. As a result, traditional energy resources such as coal, crude oil, and natural gas are being depleted, and greenhouse gas emissions are on the rise [1]. To address these challenges, many countries have implemented policies to incorporate non-conventional and renewable energy sources to support electrification and transportation initiatives. However, the existing power grid-primarily relies on traditional energy sources for power generation, resulting in suboptimal power quality [2]. This low-quality power supply often leads to load shedding and blackouts, disrupting daily activities for consumers. Notably, the conventional grid uses one-third of the total generation fuel to produce electricity, with an associated eight percent loss in transmission lines for the generated power [3]. Additionally, the electricity produced is primarily used to meet peak demand, which has only a five percent probability of occurrence, leading to reduced reliability. Furthermore, traditional power generation fails to utilize the heat it produces for any other applications.

To overcome the limitations of the traditional grid, incorporating local renewable energy sources or distributed generation (DG) can reduce transmission losses and maximize output, including generated heat. However, dispatchable energy sources like wind and photovoltaics (PV) pose a challenge due to their dependence on climatic and meteorological conditions, leading to intermittent power generation [4,5]. Therefore, a hybrid energy system that combines storage elements and renewable energy sources is used to ensure a continuous power supply. For the future power grid to provide a reliable, cost-effective, and sustainable power supply to consumers, it must be intelligent. Adopting a smart grid can address the current grid challenges by controlling the complex power exchange process and planning for the growing energy demand. The future grid must also integrate communication technologies and local MG to enable efficient system control [6,7]. Furthermore, integrating renewable energy resources at the load side requires a two-way flow of power and data, with the ability to adapt to management applications that leverage technology [9,10]. The optimal control of MG operations is facilitated through the utilization of various real-time signals, such as energy price, EV charging, and solar generation signals. The implementation of MG technology enables support for a range of utility applications, including demand-side management (DSM), outage management (OM), and asset management (AM) as illustrated in Figure 1.

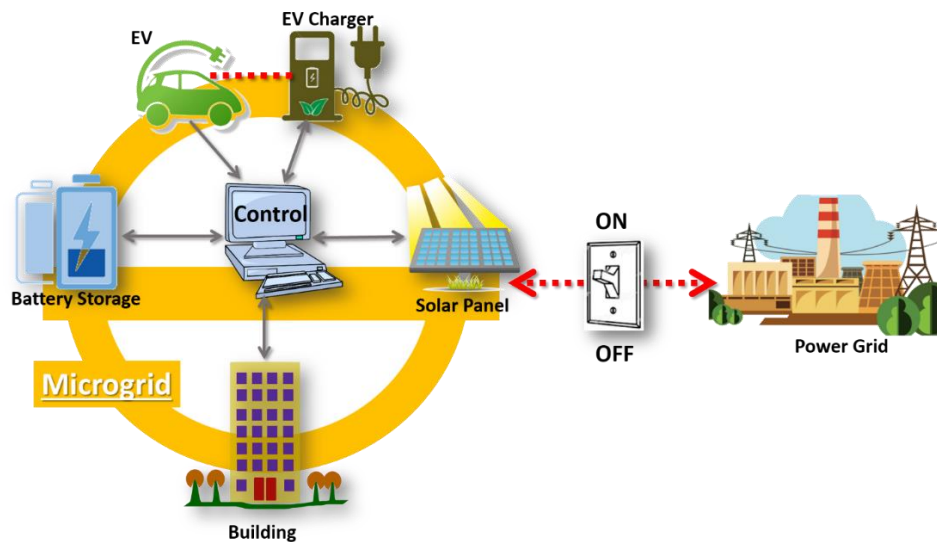


Figure 1. The implementation of MG technology enables support for a range of utility applications.

The significant contribution of the article is that it highlights the potential of intelligent control techniques in the development and optimization of MG. The article demonstrates how these techniques can improve the performance, efficiency, and flexibility of MGs by effectively managing distributed energy resources, energy storage systems, and loads. Moreover, the article showcases how intelligent control techniques can enable MGs to operate autonomously, adapting to changing conditions and responding to unexpected events. Additionally, the article highlights how these techniques can support the integration of renewable energy sources into MGs, making energy systems more efficient, resilient, and environmentally friendly. In summary, the article emphasizes the potential of intelligent control techniques to revolutionize the way that can be generated, distributed, and consumed electricity. The paper presents Intelligent Techniques for MG and is divided into several sections. The first section provides a literature review, while the second section discusses the methodology. The third section gives an overview of the MG elements, such as distribution generations, electric vehicle integration, control structure, communication, and classification. The fourth section explores intelligent techniques in MG, while the fifth section covers the standards of MG. The results and discussion are presented in the sixth section, and the article concludes with section seven.

