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Review Article

Enhancing the resilience and efficiency of microgrids through optimal integration of renewable energy sources and intelligent control systems: A review

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Abstract

Microgrids (MGs) are a critical component in modern power systems, comprising interconnected loads and distributed energy resources (DERs) that can operate autonomously or in conjunction with the main grid. This review examines the role of MGs in advancing smart grid technologies, emphasizing the optimal integration of renewable energy sources (RES) and energy storage systems (ESS) to enhance their resilience and efficiency. It provides a detailed analysis of various MG architectures, including AC, DC, and hybrid topologies, alongside their operational modes. The paper highlights the pivotal role of control systems in optimizing energy management within MGs. Additionally, the challenges associated with MG integration, such as harmonic distortion, system stability, and regulatory constraints, are discussed. The review further explores the application of intelligent control strategies, including Fuzzy Logic Controllers (FLCs) and Genetic Algorithms (GAs), to optimize battery energy storage systems (BESS) and improve overall MG performance. The findings emphasize the need for innovative optimization techniques and intelligent control systems to overcome current limitations, thus enhancing the potential of MGs in future energy systems

1. Introduction

Microgrids (MGs) are decentralized energy systems comprising interconnected loads and distributed energy resources (DERs) that operate within specific electrical boundaries. As defined by the U.S. Department of Energy, MGs possess the unique capability to operate autonomously in island mode or coordinate with the main grid in grid-connected mode [1]. This versatility enables them to adapt to varying energy demands and operational contexts, making them vital in modern energy systems. Typically composed of distributed generation (DG) units such as renewable energy sources like photovoltaic (PV) systems, wind turbines, and fuel cells MGs also include energy storage systems (ESS) and advanced control devices [2-5]. The integration of these components facilitates enhanced local energy efficiency and operational flexibility, with ESS playing a crucial role in supporting renewable energy integration, load balancing, and black-start capabilities, essential for restoring functionality after a system shutdown [6]

As illustrated in Figure 1, a typical microgrid configuration interconnects DGs, ESSs, and adaptable loads via power converters, promoting an efficient energy ecosystem. Current research initiatives focus on advancing MG technologies to overcome technical and economic challenges, including the coordinated management of diverse energy sources and the seamless integration of hybrid AC/DC power networks [7]. These efforts aim to improve MG performance across various dimensions, including planning, operation, protection, and control. Historically, conventional power systems were centralized, with electricity flowing in one direction from large generators to consumers. However, increasing environmental concerns, resource limitations, and grid reliability issues have intensified interest in alternative architectures like MGs. According to the European Technology Platform for Smart Grids, MGs provide a promising solution by integrating DERs, including solar PV systems, biomass, batteries, and micro-turbines, into the existing power grid, thereby ensuring reliable and sustainable power delivery at competitive prices [8,9]. In this evolving landscape, microgrids play a pivotal role in the advancement of modern smart grids, consolidating energy sources and loads while enhancing resilience for sustainable power generation and distribution. The integration of renewable energy sources (RESs) is crucial for maintaining system reliability but poses challenges due to their inherent variability and dependence on weather conditions. Therefore, researchers emphasize the importance of incorporating ESS within MGs to mitigate these challenges and ensure future energy reliability [10].

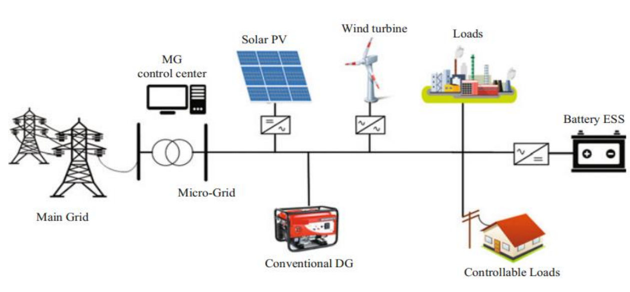

Figure 1: A typical Microgrid setup

2. Methodology

This study adopts a comprehensive literature review methodology to analyze existing microgrid (MG) architectures and control strategies. A systematic evaluation of case studies is conducted to assess the performance, integration challenges, and operational efficiency of MGs in real-world applications. To complement the review, simulations of intelligent optimization techniques, including Fuzzy Logic Controllers (FLCs) and Genetic Algorithms (GAs), are incorporated, demonstrating their effectiveness in managing battery energy storage systems (BESS) within MG environments. Additionally, a qualitative assessment of regulatory frameworks and economic factors influencing microgrid deployment is performed, offering valuable insights into the broader context of MG integration and scalability [11-15].

The literature search was conducted using reputable academic databases, including IEEE Xplore, Scopus, Web of Science, ResearchGate, and Google Scholar. A targeted approach employing keywords such as "Microgrids," "Microgrid control," "Optimal and Classical Control in Microgrid," "Frequency Control," "Voltage Regulation in Microgrid," "Smart Grid," "Optimization Techniques Applied for MG Control," "Fuzzy Logic Controllers," "Genetic Algorithms," "Energy Storage Systems," and "Renewable Energy Optimization" was used to identify relevant articles published in peer-reviewed journals. This process yielded a total of 88 articles, which were carefully selected and analyzed for their relevance to the study objectives.

A critical analysis of the synthesized findings from the literature search was carried out to evaluate the strengths and limitations of existing research, identify knowledge gaps, and explore the implications for enhancing the resilience and efficiency of microgrids. The findings were interpreted within the context of the reviewed articles, emphasizing their relevance and potential to advance the understanding of microgrid performance, optimization strategies, and integration challenges. This multi-faceted approach provides a robust foundation for exploring innovative solutions to improve the reliability, sustainability, and cost-effectiveness of microgrid systems.

3. Microgrids

Microgrids (MGs) are intricate systems consisting of interconnected components that enable local power generation, consumption, energy storage, and a point of common coupling (PCC) with the main grid as shown in Figure 2. Local generation sources include various distributed energy resources (DERs), such as diesel generators and renewable energy technologies like wind turbines and solar panels, which supply electricity to local consumers. The consumption side encompasses a range of devices and systems that utilize electricity, with controllable loads providing the flexibility to manage demand effectively. Energy storage systems (ESSs) are crucial for maintaining system stability and efficiency [16]. They enhance power quality, regulate frequency and voltage levels, mitigate the variability of renewable energy output, and offer backup power during emergencies. The PCC serves as the interface between the microgrid and the main utility grid, allowing grid-connected microgrids to exchange power seamlessly. In contrast, isolated (off-grid) microgrids, often deployed in remote areas, lack a PCC, highlighting their independence from larger grid infrastructures due to technical or economic constraints. These interconnected components collectively form the backbone of microgrids, ensuring efficient and resilient energy management tailored to diverse user requirements [17,18]. Microgrids can be classified based on various factors, including their type, size, application, operational mode, configuration, and feeder characteristics, which are explored in detail in the subsequent sections.

Figure 2: Schematic Diagram of Microgrid

3.1 Types of Microgrids

Microgrids (MGs) can be broadly classified into three main types namely, remote, grid-connected, and networked. Each type is distinct in terms of its design, operational modes, and applications, offering unique advantages based on its environmental and infrastructure context. Understanding these categories helps highlight the adaptability of MGs in addressing various energy challenges and meeting diverse user needs.

