IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 July 2024, accepted 1 August 2024, date of publication 8 August 2024, date of current version 11 September 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3440885

TOPICAL REVIEW

# Review of Computational Intelligence Approaches for Microgrid Energy Management

**MOHD BILAL**[1], **ABDULLAH A. ALGETHAMI**[2], **(Member, IEEE)**, **IMDADULLAH**[3], **(Senior Member, IEEE), AND SALMAN HAMEED**[1]
[1]Department of Electrical Engineering, Zakir Husain College of Engineering and Technology, Aligarh Muslim University, Aligarh 202002, India
[2]Department of Mechanical Engineering, College of Engineering, Taif University, Taif 21944, Saudi Arabia
[3]Electrical Engineering Section, Faculty of Engineering and Technology, University Polytechnic, Aligarh Muslim University, Aligarh 202002, India
Corresponding author: Mohd Bilal (mohd_bilal@zhcet.ac.in)

This work was supported by Taif University, Taif, Saudi Arabia, under Project TU-DSPP-2024-285.

**ABSTRACT** This research investigates implementing and optimizing microgrid energy management systems (EMS) utilizing artificial intelligence (AI). Inspired by the need for efficient resource utilization and the limitations of traditional control methods, it addresses essential aspects of microgrid design, such as cost-effectiveness, system capacity, power generation mix, and customer satisfaction. The primary goals are to optimize energy management, control techniques, and AI applications in microgrids. The study critically examines the classification of energy management systems, various EMS applications, and their associated challenges. Additionally, it discusses different optimization techniques relevant to EMS, highlighting their applications, benefits, and challenges. The research emphasizes the importance of hybrid systems, demand-side management, and energy storage in addressing the intermittency of renewable energy sources. AI techniques, such as unsupervised learning (USL), supervised learning (SL), and semi-supervised learning (SSL), are extensively analyzed in relation to their specific applications. The study explores AI-based hierarchical controls at primary, secondary, and tertiary levels. Furthermore, AI methods like deep learning for load forecasting and reinforcement learning for optimal control are emphasized for their substantial contributions to enhancing microgrid reliability and efficiency. The research concludes that integrating distributed energy resources (DER) and using advanced optimization algorithms can lead to significant financial benefits and improved sustainability in microgrid operations. Over 200 research papers were referenced in this study.

**INDEX TERMS** Artificial intelligence, control, distributed generation, energy management, energy storage, environment, machine learning, microgrid, optimization, renewable energy.

## I. INTRODUCTION

The microgrid is the electrical network that produces, consumes, stores, and controls the electrical power locally [1]. A centralized power grid generates units at a more considerable distance from the consumers. A large and complex network from generating units to end consumers is needed for transmission, distribution, and controlling of power [2]. A long transmission network requires extensive infrastructure and has significant transmission losses. Failure of a small entity may cause power failure in the whole system, which may become problematic for critical and sensitive loads. Reliability and security are the points of concern in the case of a centralized power system network. For the planning and operation of a reliable and stable system, the power system's resilience and consideration of the low probability and high-impact events are crucial [3]. Distributed generation is used in microgrids [4]. Microgrids generate, consume, control, and store power in the same locality (as shown in Fig. 1), so they are reliable, resilient, and secure [5], [6], [7].

The associate editor coordinating the review of this manuscript and approving it for publication was Arturo Conde.

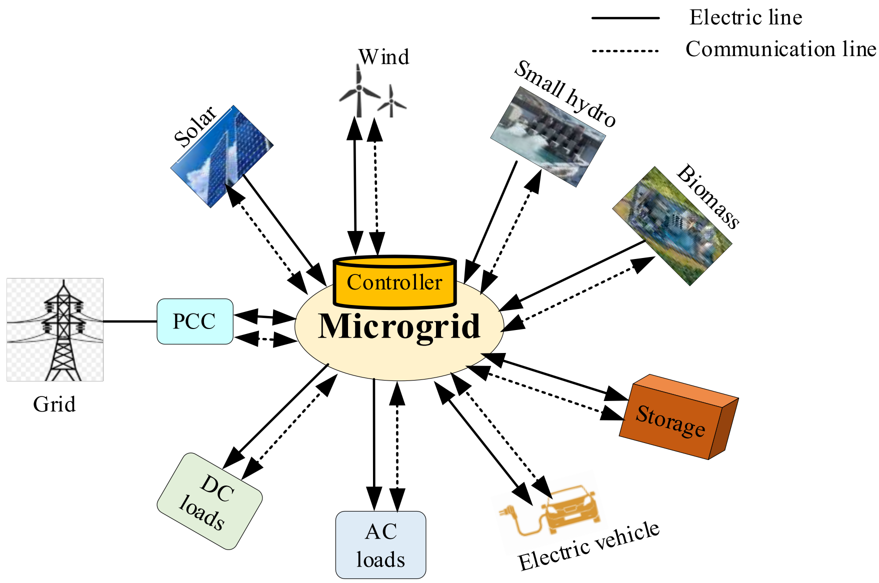


**FIGURE 1.** Microgrid architecture.

Self-sufficiency and autonomy create an energy system that makes users and different stakeholders equal, with a balanced distribution of costs and benefits [8].

Conventional energy sources include coal and oil, and most power-generating units are based on thermal power plants. Coal is used as a fuel in thermal power plants, and the burning of coal produces harmful oxides of nitrogen, oxides of carbon, and particulate matter. The emission of harmful components in the environment deteriorates the air quality, which results in many deadly diseases [9]. A significant percentage of microgrids' energy-generating sources are renewable. Renewable and non-renewable energy sources like wind, photovoltaic cells, geothermal energy, biomass, wave power, diesel engines, gas turbines, and microturbines generate electricity [10]. The generation of electricity from renewable sources of energy results in less pollution being released into the atmosphere. Using renewable energy sources does not incur any financial cost and is accessible in massive quantities [11]. Thus, it reduces the operational cost of microgrids. Since many RES depend on geographical location, combining two or more RES can be utilized to form a hybrid microgrid [12].

Microgrids (MG) have different operation ranges, such as low and medium voltage, which is between 400V and 69kV. MG can be a small unit in a few kW range, supplying a small number of consumers. On the other hand, it can be a large and complex network with a range in MW that has multiple generating resources, storage units, and power supply to large loads [13]. Depending upon the functionalities, microgrids have two different configurations. They exist in islanded and grid-connected forms. Microgrids are dynamic since they can link and disengage themselves from the utility grid at any time [14]. In an isolated operation, the microgrid provides electricity to the neighbourhood's users without being connected to the utility grid. Examples of islanded microgrids include shipboard microgrids and small satellite microgrids [15], [16], [17]. Different types of microgrids are mentioned in Fig. 2.

In the context of microgrid operations, it is critical to use energy management systems (EMS) to maximise power production, minimise operating expenditures, prolong the lifetime of energy storage systems, and reduce environmental costs. In order to ensure proper functioning when isolated from the main power grid, microgrids generally require implementing a control mechanism that can effectively manage the real and reactive power equilibrium in real-time [18]. Additionally, this control strategy must be capable of determining the optimal allocation of resources over an extended period. Determining the appropriate timing and method for connecting to and disconnecting from the power grid is an essential control system function.

The combination of hardware and software components known as control in a microgrid system provides stability, reliability, and optimality [19]. Instead of using a single controlling unit, the microgrid's components may have a local control function. The control units' primary duties include preserving the proper voltage, current, and frequency ranges, balancing the power supply and demand, carrying out economic dispatch and demand side management, and switching between an islanded and a grid-connected mode of operation [20]. The communication network between the main control unit, switches, components, and metering devices is integrated inside the microgrid. Microgrid control can be on a local basis, known as decentralized control, and it can have control on a centralized basis, referred to as centralized control. Decentralized and intelligent control has better

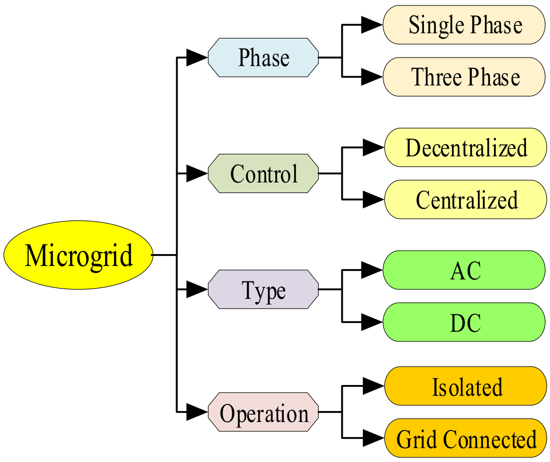


**FIGURE 2.** Microgrid classifications.

voltage control solutions [21]. Distributed control, in contrast to decentralized control, interacts among the units. In the standard mode of operation, a hierarchical control approach can be used, which involves the implementation of primary, secondary, and tertiary-level controllers across the microgrid system. This strategy is aimed at ensuring optimal power transfer to the utility grid. The number of control levels in a microgrid's hierarchical control system is determined by various factors, including but not limited to functionality, degree of control, communication requirements, and energy supply. High penetration of RES in power systems causes degradation in power quality [22]. Renewable energy generation is naturally intermittent. Integrating renewable energy sources in microgrid applications with an energy storage system (ESS) is noteworthy since it stores energy during off-peak hours and delivers it during peak load periods. In microgrids, batteries, supercapacitors, Superconducting magnetic energy storage, and flywheels may be employed as ESS [23]. Microgrids utilise ESS for energy arbitrages, peak cutting, load surging, spinning surpluses, voltage support, black start, frequency regulation, power quality, power reliability, RES transitioning, stabilising transmission and distribution upgrade restriction, congestion relaxation, and off-grid services. Energy storage placement decisions are taken using optimization techniques. However, the need for a proper energy management system for the ESS is still a challenging task [24]. EMS is used for intelligent control for power sharing and load shedding [25]. Given their simplicity and effectiveness in handling the energy management issue in microgrids, mixed integer programming methods may be used extensively in EMS. Due to the decentralised character of the EMS issue in microgrids and the capacity of multi-agent-based approaches and meta-heuristics algorithms to operate effectively in such settings, these strategies surpassed the other traditional solutions regarding system efficiency [26]. Accurate microgrid control is typical for DERS because of their stochastic and highly uncertain nature. Many microgrids are interconnected to form the network microgrid system for effective remedies for operating large numbers of DERS. Network microgrids enhance the reliability, security, and resiliency of microgrid systems.

In addition, the use of sophisticated optimization approaches in forecasting and demand management is restricted. In a community microgrid, there is a requirement for an end-to-end energy management solution and a transactive/collaborative energy-sharing capability [27]. For the complex and heavy data of the microgrids, AI finds its application to make the microgrid's operation safe, reliable, and better controlled. Machine learning (ML) and deep learning (DL) are the two subbranches of AI [28]. Based on the type of training data set, whether trained or untrained, ML and DL models are categorized as supervised or unsupervised. To overcome the issues associated with observability and controllability, effective microgrid management and analysis demand physical and data-driven models [29]. Integrating artificial intelligence (AI) technologies into the present framework can potentially enhance the precision, velocity, and effectiveness of microgrid management and functioning [30]. A requisite for implementing model-based conventional control strategies is a thorough understanding of the system's dynamics. ML algorithms, such as Deep reinforcement learning (DRL) algorithms, which acquire knowledge from their environment and establish a correspondence between inputs and outputs, exhibit significant promise for model-free design [31]. Thus, EMS is a crucial tool for efficiently managing and regulating the functioning of renewable energy generation, consumption, storage, transmission, and sub-transmission systems.

The organization of the remaining paper is as follows. Section III describes the energy management of microgrids, section IV gives a detailed analysis of optimization techniques used in EMS, while section V provides the critical analysis of control techniques in EMS, Artificial Intelligence techniques for EMS in microgrids are comprehensively analyzed in section VI, the discussion is written in section VII, and the paper is concluded in section VIII.

## II. METHODOLOGY

The methodology of the systematic literature review in this paper is explained in Fig. 3. The process starts with identifying databases, selecting keywords, and formulating search strings depending on the inclusion and exclusion criteria. In this article, a total of 879 papers were initially identified. Out of these peers, only 169 were chosen. After the screening process, 109 were taken for study objectives. Fig. 4 illustrates the categories of papers included in this research.The pie graphic illustrates that 93% of the articles are journal papers, 4% are conference papers, and the remaining 3% are from other sources in the relevant research area.

### *A. METHODS AND MATERIALS*

This article is written using the two major processes:

1. The first process is the conduction of a survey of 879 papers related to microgrids, energy management

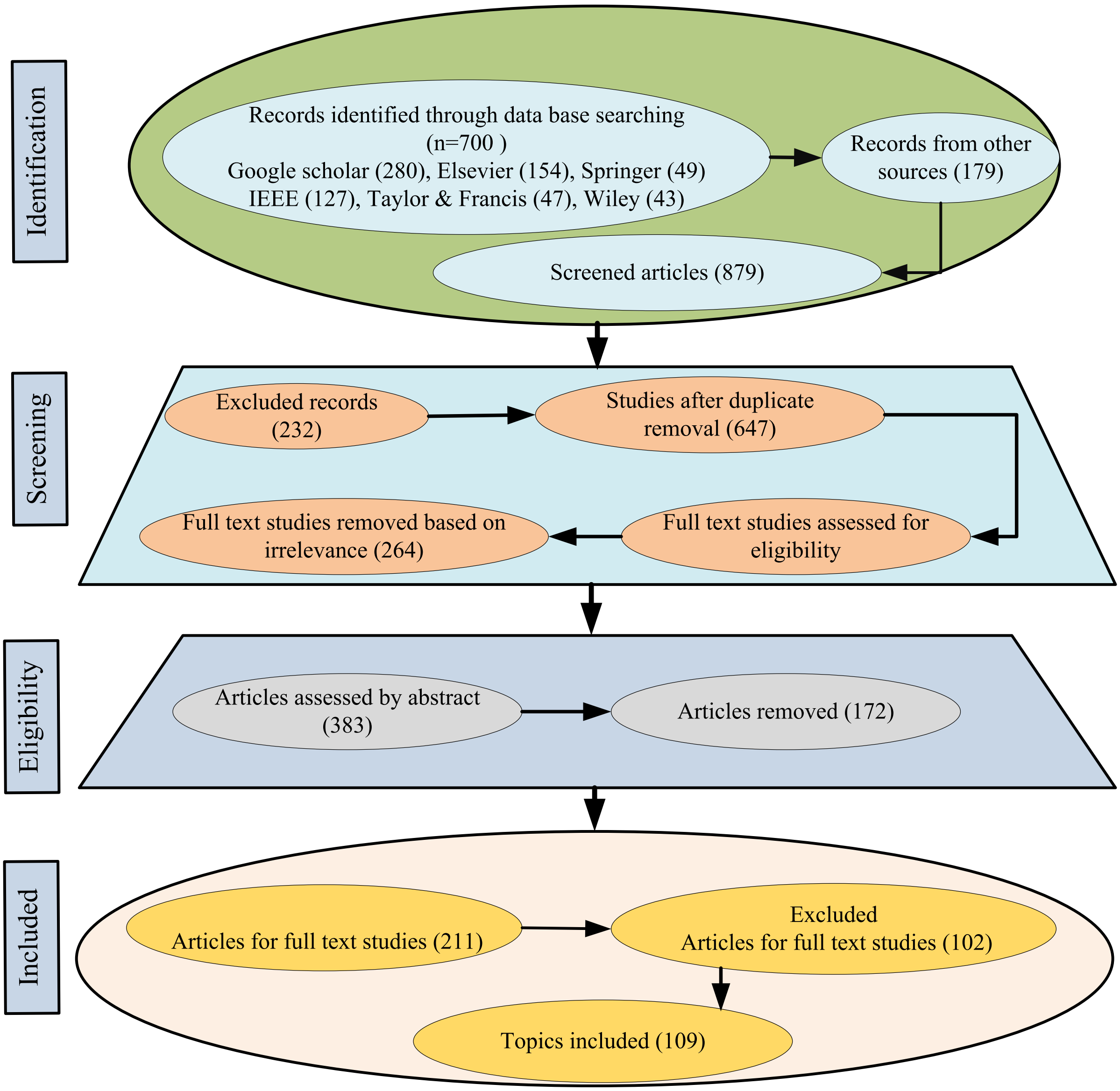


**FIGURE 3.** Prisma framework explaining the methodology of research work.

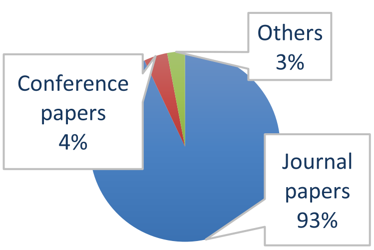


**FIGURE 4.** Pie chart for the selected papers.

in microgrids, control in microgrids, centralized and decentralized control in microgrids, and Artificial intelligence control in microgrids that resulted in 109 papers that aligned with the objectives of the review study.