LITERATURE REVIEW

Intelligent control techniques have gained immense popularity in recent years due to their ability to enhance the performance of MGs in terms of stability, reliability, and efficiency. The application of intelligent control techniques in MGs is particularly important because of the complex and dynamic nature of MGs, which consist of distributed energy resources (DERs) and loads that are often intermittent and unpredictable. With the growing concern about the environmental impact of conventional power generation and the increasing penetration of renewable energy sources, MGs have emerged as a promising solution for achieving a sustainable and resilient energy system. However, the integration of intermittent renewable energy sources and the dynamic nature of MGs pose significant challenges to the effective control and operation of MGs. In this context, the literature on intelligent control techniques in MGs has been growing rapidly in recent years, with numerous studies exploring various approaches for improving the performance of MGs using intelligent control techniques. This literature review aims to provide an overview of the recent advancements in intelligent control techniques for MGs, focusing on the different approaches, algorithms, and techniques used for controlling and managing MGs.

This paper [11] provides a comprehensive overview of MG, including its definitions, advantages, components, and control methods, with a focus on low-bandwidth, wireless, and wired control approaches. Microgrids are small-scale power grids consisting of local loads, energy storage devices, and distributed energy resources, operating in both islanded and grid-tied modes. They offer numerous benefits, such as enhanced network stability, reliability, efficiency, and integration of clean and renewable energies into the system. The paper [12] examines the development of efficient control systems for different types of MG, with a particular focus on low-bandwidth communication-based control methods due to their low expenses, recent developments, and high stability. The paper aims to provide a literature review and identify research gaps in the field of MG control. The paper [13] discusses the technical issues associated with the uncoordinated charging of battery electric vehicles (BEVs) in hybrid microgrid-powered charging stations, which can result in ineffective utilization of renewable energy sources and overloading the utility grid. The paper proposes an energy management strategy to minimize the usage of utility grid power and store PV power when the vehicle is not

connected for charging. The proposed energy management strategy was modeled and simulated using MATLAB/Simulink, and its different modes of operation were verified. A laboratory-scale experimental prototype was also developed, and the performance of the proposed charging station was investigated.

METHOD

There are several intelligent control techniques utilized in MG. To begin with, the method is Fuzzy logic systems and neural networks (NN), which have emerged as effective computational tools for processing large amounts of numerical data such as signals or images. These methods are characterized by nonlinear algorithms that offer computational flexibility, ranging from small software programs to large hardware systems. By continuously making decisions, these systems can learn and store acquired knowledge as internal weight parameters. Moreover, Machine learning is an emerging technology that has been widely applied in the energy sector, including MG applications. Microgrids are small-scale power systems that can operate independently or in parallel with the main grid, and machine learning techniques have been used to optimize their performance and increase their efficiency. Another method is Bayesian controllers, which use probabilistic models to incorporate uncertainty and provide a more robust control strategy. Fuzzy logic controllers use linguistic variables to describe the control strategy, allowing for a more human-like approach. Additionally, swarm intelligence techniques, such as particle swarm optimization (PSO) and ant colony optimization (ACO), can be used to optimize the control strategy. These techniques can be applied to various aspects of MG control, including voltage and frequency regulation, power dispatch, and energy management. Thus, intelligent control techniques offer a promising approach to improving the efficiency, stability, and reliability of MG.

OVERVIEW OF MICROGRID

Microgrids are small or medium-scale distribution systems that integrate various distributed energy resources, energy storage units, and smart control infrastructure to provide reliable and resilient power supply to end-users. The concept of MG has gained significant attention in recent years as a sustainable and efficient solution to address the challenges posed by centralized power systems, such as transmission losses, high costs, and vulnerability to outages.

1. *Microgrid Components*

A MG refers to a compact or moderate-scale distribution system equipped with intelligent infrastructure, which can effectively maintain equilibrium between demand and supply, while also providing security, autonomy, reliability, and resilience. The MG incorporates distributed generations (DGs), such as photovoltaics (PV), wind turbines (WT), micro-turbines (M-T), fuel cells (FC), and energy storage units (ESU), that are capable of supplying electricity without interference from the main grid. However, the high penetration of DGs may pose significant challenges to power system stability in large areas. Consequently, the concept of MG has been proposed to mitigate such risks. A MG typically comprises a small-scale low- or medium-level voltage distribution system, consisting of distributed energy resources (DERs), intermittent storage, communication, protection, and control units, that operate in coordination with each other to supply reliable electricity to end-users [14,15].