1. Remote Microgrids

Remote microgrids operate independently from the main utility grid, making them ideal for serving remote or isolated communities and industrial sites. As depicted in Figure 3, these systems are typically powered by renewable energy sources such as solar and wind, often supplemented by battery storage systems to enhance reliability and ensure continuous energy supply. The primary advantage of remote microgrids lies in their ability to provide energy access to areas lacking traditional grid infrastructure, effectively addressing energy inequities in underserved regions. By operating autonomously, these microgrids promote energy independence, reducing reliance on fossil fuels or costly energy imports. Their reliance on renewable energy sources further supports environmental sustainability while minimizing carbon footprints. Additionally, the integration of advanced storage technologies enhances system resilience, ensuring reliable power delivery even during periods of fluctuating renewable energy generation. Remote microgrids play a critical role in bridging energy gaps, fostering development in isolated regions, and supporting industrial operations in off-grid settings. Figure 3 illustrates a typical configuration, showcasing the interplay of renewable energy sources and storage systems in achieving sustainable, standalone energy solutions [19].

Figure 3: Schematic Diagram of Remote Microgrid

2. Grid-Connected Microgrids

Grid-connected microgrids maintain a physical connection to the main utility grid while retaining the flexibility to operate autonomously during grid outages. These systems are designed for bidirectional power flow, allowing them to draw electricity from the grid or supply surplus energy back to it. Typically deployed in urban areas and industrial facilities, grid-connected microgrids are instrumental in improving the overall performance and resilience of the grid. A key advantage of these systems lies in their ability to enhance grid stability by balancing local energy demand and generation, thereby reducing the risk of power disruptions. They also contribute to reduced energy costs through the integration of renewable energy sources and the efficient use of energy storage, minimizing reliance on expensive grid electricity during peak periods. Furthermore, grid-connected microgrids facilitate the seamless incorporation of renewable energy technologies such as solar and wind power, advancing global decarbonization goals. Their capacity to operate autonomously during outages ensures reliable power supply for critical loads, enhancing the system's resilience and sustainability. Figure 4 illustrates a typical configuration of a grid-connected microgrid, showcasing the interplay between distributed generation (DG), energy storage systems (ESS), and the main utility grid. This setup highlights the adaptability of grid-connected microgrids in meeting the evolving demands of modern energy infrastructure while supporting environmental and economic objectives [19].

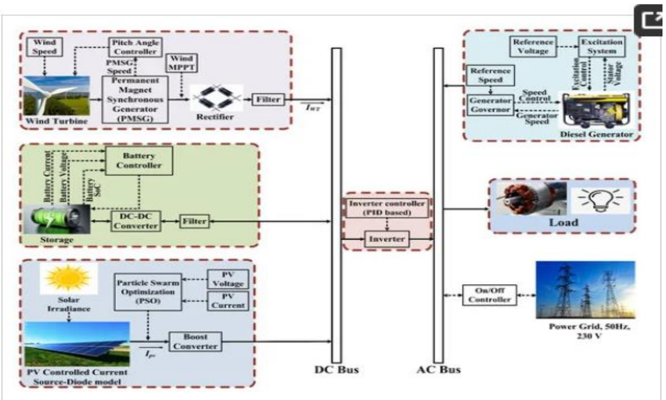

Figure 4: Schematic diagram of Grid-connected microgrids

3. Networked Microgrids

Networked microgrids consist of multiple interconnected distributed energy resources (DERs) within a specific segment of the utility grid, enabling efficient resource sharing and enhancing overall grid resilience. These systems are increasingly implemented in smart city projects and community-based energy initiatives, where their scalability and adaptability are particularly advantageous. The primary benefit of networked microgrids lies in their ability to optimize energy distribution by dynamically balancing supply and demand across interconnected systems. This interconnectedness facilitates efficient resource sharing, allowing energy surplus in one microgrid to meet deficits in another. Such configurations not only improve energy utilization but also enhance the resilience and reliability of the larger grid, making them well-suited for managing varied and dynamic energy demands. Additionally, networked microgrids support flexible and adaptive solutions for diverse grid configurations, enabling them to seamlessly integrate renewable energy sources while improving grid management. These systems are vital in advancing smart city infrastructure, where scalability and efficient energy management are critical for meeting urban energy needs. Figures 5 illustrate how networked microgrids interconnect DERs, showcasing their potential for resource optimization and resilience in modern energy systems [19,20].

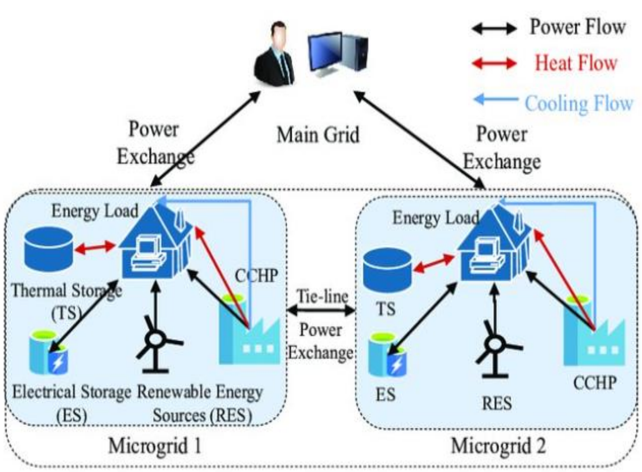

Figure 5: Schematic diagram of Networked Microgrids

3.1.2 Configuration of Microgrids

To efficiently integrate diverse energy sources into the power grid, various architectural configurations are employed, resulting in three primary microgrid topologies: AC, DC, and hybrid. The architecture of these topologies ensures that microgrids can effectively manage the varying energy profiles of different power sources, optimizing energy distribution within the microgrid ecosystem [19,21].

1. Alternating Current Microgrid

AC Microgrid Topology connects power sources that produce alternating current (AC) to a central AC bus through AC/AC converters, ensuring uniform frequency and voltage. This configuration is prevalent due to the dominance of AC power systems in conventional grids. In a typical AC microgrid configuration (as shown in Figure 6), various components are interconnected through a shared AC bus, allowing for seamless integration with conventional AC power systems. This configuration enhances controllability and flexibility. However, integrating DC components into an AC system requires DC/AC converters, which can reduce overall efficiency due to energy losses during conversion processes, as highlighted by several studies [22,23].

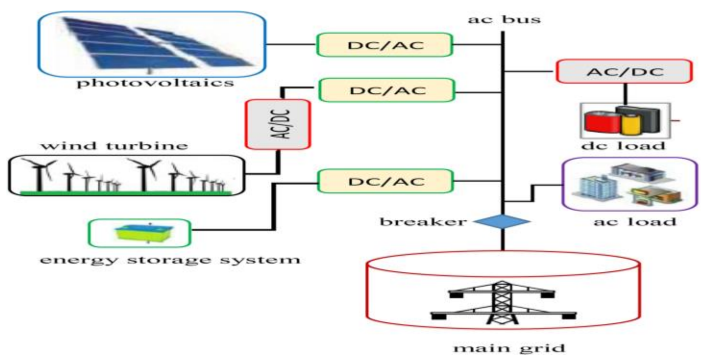

Figure 6: AC microgrid configuration [24]

2. Direct Current (DC) Microgrid

DC Microgrid Topology is designed for integrating power sources with direct current (DC) output, connecting directly to a DC bus or through DC/DC converters. AC power sources are interfaced with the DC bus via AC/DC converters, facilitating the integration of both AC and DC technologies. DC microgrids (DC-MGs) typically feature a centralized DC bus that interconnects various components, enabling direct integration with the main grid through a DC/AC power converter, as depicted in Figure 7. While both DC and AC microgrids operate on similar fundamental principles, DC-MGs offer several distinct advantages over their AC counterparts [22].