2. The second process is articulating recommendations and best practices derived from a comprehensive evaluation and assessment of the extensive literature.

### *B. RESEARCH QUESTIONS AND FORMALIZATION*

Considering the problems the engineers face in energy management in microgrid implementation and control, this study addresses the issues. This work is done with motivation and objectives towards solving the issues about the microgrid domain. Special focus is placed on the energy management, optimization, control, and application of artificial intelligence in microgrid operations and control.

Motivation is based on the following:

i. Energy management is necessary for better utilization of resources.

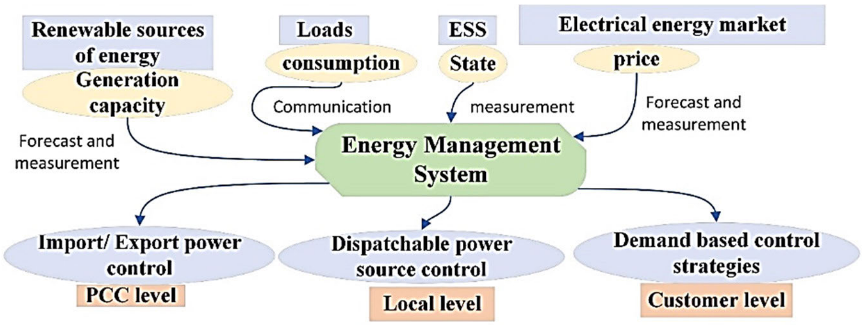


**FIGURE 5.** Energy management in microgrid.

ii. The traditional operation system of microgrids is sluggish and costly.
iii. Control techniques are less efficient than novel, developed, and state-of-the-art approaches.
iv. Artificial intelligence control is efficient and reliable for better operation of microgrids.

The main objective of this study is to perform a detailed analysis of energy management techniques in microgrids. The following are the research questions that are intended to address in this study:

RQ1: How are the different resources utilized for better energy management?
RQ2: What is the role of optimization techniques for the best output of different components in the microgrid?
RQ3: What is the role of traditional control methodologies and their impact in the current arena?
RQ4: What is the impact of artificial intelligence technologies on microgrid management?

### C. SOURCE SELECTION

The databases chosen for this research encompass IEEE Xplore, ScienceDirect – Elsevier, SpringerLink, and Google Scholar. "title," "Abstract," and "entire document" are the parameters that have been considered for inclusion and exclusion. Works directly linked to research questions are included, and papers not directly linked to research questions are excluded as shown in table 1.

**TABLE 1.** Keywords and the search string.

| Keyword | Search string |
|---|---|
| Microgrid, energy management, control, optimization, artificial intelligence | (Microgrid <AND> energy management) OR<br>(Microgrid <AND> optimization) OR<br>(Microgrid <AND>control)<br>(Microgrid <AND> artificial intelligence) |

### D. SELECTION EXECUTION

In the initial phase of this study, literature articles related to the objectives are selected. The inappropriate articles that do not precisely meet the objectives are excluded. The appropriate and efficient issues addressing papers are selected for the detailed study.

## III. ENERGY MANAGEMENT

*RQ1: How are the different resources utilized for better energy management?*

Although there are numerous benefits of using a microgrid, designing a microgrid that is both cost-effective and efficient is a complicated process since it requires considering all available options simultaneously. Since each decision in the planning process will have an impact on the capacities of the system. Every planning process depends on a constraint (technical, environmental, geographical, social and regulatory constraints) or goal. Uncertainties also have an enormous impact on the planning process. A few issues must be considered when designing microgrids, including power generation mix selection and sizing, location, and operating schedule. Customer satisfaction (reliability, quality, and environmental friendliness) and cost efficiency are two objectives that should be addressed throughout the design phase of a microgrid project. One strategy for designing a microgrid is considering it a series of optimization issues. Depending on the circumstances, an appropriate optimization strategy is selected for the application [32]. Energy management of microgrids can be explained using Fig. 5. Energy management are classified as AI based and conventional techniques based as demonstrated in Fig.6.

The intermittency of demands and renewable energy sources makes it difficult for microgrids to provide the required energy. Therefore, an energy management system (EMS) must tackle these issues. EMS considers hybrid systems, demand-side management (DSM), non-renewable energy sources, and energy storage systems (ESS). Load and renewable energy forecasting can be done using deep learning [33]. To manage the deregulated electricity system, DSM plays a vital role in the management of the load as well as the intermittent nature of renewable energy sources (RES) that

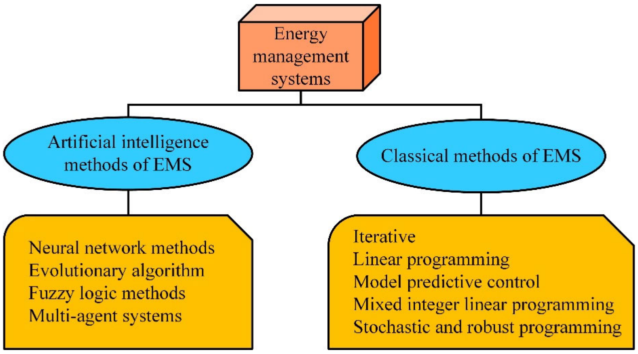


**FIGURE 6.** Energy management classifications.

generate power. To get a smooth load profile via the use of the demand response (DR), proper switching and efficient storage are required [34]. The primary goal of DSM is to reduce the peak demand and the cost of power while simultaneously increasing the use of RES to lower emission rates [35]. Controllable and uncontrolled power sources, energy storage systems (ESS), hybrid electric vehicle (EV), and demand response (DR) programs are the components that make up the coordinated functioning of a grid-connected microgrid. The stochastic optimization algorithm can find the optimal generation schedule, battery performance, and cost-effective DR program. The optimized DER integration leads to financial benefits for the utility. The profitability of prosumers in a microgrid is augmented through the DR program, which boosts RE utilization [36]. EMS may be implemented using modeling approaches, aim functions, constraints, and optimization methods. From a source point of view, EMS is aimed at the optimal use of Distributed generation to feed the loads. EMS aims to provide the load generation balance, reduce emissions to net zero, and optimize microgrid power exchanged based on the market price and security constraints [37]. An energy management system (EMS) utilizes the microgrid elements optimally for reliable and efficient operation. It may contain the implementation of robust and fast decisions for critical operation objectives. It mainly contains the control and communication in the microgrid [38]. EMS is holistic information based on forecasting, load sharing, load forecasting, weather forecasting, and planning. It is designed to deal with dynamic and steady-state features of DER, the intermittent nature of sources, the planning and management of ESS, the type of operation of the microgrid, and power quality. Thus, EMS is a comprehensive automated and real-time system used for automated scheduling and management of distributed energy resources(DRS) and control loads operating within an electrical distribution system [39]. The EMS provides the data management, grid information, supervision, and control over all the automated distributed generation sources (DGS) and energy storage systems (ESS) that compose the microgrid [40], [41]. Demand on an hourly basis can be forecasted using state-of-the-art techniques such as deep learning. Table 2 discusses the benefits of energy management while Energy management classifications are discussed in table 3.

EMS manages all the DGS, ESS, and controllable loads in case of resynchronization of the microgrid with the main grid [42], [43].

**TABLE 2.** Benefits of energy management systems.

| Maximizing | Minimizing |
|---|---|
| • Power availability<br>• Reliability<br>• Use of renewable energy resources<br>• Power quality | • Energy and operational losses<br>• Gas emissions<br>• Fuel consumption<br>• Energy purchased outside the microgrid |

EMS is used for intelligent power-sharing and load-shedding management [46]. Although microgrid has many advantages, planning a cost-effective microgrid is a complex process because of considering all alternatives at a time. The classification of EMS methods is discussed in Table 3. Since each decision in the planning process will impact the system's capacities, centralized and decentralized schemes are widely used in EMS. Centralized EMS (CMES) has a great role to play in the optimization of microgrids, while decentralized EMS has the primary goal of maximizing power production to meet the load demands and export surplus power to the utility. Fig. 7 and Fig. 8 show the structure of centralized and decentralized EMS (DEMS) schemes.

### A. CENTRALIZED EMS

In microgrids, a centralised controller manages and regulates distributed energy resources (DERs) such as solar panels, wind turbines, and energy storage devices. This enables centralised energy management as shown in Fig. 7. The controller strategically allocates resources based on real-time data on energy output, consumption, and grid conditions to meet demand, maintain grid balance, and ensure stability [47]. This technology enables the seamless integration of renewable energy sources, enhances the power grid, and creates opportunities for energy markets and demand response programmes. Centralised energy management aims to achieve maximum system efficiency, minimise running costs, and reduce greenhouse gas emissions [48]. Utilising advanced optimisation algorithms and fault detection systems enables the achievement of this goal [49]. In light of various factors, this contributes to the microgrid's transformation into a reliable and sustainable energy ecosystem. Table 4 explores the centralized control in details.

### B. DECENTRALIZED EMS

The decentralisation of energy management in microgrid control involves distributing decision-making among multiple points within the microgrid system, rather than relying on a single controller. Fig.8 depicts the decentralization control of EMS in microgrid. Every node, representing either an

**TABLE 3.** Classification of EMS methods.

| EMS method | Technique | Benefits | Limitations |
|---|---|---|---|
| **Classical** | Iterative | Flexible adapting dynamic conditions | Significant Computational resources are required.<br><br>Sensitive to initial conditions |
| | Linear programming | Efficient | Application in nonlinear systems |
| | Model predictive methods | Efficient in dynamic conditions | Computational complexity |
| | Mixed integer linear programming | Flexible in model discrete conditions | Application in large microgrids<br><br>Computational complexity |
| | Robust programming | Efficient in variable conditions | Require accurate estimation of the probability distribution |
| | Stochastic programming | Good performance in variable conditions | In some cases, it may lead to suboptimal performance |
| **AI based methods** | Neural network | Adaptive learning | Functions like black box type<br><br>Training of data required |
| | Evolutionary algorithms | Good in complex nonlinear problems | Computational intensity<br>Sensitive to parameters tuning |
| | Fuzzy logic methods | Sensational uncertainties modeling | Lack of precision in some cases |
| | Multi agent systems | Adaptive to dynamic systems | Developing communication protocols is difficult |

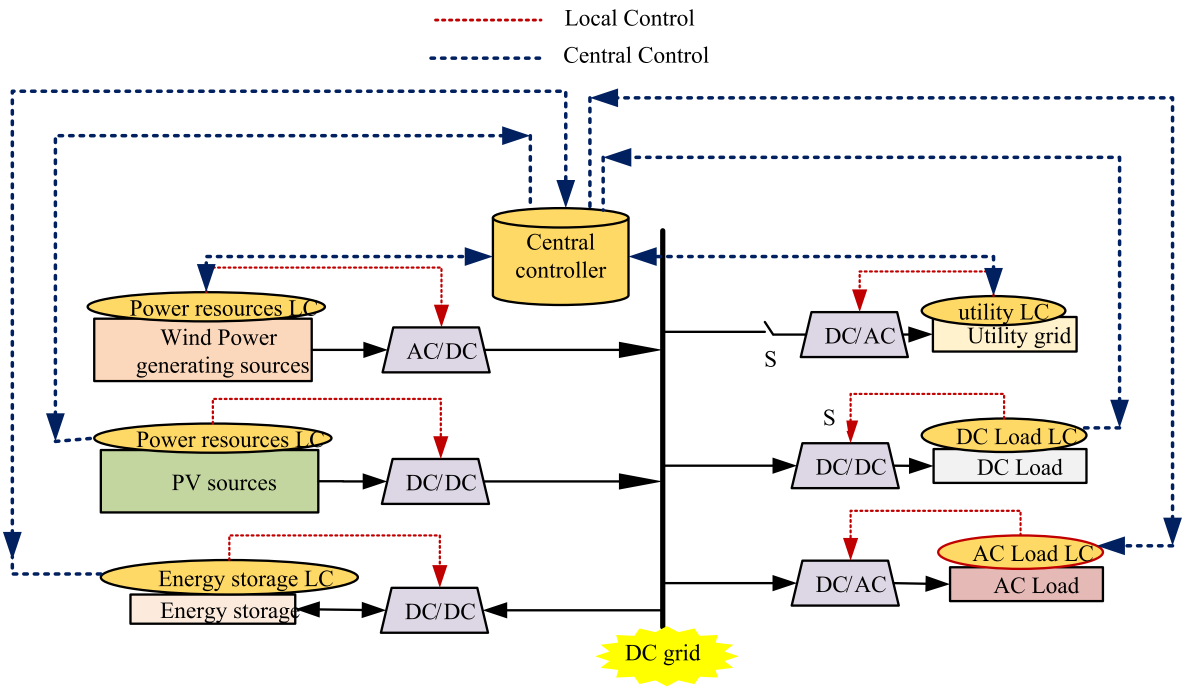


**FIGURE 7.** Centralized control of EMS.

individual DER or a smaller group of assets, independently makes decisions [55]. The decisions are informed by local data, such as energy production and consumption levels, as well as the condition of the power grid. This network of linked nodes enables the decentralisation of energy production, storage, and usage. Protocols facilitate communication and collaboration between entities [55]. The objectives of this approach aim to enhance system security and mitigate the impact of communication issues. Microgrids are capable of promptly adapting to fluctuations in the power grid's operations or issues due to their autonomous energy management system. In addition, they have the ability to efficiently integrate various energy sources and adapt to fluctuations in demand. Table 5 explores the centralized control in details.