2. *Distribution Generations (DGs)*

In the realm of energy generation, conventional generation (CG) methods have historically been utilized to provide centralized electricity over long distances. These methods include coal-based thermal power plants, hydropower plants, wind-generation farms, and large-scale solar and nuclear power plants. In contrast, decentralized generation is defined as energy generated by end-users through the use of small-scale energy resources. When compared to conventional power systems, local generation substantially reduces transmission losses and the associated costs. Generation capacity can range from 1 kW to a few hundred MW, and these units are typically utilized to support peak load demand [15]. Distributed generation sources encompass both renewable and non-renewable sources, such as wind generators, PV panels, small hydropower plants, and diesel generators. Combined heat and power (CHP) technology involves the integration of heating with electricity generation. CHP systems employ Stirling engines, internal combustion engines, and micro-turbines (M-T) that utilize biogas, hydrogen, and natural gas [17,18]. CHP technology stores excess energy and achieves optimal performance, leading to an efficiency of over 80%, as compared to about 35% for centralized power plants.

3. *Electric Vehicles Integration*

The escalation in environmental pollution has propelled the transition from conventional fossil-fuel-based automobiles to electric vehicles, which offer vast potential for environmental and energy-related applications [19,20]. Among the applications of electric vehicles are vehicle-to-grid (V2G) and vehicle-to-vehicle (V2V) power supplies [19,20]. Figure 2 illustrates the connection of electric vehicles to the MG through the charging station

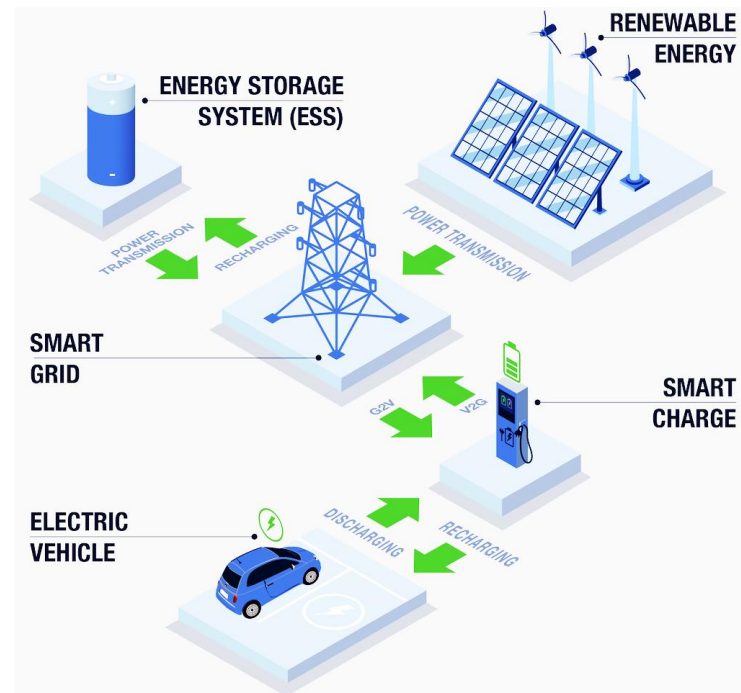


Figure 2. The connection of electric vehicles to the MG through the charging station.

The concept of V2G involves utilizing electric-powered vehicles to supply power to the local grid during periods of high demand or to participate in the energy market by reducing the overall cost of bidding during peak periods of increased electricity prices. The implementation of V2G requires communication with the power grid to return the electricity or by regulating the charging rate, which enables EVs to support renewable energy sources, as they are not controllable [42]. Battery electric vehicles (BEV), plug-in hybrid vehicles (PHEV), and fuel cell electric vehicles (FCEV) are among the types of EVs that support V2G. When EV batteries are not in use, they can be used to supply electricity to the grid or charge other storage devices. As the use of electric vehicles is projected to increase in the future, it is essential to improve the storage capacity to balance the demand-supply of the MG. This leads to improved performance in the stability and reliability of the system.

4. Control Structure of MG

An MG is a complex electrical distribution network that presents numerous variables and constraints to control. To address these challenges, an energy management system (EMS) is implemented to plan, supervise, and manage the system's supply-demand balance while ensuring reliable, cost-effective, and efficient operation [21]. This management system must account for a diverse range of technical and economic factors, timescales, and infrastructure levels, necessitating the use of a structured control system. The hierarchical control scheme is a widely accepted solution that involves three distinct levels, each with its own operating time, data inputs, and control equipment. These levels include the primary level, which oversees the control of DER units, the secondary level, which manages voltage and frequency changes in coordination with the primary level, and the tertiary level, which is responsible for the core control of the system, such as demand-supply management, storage management, renewable integration, power flow control, optimization of parameters, and control strategies. The tertiary level is also referred to as the energy management system [22].