One key advantage is the reduced power conversion losses in DC-MGs. Unlike AC microgrids, which often require multiple conversion stages (e.g., AC/DC and DC/AC conversions), DC-MGs involve fewer conversions. This streamlined process leads to enhanced overall efficiency, reduced operational costs, and a more compact system design. Furthermore, DC microgrids offer improved stability because they do not involve reactive power, a factor that often complicates power management in AC systems [21-23]. This characteristic makes DC-MGs particularly well-suited for integrating DERs, such as solar PV systems and battery storage, which inherently generate DC power. Common DC microgrid structures include bipolar, monopolar, and homopolar configurations, each offering unique benefits depending on the application. Bipolar configurations, for instance, provide greater operational flexibility by supporting multiple voltage levels, while monopolar and homopolar configurations are simpler and more cost-effective for specific use cases [22,25, 26].

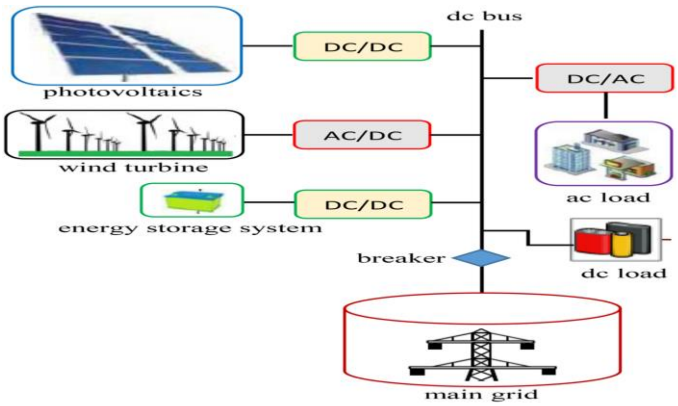

Figure 7: DC microgrid configuration [24]

3.2 Hybrid Microgrid

Hybrid Microgrid Topology combines both AC and DC power sources, enabling efficient energy flow between the AC and DC buses through bidirectional converters [27]. This configuration is particularly suited to microgrids incorporating diverse energy sources, allowing seamless energy exchange between different systems. Hybrid microgrids (HMGs) combine both AC and DC microgrid components within a single distribution system, enabling the direct integration of AC and DC elements, as shown in Figure 8. By capitalizing on the strengths of both AC and DC systems, HMGs provide a range of advantages that enhance overall performance and efficiency [28].

One of the key benefits of HMGs is the reduction in the number of interface devices required. By allowing AC and DC components to connect directly to their respective buses, HMGs minimize the need for conversion stages, which in turn reduces power losses and system complexity [27]. This streamlined integration of DERs and ESSs results in lower operational costs and a more compact system design. Additionally, HMGs offer improved reliability due to the flexibility in connecting AC and DC components without the need for synchronization between generation and storage units. This capability enables a more robust and resilient system, as AC and DC resources can operate independently while still contributing to the overall energy mix. HMGs are particularly advantageous for applications where both AC loads (such as conventional appliances) and DC loads (like solar PV systems and battery storage) coexist, ensuring optimal energy management across different energy domains. In summary, hybrid microgrids deliver the best of both AC and DC systems, offering reduced conversion losses, lower costs, and enhanced flexibility [28]. These benefits make HMGs an effective solution for integrating diverse energy sources while maintaining high reliability and efficiency in modern power distribution networks [20, 29]

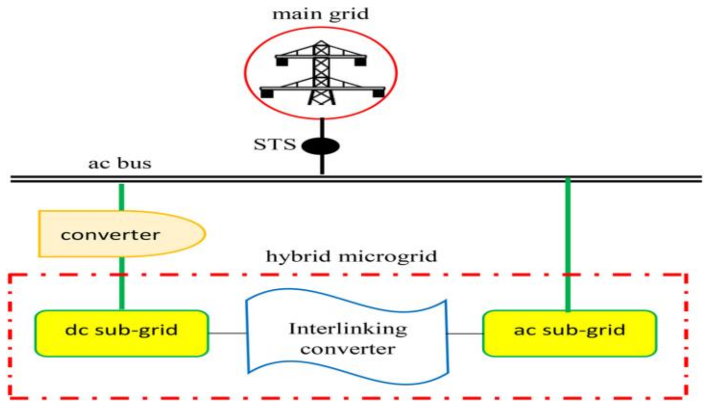

Figure 8: Hybrid microgrid configuration [24,29]

3.3 Advantages, Challenges, and Solutions of Microgrids

By decentralizing energy generation and promoting the use of renewable energy sources (RES), microgrids enable localized energy production that reduces transmission losses and supports cleaner power solutions [33]. However, despite these advantages, MGs face several technical, operational, and economic challenges. These challenges include managing harmonic distortion, maintaining grid stability in low-inertia systems, and ensuring reliable protection and fault detection. To overcome these obstacles, innovative technologies and optimization strategies are being developed, including advanced grid stabilization devices, microprocessor-based protection systems, and intelligent energy management algorithms [34]. By addressing these challenges, the future of microgrids can be realized as a robust, flexible, and sustainable component of the global energy landscape.

3.3.1 Advantages of Microgrids

MGs offer a range of benefits that make them vital to modern power systems, especially in terms of enhancing energy resilience, efficiency, and sustainability. One of their most significant advantages is the localization of energy generation, which reduces transmission losses by producing and distributing power near the point of use. This proximity to demand not only minimizes energy waste but also enhances grid stability, particularly in regions prone to blackouts [35]. By facilitating the integration of RES like solar and wind, microgrids play a crucial role in lowering carbon emissions and mitigating climate change. These systems are especially valuable in islanded mode, where they can function independently from the main grid, ensuring a reliable and uninterrupted power supply during grid outages or emergencies [36].

Additionally, MGs offer operational flexibility, seamlessly transitioning between grid-connected and islanded modes, depending on grid conditions or energy needs [37]. This bidirectional power flow allows microgrids to feed excess energy back to the main grid or draw power when required, improving the overall reliability and stability of the energy system. Economically, microgrids lower infrastructure costs by reducing the need for extensive grid expansion, while combined heat and power (CHP) systems in microgrids enhance efficiency, particularly for critical loads like hospitals or data centers. These factors make microgrids an attractive solution for both urban and rural energy management [38,39].

3.3.2 Challenges of Microgrids

While the benefits of microgrids are substantial, they also present several technical and economic challenges that hinder widespread deployment and integration. One prominent challenge is harmonic distortion, a result of the increased use of power-electronic-based (PEL) devices within microgrids. These devices, which are commonly used in renewable energy integration, generate harmonic currents that can destabilize the system. Both active and passive filtering techniques are required to manage these distortions effectively [40,41].

Another significant challenge is low network inertia, especially in microgrids that heavily rely on RESs. Traditional power grids have higher inertia, which helps maintain frequency stability. In contrast, the lower inertia of microgrids leads to frequency regulation issues and voltage instability, especially during periods of fluctuating power output from DERs [42,43]. Additionally, coordinating DERs and managing ESS is complex, requiring sophisticated control strategies to balance supply and demand, ensure reliability, and optimize operational costs [44].

Protection and fault detection also present challenges. In grid-connected and islanded modes, MGs require reliable protection schemes to prevent system-wide failures. Smart devices and fast static switches are essential for rapid fault detection and isolation, but these solutions come with high costs and technical complexity [45]. Furthermore, regulatory and economic barriers persist, with many regions lacking clear frameworks for MG integration and interconnection with utility grids. The high initial costs of microgrid implementation also limit their widespread adoption [46].