Different EMS techniques can be implemented to address the management issues of microgrids. Many energy management strategies can be applied to obtain the desired output. Different algorithms for different constraints find application

**TABLE 4.** Centralized EMS.

| | | Ref |
|---|---|---|
| **Features** | • Information is gathered and analyzed by a central controller.<br>• DERS is scheduled using all available data from all sources.<br>• Enables online dispatch process since all information is at the controller.<br>• More appropriate for smaller microgrids that function primarily while linked to the grid system.<br>• Local controller (LC) is central controller-dependent | [50]–[54] |
| **Advantages** | • Extensive microgrid monitoring Taking into account every single DERS at once<br>• Online habit formation is possible.<br>• The trustworthiness of operational data collected at the central controller<br>• Real-time system monitoring<br>• Simple inception and realization<br>• With a safeguarding control system in place<br>• Easily implemented and inexpensive to maintain.<br>• Provides system-wide oversight and control. | |
| **Limitations** | • Slow<br>• Complex and time-consuming to compute<br>• Depending on communications reduces system dependability.<br>• No plug-and-play<br>• Single-point-of-failure<br>• Low adaptability<br>• High data exchanges | |

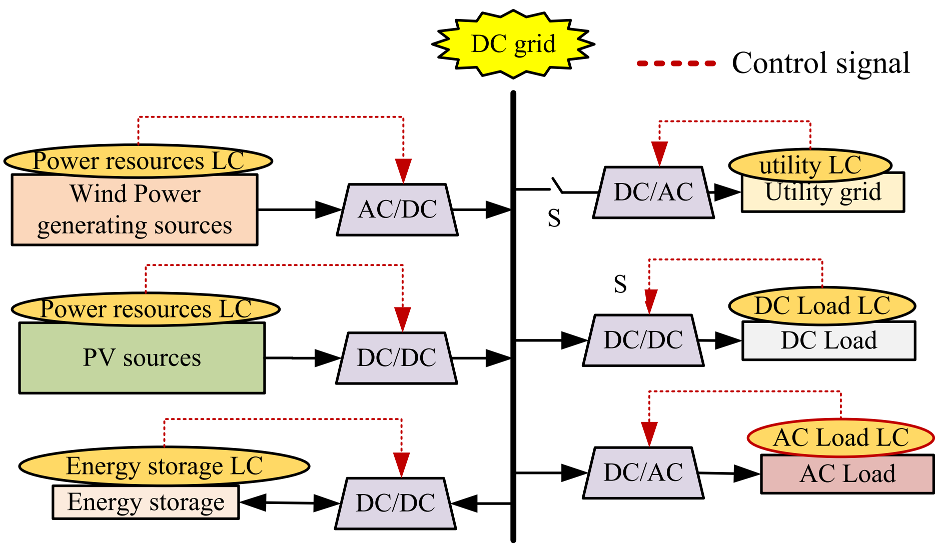


**FIGURE 8.** Decentralized control of EMS.

in strategy making. Table 6 demonstrates the understanding of different EMS strategies.

## IV. OPTIMIZATION IN EMS

RQ2: What is the role of optimization techniques for the best output of different components in the microgrid?

Optimization techniques are the actions that optimize the value of the objective function. Fig. 9 shows the flow chart of optimization solution. The concept of computational optimization refers to a range of mathematical procedures centred on selecting the best possible solution from among a number of accessible options. The term "optimization" refers to determining the optimal solution for an objective function

**TABLE 5.** Decentralized EMS.

| | | Ref |
|---|---|---|
| **Features** | • LC makes decisions<br>• Multiagent system often used (MAS)<br>• Multiple agents interact to attain the goal and local goals.<br>• Used in larger systems<br>• A distributed process is used to make all decisions. | |
| **Advantages** | • Reliability and robustness improved.<br>• Single-point failure avoided<br>• Gives DERs and loads LC autonomy<br>• According to its inherent qualities, each agent may maximize its operational goal.<br>• Connectivity, information amount, kind, and agent functionality determine EMS performance.<br>• Each entity makes its own decision in accordance with the local controller.<br>• Massive data is analyzed quickly.<br>• Reduces workload<br>• Plug-and-play ease | [52]–[54], [56]–[59] |
| **Limitations** | • SOC data deficiency<br>• insufficient grid voltage<br>• It is incapable of carrying out actions demanding high degrees of coordination.<br>• ESS may not be resilient<br>• Synchronization required<br>• Synchronization requires robust communication.<br>• Requires quick periodical reconfiguration | |

given a list of constraints. This process may be used for various objective functions and domains [101]. A large field of applied mathematics is used to expand optimization theory and methodologies.

Optimization techniques play a critical role in the energy management of microgrid control systems, but their effectiveness hinges on several factors. While these techniques leverage algorithms and models to allocate resources efficiently and minimize operating costs, they often face challenges in accurately predicting complex and dynamic energy patterns within microgrid [102]. Factors such as variable renewable energy generation, uncertain load demands, and grid disturbances introduce significant uncertainty, making it difficult for optimization algorithms to achieve optimal solutions in real-time. Moreover, the computational complexity of these algorithms can lead to increased processing times, limiting their ability to respond quickly to changing conditions [103]. Additionally, the implementation of optimization techniques may require accurate data, which can be challenging to obtain due to issues such as sensor inaccuracies or communication delays. Furthermore, the trade-offs between conflicting objectives such as cost minimization, system reliability, and environmental sustainability present additional challenges in designing effective optimization strategies [104]. Thus, while optimization techniques hold promise for improving the efficiency and performance of microgrid energy management, addressing these challenges is crucial to realizing their full potential in real-world applications.

Since effort/resources or output expectations in every assignment/work/project may be connected with a particular decision variable, optimization can be utilised to find the circumstances that maximise or minimise that function. Technically, optimization is not new; it has been known since the times of Newton, Lagrange, and Cauchy.

No single optimization approach effectively analyses all circumstances and constraints. Various optimization approaches have been developed. The optimum-seeking approaches are used in operation mathematics research for decision-making issues with optimal solutions. Operation research was used in World War II [105]. Various operational research methodologies include (1) stochastic process, (2) statistical methods (3) Programming or optimization methods based on mathematics: Included in these optimization techniques are Calculus methods, Calculus of variations, Non-linear programming, Geometric programming, Quadratic programming, Linear programming, Dynamic

**TABLE 6.** Energy management systems in microgrid.

| Strategy | Application | Challenges | Ref |
|---|---|---|---|
| **Hybrid microgrid Architecture (HMG)** | Commercial buildings<br><br>capable of recon<br><br>uring architecture based on BLP and DG power | Low BEC and high RI are challenges due to stochastic BLP and renewable energy generation. | [60] |
| **Advanced metering Infrastructure-based energy management (AMI-EMS)** | It is used in quasi-real-time and adaptive energy management for islanded microgrids. | Problems establishing credible historical baselines to gauge improvement. | [61], [62] |
| **Two-level pricing framework** | Retail power pricing.<br><br>Interval predictions analyze prediction errors and improve pricing regulation to adapt to uncertain load behavior and DG power generation. | Participant competition.<br><br>Decentralize DER coordination, cooperation, and service utilization. | [63], [64] |
| **Demand Response Scheme (DRS)** | Low-cost electricity and heating.<br><br>Cost-effective and resilient. | Renewable energy's unpredictability. | [65], [66] |
| **Distributed robust model predictive control (DRMPC) energy management** | To reduce the uncertain nature of renewable energy sources, the DRPC model is proposed for islanded multi-microgrid. | Prediction of load and generation supply | [67] |
| **Dynamic price-enabled strategic energy management (DPES-EMS)** | Cooperation among the prosumers by the microgrid. | Energy supply by prosumers | [68] |
| **Novel Deep reinforcement approach for Industrial Internet of things (IIoT)** | Network resilience<br><br>Bandwidth usage reduction<br><br>Fast learning system with a smaller number of training samples. | Identifying the neural network's meta parameters and key information | [69] |
| **Advanced microgrid energy management system (AMEMS)** | Flexible time frames and DERs schedules allow MG to employ the latest renewable and load predictions.<br><br>Optimal power flow-based energy dispatch combines microgrid operating limits in real-time control. | constraints that limit the rate of change of the generated power | [70], [71] |
| **Two-layer stochastic power management** | Energy losses, EENS, and voltage symmetry are minimal. | Limitations of Reliability, Operation, Security, and Flexibility. | [72] |
| **Blockchain-based stochastic energy management** | Used for interconnected microgrids<br><br>System security enhancement<br><br>Reducing the operational cost | the lack of smart grid-centric incentive mechanisms | [73], [74] |
| **Demand response management (DRM)** | It's AI-based<br>Used in a DRM system involving a service provider, consumers, and utilities. | Maintaining and installing control devices is expensive.<br><br>Increasing storage systems due to cheap local storage must be resolved. | [75], [54] |
| **Adaptive and predictive energy management (APEM)** | Used in virtual power plants<br><br>Real-time optimal power dispatch from VPPs integrated with REs and ESS | computational time complexity.<br><br>Consideration of DR | [76], [54] |
| **Stochastic energy management (SEM)** | Unscheduled microgrid islanding induced by main grid interruptions.<br><br>Minimized operation costs.<br><br>Load loss risk by unpredictable parameters is mitigated. | Stochastic programming costs more than deterministic since it's closer to reality. | [77], [54] |
| **Fuzzy logic-based energy management system (FLEMS)** | used to smooth the power profile. | Adjustable settings; data training required | [78]–[80] |
| **Coordinated optimal voyage planning and energy management system (COVP-EMS)** | Marine transportation | Size of ESS depending on economic feasibility, environmental effect, and operational task needs | [81] |
| **Neural network-based prediction system** | Management of virtual power plants | Sensitive to membership distribution; has several factors for modification | [82], [79] |
| **Non-intrusive load monitoring-** | Optimizing distributed generation. | Developing a sophisticated EMS with | [83] |

**TABLE 6.** *(Continued.)* **Energy management systems in microgrid.**

| | | | |
|---|---|---|---|
| **based EMS (NILM)** | Scheduling controllable loads for customer satisfaction. | NILM for various uses. | |
| **Holistic power management** | Mitigation of voltage deviation<br><br>Reduction in operation cost | Consider more objectives from power source, converter, and power line while building and manipulating operational zones. | [84] |
| **Lyapunov optimization-based EMS** | Economic operation<br><br>Control of charging and discharging power of ESS | Consideration of vehicles as load which can be discharged and can degrade<br><br>Development of intelligent algorithm that has different time scale | [85], [86] |
| **Cooperative adaptive droop-based EMS (CAD-EMS)** | SoC balancing during CC mode, and progressive derating from PV array during CV mode such that BESS charging current starts decreasing to zero.<br><br>Optimal voltage regulation | Divergent solutions due to impact of time delay in control | [87], [88] |
| **Incentivized prosumer coalition with energy management (IPCEM)** | Reduction in Variability of local network load profile. | Computational complexity while dealing large number of prosumers | [89] |
| **Distributed transactive framework (DTF)** | Congestion management of multiple microgrid distribution system | Distributed learning method for the optimal policy<br><br>Adaption to uncertainty realized in intra-day stage | [90] |
| **Battery management system control (BMSC)** | Frequency improvement | Ensuring that the BMSC can regulate electrical variables, disconnect main and non-main loads, and consider power market economics. | [91] |
| **Model free EMS** | For controlling the Hybrid microgrid as single controllable entity | Incorporation of a battery bank of many technologies | [92] |
| **EMS with advance converts and control of PV battery storage** | Improvement of energy resiliency<br><br>Reduction in operational cost | Supplying PV electricity to grid while charging battery and powering load. | [93] |
| **Fair optimal Bilevel transactive EMS (FOBT-EMS)** | Use in community of microgrids<br><br>Reduction in consumer cost.<br><br>Optimality in network | Instead of day-ahead control, designing model predictive control for online structural control. | [94] |
| **Data driven EMS** | Used in interconnected microgrids<br><br>Renewable and load forecasting by sharing the information among grids | Battery size and COE savings. | [95] |
| **Markov chain based solar generation model** | Predicting the solar energy work and manage its storage | Adding wind power. | [96] |
| **Prosumer energy management (PEM)** | Optimal utilization of resources such as RES, EV, ESS. | Insufficient distribution grid analysis | [97], [98] |
| **Metrices analysis framework (MAF)** | Resiliency improvement | More processing time | [99], [100] |

programming, Integer programming, Stochastic programming, Separable programming, Multi-objective programming, Network methods: CPM and PERT, and Game theory. Genetic algorithms, Simulated annealing, Ant colony optimization, Particle swarm optimization, Neural networks, and Fuzzy optimization are non-traditional or contemporary optimization approaches.

The microgrid uses both AC and DC types of sources. The microgrid largely uses renewable energy, among which solar cells, fuel cells, and batteries are DC sources, whereas wind turbines and microturbines are examples of AC sources. Since the AC sources are of variable frequency and voltages, both types of sources, i.e., AC and DC, use inverters to get a fixed range of voltage and frequency. AC sources use a rectifier for conversion to DC and AC by the inverter. Similarly, the DC source utilizes the inverter to convert the DC to AC [106]. The control methods determine the output frequency, voltage and current parameters. Different application strategies are adopted for power flow control management based on the number of sources used. The energy management system is utilized for the sources' activation and deactivation [107]. The grid-connected mode uses control strategies such as Sliding mode control, Model predictive control, Power reactive control, Droop control, Fuzzy logic control, and Distortions in

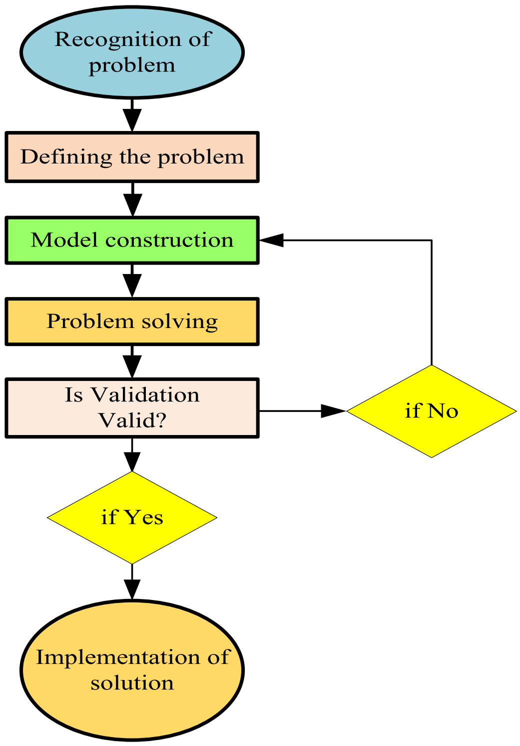


**FIGURE 9. Flow chart for optimization solution.**

different parameters of the microgrid system to cause fault conditions.

The dynamic response of grid-connected microgrids can be analyzed using different control strategies. The control methods comprise the single or hybrid algorithm. The performances of these methods are different for the same cases; therefore, they have some advantages and disadvantages concerning each other in table 7. Optimization algorithms can control transient stability in frequency, voltage regulation, and current ripples in islanded microgrid operation [108].

## V. CONTROL IN MICROGRIDS

RQ3: What is the role of traditional control methodologies and their impact in the current arena?