5. Communication of the Microgrid

The integration of communication systems with the conventional power network has been an essential step toward the creation of a smart grid. By connecting the generation, transmission, distribution, and utilization systems to a central management center, communication enables the processing of real-time data for maintaining stability [23,24]. There are several wired and wireless technologies available for this purpose, each with unique features like data rate, latency, coverage area, reliability, and power consumption. The increase in data collection through sensors and monitors in smart homes and cities has highlighted the need for cost-effective communication infrastructure while ensuring reliable operation [25,26]. Recent trends in MG integration and IoT devices have further reinforced the need for wireless communication technologies to expand the scope of their applications.

6. Energy Storage System (ESS)

Energy storage refers to devices that can store electrical energy in a storable form and convert it back to electricity when required. Different categories of energy storage technologies exist based on the form of stored energy, including mechanical energy storage (MES), thermal energy storage (TES), chemical energy storage (CES), and electrical energy storage (EES). The energy storage units are key components in MG energy management systems (EMS) that regulate supply and demand balance during distributed generation (DG) operations. Studies have shown that the MG system with multiple micro sources requires storage systems to maintain balance for intermittent sources in islanded mode [27]. Commonly used energy storage devices in MG include batteries, flywheels, and supercapacitors, with batteries being the most cost-effective option despite their negative environmental impact. Fuel cells are also utilized in MG, using a chemical process to convert fuel into electricity, and hydrogen fuel cells are becoming increasingly popular due to their clean and safe operation [28,29]. They store excess energy produced during times of low demand and release it when demand is high, thereby ensuring a reliable and stable power supply. ESS also provides a backup power source in the event of a grid outage or disturbance, allowing the MG to maintain power supply to critical loads. The integration of energy storage systems with renewable energy sources such as solar and wind power also helps to mitigate their intermittent nature, increasing their reliability and availability. The energy storage systems contribute to the efficiency, resilience, and sustainability of MGs. Energy storage systems (ESSs) in MGs can be classified based on the form of stored energy [30]. The main categories of ESSs are:

- Electrical Energy Storage (EES): These systems store energy in an electrical form using batteries, supercapacitors, or other electrical storage technologies.
- Mechanical Energy Storage (MES): This type of system stores energy in mechanical form, using flywheels, compressed air, or pumped hydro storage.
- Chemical Energy Storage (CES): CES stores energy in a chemical form, such as hydrogen fuel cells or flow batteries.
- Thermal Energy Storage (TES): These systems store energy in a thermal form, such as through the use of phase-change materials, ice storage, or molten salt storage.

The category of EES systems is electrical storage, which includes devices that store electrical energy directly. This category includes various types of batteries, supercapacitors, and flywheels. Electrical energy storage devices are widely used in MG due to their high efficiency and fast response time. They can provide fast and accurate voltage regulation, frequency control, and load leveling, which are essential for maintaining system stability and reliability. Batteries are the most commonly used electrical energy storage devices in MG, and they come in various types such as lead-acid, lithium-ion, nickel-cadmium, and sodium-sulfur. Batteries are cost-effective and have a high energy density, making them suitable for a wide range of applications. However, batteries have a limited lifespan, and their performance can be affected by temperature, depth of discharge, and charging rate. Each type of EES system has its advantages and disadvantages, and the choice of system depends on the specific requirements of the MG application [30].

7. Classifications of Microgrids

Microgrids (MGs) are typically connected to the power grid via a static transfer switch (STS) at the point of common coupling (PCC), allowing the grid to manage voltage and frequency stability. In the case of a grid disturbance or failure, the MG can ensure system stability by isolating itself from the main power grid, creating an islanded condition. To guarantee high-quality output power, renewable energy sources such as solar, hydro, wind, and bioenergy, are connected to the MG using power electronic converters (PECs), which offer a resilient, reliable, continuous, and efficient power supply. MGs can be classified into AC source MGs, DC source MGs, and (AC/DC) hybrid MGs, depending on the type of output produced. AC MGs are preferred because they allow for flexible voltage-level transmission using transformers. In an AC MG, an AC supply bus is introduced, and all distributed energy resources (DERs), whether with DC or AC sources, are connected to AC loads via PECs. Since almost all loads in the power system are AC, AC MGs are highly sought after. The DC MG configuration comprises a DC bus that serves as a link for both AC and DC sources to transmit power to loads [31]. The rationale behind adopting a DC supply is to minimize the number of power electronic converters (PECs) required as DC sources are more readily available than AC sources. Moreover, the usage of a DC supply eliminates the possibility of harmonics caused by PECs that are typically present in an AC supply [32]. The increasing demand for DC sources in portable devices, such as laptops and mobile phones, as well as for powering household appliances in remote areas, has led to the development of DC MG. Figure 2 illustrates the structure of an AC DC MG.