3.3.3 Solutions to Microgrid Challenges

Despite these challenges, several solutions have been proposed to enhance the reliability and efficiency of microgrids. One effective approach is the implementation of Flexible AC Transmission Systems (FACTS), which includes devices such as static VAR compensators (SVCs), static synchronous compensators (STATCOMs), and unified power flow controllers (UPFCs). These devices help stabilize the grid, mitigate harmonic distortions, and ensure reliable power flow, particularly when integrating variable RESs [47]. To address protection challenges, researchers have developed advanced protection techniques, including microprocessor-based systems equipped with overcurrent relays and fault current limiters. These systems can quickly detect faults and isolate affected sections of the grid, minimizing the impact on the overall microgrid operation [48].

Optimization algorithms also play a crucial role in improving the efficiency of MGs. For instance, rolling-horizon optimization algorithms help manage economic and operational challenges by optimizing energy costs in real-time, while islanding criteria optimization enhances system performance during transitions between grid-connected and islanded modes [49]. Finally, the development of intelligent hybrid transfer switches offers a solution for smoother mode transitions. These switches enable more reliable detection and management of islanding scenarios, ensuring that the microgrid operates seamlessly whether connected to or independent from the main grid [50, 51]. In summary, microgrids offer numerous advantages, including improved grid stability, enhanced energy resilience, and integration of renewable energy. However, they also face challenges related to harmonic distortion, low inertia, and protection mechanisms. Solutions such as FACTS devices, advanced protection systems, and optimization algorithms provide promising pathways to address these challenges, ensuring that microgrids can continue to evolve as a cornerstone of modern energy infrastructure

3.4 Traditional Optimization Techniques for Microgrids

Traditional optimization techniques play a crucial role in enhancing the design, operation, and control of microgrids (MGs). These techniques aim to optimize various factors such as energy generation, load demand, storage capacity, and control strategies to achieve a balance between reliability, cost-effectiveness, and sustainability. The optimization approaches can be broadly classified into four categories: Classical, Heuristic, Nature-Inspired, and Optimization techniques. Each of these methods has been applied in different contexts to improve microgrid performance, addressing key challenges like energy stability, cost reduction, and integration of renewable energy sources. The following subsections explore how each of these techniques contributes to optimizing microgrid systems:

3.4.1. Classical Optimization Techniques

Classical optimization techniques utilize mathematically rigorous approaches to solve optimization problems involving well-defined objective functions and constraints. These techniques include methods such as Linear Programming (LP), Integer Programming (IP), and Dynamic Programming (DP), which are grounded in established mathematical algorithms. Classical optimization is particularly valuable when dealing with deterministic problems where the relationships between variables are linear or can be approximated as such.

Application of Classical Optimization Techniques in Microgrid Control

1. **Energy Demand Estimation and Sizing**: Classical optimization techniques, particularly LP and IP, are widely applied to estimate energy demand and determine the optimal configuration of energy generation sources

in microgrids. These techniques allow for modeling the integration of various renewable energy sources (RES) such as solar and wind, alongside energy storage systems. The goal is to minimize both operational costs and environmental emissions while ensuring a reliable and stable energy supply. By formulating objective functions that reflect cost minimization and emission reduction, classical methods offer an efficient way to determine the most cost-effective mix of energy sources and storage capacities to meet local energy demands.

2. **Economic and Stability Evaluations**: In microgrid design, economic viability and stability are critical factors for ensuring long-term sustainability. Classical optimization techniques are instrumental in evaluating the financial feasibility and operational stability of microgrids, especially in rural or off-grid areas where energy access is limited. Researchers often apply LP and IP to assess hybrid systems, such as those combining Combined Heat and Power (CHP) systems, renewable energy sources (RES), and energy storage solutions. These evaluations help identify cost-effective configurations that provide a reliable energy supply while maintaining economic and technical stability.

Hence, many studies have applied linear and integer programming to optimize the design and operation of microgrids in rural areas, with a focus on minimizing costs and ensuring energy reliability and sustainability [52, 53]. These methods have been essential in identifying optimal solutions for energy generation, storage, and distribution in regions with limited access to grid infrastructure.

3.4.2. Heuristic Techniques

Heuristic methods are employed to find approximate solutions to complex optimization problems, particularly when obtaining exact solutions is impractical due to time or computational limitations. These methods are especially useful for addressing problems where multiple variables and constraints interact in non-linear and dynamic environments [54]. Algorithms such as Genetic Algorithms (GA), Simulated Annealing, and Particle Swarm Optimization (PSO) are common in this category, as they are capable of exploring large solution spaces efficiently and finding near-optimal solutions in a reasonable amount of time.

Application of Heuristic Techniques in Microgrid Control

1. **Optimization of Hybrid Energy Systems**: Heuristic techniques are commonly applied in the optimization of hybrid energy systems within remote microgrids. These systems often integrate renewable energy generation sources, such as solar and wind, with energy storage systems (ESS) to provide reliable power [55]. Heuristic methods, including GA and PSO, are particularly effective in determining the optimal sizing and integration of both generation and storage capacities. These algorithms address multi-objective optimization problems, balancing factors such as cost reduction, emissions minimization, and reliability maximization. Their flexibility in handling complex constraints and large solution spaces makes them ideal for optimizing microgrid configurations in scenarios where exact solutions are difficult to derive.
2. **Battery Storage Integration**: Heuristic methods are also instrumental in optimizing the operation of energy storage systems, such as lithium-ion batteries, in microgrids. These techniques help determine optimal strategies for charging and discharging storage systems, ensuring efficient energy use. By absorbing excess energy during periods of high generation and providing power during low generation periods, heuristic algorithms contribute to maintaining energy balance and improving overall system efficiency. The adaptability of these methods allows for dynamic optimization, ensuring that storage systems operate in a manner that maximizes their lifespan and performance under varying load and generation conditions.

Furthermore, several studies have successfully applied Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) for energy storage optimization in microgrids, demonstrating their effectiveness in optimizing battery storage operations and hybrid energy system configurations [55, 56]. These methods are particularly valuable for solving the multi-objective optimization problems inherent in microgrid energy management.

3.4.3 Nature-Inspired Techniques

Nature-inspired optimization techniques draw inspiration from natural phenomena and biological processes such as evolutionary dynamics, swarm intelligence, and self-organizing systems. These algorithms, including Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Firefly Algorithms, mimic the adaptive behaviors observed in nature to solve complex optimization problems [57,58]. These methods are particularly effective in scenarios where traditional approaches may struggle to find optimal solutions due to the complexity and dynamic nature of the system.

Application of Nature-Inspired Techniques in Microgrid Control

1. **Renewable Energy Sourcing and Battery Integration**: Nature-inspired techniques are widely used to optimize the integration of renewable energy sources, such as solar and wind, within microgrids. Algorithms like ACO and ABC are applied to identify optimal locations for energy generation systems, determine the best configuration for solar and wind installations, and ensure that energy storage systems are efficiently integrated into the overall microgrid architecture. These techniques excel in handling multi-dimensional optimization problems, where the aim is to minimize operational costs, reduce emissions, and maximize energy stability. Their ability to explore large search spaces and adapt to changing conditions makes them well-suited for

optimizing microgrid designs that rely on variable renewable energy sources.

2. **Energy Storage Systems**: Nature-inspired optimization techniques also play a crucial role in designing control strategies for energy storage systems. For instance, the interaction between supercapacitors and lithium-ion batteries can be optimized using these methods to ensure efficient energy storage and discharge. By enabling rapid bursts of power during periods of high demand, while simultaneously ensuring long-term storage efficiency, these algorithms help maintain energy balance and improve the reliability of microgrids. They contribute to developing dynamic control strategies that adapt to real-time fluctuations in energy generation and consumption, further enhancing microgrid performance.