The controllability of a microgrid is one of the primary characteristics that set it apart from a normal distribution system. Proper control techniques are necessary for microgrids' minimum consumption and cost-effective operation [80]. In the transition from isolated to grid-connected operation and vice versa, power flow between microgrids and the main grid plays a vital role in controlling the stochastic behavior of distributed generation sources control techniques. This property allows microgrids to function as coordinated and controlled modules linked to an upstream network [148]. Network interface upstream, microgrid protection and control and local control are three Control functions in microgrid. The upstream network decides whether a grid-connected or isolated mode of operation is used. Control of the microgrid regulates voltage and frequency, P and Q control, forecasting of load and scheduling, monitoring, and microgrid protection [149]. In local control, regulation of primary voltage and frequency, primary P and Q control for local generating and ESS units is done. PQ control, V/F control, and droop control are three major control methods in microgrids. PQ control keeps the active and reactive power of the power source constant while keeping voltage and frequency within acceptable limits. However, V/F control maintains the voltage and frequency constant irrespective of output active and reactive power [150], [151]. Droop control helps share the demand to the generating units so that the generator can change its output power based on the frequency division [152]. Fig. 10 represents the classification of control techniques. Conventional control techniques can stabilize frequency and maintain standard voltage limits during disturbing events. Table 8 explains the classification of control methods.

Conventional techniques comprise droop control, MPPT, MAS control, virtual impedance, and primary-secondary control. Droop control utilizes frequency to control active power. For the prevention of overloading droop control technique is implemented [153]. Maximum power point tracking (MPPT) technique can be implemented for maximizing the power production from the solar or wind energy sources [154], [155]. A multiagent system (MAS) comprises two or more intelligent agents assigned for a specific assignment. It depends on constraints and stabilizes the variable voltages, frequency, and power [151], [156]. A decentralized type of MAS is utilized to improve security and stabilise microgrids. Frequency-based control strategies are looking after microgrid outages. MAS is majorly used in planning, monitoring, control, and automation. Virtual output impedance technology is implemented to improve power-sharing accuracy. It also improves transient and steady-state responses [157]. Interface converters of generating units and microgrid systems can be coordinated using primary-secondary technology. During power outages, the primary device's voltage can be utilized by the secondary device as a reference. PCC can regulate the utility grid and MG by implementing the primary-secondary technique [158]. In a standalone mode of operation, DG or ESS works as the primary unit [159]. This technique is difficult to implement in larger systems.

Using novel control techniques enhances performance as it utilizes more sophisticated methods [160], [161]. Smart and flexible technologies are implemented for robust controllers to optimise constraints in the control process [162]. In microgrid intelligent techniques, during the operation of the MG unit, the implementation of intelligent techniques improves the stability and performance of DG units [29]. System adjustment for an increased number of parameters is a complicated process. Many approaches are effective for the regulation of those parameters. Adaptive control techniques are used to maintain stability, resiliency, convergence,

**TABLE 7.** Optimization techniques used in Microgrid.

| Optimization | Applications | Benefits | Challenges | Ref. |
|---|---|---|---|---|
| **Heap optimization (HO)** | Solve the optimum power flow problems | Fuel cost reduction | Inapplicable for non-renewable energy sources | [109]–[111] |
| | | | | |
| **Particle swarm optimization algorithm (PSO)** | Performing energy arbitrage<br><br>Solve non-linear multi-objective functions. | Battery lifetime increases substantially. | Easily converges to a local optimum.<br><br>Low iterative convergence | [112], [113] |
| **Adaptive Differential Evolution (ADE) algorithm** | Optimizing droop control virtual resistances of a grid-connected converter | Cost saving in the expansion of dispatchable units. | Stagnation, premature convergence, sensitivity/insensitivity to control parameters, | [114], [115] |
| **Perturb and observe optimization (P&O)** | Maximum power production from PV array | Performs well in fluctuating wind speeds, linear and nonlinear unbalanced loads, and shedding PV insolation. | At a steady state, the operating point oscillates around the MPP | [116], [117] |
| **Genetic Algorithm (GA)** | Cost minimization of microgrid | Easy to implement and faster for power systems problems | Tendency to fall into the local optimum solution<br><br>Slow convergence | [118], [119] |
| **Sunflower optimization (SFO)** | Frequency regulation<br><br>Power management | Improvement in stelling time<br><br>Maintaining active and reactive power simultaneously.<br><br>Tracking reference voltage | Premature convergence in some cases | [120]–[122] |
| **Cuckoo search optimization (CSO)** | Coordinating microgrid relays<br><br>Removes defective network from healthy network. | Predefined parameters aren't limited | Can fall to the local optimal solution | [123]–[125] |
| **Whale optimization (WO)** | Effective day-ahead resource scheduling framework for a microgrid (MG), | Intended to minimize the total cost of operation over a 24-h horizon. | Slow convergence<br>Search stagnation<br>Easy fall into local optimization | [126], [127] |
| **Fuzzy Algorithms** | Reduce the system costs | Economic operation | More processing time | [128], [129] |
| **Moth Flame Optimization (MFO)** | Implementation of DSM in smart grid systems | The multi-agent and evolutionary approaches are less costly in the residential and commercial sectors. | Premature convergence<br><br>Slow population diversity | [130], [131] |
| **Robust Method** | Can handle various control strategies of the DGs, such as ISOC, droop, and constant power effectively | Provides accurate steady-state solution in comparison to other state-of-the-art algorithms. | Modelling multiple uncertainties | [132]–[134] |
| **Simulated annealing (SA)** | Reduce the energy cost for the end users | Optimized cost | Slow<br><br>Premature convergence | [135] |
| **Grass-hopper optimization algorithm (GHO)** | Maximum power extraction in shedding conditions in PV array | Better performance than its counterparts in power extraction, convergence, conversion efficiency, dynamic response and oscillations. | Can converge at local minima | [136], [137] |
| **Ant colony optimization (ACO)** | Ship integrated power system<br><br>Allocation of dumped load in islanded microgrid systems | Minimize the frequency and voltage deviation<br><br>Reduces system losses | Slow convergence<br><br>Possibility to converge on local optimum | [138], [139], [140] |
| **Bee Colony Algorithm (BCA)** | Energy cost optimization<br><br>Multiple demand response program | Reduction in peak load demand and energy cost. | Slow convergence | [141], [142] |
| **Harmony Search optimization (HSO)** | Optimal day-ahead scheduling | Solve the complicated constrained optimization problem. | High randomness | [143], [144] |

**TABLE 7.** *(Continued.)* **Optimization techniques used in Microgrid.**

| | | | | |
|---|---|---|---|---|
| **Artificial Fish Swarm optimization (AFSO)** | Optimized scheduling of energy generation from renewable sources | Day ahead generation scheduling | High time complexity<br><br>Cannot balance between local and global optimum | [145], [146] |
| **JAYA algorithim** | Optimization of distributed energy resources | Simple and easy to implement<br><br>Faster convergence rate | May be stuck at the local minima for a complex problem | [147] |

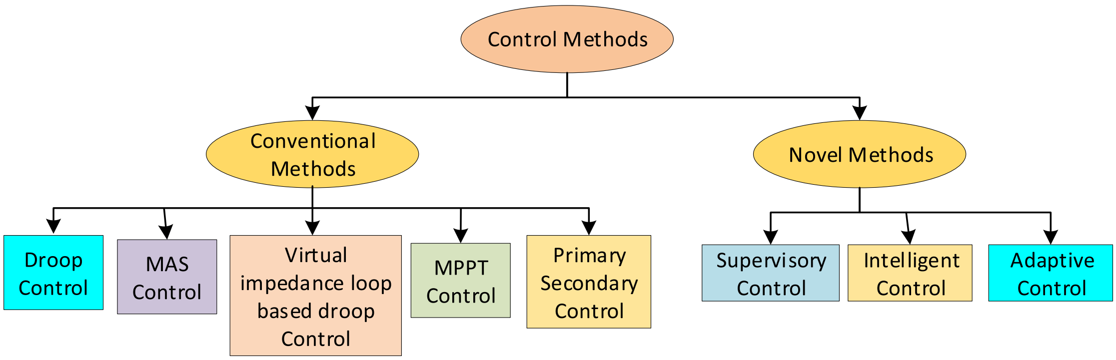


**FIGURE 10.** Classification of control methods in MG.

**TABLE 8.** Attributes of control methods in MG.

| Control method | Technique | Benefits | Limitations |
|---|---|---|---|
| **Conventional control techniques** | Droop control | Easy implementation | Voltage deviation |
| | Master slave control | Central coordination | Single point failure |
| | Virtual impedance control | Stability improvement | Complex Overdamping |
| | MPPT control | Large power extraction<br><br>Efficient | Sensitive |
| | MAS control | Decentralized operation | |
| **Novel control techniques** | Supervisory control | Coordination among different DERs | Computational complexity |
| | Intelligent control | Improved decision making<br><br>Adaptive to dynamic and nonlinear systems | Training data needed |
| | Adaptive control | Robust | Complexity in tuning adaptive laws |

and optimization [163], [164]. This technique finds application in the solution of uncertain constraints and disturbance events. For optimal power production, adaptive control regulates the voltage and frequency variations [165]. Microgrid supervisory controllers are used to make the system advanced and smarter [166]. It can be centralized or decentralized types [167], [168]. It has additional control features, such as quality control for performance enhancement. Hierarchical control is a sub-part of supervisory control.

In novel control techniques, the hierarchical control techniques perform a challenging task as it must provide real-time frequency and voltage stability at the time of disturbance caused in the microgrid [169]. Generation from RES is controlled by using a central controlling unit, which predicts the demand and power generation so that operation planning can be done using that information. In a grid-connected mode of operation, the IEEE 1547-2003 standard is followed by a microgrid using a valid detection algorithm [170], [171]. In a standalone system, P and Q are generated within specified voltage ranges at constant frequency. In hierarchical control of microgrids, there are three different levels of control, which comprise of primary, secondary and tertiary levels of controls as shown in Fig.11 [172]. In this control scheme, the primary level of control deals with local energy control and distributed energy sources. Meanwhile, the secondary control in the hierarchy must look after the primary deviation in the frequency variable and the voltages.

In the case of AC microgrids, the secondary level of control deals with the voltage and frequency, while in the case of DC microgrids, it controls the voltages only. Energy Management System(EMS) is the tertiary level of control in the hierarchy as mentioned above it uses the intelligence system to manage and coordinate the operational power flow between different microgrids as well as in the main grid [40], [173].

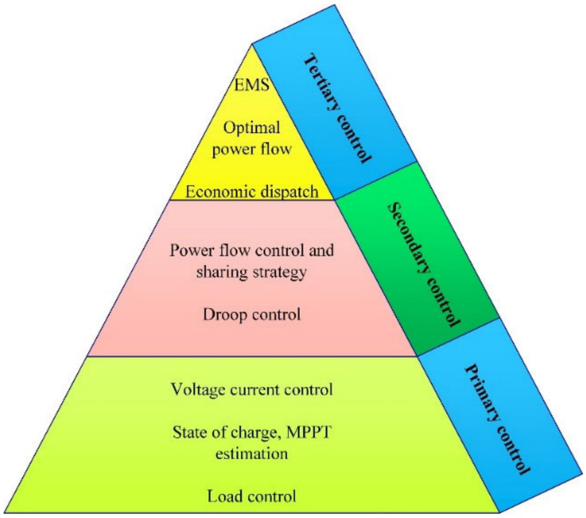


**FIGURE 11.** Hierarchical control of microgrid.

## VI. AI IN MICROGRID CONTROL

RQ4: What is the impact of artificial intelligence technologies on microgrid management?

AI-based microgrid control offers promising prospects for enhancing energy management, but it also entails other crucial factors that need to be taken into account. First and foremost, the use of AI algorithms brings about challenges in the design and implementation of systems, namely in terms of the understandability and reliability of the models [174]. The complex nature of some AI models presents a difficulty in interpreting the underlying reasoning behind their decisions, hence generating issues over accountability and transparency, particularly in crucial domains such as energy management. Furthermore, the efficiency of AI-driven control systems is greatly influenced by the accessibility and calibre of data used for training and validation purposes. Erroneous or prejudiced data might result in less than ideal performance and may even worsen preexisting inequalities in energy accessibility and cost [175]. In addition, AI algorithms may have difficulties in adjusting to unexpected or severe occurrences, such as natural calamities or cyber assaults, that might interrupt regular operational circumstances and jeopardise grid stability. Moreover, the use of AI in microgrid control gives rise to ethical concerns about privacy, autonomy, and socioeconomic effects, emphasising the need of strong governance structures and involvement of stakeholders [176]. Hence, it is crucial to overcome these crucial difficulties and guarantee responsible and fair deployment in practice in order to fully harness the potential of AI in boosting microgrid energy management.

AI has machine learning as its major part, which can be used to improve the operation and control of the microgrid functioning. Based on the data, the ML techniques can be categorized into four subsets: Supervised learning, Unsupervised learning, semi-supervised learning, and reinforcement learning [177].

The flow chart shown in Fig. 12 depicts the different types of machine-learning technologies used in microgrid systems [29], [175], [178], [179], [180], [181], [182], [183], [184], [185], [186], [187].

### A. AI-BASED HIERARCHICAL CONTROL

The use of artificial intelligence (AI) in the hierarchical control of microgrid energy management presents both potential benefits and significant obstacles. Hierarchical control structures provide a scalable framework for effectively controlling large microgrid systems. These structures organise control tasks into various levels, including local, distributed, and centralised control layers. Artificial intelligence methods, such as machine learning and optimisation algorithms, may be used at every level to enhance decision-making and enhance system performance. Nevertheless, the successful implementation of AI-based hierarchical control in microgrids requires meticulous evaluation of several pivotal elements [188]. Initially, the incorporation of AI algorithms into control frameworks presents difficulties concerning the transparency, interpretability, and dependability of the algorithms. The opaque nature of many AI models might impede comprehension and confidence in decision-making procedures, perhaps resulting in operational inefficiencies or safety issues. In addition, hierarchical control systems depend on abundant data inputs to train AI models and make well-informed judgements, which raises problems around data privacy, security, and quality. Preserving the authenticity and secrecy of sensitive information in microgrid systems is of utmost importance, particularly due to the possibility of cyber threats and hostile assaults [189]. Furthermore, the implementation of AI-based hierarchical control may face challenges in adjusting to dynamic and unpredictable operating circumstances, such as variations in renewable energy production or sudden increases in demand. Strong and reliable methods for confirming the accuracy of models, measuring uncertainty, and adjusting learning processes are crucial for improving the ability of AI-controlled systems in microgrids to withstand challenges and operate effectively [190]. Moreover, hierarchical control structures need to include socio-technical aspects such as stakeholder preferences, regulatory requirements, and market dynamics in order to guarantee that they are in line with wider energy transition objectives and societal values. Ensuring a harmonious combination of technical intricacy, user-friendliness, and inclusivity is essential for promoting the acceptance and implementation of AI-driven hierarchical control systems across various individuals and groups within microgrid communities [191]. To fully harness the potential of AI-based hierarchical control in microgrids for improving energy management, it is crucial to tackle key challenges such as transparency, data governance, adaptability, and socio-technical factors. This will ensure the realisation of sustainable and fair energy systems.