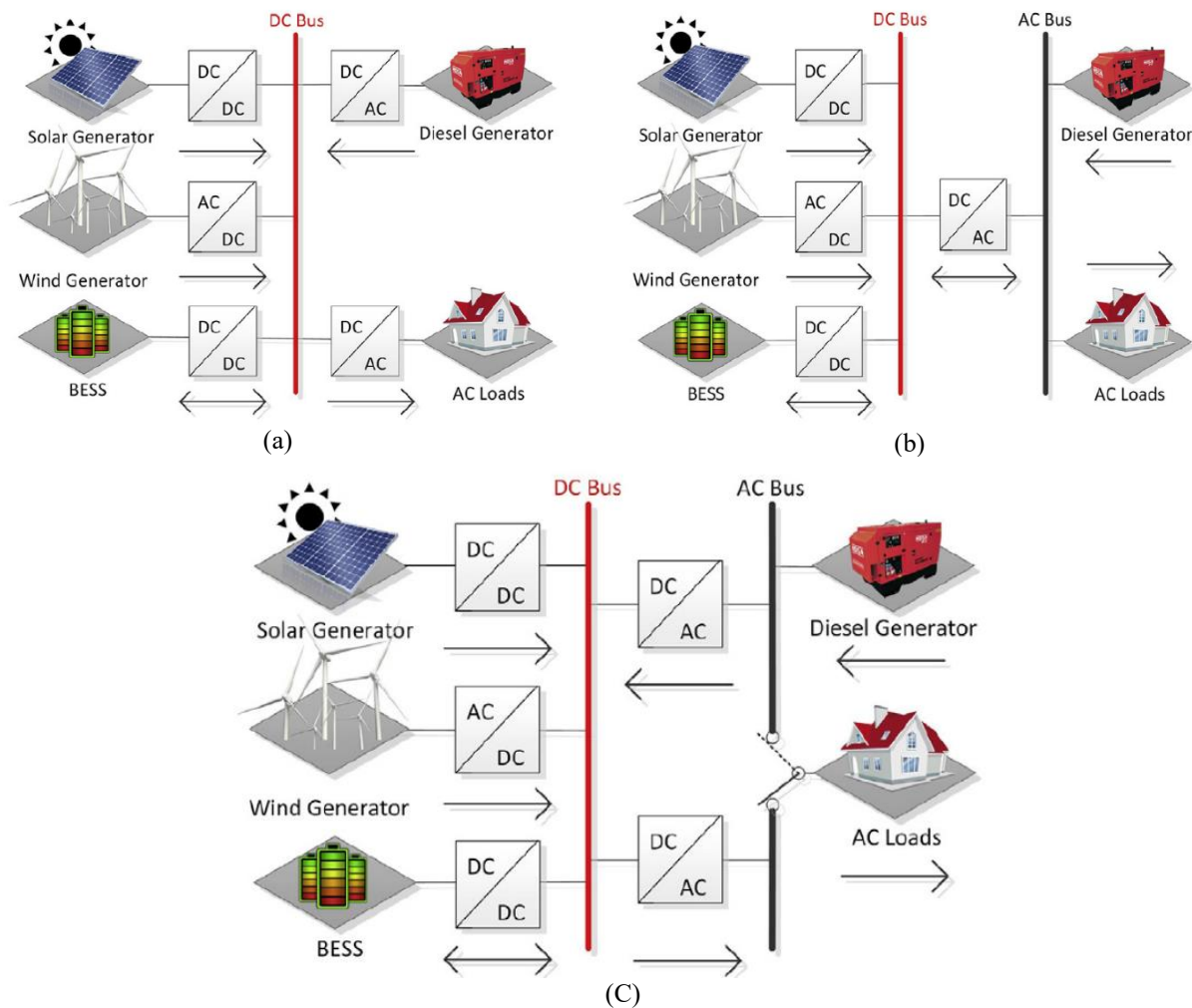


Figure 3. The structure of an MG: (a) DC;(b) AC; (c) Hybrid

An AC/DC hybrid MG has been proposed to integrate both AC and DC sources and consumers into a single system. To implement this, AC sources and DC sources are connected to their respective buses where the outputs are directed to the consumers as required. The main objective of an AC/DC hybrid MG is to simultaneously use the supply from both DC and AC sources to minimize overall power consumption. This can be achieved by the power electronic converters (PEC) installed at both supply buses that facilitate the bi-directional exchange of power between the source and load.