Recent studies have investigated the use of Ant Colony Optimization (ACO) for optimizing the integration of renewable energy sources and energy storage systems in microgrids. ACO has proven effective in addressing complex optimization challenges related to energy storage and renewable energy sourcing, resulting in more efficient operations and cost-effective solutions [59, 60]. These techniques are especially valuable for optimizing system configurations in scenarios where traditional optimization methods may not perform as effectively.

3.4.4 Optimization Techniques in Microgrid Control

Optimization techniques refer to methods aimed at enhancing the performance of systems by adjusting variables to achieve the best possible outcome, based on defined objectives. These techniques can be classified into both traditional and modern approaches, often incorporating **multi-objective optimization (MOO)**. MOO is particularly relevant in microgrid control, as it addresses the challenge of optimizing several competing objectives simultaneously, such as cost, emissions, and reliability [59,61].

Application of Optimization Techniques in Microgrid Control

1. **Multi-objective Optimization**: In microgrid control, optimization often involves balancing multiple objectives, which are frequently in conflict. For example, a microgrid must minimize operational costs while reducing emissions and maintaining high reliability. Multi-objective optimization techniques are employed to simultaneously optimize these competing factors, ensuring that no single objective is excessively compromised. Advanced control strategies integrate energy storage systems and renewable energy sources, such as solar and wind, to meet the energy needs while carefully managing trade-offs between cost reduction, emissions, and reliability. These methods allow for a more nuanced and comprehensive approach to microgrid optimization, ensuring that the system performs optimally across multiple dimensions.
2. **Microgrid Sizing and Configuration**: Optimization techniques are also crucial in determining the appropriate size and configuration of energy generation systems and energy storage capacities in microgrids, particularly in rural and isolated regions. By applying optimization methods, the right mix of technologies such as solar, wind, and storage solutions like lithium-ion batteries can be selected to minimize operational costs, enhance energy reliability, and reduce the carbon footprint of the system. These techniques ensure that microgrids are not only financially viable but also sustainable and resilient in meeting local energy demands.

Moreover, several studies have explored multi-objective optimization in the context of microgrid design and operation, demonstrating its effectiveness in addressing the complex trade-offs inherent in microgrid systems [58, 59]. These methods play a crucial role in optimizing microgrid configurations, ensuring that economic, environmental, and technical objectives are balanced for optimal system performance.

3.5 Improvement Suggestions for Microgrid Optimization Techniques

1. **Integration of Hybrid Techniques**: Combining classical, heuristic, and nature-inspired optimization methods can enhance the efficiency of multi-objective optimization in microgrids. Classical methods, such as linear programming or dynamic programming, can be employed for initial system sizing and configuration, providing a robust starting point. Heuristic or nature-inspired algorithms, like genetic algorithms (GA) or ant colony optimization (ACO), can then refine the design and operational parameters, ensuring optimal performance under dynamic and uncertain conditions. This hybrid approach leverages the strengths of each method, addressing both structured and complex optimization challenges [61].
2. **Advanced Storage Technologies**: The inclusion of emerging storage technologies, such as solid-state batteries and next-generation supercapacitors, offers significant potential for improving microgrid performance. Solid-state batteries provide higher energy density, enhanced safety, and longer lifespans compared to conventional lithium-ion solutions. Similarly, next-generation supercapacitors deliver rapid charge-discharge capabilities with increased energy capacity, making them ideal for handling peak demand and smoothing renewable energy fluctuations. Optimization techniques should incorporate these advanced technologies to evaluate their integration and operational strategies effectively.
3. **Data-Driven Optimization**: Machine learning (ML) and artificial intelligence (AI)-based optimization methods can complement traditional techniques, enabling more adaptive and intelligent decision-making for microgrid operations. By analyzing large datasets, such as weather forecasts, energy demand patterns, and system performance metrics, ML algorithms can predict and optimize energy flows in real-time. AI-driven

control systems can dynamically adapt to changes in generation and demand, improving energy efficiency, reducing costs, and enhancing reliability. Integrating these data-driven approaches with existing methods allows microgrids to operate more effectively in diverse and complex scenarios [62].

By incorporating hybrid approaches, exploring advanced storage technologies, and leveraging data-driven optimization, microgrid systems can achieve improved efficiency, cost-effectiveness, and sustainability. These advancements will support a wide range of applications, from urban centers to remote rural areas, driving progress toward a more resilient and renewable energy future.

3.6 Cost and Optimization in Microgrid Design

Cost considerations play a pivotal role in the selection of energy storage technologies for MGs. Research into different storage solutions has shown that while some options are promising for specific applications, they remain expensive. Optimism for future cost reductions is driven by factors such as the increased adoption of renewable energy sources, favorable government policies, and advances in power grid infrastructure [63,64]. This suggests that continued innovation in energy storage technology is essential to improving the cost-effectiveness and performance of MGs.

Conventional optimization methods for microgrids, particularly regarding battery storage charging and discharging techniques, have been extensively studied. Techniques like constant current-constant voltage (CC-CV), pulse charging, reflex charging, and trickle charging are widely used but face challenges such as overcharging risks, prolonged charging times, and inefficiencies due to temperature regulation [12,4]. These conventional methods, though effective in many cases, often struggle with maintaining battery health and optimizing charging times, especially for lithium-ion batteries. Recent studies have shifted towards more sophisticated charging and discharging methods. For instance, improvements in state-of-charge (SOC) estimation and optimization of charge cut-off voltages have resulted in better charging efficiency. These advancements take into account factors like polarization effects and thermal behavior to dynamically adjust charging parameters, reducing battery wear and increasing overall system performance [65].

3.7 Novel Charging Techniques and Battery Management

New charging techniques are being explored to address the limitations of traditional methods. The scholar in [66] introduced a novel closed-loop charging method known as CT-CV (Constant Temperature-Constant Voltage), which dynamically adjusts the charging current based on real-time monitoring of battery voltage and temperature. This method achieved a 20% faster charging rate compared to the conventional CC-CV method without significantly increasing battery temperature. This innovation is particularly useful for lithium-ion batteries and can be applied to larger battery packs when integrated with battery management systems (BMS).

Another significant advancement was made by [67] who used Taguchi orthogonal arrays to optimize pulse charging parameters for lithium-ion batteries. Their findings showed a 47.6% reduction in charging time and improvements in energy efficiency, positioning pulse charging as a viable alternative to traditional CC-CV methods. In the context of DC microgrids (DC-MG), [68,69] proposed an innovative bidirectional DC charger based on reflex charging principles. This charger, designed for light electric vehicle (LEV) batteries, integrates an unregulated level converter and a two-phase interleaved buck-boost charge pump converter, offering significant efficiency gains and extended battery life. This technology is particularly relevant for sustainable vehicle operation within DC-MGs.