#### 1) PRIMARY CONTROL

Primary control (as shown in Fig. 13) in hierarchical control deals with inertia control, power sharing, and maximum

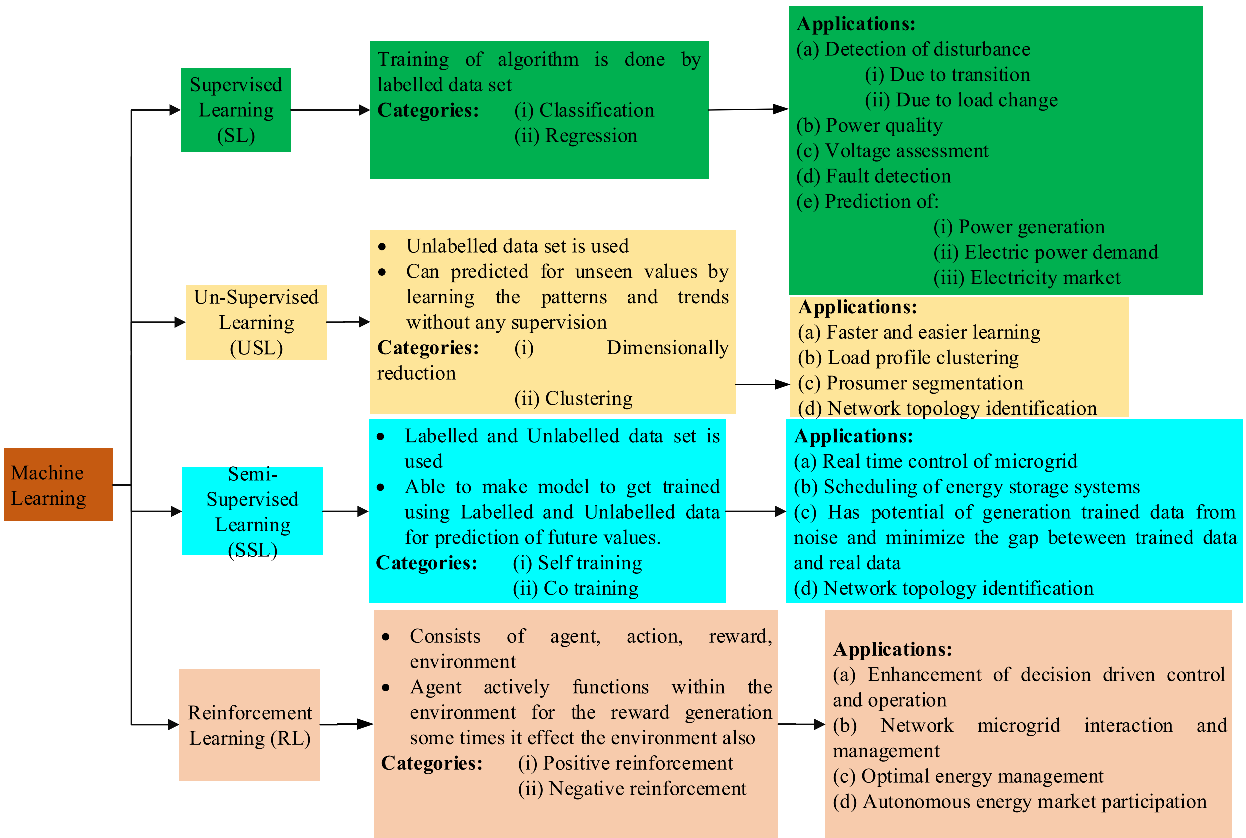


**FIGURE 12.** Machine learning in microgrid.

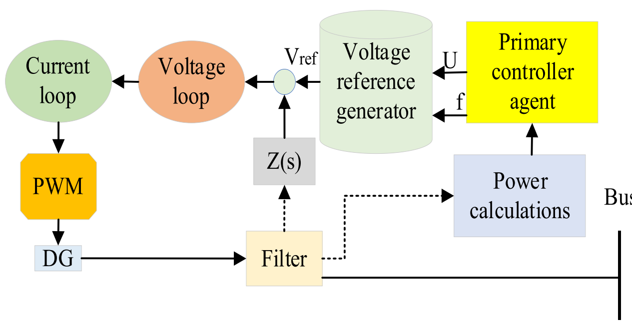


**FIGURE 13.** Primary control flow chart using ML techniques.

power point tracking control. Since power sharing is a complex assignment, implementing AI can boost the primary control function of microgrids. AI helps improve the inertia in microgrids, which have non-rotational generating sources. Compared to the conventional control techniques, AI can track MPPT more accurately, giving the best results.

### 2) SECONDARY CONTROL

The primary level of control can cause v/f variation. This variation can be compensated by applying the secondary level of hierarchical control as shown in Fig. 14. Response delay, accuracy, communication infrastructure, protection and stability are the major challenges in conventional secondary control. Therefore, Novel AI techniques can be implemented to address these challenges.

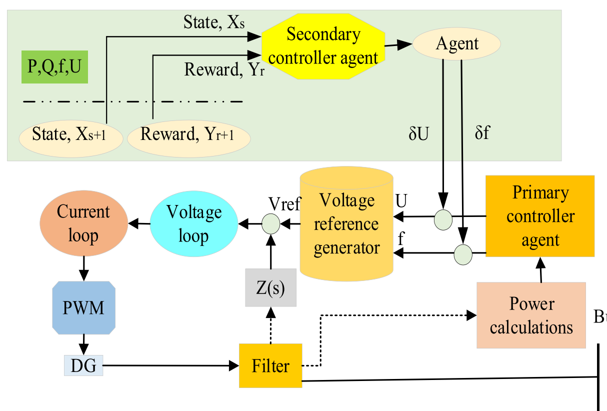


**FIGURE 14.** Secondary control flow chart using ML techniques.

### 3) TERTIARY CONTROL

It is the zenith of a hierarchical control system. It deals with energy exchange with the utility grid.

Tertiary-level control ensures optimized power dispatch and cost-effective operation as depicted in Fig 15. Large

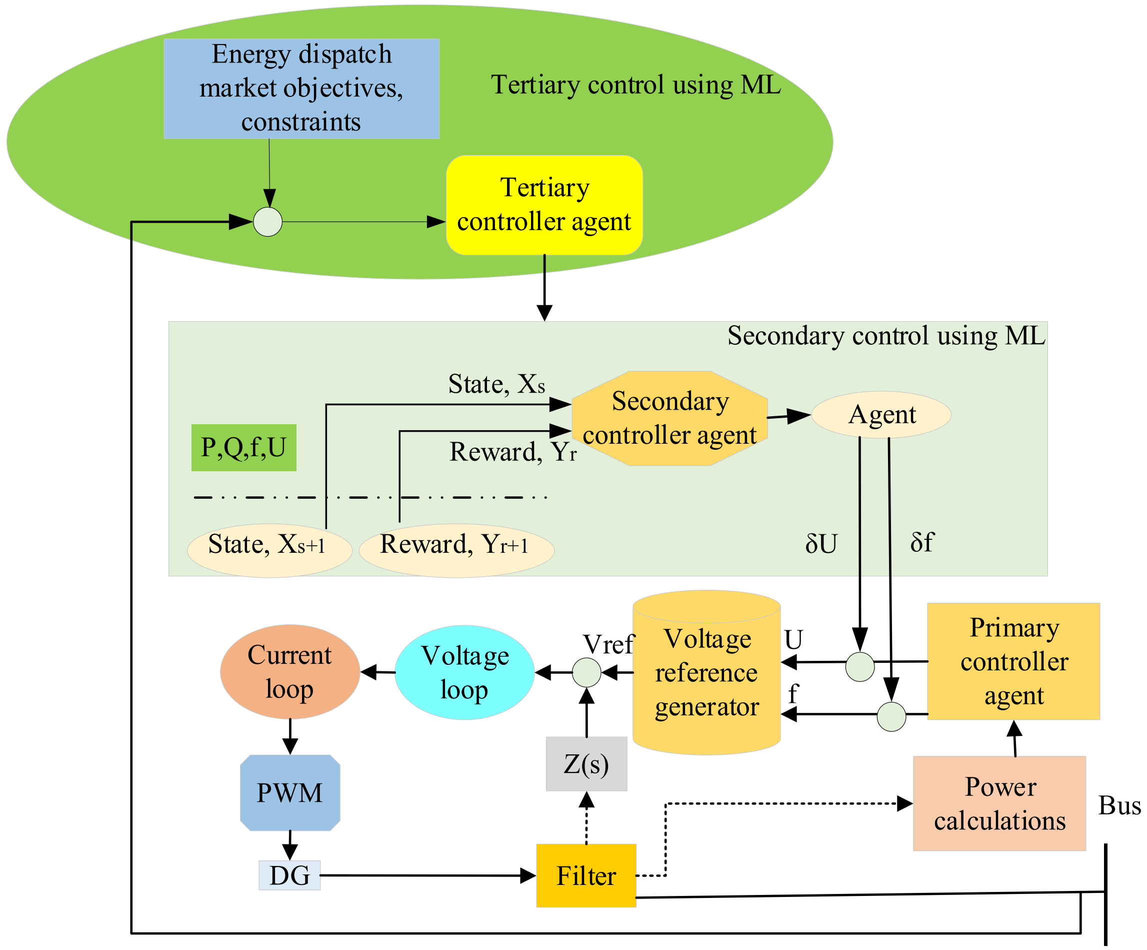


FIGURE 15. Tertiary control flow chart using ML techniques.

data can be easily used for optimal power exchange and AI techniques can easily manage the control scheme.

The flow chart depicted in Fig. 16 gives a detailed analysis of all three categories of hierarchical control [29], [162], [172], [182], [192], [193], [194], [195], [196], [197], [198], [199], [200], [201], [202], [203], [204]

The table 9 depicts the different AI techniques used for three levels of hierarchical control. Every technique is represented for its application in control, and its associated challenges are also analysed.

## VII. DISCUSSION AND INTERPRATATION

The primary source of power production is renewable energy sources, which are abundant, economically feasible, and environmentally beneficial. Designing microgrids while simultaneously considering all aspects is a complex procedure. It is important to remember that each step of the planning process substantially influences the overall capability and efficiency of the renewable energy system. As a result, it is essential to examine a variety of criteria while putting in place an Energy Management System (EMS). Customer satisfaction, renewable energy sources (RES), cost efficiency, regulatory compliance, geographical limits, environmental effects, demand-side management (DSM), energy storage systems (ESS), and switching are among these considerations. EMS delivers a sustainable load-generating solution that reduces pollution and maximizes power exchange efficiency while prioritizing market pricing and security considerations inside the microgrid.

It is critical to emphasize that EMS technology offers a long-term solution for producing power without emitting hazardous pollutants. Furthermore, it enables efficient power exchange based on market rates and protects the microgrid system's security. Implementing an Energy Management System (EMS) may improve power availability and reliability while increasing the amount of renewable energy used. An EMS may also increase power quality, minimize operating and emission losses, limit energy losses, reduce fuel usage, and lessen dependency on grid power input. Based on the EMS's operating mechanism, it might be used for intelligent load-shedding management and power sharing. Centralized and distributed energy management systems may improve microgrid performance and enhance power generation. The central controller controls data collecting, online dispatch, and distributed resource scheduling in a centralized control energy management system.

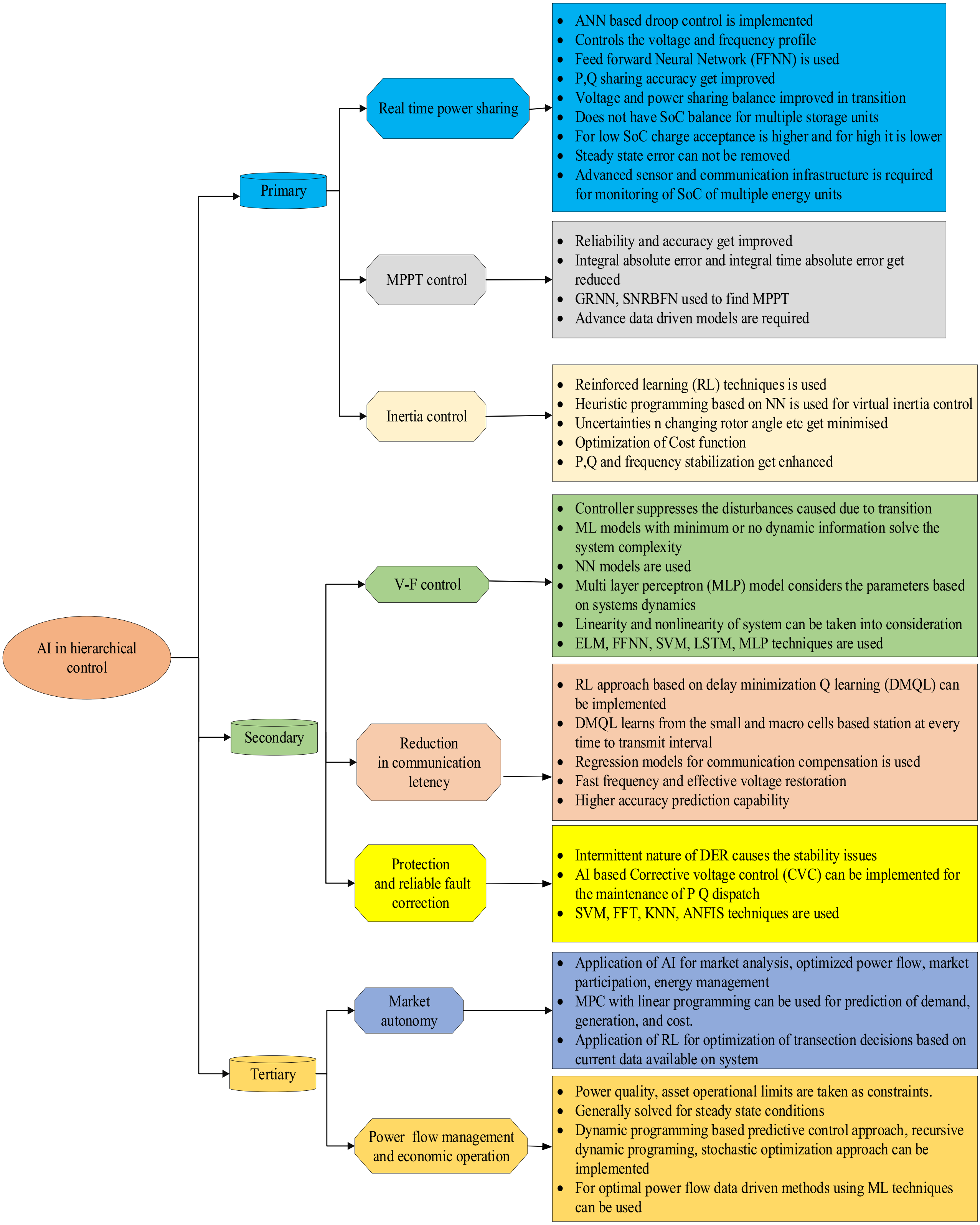


**FIGURE 16.** **Flow chart of AI-based hierarchical control in microgrid.**

**TABLE 9.** Attributes of hierarchical control in microgrid.

| Hierarchical control | Technique | Control type | Application | Challenges | Ref |
|---|---|---|---|---|---|
| Primary | Data driven control based convex optimization method | Distributed | Enhancement of transient condition performance | Poor scalability | [205], [176] |
| | FFNN | Centralized | Droop control, Power sharing | Stability | [206] |
| | ANN based controller in current loop | Distributed | Power sharing | Stability | [207] |
| | ANFIS | Centralized, distributed, decentralized | Q sharing, V/F control | Communication delay | [208], [209] |
| | DRL | Distributed | Load sharing | Effect of line impedance | [210] |
| | Q learning | Distributed | Voltage and frequency synchronization | Communication delay | [211] |
| | Data driven control based on discrete time distributed NN | Distributed | Voltage regulation, power sharing | Integrated optimization analysis | [212] |
| Secondary | Brain emotional learning | Distributed | Calculation reduction, high BW with low steady state fluctuations | Analysis of multiple DG complex scenario | [213] |
| | Adaptive neuro fuzzy inference system | Distributed | Fast frequency recovery | Large calculations | [214] |
| | ANN | Centralized, decentralized, distributed | Energy management | Communication delay | [215] |
| | Adaptive NN | Centralized | Robustness and self-adaptation | Communication delay | [216] |
| | DPPG | Distributed | Voltage restoration, current sharing | Stability analysis | [217] |
| | DL based ANN | Distributed | Power quality | Stability | [218] |
| | RL based on proximal policy | Distributed | Good transfer capabilities | Computational efficiency | [219] |
| Tertiary | Regression machine learning | Distributed | Optimal power flow | Transient | [220] |
| | RL | Centralized | Energy trading | Communication delay | [221] |
| | Cloud-based ML using ANN | Centralized | Islanded detection | Operation under complex conditions | [222] |
| | MINLP-QL | Centralized | Energy management, cost reduction | Large calculations | [223] |
| | Monte Carlo tree-based RL | Centralized | Power flow | Transient analysis | [225] |
| | DNN | Distributed | Optimal power flow, fast computation | Storage system | [225] |
| | SVR | decentralized | Power flow | Stability analysis | [226] |