INTELLIGENT TECHNIQUES IN MG

MG has emerged as a promising solution for distributed energy generation, offering numerous benefits such as enhanced network stability, reliability, and increased integration of clean and renewable energy sources into the system. However, efficient control and management of microgrids are critical for their successful operation. Intelligent techniques such as artificial intelligence, machine learning, and optimization algorithms have been increasingly applied to microgrid control to improve their performance, efficiency, and reliability. This approach enables microgrids to optimize their energy management strategies and achieve optimal operation under various conditions. In this context, the use of intelligent techniques has become a topic of great interest in the field of microgrid research, providing opportunities to explore innovative solutions for future energy systems.

1. Fuzzy Control and Neural Networks

Fuzzy logic systems and neural networks (NN) have emerged as effective computational tools for processing large amounts of numerical data such as signals or images. These methods are characterized by nonlinear algorithms that offer computational flexibility, ranging from small software programs to large hardware systems [33,34]. By continuously making decisions, these systems can learn and store acquired knowledge as internal weight parameters. When fuzzy logic is used to control a system based on a set of rules that consider constraints, it is called fuzzy logic control (FLC). FLC has

been applied to enhance battery state of charge (SOC), smooth voltage profile, and grid-to-vehicle (G2V) charge transfer. On the other hand, neuro-fuzzy, a combination of fuzzy logic and neural networks, adjusts a fuzzy inference system (FIS) with data provided to NN learning rules. This approach offers improved speed, accuracy, and strong learning skills, along with simple execution. A neural network is a complex interconnection of neurons, which can be implemented in a physical system to enable control through layers of connection, referred to as an artificial neural network (ANN). ANN is commonly used for adaptive control and model predictive analysis in various applications, including MGs. ANN is trained through a dataset, which provides experiences or outputs for self-learning. By utilizing ANN in MG's energy management system (EMS), complex operations such as demand response (DR) forecasting and MG control can be carried out. A recurrent neural network (RNN) is a subclass of ANN that enables temporal dynamic behavior, where the network structure connects the temporal sequence through the graph between the nodes [35]. RNN, like ANN, processes variable-length sequences using internal memory, while RNN has an internal state memory that uses short-term memory (STM) or long short-term memory (LSTM) for energy and economic predictions [36,37].

2. Machine learning

Machine learning is an emerging technology that has been widely applied in the energy sector, including MG applications. Microgrids are small-scale power systems that can operate independently or in parallel with the main grid, and machine learning techniques have been used to optimize their performance and increase their efficiency [38]. One of the primary applications of machine learning in MG systems is load forecasting. Machine learning algorithms can be trained on historical data to predict future load demands, which can be used to optimize the operation of the MG system. Machine learning can also be applied to control strategies, where algorithms can learn from past data to optimize MG energy management and storage systems [39]. Another application of machine learning in MG is in fault detection and diagnosis. By analyzing sensor data in real-time, machine learning algorithms can detect and diagnose faults in the MG, allowing for faster and more accurate fault detection and response. Machine learning has also been used in MG design and planning. By analyzing historical data and considering various factors, such as renewable energy sources, load demands, and weather patterns, machine learning algorithms can optimize the design and planning of MG for maximum efficiency and performance [40]. Overall, machine learning techniques have shown promising results in the optimization and control of microgrid systems, and their use is likely to continue to grow as microgrids become more prevalent in the energy sector.

3. Genetic algorithm

Genetic algorithm (GA) is a type of metaheuristic optimization algorithm that mimics the process of natural selection and evolution. It has been widely used in various engineering applications including MG design and optimization [41,42]. In MG, GA can be used to determine the optimal configuration, size, and placement of different components such as renewable energy sources, energy storage systems, and control devices. The GA process involves the generation of a population of candidate solutions, which are evaluated based on their fitness concerning the objectives and constraints of the problem. The fittest solutions are then selected for breeding, where they undergo genetic operations such as crossover and mutation to generate new offspring. This process continues for multiple generations until a satisfactory solution is obtained [43]. By using GA, it is possible to search through a large space of possible solutions to find the optimal one. GA can handle nonlinear, non-convex, and multi-objective optimization problems, which are commonly encountered in MG design and operation. Furthermore, GA can be easily integrated with other optimization and simulation tools to provide a comprehensive analysis of MG performance. Thus, GA is a powerful tool for MG optimization and can provide valuable insights into the design and operation of MG [44].

4. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a popular optimization technique in MG control due to its simplicity and efficiency. PSO is a swarm-based optimization algorithm. It starts by initializing a population of candidate solutions, called particles, and then updates their positions and velocities iteratively based on the best solution found so far by the swarm and the personal best solution of each particle. The update rule combines the current velocity, a random factor, the distance to the best positions, and the personal best positions of each particle [44]. The algorithm is repeated until a stopping criterion is met, usually a maximum number of iterations or a convergence threshold. PSO has been applied to various control problems in MG, such as optimal dispatch, economic dispatch, and load frequency control. In optimal dispatch, PSO is used to find the optimal power output of each generator and storage unit to minimize the total operating cost while satisfying the load demand and system constraints. In economic dispatch, PSO is used to minimize the total fuel cost of the generators while meeting the load demand and transmission constraints. In load frequency control, PSO is used to tune the PID parameters of the controllers to regulate the frequency and tie-line power flow within acceptable limits. PSO has shown promising results in MG control, achieving better performance than traditional optimization techniques such as linear programming and gradient-based methods. However, the performance of PSO depends on the selection of the swarm size, velocity limits, inertia weight, and social and cognitive parameters [45,46]. In addition, PSO may suffer from premature convergence or stagnation, leading to suboptimal or non-optimal solutions. To address these

issues, several modifications and hybridizations of PSO have been proposed in the literature, such as adaptive PSO, chaotic PSO, and PSO combined with other techniques like fuzzy logic and neural networks.

5. *Ant Colony Optimization*

Ant Colony Optimization (ACO) is a meta-heuristic optimization algorithm that is inspired by the foraging behavior of ants. In MG applications, ACO has been applied for various control and optimization tasks, including optimal energy management, distributed generation placement, and load balancing. ACO algorithms work by simulating the behavior of ant colonies in finding the shortest path between their nest and a food source. The algorithm maintains a pheromone trail that ants use to communicate with each other and guide their search for the food source. The pheromone trail evaporates over time, causing ants to focus their search on the most promising paths. In the context of MG control, ACO algorithms can be used to optimize the operation of distributed energy resources (DERs) and balance the load across the MG. For example, ACO can be used to determine the optimal dispatch of DERs, such as solar PV panels and energy storage systems, based on the current load and energy prices. ACO can also be used to optimize the placement of DERs in the MG, taking into account factors such as energy demand, available space, and the cost of installation [47,48]. ACO algorithms can also be used to balance the load across the MG by adjusting the output of DERs in response to changes in energy demand. Thus, ACO is a promising technique for MG control and optimization, offering the potential for efficient and effective management of DERs and load balancing. However, further research is needed to fully evaluate the performance of ACO in MG applications and to develop more sophisticated algorithms that can handle the complexity and variability of real-world MG.

6. *Model Predictive and Multi-Agent*

Model predictive control (MPC) is an advanced algorithm employed for regulating and controlling systems by leveraging the moving or rolling horizon approach within a specified timeframe. Its primary role involves minimizing the sensitivity of the system to various variables while ensuring optimal control of the physical processes. MPC can be performed online while accommodating uncertainty constraints. In online methods, the current system parameters and forecasted parameters aid in updating the decision variables in real time. Although the MPC approach provides an optimal solution, its complexity increases with a surge in variables, thus making it suitable for application in smaller systems. Within a multi-agent system (MAS), the system objectives are achieved via intelligent agents that communicate with other neighboring agents while participating in the formation of a configuration [49,50]. This approach is highly effective in controlling EMS, optimizing energy management, and managing the energy market.

7. *Deep reinforcement learning (DRL)*

Deep reinforcement learning (DRL) is a sophisticated algorithmic approach that addresses intricate decision-making problems through training or learning. It integrates reinforced learning (RL) and deep learning (DL) to enable agents to perform decision-making tasks across diverse applications. DRL is a subset of intelligent machine learning and falls within the purview of artificial intelligence, where a system imbibes knowledge from the decisions it executes, akin to human learning experiences [51,52]. The agent's learning process is based on a reward and penalty system that evaluates its decision policy.

8. *Game theory (GT)*

Game theory (GT) provides a mathematical framework to analyze interactions between multiple decision-making variables in a given environment. Each strategic decision-making variable is introduced to the game to achieve the desired outcome. The Nash equilibrium is a crucial solution concept in game theory, where the actions of other players are held constant while no player changes their strategy to increase their revenue. This results in an optimal mutual response from all the players [53,54]. In non-cooperative game theory, where there is no clear leader-follower relationship, the Nash equilibrium strategy is used to improve the utility parameter by enabling every player to compete against each other, thereby finding the optimal solution.

9. *Network reconfiguration*

The optimization problem of network reconfiguration involves identifying the most optimal radial topology of the distribution network from a set of all available topologies. The primary objectives of network reconfiguration typically include the reduction of power loss, the harmonization of voltage profiles, and the equitable distribution of network loading through the implementation of a multi-objective framework. To achieve these goals, both deterministic and stochastic methods are commonly utilized [55,56]. In the context of distribution systems, significant attention has been devoted to the meta-heuristic approach to reconfiguration, which involves the manipulation of radial topologies via the interchange of tie lines.