3.8 Optimization Approaches in Microgrid Control

Optimizing power flow in MGs requires advanced control techniques. The researcher in [70] introduced a convex model predictive control (MPC) approach to optimize dynamic power flow between battery energy storage (BES) systems in AC microgrids (AC-MGs). By using a linear d-q reference frame voltage-current model and linearized power flow approximations, this method enables the use of fast and efficient solvers, reducing computation time significantly compared to traditional non-convex optimization methods. This advancement improves real-time MG management and enhances system stability. Despite these improvements, traditional optimization techniques still face limitations. Techniques like droop control and MPC have advanced MG design, but they introduce challenges such as harmonic distortion, slow dynamic response, and complex mathematical calculations [10,3]. Overcoming these challenges requires further research into more efficient, cost-effective, and reliable MG control strategies, particularly as MGs become more complex with the integration of renewable energy sources and energy storage technologies. Table 1 depicts the Distinctive features and limitations of the traditional charging-discharging methods**.**

Table 1: Distinctive features and limitations of the traditional charging-discharging methods [10]

S/n	Methods	Features	Limitations
1	CC	It involves mitigating overcurrent, enhancing charging efficiency, and aligning with slow charging needs.	This involves unregulated battery voltage, high temperature, and a straightforward charging mode
2	CV	This encompasses regulating the initial charging current, mitigating overvoltage stress, and enhancing charging capacity	This includes slow charging speed, reduced efficiency, temperature elevation, diminished battery lifespan, and a straightforward charging mode.
3	CC-CV	This involves regulated implementation, and a simplified approach aimed at curbing capacity degradation	This encompasses a straightforward charging mode, elevated temperature, and suboptimal charging speed and efficiency.
4	PC	This involves maintaining battery	This entails a complex nature that adversely

		voltage stability and implementing voltage pulses through the regulation of the duty cycle	affects both charging performance and battery lifespan
5	MPC	This prolongs battery lifespan, shortens charging duration, and minimizes active power fluctuations.	It involves intricate operational processes and necessitates extensive maintenance efforts.
6	PI	It entails achieving stability and eliminating steady-state errors.	This implies the absence of rapid charging capabilities, elevated power losses, and challenges in establishing consistent coefficients for diverse operating conditions.

3.9 Intelligent Optimization Techniques

In the realm of energy management and battery control, intelligent optimization techniques have become essential tools for improving system Intelligent Optimization Techniques efficiency and reliability. Various optimization algorithms have been introduced to overcome specific challenges in energy storage, charging, and discharging processes. This section explores key techniques and their practical applications, with a focus on improving system performance and addressing existing limitations.

3.9.1 Particle Swarm Optimization (PSO)

PSO in controlling the charging and discharging processes of lithium-ion batteries. The system incorporated a bidirectional flyback DC-DC converter to facilitate energy exchange between the batteries, enhancing charge performance [71,72]. Despite its advantages, PSO faces issues such as particle scattering, premature convergence, and local minima entrapment, which hinder its performance in more complex or dynamic systems. Improvements to PSO can be achieved by incorporating strategies like adaptive velocity adjustments or hybridizing PSO with other optimization techniques such as Genetic Algorithms (GA) or Differential Evolution (DE). These approaches enhance PSO's ability to explore solution spaces more effectively, reducing the likelihood of getting trapped in suboptimal solutions.

3.9.2 Genetic Algorithms (GA)

Genetic Algorithms have been widely applied in battery energy storage optimization, offering robust search capabilities across large solution spaces. The scholar in [73] optimized the charging and discharging schedules of electric buses in a transportation system using GA, improving system efficiency but encountering issues related to computational complexity and prolonged calculation times. To address these challenges, introducing parallel GA or distributed computing frameworks can significantly reduce computation time, making GA more suitable for real-time applications. Moreover, applying adaptive GA variants, which dynamically adjust mutation and crossover rates based on solution quality, can further optimize performance. In GA, a chromosome is a representation of a potential solution to an optimization problem, encoded in a format suitable for evolutionary operations like crossover and mutation. Each chromosome consists of genes, which correspond to the input variables or decision parameters of the problem. For optimizing a battery storage system, the chromosome encodes the system's key parameters that influence performance. These could include battery capacity, charge/discharge rates, state of charge (SOC), power demand, and temperature. Each gene represents one of these variables, and the entire chromosome defines a specific configuration of the battery storage system as represented in equation (1)-(8).

$$C = \{x_1, x_2, \ldots\ldots, x_n\} \tag{1}$$

Where C is the chromosome, and $x_1, x_2, \ldots\ldots, x_n$ are the decision variables

Initialization

A population of N chromosomes is initialized randomly. Each chromosome represents a candidate solution, with each gene in the chromosome being a possible value for the decision variables.

$$P = \{C_1, C_2, \ldots\ldots, C_N\} \tag{2}$$

Fitness Function

The fitness function evaluates how good a solution (chromosome) is, based on the objectives of the system.

Let $f(C_i)$ be the fitness of chromosome C_i which could be defined as:

$$f(C_i) = \frac{1}{1 + E(C_i)} \tag{3}$$

Selection

Selection is the process of choosing chromosomes from the population to create offspring. Higher fitness chromosomes are more likely to be selected. One common selection method is roulette wheel selection, where the probability of selecting chromosome C_i is proportional to its fitness.

$$P\left(C_i = \frac{f(C_i)}{\sum_{j=1}^{N} f(C_j)}\right) \tag{4}$$

Crossover (Recombination)

Crossover combines two parent chromosomes to create offspring. A common method is single-point crossover, where a crossover point is randomly selected, and the two parents exchange parts of their chromosomes at that point.

For parents

$C_1 = \{x_1,....,x_k, x_{k+1},....,x_n\}$ and
$C_2 = \{y_1,....,y_k, y_{k+1},....,y_n\}$, the offspring would be:

$$C_{child1} = \{x_1,....,x_k, x_{k+1},....,x_n\} \quad (5)$$

$$C_{child2} = \{y_1,....,y_k, y_{k+1},....,y_n\} \quad (6)$$

Mutation

Mutation introduces small random changes to the genes in a chromosome, helping to maintain genetic diversity and avoid local optima. For a gene x_i in a chromosome C, a mutation might add a small random value δ:

$$x_i^1 = x_i + \delta, \delta \approx N(0, \sigma) \quad (7)$$

Where: δ is a normally distributed random variable with mean 0 and standard deviation σ.

Stopping Criterion

The GA stops when either:
A predefined number of generations is reached, or the fitness of the best chromosome reaches a desired threshold as shown in equation (8).

$$\max(f(C)) \geq \text{Fitness Threshold} \quad (8)$$

Salp Swarm Algorithm (SSA)

The scholar in [17] used the Salp Swarm Algorithm (SSA) to identify real battery capacities in a load-sharing method for parallel batteries within a DC microgrid. The use of SSA, combined with bidirectional DC-DC converters, significantly enhanced precision in charge and discharge management while ensuring proportional power distribution and extending battery life. SSA's performance could be enhanced by incorporating chaotic mapping or multi-objective optimization techniques to improve population diversity and exploration in complex, multi-faceted scenarios like hybrid energy systems.

3.9.3 Binary Particle Swarm Optimization (BPSO)

BPSO, as demonstrated by [74,62], proved effective in optimizing energy management in virtual power plants, significantly reducing energy consumption and emissions. This technique, although promising, can be limited by premature convergence in large-scale systems. To overcome this, integrating local search techniques with BPSO or introducing a dynamic inertia weight strategy can ensure a balance between exploration and exploitation, thus improving convergence toward the global optimum.

3.9.4 Fuzzy Logic Controllers (FLCs)

Fuzzy Logic Controllers (FLCs) have emerged as popular tools for managing complex, non-linear systems, particularly in microgrid applications. Research by [75,76] demonstrated the efficacy of FLCs in controlling battery charge and discharge operations within microgrids. FLCs offer clear linguistic rules and easy implementation, making them suitable for dynamic systems with unpredictable behavior. However, FLCs are constrained by their reliance on expert knowledge for defining rules and variables, leading to subjectivity and computational inefficiency. Hybrid methods, such as combining FLC with Neural Networks or Evolutionary Algorithms, have shown promise in enhancing the controller's robustness by optimizing membership functions and refining rule bases dynamically.