On the other hand, local controllers make all required choices in a decentralized energy management system. The Centralized Energy Management System (CEMS) is typically used in small-scale microgrids but is also utilized in larger microgrids. DEMS (Decentralized Energy Management Systems) are intended to manage enormous volumes of data and high workloads effectively. This enables local controllers to handle the system seamlessly, guaranteeing optimum renewable energy use. Because of its slower processing speed, complexity, and restricted flexibility, CEMS may create specific issues. With its speedier processing capabilities, dependability, and resilience, DEMS looks to provide a more efficient and trustworthy option. In the context of CEMS and DEMS, single controlling units in CEMS may increase the chance of failure, while DEMS are intended to prevent single-point failures.

Table 6 illustrates various methodologies that are being implemented in a wide range of contexts. Commercial buildings employ HMG technology that can adapt design according to BLP and DG power. However, due to the stochastic nature of BLP and RES intermittency, HMG has a low BEC and a significant RI. The utilization of FOBT-EMS, EMS with enhanced converter and control of PV battery storage, holistic power management, stochastic energy management, and DRS is implemented to achieve economical operation. The Advanced Metering Infrastructure-Energy Management System is employed to operate an isolated Microgrid. The DRMRC-EMS, COVP-EMS, and SEM methodologies are currently being employed. The utilization of MAF and IIOT has the potential to enhance the robustness of MG DRS. DTF, EMS based on a model-free approach, FOBT-EMS, and EMS based on data-driven techniques are potential methods for stochastic energy management in multi-microgrid network systems. Various types of EMS, such as AMEMS, APEM, NILM-EMS, CAD-based EMS, and data-driven EMS, are employed to achieve optimal energy production.

The optimization of energy management in ESS can be achieved through the utilization of Lyapunov optimization-based EMS, APEM, Markov chain-based solar generation model, and Prosumer energy management techniques. System security management can be effectively achieved through stochastic energy management based on blockchain technology. A smooth power profile and frequency improvement can be managed using FLEMS and BMSC. The utilization of CAD-EMS is implemented to achieve efficient voltage regulation. The load profile management can be effectively executed using IPCEM and NLIM methodologies.

The utilization of DRS, DRMPC, AMEMS, HMG, APEM, Markov chain-based model and EMS with advanced converter control of a PV battery system presents certain challenges in power generation. The phenomenon of time delay challenge is observed in CAD-EMS, APEM, and MAF, while the level of computational intricacy is the primary aspect of consideration in IPCEM. Energy storage challenges are observed in various energy management systems such as COVP-EMS, DRM, model-free EMS, EMS with advanced converter control of PV battery, and data-driven EMS. The implementation of control mechanisms in Demand Resource Management (DRM) can be a costly endeavor. Developing Model Predictive Control (MPC) for online structured control also poses challenges in the context of fair-optimal bilevel transactive energy Management Systems (FOBT-EMS). The challenges in implementing two-layer stochastic power management primarily stem from reliability, operation, and security limitations. Despite these challenges, this approach can effectively reduce energy losses. Collaboration amongst prosumers is a favorable aspect of DPES-EMS. However, it presents certain obstacles in prosumer energy provisioning. Implementing a dual pricing system in retail electricity pricing has encountered challenges in market competition among participants. Implementing blockchain technology in stochastic energy management systems exhibits favorable system security and cost-efficiency benefits, rendering it a viable option for deployment in interconnected microgrid networks. Nevertheless, it encounters obstacles in incentive mechanisms centring on smart grid systems.

Based on the data presented in Table 7, it is evident that a uniform methodology is not employed across all instances. A novel methodology is employed to optimise various limitations and achieve optimal gains. The efficacy of certain techniques is contingent upon the specific constraints to which they are applied and may not necessarily yield optimal results when applied to alternative constraints. Various techniques such as HO, ADE, WO, fuzzy algorithm, MFO, SA, and BCA are employed to optimise operational expenses. Additionally, AFSO and HSO are utilised to forecast power generation schedules for the upcoming day. The ACO, SA, WO, BCA, GA, and Fuzzy algorithms exhibit limitations in achieving rapid convergence. The phenomenon of HSO exhibits a high degree of stochasticity, while the robust approach is constrained in its ability to account for multiple sources of variability. The utilization of GA in power systems has been observed to exhibit higher computational speed. However, it is important to note that this approach may converge to a local optimum. The utilization of CSO presents the benefit of unconstrained parameter limitations. The settling time of SFO is superior. However, the issue of premature convergence remains a point of concern. The PSO algorithm exhibits superior performance in the presence of fluctuating power sources and linear and nonlinear loads. However, it is susceptible to oscillations in the operating point around the maximum power point. The GHO, MFO, WO, CSO, and PSO algorithms have reached their local optimal constraints. PSO is a viable technique for enhancing battery longevity. The implementation of ACO has the potential to mitigate frequency and voltage fluctuations.

Implementing control mechanisms is imperative for the efficient and sustainable functioning of microgrids. Implementing local control functions is crucial in regulating primary voltage and frequency and P and Q while ensuring a constant v/f ratio. The control of unit demand can be regulated by implementing drop control techniques. Various applications employ both traditional and innovative control methodologies. The established methodologies encompass MAS, MPPT, droop control, virtual impedance approach, and primary-secondary technique. Contemporary control methodologies rely on cutting-edge technology. Artificial intelligence (AI) methods exhibit high levels of intelligence, adaptability, and speed. Implementing SL, SSL, USL, and RL machine learning methodologies has diverse use cases in managing energy in microgrids. The research discusses various applications of primary, secondary, and tertiary control levels in hierarchical control that are based on artificial intelligence. GRNN and SNRBFN are viable for detecting maximum power point tracking, whereas RL can be effectively executed for inertia management. The primary level of hierarchical control enables real-time power sharing of microgrids. Implementing V-f control at the secondary level can be achieved by utilising ELM, FFNN, SVM, LSTM, and MLP techniques. Reinforcement learning (RL) and DMQL techniques are employed to minimise communication latency. On the other hand, support vector machines (SVM), fast Fourier transform (FFT), k-nearest neighbours (KNN), and ANFIS control methods are utilised for fault prediction and correction at the secondary control level. The tertiary level of hierarchical control can regulate market autonomy, power flow management, and economical operation.

Table 9 illustrates various artificial intelligence (AI) methodologies for optimising the functionality of energy systems, as well as the challenges associated with their implementation. The primary level control's distributed control category includes DRL, Q learning, data-driven control, and FFNN. Implementing ANN for power sharing is feasible. However, stability remains a critical concern. The implementation of voltage regulation can be achieved by utilising Q learning, DTDNN, and data-driven control techniques. The primary obstacle encountered in Q learning and ANFIS control is the issue of communication latency. At the secondary level of hierarchical control, the use of BEL can result in reduced computational requirements. The implementation of ANFIS control for frequency regulation necessitates extensive computations. Implementing artificial neural network (ANN) technique has shown promise in enhancing power quality. However, the issue of communication delay poses a significant challenge in this regard. At the tertiary level of hierarchical control, the optimal power flow can be achieved through the utilisation of RML and DNN techniques. These methods present challenges in the form of transients and storage systems, respectively. The detection of microgrids in an islanded state can be achieved through the utilisation of cloud-based machine learning techniques, specifically artificial neural networks.

Additionally, mixed-integer nonlinear programming with quadratic constraints and linear objectives can effectively manage energy. The analysis of transients poses a challenge in Monte Carlo tree-based reinforcement learning, whereas stability analysis is a challenge in support vector regression. Reinforcement learning (RL) has demonstrated efficacy in energy trading, while legs are useful in mitigating communication delays.

## VIII. CONCLUSION

The concept and applications of microgrids are thoroughly discussed, along with energy management systems that include centralized and decentralized approaches. The integration of advanced optimization techniques and machine learning models addresses the inherent challenges of renewable energy intermittency and system efficiency. Detailed discussions cover optimization techniques applicable to these energy management systems and various control techniques for managing energy in microgrids. The research highlights the critical role of EMS in balancing load generation, reducing emissions, and optimizing power exchange within microgrids. Additionally, the role of artificial intelligence techniques in microgrid control is explored in depth. The study concludes that AI-driven approaches are pivotal for the future of microgrid energy management and control. AI applications, including deep reinforcement learning and data-driven control schemes, demonstrate significant potential in enhancing operational reliability and cost-effectiveness. The findings show that adopting these innovative methods achieves sustainable and economically viable microgrid systems. Future research should focus on refining AI models and exploring their scalability across different microgrid configurations to maximize their impact on global energy management practices. Developing novel optimization techniques for complex microgrids is essential to enhance their efficiency. Additionally, implementing more applications of state-of-the-art technologies can significantly improve microgrid operations. To achieve this, infrastructure must be developed to support the integration of artificial intelligence techniques in microgrid operations.

## REFERENCES

[1] P. H. A. Barra, D. V. Coury, and R. A. S. Fernandes, "A survey on adaptive protection of microgrids and distribution systems with distributed generators," *Renew. Sustain. Energy Rev.*, vol. 118, Feb. 2020, Art. no. 109524, doi: 10.1016/j.rser.2019.109524.

[2] A. Rajaei, M. Rashidinejad, P. Afzali, and S. Dorahaki, "Empowering sustainable energy communities: Optimizing multi-carrier energy systems with green energy, uncertainty management, and demand response," *e-Prime Adv. Electr. Eng., Electron. Energy*, vol. 8, Jun. 2024, Art. no. 100560, doi: 10.1016/j.prime.2024.100560.

[3] A. Younesi, H. Shayeghi, Z. Wang, P. Siano, A. Mehrizi-Sani, and A. Safari, "Trends in modern power systems resilience: State-of-the-art review," *Renew. Sustain. Energy Rev.*, vol. 162, Jul. 2022, Art. no. 112397, doi: 10.1016/j.rser.2022.112397.

[4] A. Muhtadi, D. Pandit, N. Nguyen, and J. Mitra, "Distributed energy resources based microgrid: Review of architecture, control, and reliability," *IEEE Trans. Ind. Appl.*, vol. 57, no. 3, pp. 2223–2235, May 2021, doi: 10.1109/TIA.2021.3065329.

[5] A. Hirsch, Y. Parag, and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues," *Renew. Sustain. Energy Rev.*, vol. 90, pp. 402–411, Jul. 2018, doi: 10.1016/j.rser.2018.03.040.

[6] M. Sandelic, S. Peyghami, A. Sangwongwanich, and F. Blaabjerg, "Reliability aspects in microgrid design and planning: Status and power electronics-induced challenges," *Renew. Sustain. Energy Rev.*, vol. 159, May 2022, Art. no. 112127, doi: 10.1016/j.rser.2022.112127.

[7] M. S. Javed, J. Jurasz, M. McPherson, Y. Dai, and T. Ma, "Quantitative evaluation of renewable-energy-based remote microgrids: Curtailment, load shifting, and reliability," *Renew. Sustain. Energy Rev.*, vol. 164, Aug. 2022, Art. no. 112516, doi: 10.1016/j.rser.2022.112516.

[8] Z. Fan, B. Fan, J. Peng, and W. Liu, "Operation loss minimization targeted distributed optimal control of DC microgrids," *IEEE Syst. J.*, vol. 15, no. 4, pp. 5186–5196, Dec. 2021, doi: 10.1109/JSYST.2020.3035059.

[9] G. M. Cabello, S. J. Navas, I. M. Vázquez, A. Iranzo, and F. J. Pino, "Renewable medium-small projects in Spain: Past and present of microgrid development," *Renew. Sustain. Energy Rev.*, vol. 165, Sep. 2022, Art. no. 112622, doi: 10.1016/j.rser.2022.112622.

[10] Z. Fan, B. Fan, and W. Liu, "Distributed control of DC microgrids for optimal coordination of conventional and renewable generators," *IEEE Trans. Smart Grid*, vol. 12, no. 6, pp. 4607–4615, Nov. 2021, doi: 10.1109/TSG.2021.3094878.

[11] R. Jain, Y. N. Velaga, K. Prabakar, M. Baggu, and K. Schneider, "Modern trends in power system protection for distribution grid with high DER penetration," *e-Prime Adv. Electr. Eng., Electron. Energy*, vol. 2, 2022, Art. no. 100080, doi: 10.1016/j.prime.2022.100080.

[12] A. Safdarian, M. Fotuhi-Firuzabad, and F. Aminifar, "Compromising wind and solar energies from the power system adequacy viewpoint," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 2368–2376, Nov. 2012, doi: 10.1109/TPWRS.2012.2204409.

[13] M. Farrokhabadi et al., "Microgrid stability definitions, analysis, and examples," *IEEE Trans. Power Syst.*, vol. 35, no. 1, pp. 13–29, Jan. 2020, doi: 10.1109/TPWRS.2019.2925703.

[14] N. Nasser and M. Fazeli, "Buffered-microgrid structure for future power networks; a seamless microgrid control," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 131–140, Jan. 2021, doi: 10.1109/TSG.2020.3015573.

[15] M. Yaqoob, A. Lashab, J. C. Vasquez, J. M. Guerrero, M. E. Orchard, and A. D. Bintoudi, "A comprehensive review on small satellite microgrids," *IEEE Trans. Power Electron.*, vol. 37, no. 10, pp. 12741–12762, Oct. 2022, doi: 10.1109/TPEL.2022.3175093.