10. *Bayesian controllers*

Bayesian controllers in MG refer to the use of Bayesian statistical inference techniques to design and implement control algorithms for managing and optimizing the operation of MG. Bayesian controllers use a probabilistic approach

to modeling the behavior of the MG and the uncertainties associated with its operation, such as renewable energy sources and load demand [57]. Bayesian controllers make use of prior knowledge, such as historical data, to make predictions behavior of the MG. They then update these predictions based on real-time measurements and use this updated information to determine the optimal control actions to achieve a specific objective, such as minimizing energy costs or maximizing renewable energy utilization. One advantage of Bayesian controllers is their ability to handle uncertainties and incomplete information in a principled way [58]. They also allow for the integration of prior knowledge and can adapt to changing conditions over time. Bayesian controllers have been applied in various MG control applications, including the optimal dispatch of distributed energy resources, voltage and frequency control, and demand response.

STANDARDS OF MG

Standards are crucial parameters or processes that ensure a product's performance levels meet the safety and quality requirements set by utility market regulations. They are developed to establish market standards that ensure consumer safety by introducing a set of verification procedures that test the quantification's performance and compare it with the minimum requirements. In the context of MG, standards are essential to provide configuration, topology, and regulations that control the MG and its integration with renewable sources. Different configurations can be implemented with MG blocks to perform various operations. Distributed network operators and MG operators carry out a set of testing procedures with parameters designed to compare their control functions and test the system's endurance. Some of the standards that exist for smart grid distribution networks include the Institute of Electrical and Electronics Engineers (IEEE 1547), which offers guidelines for interconnecting dispatchable sources into the electric power grid, and IEEE 2030, which provides inter-operability guidance between smart grids and MG. The International Electro-Technical Commission (IEC) is another standardization body for MG, with IEC 62,898 providing guidelines for MG design and implementation.

RESULT AND DISCUSSION

Intelligent control techniques have been gaining popularity in the MG control system due to their ability to provide efficient and effective control of distributed energy resources (DERs). The application of intelligent control techniques such as artificial neural networks, fuzzy logic controllers, and model predictive control has been investigated in various studies for MG control. The fuzzy logic controller was implemented for the control of MG with renewable energy sources. The results showed that the fuzzy logic controller provided stable and efficient control of the MG, maintaining the voltage and frequency within the acceptable range. This article also investigated the use of an artificial neural network-based controller for the control of MG with wind and solar power sources. The results showed that the neural network controller provided better control of the MG compared to conventional controllers, improving the power quality and reducing the power losses. Model predictive control has also been applied in MG control systems to optimize the operation of DERs. A study investigated the use of model predictive control for the control of MG with a combination of wind and solar power sources. The results showed that model predictive control provided optimal control of the MG, reducing the power losses and improving the power quality. The application of these techniques could help in the efficient integration of renewable energy sources and improve the overall operation of MG.

CONCLUSION

This manuscript presents a comprehensive survey of recent developments in intelligent control techniques for MG. In addition, it provides an overview of MG architecture, various classifications, constituent components, communication technologies, implementation standards, and ancillary services essential for MG operations. In conclusion, the implementation of intelligent control techniques is essential for the efficient and reliable operation of MGs. In this direction, fuzzy logic systems and neural networks (NN) have emerged as effective computational tools for processing large amounts of numerical data such as signals or images. These methods are characterized by nonlinear algorithms that offer computational flexibility, ranging from small software programs to large hardware systems. In Addition, machine learning techniques have been used to optimize their performance and increase their efficiency. One of the primary applications of machine learning in MG systems is load forecasting. Machine learning algorithms can be trained on historical data to predict future load demands, which can be used to optimize the operation of the MG system. Moreover, genetic algorithms can be used to determine the optimal configuration, size, and placement of different components such as renewable energy sources, energy storage systems, and control devices. Besides that, particle swarm optimization (PSO) is a popular optimization technique in MG control due to its simplicity and efficiency. PSO is a swarm-based optimization algorithm. It starts by initializing a population of candidate solutions, called particles, and then updates their positions and velocities iteratively based on the best solution found so far by the swarm and the personal best solution of each particle. Due to ant colony optimization (ACO), is a meta-heuristic optimization algorithm that is inspired by the foraging behavior of ants. In MG applications, ACO has been applied for various control and optimization tasks, including optimal energy management, distributed generation placement, and load balancing. Further research is required to develop more efficient and effective energy management techniques that consider dynamic market pricing, renewable energy integration, and the reliability of the MGs system. With the rapid growth of MGs, the development of advanced energy management systems will be crucial for the sustainable and reliable operation of these systems.

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