3.9.5 Hybrid Optimization Approaches

Hybrid methods are gaining popularity for their ability to combine the strengths of multiple optimization techniques. For instance, [12] introduced a hybrid PSO-based FLC that optimized membership functions for variables such as power demand and state of charge (SOC), leading to significant reductions in energy consumption and costs. Similarly, the author in [77], employed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to manage photovoltaic systems, improving efficiency under varying weather conditions. Further research could focus on refining hybrid models by incorporating machine learning to predict system behavior more accurately, allowing the optimization algorithms to adapt dynamically to changing conditions, further improving efficiency and resilience. Despite the advances in optimization techniques, several key challenges remain. For example, temperature effects, which significantly impact battery performance, are often overlooked in optimization models. Developing comprehensive strategies that incorporate thermal dynamics and other factors such as aging models could enhance battery longevity and overall system reliability. Moreover, optimization models often use simplified charging patterns, which may not fully leverage the potential of FLCs or other techniques. Multi-level charging patterns, which take into account dynamic energy demand and supply fluctuations, could improve the accuracy and efficiency of battery management systems.

3.9.6 Sugeno-Takagi Fuzzy Controllers

This study proposes the adoption of a Sugeno-Takagi fuzzy controller, which is better suited for non-linear systems with sudden variations in operating conditions. The Sugeno-Takagi model offers faster computational speeds compared to the Mamdani model due to its mathematical formulation, making it ideal for real-time applications. By combining Sugeno-Takagi with ANFIS, the system can automatically adjust the controller's parameters based on real-time data, further improving performance [78]. In cases where the input-output relationship is unknown, Genetic Algorithms or Particle Swarm Optimization can be used to fine-tune the fuzzy rules, ensuring optimal system performance even in highly uncertain environments.

Intelligent optimization techniques have shown immense potential in enhancing energy management and battery control, but significant improvements can still be made. Hybrid models that integrate multiple optimization methods offer the most promise for future applications, as they can better handle the complex, multi-variable nature of modern energy systems [79]. Additionally, developing more sophisticated models that account for factors such as temperature, battery degradation, and dynamic energy demands will be critical for further improving the efficiency, reliability, and sustainability of these systems [80].

3.9.7 Fuzzy Logic Control System

A Fuzzy Logic Control System (FLCS) is an advanced control mechanism that employs fuzzy logic principles to analyze input values and make decisions. Unlike traditional control systems, which operate using binary logic (true/false or 1/0), fuzzy logic employs a continuum of truth values ranging from 0 to 1. This characteristic enables fuzzy systems to effectively manage uncertain or imprecise inputs, allowing for more nuanced decision-making in complex scenarios [81]. Fuzzy logic is particularly beneficial in situations where establishing definitive rules is challenging, as it closely resembles human decision-making processes, thus facilitating easier design and interaction with the system. Fuzzy Logic Controllers (FLCs) are widely applied across various sectors, including industrial automation, medical devices, and, notably, renewable energy systems, where the inherent complexity often precludes the use of conventional control techniques [82].

3.9.7.1 Advantages of Fuzzy Logic Control

The primary advantage of fuzzy logic control lies in its capability to handle uncertainty and imprecision effectively. FLCs exhibit robustness, adapting seamlessly to diverse operating conditions. Their customizable nature allows them to emulate human reasoning, making them particularly valuable for automating tasks traditionally performed by humans. For instance, in renewable energy applications such as solar tracking systems, fuzzy controllers can adjust the position of solar panels based on varying environmental conditions, maximizing energy capture without precise measurements of sunlight intensity. However, despite these benefits, fuzzy logic systems have limitations. They often require substantial datasets and considerable human expertise for design and maintenance. Additionally, fuzzy rules need continuous updates to reflect changing conditions, and performance may diminish when confronted with data that significantly deviates from historical patterns [81,83].

3.9.7.2 Applications of Fuzzy Logic Control

Fuzzy control systems have gained popularity across diverse fields due to their flexibility and effectiveness in managing complex systems. Their applications span industries, including automotive engineering, robotics, aerospace, and renewable energy systems like wind turbine control and grid management. FLCs can optimize energy output and maintain stability in power systems by managing nonlinear or dynamic behaviors. However, it is important to note that fuzzy logic systems are best suited for tasks that can accommodate some level of imprecision, as their reliance on fuzzy rules may occasionally lead to less accurate outcomes [83,82].

3.9.7.3 Components of Fuzzy Logic Control Systems

A fuzzy logic control system comprises several integral components that collaboratively process input data and produce output decisions. These components are depicted in the Figure 9.

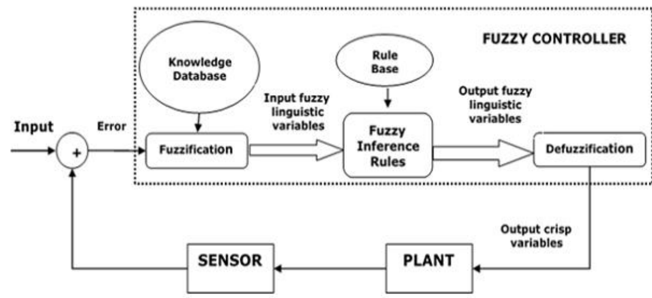

Figure 9: The structure and components of a fuzzy logic system [83]

1. Fuzzifier: The fuzzifier serves as the initial stage of the fuzzy logic control system. Its primary function is to transform precise, real-world input data often in crisp form into fuzzy values. These fuzzy values are categorized into fuzzy sets that describe degrees of truth rather than binary outcomes. The fuzzifier empowers the system to interpret ambiguous, uncertain, or imprecise data, which is common in real-world environments.

2. Fuzzy Knowledge Base: The fuzzy knowledge base complements the rule base and is comprised of two key components: the database and the membership functions.

Database: This segment defines the fuzzy sets associated with each input and output variable. It encompasses the range of values that the system can interpret and categorize into fuzzy subsets.

Membership Functions: These mathematical functions quantify the degree to which a particular input belongs to a fuzzy set. They facilitate the mapping of fuzzy values onto real-world conditions, enhancing the system's interpretative capabilities.

3 Fuzzy Rule Base: The fuzzy rule base houses the decision-making rules for the system. These rules, formulated by human experts or derived from data, elucidate the relationship between inputs and outputs. Typically structured as IF-THEN statements, these rules articulate the system's behavior in terms of fuzzy logic. By utilizing linguistic variables, fuzzy rules enable the system to operate in a manner that closely mirrors human decision-making [84].

Inference Engine: The inference engine constitutes the core decision-making unit of the fuzzy logic control system. It applies the fuzzy rules from the rule base to the fuzzy input data, analyzing the inputs in accordance with the predefined rules and generating fuzzy outputs based on applied logic. By synthesizing all fuzzy rules, the inference engine produces a set of fuzzy conclusions that dictate the expected output in fuzzy terms [84,85].

Defuzzifier: The defuzzifier represents the final stage of the fuzzy logic control system. Its role is to transform the fuzzy outputs generated by the inference engine into crisp, actionable outputs. This process, known as defuzzification, is essential because real-world systems typically necessitate precise, concrete outputs rather than fuzzy values. Various methods exist for performing defuzzification, including the centroid method, max-membership method, and mean of maximum, each calculating the crisp output differently based on the specific application requirements [85,86]. Together, these components enable FLCS to manage imprecise inputs effectively and produce actionable outputs, making them essential in the field of renewable energy [84-90].