[16] L. Xu, J. M. Guerrero, A. Lashab, B. Wei, N. Bazmohammadi, J. C. Vasquez, and A. Abusorrah, "A review of DC shipboard microgrids—Part I: Power architectures, energy storage, and power converters," *IEEE Trans. Power Electron.*, vol. 37, no. 5, pp. 5155–5172, May 2022, doi: 10.1109/TPEL.2021.3128417.

[17] L. Xu, J. M. Guerrero, A. Lashab, B. Wei, N. Bazmohammadi, J. C. Vasquez, and A. Abusorrah, "A review of DC shipboard microgrids—Part II: Control architectures, stability analysis, and protection schemes," *IEEE Trans. Power Electron.*, vol. 37, no. 4, pp. 4105–4120, Apr. 2022, doi: 10.1109/TPEL.2021.3128409.

[18] M. Mehta and B. Mehta, "Control strategies for grid-connected hybrid renewable energy systems: Integrating modified direct torque control based doubly fed induction generator and ANFIS based maximum power point tracking for solar PV generation," *e-Prime - Adv. Electr. Eng., Electron. Energy*, vol. 8, Jun. 2024, Art. no. 100575, doi: 10.1016/j.prime.2024.100575.

[19] J. D. Watson, Y. Ojo, K. Laib, and I. Lestas, "A scalable control design for grid-forming inverters in microgrids," *IEEE Trans. Smart Grid*, vol. 12, no. 6, pp. 4726–4739, Nov. 2021, doi: 10.1109/TSG.2021.3105730.

[20] S. K. Bhoi, K. Kasturi, and M. R. Nayak, "Optimisation of the operation of a microgrid with renewable energy sources and battery storage," *e-Prime Adv. Electr. Eng., Electron. Energy*, vol. 4, Jun. 2023, Art. no. 100159, doi: 10.1016/j.prime.2023.100159.

[21] W. Murray, M. Adonis, and A. Raji, "Voltage control in future electrical distribution networks," *Renew. Sustain. Energy Rev.*, vol. 146, Aug. 2021, Art. no. 111100, doi: 10.1016/j.rser.2021.111100.

[22] E. Rahmani, S. Mohammadi, M. Zadehbagheri, and M. Kiani, "Probabilistic reliability management of energy storage systems in connected/islanding microgrids with renewable energy," *Electric Power Syst. Res.*, vol. 214, Jan. 2023, Art. no. 108891, doi: 10.1016/j.epsr.2022.108891.

[23] A. Panda, A. K. Dauda, H. Chua, R. R. Tan, and K. B. Aviso, "Recent advances in the integration of renewable energy sources and storage facilities with hybrid power systems," *Cleaner Eng. Technol.*, vol. 12, Feb. 2023, Art. no. 100598, doi: 10.1016/j.clet.2023.100598.

[24] M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. B. Mansor, and F. Blaabjerg, "Review of energy storage system technologies in microgrid applications: Issues and challenges," *IEEE Access*, vol. 6, pp. 35143–35164, 2018, doi: 10.1109/ACCESS.2018.2841407.

[25] F.-J. Lin, K.-H. Tan, C.-F. Chang, M.-Y. Li, and T.-Y. Tseng, "Development of intelligent controlled microgrid for power sharing and load shedding," *IEEE Trans. Power Electron.*, vol. 37, no. 7, pp. 7928–7940, Jul. 2022, doi: 10.1109/TPEL.2022.3152167.

[26] A. P. Arunkumar, S. Kuppusamy, S. Muthusamy, S. Pandiyan, H. Panchal, and P. Nagaiyan, "An extensive review on energy management system for microgrids," *Energy Sources, A, Recovery, Utilization, Environ. Effects*, vol. 44, no. 2, pp. 4203–4228, Jun. 2022, doi: 10.1080/15567036.2022.2075059.

[27] H. Acaroğlu and F. P. G. Márquez, "A life-cycle cost analysis of high voltage direct current utilization for solar energy systems: The case study in Turkey," *J. Cleaner Prod.*, vol. 360, Aug. 2022, Art. no. 132128, doi: 10.1016/j.jclepro.2022.132128.

[28] T. B. Lopez-Garcia, A. Coronado-Mendoza, and J. A. Domínguez-Navarro, "Artificial neural networks in microgrids: A review," *Eng. Appl. Artif. Intell.*, vol. 95, Oct. 2020, Art. no. 103894, doi: 10.1016/j.engappai.2020.103894.

[29] R. Trivedi and S. Khadem, "Implementation of artificial intelligence techniques in microgrid control environment: Current progress and future scopes," *Energy AI*, vol. 8, May 2022, Art. no. 100147, doi: 10.1016/j.egyai.2022.100147.

[30] E. O'Dwyer, I. Pan, S. Acha, and N. Shah, "Smart energy systems for sustainable smart cities: Current developments, trends and future directions," *Appl. Energy*, vol. 237, pp. 581–597, Mar. 2019, doi: 10.1016/j.apenergy.2019.01.024.

[31] K. Chandrasekaran, P. Kandasamy, and S. Ramanathan, "Deep learning and reinforcement learning approach on microgrid," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 10, Oct. 2020, Art. no. e12531, doi: 10.1002/2050-7038.12531.

[32] S. Dixit, P. Singh, J. Ogale, P. Bansal, and Y. Sawle, "Energy management in microgrids with renewable energy sources and demand response," *Comput. Electr. Eng.*, vol. 110, Sep. 2023, Art. no. 108848, doi: 10.1016/j.compeleceng.2023.108848.

[33] B. Zhang, W. Hu, A. M. Y. M. Ghias, X. Xu, and Z. Chen, "Multi-agent deep reinforcement learning based distributed control architecture for interconnected multi-energy microgrid energy management and optimization," *Energy Convers. Manage.*, vol. 277, Feb. 2023, Art. no. 116647, doi: 10.1016/j.enconman.2022.116647.

[34] H. Golmohamadi, "Demand-side management in industrial sector: A review of heavy industries," *Renew. Sustain. Energy Rev.*, vol. 156, Mar. 2022, Art. no. 111963, doi: 10.1016/j.rser.2021.111963.

[35] W. Jiang, X. Wang, H. Huang, D. Zhang, and N. Ghadimi, "Optimal economic scheduling of microgrids considering renewable energy sources based on energy hub model using demand response and improved water wave optimization algorithm," *J. Energy Storage*, vol. 55, Nov. 2022, Art. no. 105311, doi: 10.1016/j.est.2022.105311.

[36] B. Mukhopadhyay and D. Das, "Optimal multi-objective long-term sizing of distributed energy resources and hourly power scheduling in a grid-tied microgrid," *Sustain. Energy, Grids Netw.*, vol. 30, Jun. 2022, Art. no. 100632, doi: 10.1016/j.segan.2022.100632.

[37] S. C. Shandiz, B. Rismanchi, and G. Foliente, "Energy master planning for net-zero emission communities: State of the art and research challenges," *Renew. Sustain. Energy Rev.*, vol. 137, Mar. 2021, Art. no. 110600, doi: 10.1016/j.rser.2020.110600.

[38] M. F. Roslan, M. A. Hannan, P. J. Ker, M. Mannan, K. M. Muttaqi, and T. I. Mahlia, "Microgrid control methods toward achieving sustainable energy management: A bibliometric analysis for future directions," *J. Cleaner Prod.*, vol. 348, May 2022, Art. no. 131340, doi: 10.1016/j.jclepro.2022.131340.

[39] Q. T. Tran, V. H. Nguyen, N. A. Luu, and E. Amicarelli, "Distributed energy resource management system," *Local Electr. Mark.*, pp. 159–175, Jan. 2021, doi: 10.1016/B978-0-12-820074-2.00014-9.

[40] Y. E. G. Vera, R. Dufo-López, and J. L. Bernal-Agustín, "Energy management in microgrids with renewable energy sources: A literature review," *Appl. Sci.*, vol. 9, no. 18, p. 3854, Sep. 01, 2019, doi: 10.3390/app9183854.

[41] F. Katiraei, R. Iravani, N. Hatziargyriou, and A. Dimeas, "Microgrids management," *IEEE Power Energy Mag.*, vol. 6, no. 3, pp. 54–65, May 2008, doi: 10.1109/MPE.2008.918702.

[42] M. S. Jonban, L. Romeral, A. Akbarimajd, Z. Ali, S. S. Ghazimirsaeid, M. Marzband, and G. Putrus, "Autonomous energy management system with self-healing capabilities for green buildings (microgrids)," *J. Building Eng.*, vol. 34, Feb. 2021, Art. no. 101604, doi: 10.1016/j.jobe.2020.101604.

[43] H. Shayeghi, E. Shahryari, M. Moradzadeh, and P. Siano, "A survey on microgrid energy management considering flexible energy sources," *Energies*, vol. 12, no. 11, p. 2156, Jun. 2019, doi: 10.3390/en12112156.

[44] A. Kafetzis, C. Ziogou, K. D. Panopoulos, S. Papadopoulou, P. Seferlis, and S. Voutetakis, "Energy management strategies based on hybrid automata for islanded microgrids with renewable sources, batteries and hydrogen," *Renew. Sustain. Energy Rev.*, vol. 134, Dec. 2020, Art. no. 110118, doi: 10.1016/j.rser.2020.110118.

[45] N. Eghbali, S. M. Hakimi, A. Hasankhani, G. Derakhshan, and B. Abdi, "Stochastic energy management for a renewable energy based microgrid considering battery, hydrogen storage, and demand response," *Sustain. Energy, Grids Netw.*, vol. 30, Jun. 2022, Art. no. 100652, doi: 10.1016/j.segan.2022.100652.

[46] A. Hussain, V.-H. Bui, and H.-M. Kim, "An effort-based reward approach for allocating load shedding amount in networked microgrids using multi-agent system," *IEEE Trans. Ind. Informat.*, vol. 16, no. 4, pp. 2268–2279, Apr. 2020, doi: 10.1109/TII.2019.2929284.

[47] C. L. Bhattar and M. A. Chaudhari, "Centralized energy management scheme for grid connected DC microgrid," *IEEE Syst. J.*, vol. 17, no. 3, pp. 3741–3751, Jul. 2023, doi: 10.1109/JSYST.2022.3231898.

[48] P. Tenti and T. Caldognetto, "Integration of local and central control empowers cooperation among prosumers and distributors towards safe, efficient, and cost-effective operation of microgrids," *Energies*, vol. 16, no. 5, p. 2320, Feb. 2023, doi: 10.3390/en16052320.

[49] A. Arabpour and H. Hojabri, "An improved centralized/decentralized accurate reactive power sharing method in AC microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 148, Jun. 2023, Art. no. 108908, doi: 10.1016/j.ijepes.2022.108908.

[50] D. Espín-Sarzosa, R. Palma-Behnke, and O. Núñez-Mata, "Energy management systems for microgrids: Main existing trends in centralized control architectures," *Energies*, vol. 13, no. 3, p. 547, Jan. 2020, doi: 10.3390/en13030547.

[51] J. B. Almada, R. P. S. Leão, R. F. Sampaio, and G. C. Barroso, "A centralized and heuristic approach for energy management of an AC microgrid," *Renew. Sustain. Energy Rev.*, vol. 60, pp. 1396–1404, Jul. 2016, doi: 10.1016/j.rser.2016.03.002.

[52] C.-S. Karavas, G. Kyriakarakos, K. G. Arvanitis, and G. Papadakis, "A multi-agent decentralized energy management system based on distributed intelligence for the design and control of autonomous polygeneration microgrids," *Energy Convers. Manage.*, vol. 103, pp. 166–179, Oct. 2015, doi: 10.1016/j.enconman.2015.06.021.

[53] C.-S. Hwang, E.-S. Kim, and Y.-S. Kim, "A decentralized control method for distributed generations in an islanded DC microgrid considering voltage drop compensation and durable state of charge," *Energies*, vol. 9, no. 12, p. 1070, Dec. 2016, doi: 10.3390/en9121070.

[54] T. Nasir, S. S. H. Bukhari, S. Raza, H. M. Munir, M. Abrar, H. A. U. Muqeet, K. L. Bhatti, J.-S. Ro, and R. Masroor, "Recent challenges and methodologies in smart grid demand side management: State-of-the-Art literature review," *Math. Problems Eng.*, vol. 2021, pp. 1–16, Aug. 2021, doi: 10.1155/2021/5821301.

[55] S. H. A. Soltani, S. Jalili, and M. K. S. E. Eslami, "Decentralized control architecture for multi-authoring microgrids," *Computing*, vol. 105, no. 12, pp. 2621–2646, Dec. 2023, doi: 10.1007/s00607-023-01201-w.

[56] M. Nabatirad, R. Razzaghi, and B. Bahrani, "Decentralized voltage regulation and energy management of integrated DC microgrids into AC power systems," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 9, no. 2, pp. 1269–1279, Apr. 2021, doi: 10.1109/JESTPE.2020.3034946.

[57] A. K. Mbodji, M. L. Ndiaye, and P. A. Ndiaye, "Decentralized control of the hybrid electrical system consumption: A multi-agent approach," *Renew. Sustain. Energy Rev.*, vol. 59, pp. 972–978, Jun. 2016, doi: 10.1016/j.rser.2015.12.135.

[58] M. W. Khan, J. Wang, M. Ma, L. Xiong, P. Li, and F. Wu, "Optimal energy management and control aspects of distributed microgrid using multi-agent systems," *Sustain. Cities Soc.*, vol. 44, pp. 855–870, Jan. 2019, doi: 10.1016/j.scs.2018.11.009.

[59] M. W. Khan and J. Wang, "The research on multi-agent system for microgrid control and optimization," *Renew. Sustain. Energy Rev.*, vol. 80, pp. 1399–1411, Dec. 2017, doi: 10.1016/j.rser.2017.05.279.

[60] K. Thirugnanam, M. S. El Moursi, V. Khadkikar, H. H. Zeineldin, and M. A. Hosani, "Energy management strategy of a reconfigurable grid-tied hybrid AC/DC microgrid for commercial building applications," *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 1720–1738, May 2022, doi: 10.1109/TSG.2022.3141459.

[61] M. Manbachi and M. Ordonez, "AMI-based energy management for islanded AC/DC microgrids utilizing energy conservation and optimization," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 293–304, Jan. 2019, doi: 10.1109/TSG.2017.2737946.

[62] Office of Electricity Delivery & Energy Reliability. (2016). *Advanced Metering Infraestructure and Customer Systems*. [Online]. Available: https://www.energy.gov/sites/prod/files/2016/12/f34/AMI SummaryReport_09-26-16.pdf

[63] L. Xiong, Y. Tang, S. Mao, H. Liu, K. Meng, Z. Dong, and F. Qian, "A two-level energy management strategy for multi-microgrid systems with interval prediction and reinforcement learning," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 69, no. 4, pp. 1788–1799, Apr. 2022, doi: 10.1109/TCSI.2022.3141229.

[64] S. Haghifam, H. Laaksonen, and M. Shafie-Khah, "Modeling a local electricity market for transactive energy trading of multi-aggregators," *IEEE Access*, vol. 10, pp. 68792–68806, 2022, doi: 10.1109/ACCESS.2022.3186309.