3.10 Further Improvements and Exploration

1. Real-World Examples: Consider including specific case studies or examples where FLCS has successfully been implemented in renewable energy systems, such as solar or wind energy management.

2. Comparison with Other Control Systems: A brief comparison between fuzzy logic control systems and other advanced control mechanisms, like PID controllers or neural networks, could provide additional context on when to use fuzzy logic.

3. Future Trends: Discuss emerging trends in fuzzy logic control systems, such as their integration with machine learning or Internet of Things (IoT) technologies in renewable energy applications.

4. Challenges and Solutions: Expand on the limitations of fuzzy logic systems by exploring potential solutions or recent advancements that address these challenges, such as automated rule generation or hybrid control systems.

In summary, fuzzy logic control systems offer a powerful alternative to traditional control mechanisms, particularly in managing complex, nonlinear, and dynamic systems. By effectively handling uncertainty and imprecision, these systems enhance decision-making processes in diverse applications, thereby demonstrating their significant utility in modern control engineering.

Table 2: Summary of Related Review on battery charging and discharging

S/N	Topic	Methodology	Contributions	Research Gaps
1	Charging and discharging model of lithium-ion battery for charge equalization control using particle swarm optimization algorithm [71]	PSO to control lithium-ion battery charging	Improved battery charge performance using bidirectional flyback DC-DC converter	Scattering issues, premature convergence, and local minima
2	Battery charging and discharging scheduling with demand response for an electric bus public transportation system [73]	GA for optimizing bus battery charging/ discharging	Optimized charging/discharging in the bus transportation system	Large population size, complexity, and extended computation times
3	Adaptive droop-based control strategy for DC microgrid including multiple batteries energy storage systems [14]	Refined load-sharing method using droop control and Salp Swarm Algorithm	Ensures proportional power distribution and extends battery life	Not specified
4	Development and application of a fuzzy control system for a lead-acid battery bank connected to a DC microgrid [76]	FCS for managing battery operations in DC-MG	Effective in battery charge/discharge management, swift response times	Not specified
5	Fuzzy-based charging–discharging controller for lithium-ion battery in microgrid applications [10]	FLC for lithium-ion batteries in MGs	Efficient battery management within safe operating limits	Lacks consideration of temperature impact on the MG
6	Fuzzy logic-based energy management system design for residential grid-connected microgrids [59]	Simplified FLC for residential MGs	Mitigates power fluctuations and stabilizes battery state of charge	Not specified
7	Backtracking search algorithm based fuzzy charging-discharging controller for battery storage system in microgrid applications [13]	FLC with Backtracking Search Algorithm for BES management	Superior charging/discharging control, improves reliability in dynamic load conditions	Not specified
8	Performance Evaluation of Different Membership Function in Fuzzy Logic Based Short-Term Load Forecasting [87]	Adaptive FLC for residential PV storage system	Achieves cost minimization in 98.6% of households, optimizes battery usage without forecasting	Not specified
9	Intelligent Control of a Photovoltaic Generator for Charging and Discharging Battery Using Adaptive Neuro-Fuzzy Inference System [77]	ANFIS for controlling photovoltaic generators in MGs	Efficient management of battery charging, discharging, and DC bus voltage	Needs optimization for unknown outputs
10	Fuzzy-based charging–discharging controller for lithium-ion battery in microgrid applications [10]	PSO-based FLC for BES management in MGs	Optimizes power use, reduces grid consumption by 42.26%, decreases energy costs by 45.11%	Lacks focus on factors like temperature in battery management
11	Particle swarm optimised fuzzy controller for charging–discharging and scheduling of battery energy storage system in MG applications [12]	GA and PSO for FLC optimization in BES systems	Improves control of battery operations, enhancing efficiency and reliability	Not specified
12	Genetic Algorithm based Fuzzy Logic Controller for Optimal Charging-Discharging of Energy Storage in Microgrid applications [11]	GA for tuning FLC parameters in energy management	Demonstrates superior performance in tuning FLC parameters, ensuring cost-effective energy supply	Not specified
13	Intelligent fuzzy control strategy for battery energy storage system considering frequency support, SoC management, and C-rate protection [88]	FLC for regulating battery SOC in MG systems	Prevents overcharging/ over-discharging while improving system reliability	Not specified

Table 2 emphasizes on both cost-based and non-cost-based optimization approaches in the literature, this research aims to investigate both methodologies comprehensively. The literature identifies several gaps in optimizing battery charging and discharging operations within microgrid (MG) systems, which this study addresses. These include:

1. The need to integrate temperature dynamics into control strategies to extend battery life cycles.
2. The development of holistic control approaches that consider all relevant factors, including temperature variations and power fluctuations.
3. Exploration of real-time adaptive strategies that can respond to sudden weather changes and varying load demands.
4. The investigation of hybrid optimization algorithms that integrate multiple techniques for enhanced efficiency
5. A focus on developing cost-effective solutions that balance operational efficiency with economic feasibility.

Addressing these gaps will facilitate the development of more advanced and adaptive control strategies, ultimately enhancing the reliability, efficiency, and economic viability of microgrid systems.

4. Findings

Recent advances in microgrid (MG) control, architecture, and optimization methodologies provide valuable insights into their design and operation. Microgrids are classified into three primary types remote, grid-connected, and networked each catering to specific operational requirements and deployment scenarios. Complementing these classifications is the evolution of AC, DC, and hybrid topologies, optimized for distinct applications. For example, DC-based systems minimize conversion losses, while hybrid configurations offer flexibility for complex energy systems. A notable advancement is the integration of intelligent control strategies to improve operational efficiency and system stability. Techniques such as Fuzzy Logic Controllers (FLCs) and Genetic Algorithms (GAs) have proven effective in enhancing Battery Energy Storage Systems (BESS) by optimizing charging/discharging cycles, reducing energy losses, and balancing grid dynamics. Furthermore, emerging methods like Model Predictive Control (MPC) and Reinforcement Learning (RL) bring adaptive and predictive capabilities, enabling real-time energy management and addressing the variability inherent in renewable energy sources.

Innovations in architecture include the adoption of modular microgrid designs, which enhance scalability and resilience through fault-tolerant configurations. Additionally, the development of multi-energy systems that integrate electricity, heating, and cooling networks has broadened the functionality of MGs, improving efficiency and sustainability in urban and industrial contexts. Despite these advancements, several challenges remain. Issues such as harmonic distortion, low network inertia, and regulatory barriers impede seamless MG integration into larger energy systems. Moreover, gaps in optimization methodologies highlight the necessity for more adaptive and hybrid strategies. These approaches should leverage real-time data, predictive analytics, and comprehensive system modeling to create robust and flexible MG operations.

5. Conclusion

Microgrids (MGs) represent a transformative paradigm in energy generation and distribution, offering significant advantages in terms of resilience, efficiency, and sustainability. The effective integration of renewable energy sources alongside intelligent control systems is essential for maximizing the performance of MGs. However, overcoming the technical and economic challenges inherent in their deployment is critical to unlocking their full potential. Future research should focus on the development of innovative optimization algorithms and the establishment of robust regulatory frameworks that enable the seamless integration of MGs into existing power grids. By addressing existing knowledge gaps and advancing microgrid technology, MGs have the potential to play a pivotal role in the evolution of decentralized energy systems, contributing substantially to a more resilient, efficient, and sustainable global energy infrastructure.

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