[65] H. Masrur, M. M. Gamil, M. R. Islam, K. M. Muttaqi, M. S. H. Lipu, and T. Senjyu, "An optimized and outage-resilient energy management framework for multicarrier energy microgrids integrating demand response," *IEEE Trans. Ind. Appl.*, vol. 58, no. 3, pp. 4171–4180, May 2022, doi: 10.1109/TIA.2022.3160683.

[66] N. Eghbali, S. M. Hakimi, A. Hasankhani, G. Derakhshan, and B. Abdi, "A scenario-based stochastic model for day-ahead energy management of a multi-carrier microgrid considering uncertainty of electric vehicles," *J. Energy Storage*, vol. 52, Aug. 2022, Art. no. 104843, doi: 10.1016/j.est.2022.104843.

[67] D. Köbrich, L. G. Marín, D. Muñoz-Carpintero, C. Ahumada, D. Sáez, M. Sumner, and G. Jiménez-Estévez, "A robust distributed energy management system for the coordinated operation of rural multi-microgrids," *Int. J. Energy Res.*, vol. 46, no. 14, pp. 19775–19795, Nov. 2022, doi: 10.1002/er.8502.

[68] A. Mondal, S. Misra, and A. Chakraborty, "Dynamic price-enabled strategic energy management scheme in cloud-enabled smart grid," *IEEE Trans. Cloud Comput.*, vol. 10, no. 1, pp. 111–122, Jan. 2022, doi: 10.1109/TCC.2021.3118637.

[69] A. Dridi, H. Afifi, H. Moungla, and J. Badosa, "A novel deep reinforcement learning approach for IIoT microgrid energy management systems," *IEEE Trans. Green Commun. Netw.*, vol. 6, no. 1, pp. 148–159, Mar. 2022, doi: 10.1109/TGCN.2021.3112043.

[70] F. Yang, X. Feng, and Z. Li, "Advanced microgrid energy management system for future sustainable and resilient power grid," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 7251–7260, Nov. 2019, doi: 10.1109/TIA.2019.2912133.

[71] M. Spiegel, E. Veith, and T. Strasser, "The spectrum of proactive, resilient multi-microgrid scheduling: A systematic literature review," *Energies*, vol. 13, no. 17, p. 4543, Sep. 2020, doi: 10.3390/en13174543.

[72] M. Veisi, F. Adabi, A. Kavousi-Fard, and M. Karimi, "A framework of electricity market based on two-layer stochastic power management for microgrids," *IEEE Access*, vol. 10, pp. 41047–41063, 2022, doi: 10.1109/ACCESS.2022.3167826.

[73] M. Dabbaghjamanesh, B. Wang, A. Kavousi-Fard, N. D. Hatziargyriou, and J. Zhang, "Blockchain-based stochastic energy management of interconnected microgrids considering incentive price," *IEEE Trans. Control Netw. Syst.*, vol. 8, no. 3, pp. 1201–1211, Sep. 2021, doi: 10.1109/TCNS.2021.3059851.

[74] E. Kapassa, M. Themistocleous, K. Christodoulou, and E. Iosif, "Blockchain application in Internet of Vehicles: Challenges, contributions and current limitations," *Future Internet*, vol. 13, no. 12, p. 313, Dec. 2021, doi: 10.3390/fi13120313.

[75] P. U. Herath, V. Fusco, M. N. Cáceres, G. K. Venayagamoorthy, S. Squartini, F. Piazza, and J. M. Corchado, "Computational intelligence-based demand response management in a microgrid," *IEEE Trans. Ind. Appl.*, vol. 55, no. 1, pp. 732–740, Jan. 2019, doi: 10.1109/TIA.2018.2871390.

[76] G. Mohy-ud-din, K. M. Muttaqi, and D. Sutanto, "Adaptive and predictive energy management strategy for real-time optimal power dispatch from VPPs integrated with renewable energy and energy storage," *IEEE Trans. Ind. Appl.*, vol. 57, no. 3, pp. 1958–1972, May 2021, doi: 10.1109/TIA.2021.3057356.

[77] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "Stochastic energy management of microgrids during unscheduled islanding period," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1079–1087, Jun. 2017, doi: 10.1109/TII.2016.2646721.

[78] D. Arcos-Aviles, J. Pascual, L. Marroyo, P. Sanchis, and F. Guinjoan, "Fuzzy logic-based energy management system design for residential grid-connected microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 530–543, Mar. 2018, doi: 10.1109/TSG.2016.2555245.

[79] M. S. Mahmoud, N. M. Alyazidi, and M. I. Abouheaf, "Adaptive intelligent techniques for microgrid control systems: A survey," *Int. J. Electr. Power Energy Syst.*, vol. 90, pp. 292–305, Sep. 2017, doi: 10.1016/j.ijepes.2017.02.008.

[80] M. F. Roslan, M. A. Hannan, P. J. Ker, and M. N. Uddin, "Microgrid control methods toward achieving sustainable energy management," *Appl. Energy*, vol. 240, pp. 583–607, Apr. 2019, doi: 10.1016/j.apenergy.2019.02.070.

[81] K. Hein, Y. Xu, G. Wilson, and A. K. Gupta, "Coordinated optimal voyage planning and energy management of all-electric ship with hybrid energy storage system," *IEEE Trans. Power Syst.*, vol. 36, no. 3, pp. 2355–2365, May 2021, doi: 10.1109/TPWRS.2020.3029331.

[82] A. Rosato, M. Panella, R. Araneo, and A. Andreotti, "A neural network based prediction system of distributed generation for the management of microgrids," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 7092–7102, Nov. 2019.

[83] H. Çimen, N. Çetinkaya, J. C. Vasquez, and J. M. Guerrero, "A microgrid energy management system based on non-intrusive load monitoring via multitask learning," *IEEE Trans. Smart Grid*, vol. 12, no. 2, pp. 977–987, Mar. 2021, doi: 10.1109/TSG.2020.3027491.

[84] Y. Shan, J. Hu, and H. Liu, "A holistic power management strategy of microgrids based on model predictive control and particle swarm optimization," *IEEE Trans. Ind. Informat.*, vol. 18, no. 8, pp. 5115–5126, Aug. 2022, doi: 10.1109/TII.2021.3123532.

[85] Z. Shen, C. Wu, L. Wang, and G. Zhang, "Real-time energy management for microgrid with EV station and CHP generation," *IEEE Trans. Netw. Sci. Eng.*, vol. 8, no. 2, pp. 1492–1501, Apr. 2021, doi: 10.1109/TNSE.2021.3062846.

[86] D. Zhu, B. Yang, Q. Liu, K. Ma, S. Zhu, C. Ma, and X. Guan, "Energy trading in microgrids for synergies among electricity, hydrogen and heat networks," *Appl. Energy*, vol. 272, Aug. 2020, Art. no. 115225, doi: 10.1016/j.apenergy.2020.115225.

[87] S. Sahoo, S. Mishra, S. Jha, and B. Singh, "A cooperative adaptive droop based energy management and optimal voltage regulation scheme for DC microgrids," *IEEE Trans. Ind. Electron.*, vol. 67, no. 4, pp. 2894–2904, Apr. 2020, doi: 10.1109/TIE.2019.2910037.

[88] S. Sahoo, S. Mishra, S. M. Fazeli, F. Li, and T. Dragicevic, "A distributed fixed-time secondary controller for DC microgrid clusters," *IEEE Trans. Energy Convers.*, vol. 34, no. 4, pp. 1997–2007, Dec. 2019, doi: 10.1109/TEC.2019.2934905.

[89] L. Han, T. Morstyn, and M. McCulloch, "Incentivizing prosumer coalitions with energy management using cooperative game theory," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 303–313, Jan. 2019, doi: 10.1109/TPWRS.2018.2858540.

[90] S. Fattaheian-Dehkordi, A. Rajaei, A. Abbaspour, M. Fotuhi-Firuzabad, and M. Lehtonen, "Distributed transactive framework for congestion management of multiple-microgrid distribution systems," *IEEE Trans. Smart Grid*, vol. 13, no. 2, pp. 1335–1346, Mar. 2022, doi: 10.1109/TSG.2021.3135139.

[91] A. Conde, G. Pérez, G. Gutiérrez-Alcaraz, and Z. Leonowicz, "Frequency improvement in microgrids through battery management system control supported by a remedial action scheme," *IEEE Access*, vol. 10, pp. 8081–8091, 2022, doi: 10.1109/ACCESS.2022.3143034.

[92] D. I. Brandao, R. P. D. Santos, W. W. A. G. Silva, T. R. Oliveira, and P. F. Donoso-Garcia, "Model-free energy management system for hybrid alternating Current/Direct current microgrids," *IEEE Trans. Ind. Electron.*, vol. 68, no. 5, pp. 3982–3991, May 2021, doi: 10.1109/TIE.2020.2984993.

[93] A. M. Mahfuz-Ur-Rahman, Md. R. Islam, K. M. Muttaqi, and D. Sutanto, "An effective energy management with advanced converter and control for a PV-battery storage based microgrid to improve energy resiliency," *IEEE Trans. Ind. Appl.*, vol. 57, no. 6, pp. 6659–6668, Nov. 2021, doi: 10.1109/TIA.2021.3115085.

[94] N. Gholizadeh, M. Abedi, H. Nafisi, M. Marzband, A. Loni, and G. A. Putrus, "Fair-optimal bilevel transactive energy management for community of microgrids," *IEEE Syst. J.*, vol. 16, no. 2, pp. 2125–2135, Jun. 2022, doi: 10.1109/JSYST.2021.3066423.

[95] L. K. Gan, P. Zhang, J. Lee, M. A. Osborne, and D. A. Howey, "Data-driven energy management system with Gaussian process forecasting and MPC for interconnected microgrids," *IEEE Trans. Sustain. Energy*, vol. 12, no. 1, pp. 695–704, Jan. 2021, doi: 10.1109/TSTE.2020.3017224.

[96] R. H. M. Zargar and M. H. Yaghmaee Moghaddam, "Development of a Markov-Chain-based solar generation model for smart microgrid energy management system," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 736–745, Apr. 2020, doi: 10.1109/TSTE.2019.2904436.

[97] S. Lakshmi, S. P. Singh, S. Padmanaban, Z. Leonowicz, and J. B. Holm-Nielsen, "Prosumer energy management for optimal utilization of bid fulfillment with EV uncertainty modeling," *IEEE Trans. Ind. Appl.*, vol. 58, no. 1, pp. 599–611, Jan. 2022, doi: 10.1109/TIA.2021.3119971.

[98] Z. Wu and B. Chen, "Distributed electric vehicle charging scheduling with transactive energy management," *Energies*, vol. 15, no. 1, p. 163, Dec. 2021, doi: 10.3390/en15010163.

[99] B. Papari, C. S. Edrington, M. Ghadamyari, M. Ansari, G. Ozkan, and B. Chowdhury, "Metrics analysis framework of control and management system for resilient connected community microgrids," *IEEE Trans. Sustain. Energy*, vol. 13, no. 2, pp. 704–714, Apr. 2022, doi: 10.1109/TSTE.2021.3129450.

[100] A. Mehbodniya, A. Paeizi, M. Rezaie, M. Azimian, H. Masrur, and T. Senjyu, "Active and reactive power management in the smart distribution network enriched with wind turbines and photovoltaic systems," *Sustainability*, vol. 14, no. 7, p. 4273, Apr. 2022, doi: 10.3390/su14074273.

[101] K. Gao, T. Wang, C. Han, J. Xie, Y. Ma, and R. Peng, "A review of optimization of microgrid operation," *Energies*, vol. 14, no. 10, p. 2842, May 2021, doi: 10.3390/en14102842.

[102] G. Indira, M. Bhavani, R. Brinda, and R. Zahira, "Electricity load demand prediction for microgrid energy management system using hybrid adaptive barnacle-mating optimizer with artificial neural network algorithm," *Energy Technol.*, vol. 12, no. 5, May 2024, Art. no. 2301091, doi: 10.1002/ente.202301091.

[103] C. A. Nallolla, V. P, D. Chittathuru, and S. Padmanaban, "Multi-objective optimization algorithms for a hybrid AC/DC microgrid using RES: A comprehensive review," *Electronics*, vol. 12, no. 4, p. 1062, Feb. 2023, doi: 10.3390/electronics12041062.

[104] G. S. Thirunavukkarasu, M. Seyedmahmoudian, E. Jamei, B. Horan, S. Mekhilef, and A. Stojcevski, "Role of optimization techniques in microgrid energy management systems—A review," *Energy Strategy Rev.*, vol. 43, Sep. 2022, Art. no. 100899, doi: 10.1016/j.esr.2022.100899.

[105] G. M. Kakandikar and V. M. Nandedkar, *Engineering Optimization*, 2018, doi: 10.4324/9781315156101-4.

[106] Z. Tang, Y. Yang, and F. Blaabjerg, "An interlinking converter for renewable energy integration into hybrid grids," *IEEE Trans. Power Electron.*, vol. 36, no. 3, pp. 2499–2504, Mar. 2021, doi: 10.1109/TPEL.2020.3018585.

[107] S. Vadi, S. Padmanaban, R. Bayindir, F. Blaabjerg, and L. Mihet-Popa, "A review on optimization and control methods used to provide transient stability in microgrids," *Energies*, vol. 12, no. 18, p. 3582, Sep. 2019, doi: 10.3390/en12183582.

[108] A. A. Z. Diab, H. M. Sultan, I. S. Mohamed, O. N. Kuznetsov, and T. D. Do, "Application of different optimization algorithms for optimal sizing of PV/wind/diesel/battery storage stand-alone hybrid microgrid," *IEEE Access*, vol. 7, pp. 119223–119245, 2019, doi: 10.1109/ACCESS.2019.2936656.

[109] A. R. G. Abdullah M. Shaheen, R. A. El-Sehiemy, and H. M.Hasanien, "An improved heap optimization algorithm for efficient energy management based optimal power flow," *Energy*, vol. 151, no. 3, pp. 201–212, 2022, doi: 10.1049/ip-gtd.

[110] M. A. M. Shaheen, H. M. Hasanien, and A. Al-Durra, "Solving of optimal power flow problem including renewable energy resources using HEAP optimization algorithm," *IEEE Access*, vol. 9, pp. 35846–35863, 2021, doi: 10.1109/ACCESS.2021.3059665.

[111] N. A. Nguyen, D. N. Vo, T. T. Nguyen, and T. L. Duong, "An improved equilibrium optimizer algorithm for solving optimal power flow problem with penetration of wind and solar energy," *Int. Trans. Electr. Energy Syst.*, vol. 2022, pp. 1–21, Jun. 2022.

[112] J. Martinez-Rico, E. Zulueta, I. R. de Argandoña, U. Fernandez-Gamiz, and M. Armendia, "Multi-objective optimization of production scheduling using particle swarm optimization algorithm for hybrid renewable power plants with battery energy storage system," *J. Modern Power Syst. Clean Energy*, vol. 9, no. 2, pp. 285–294, Mar. 2021, doi: 10.35833/MPCE.2019.000021.

[113] M. Li, W. Du, and F. Nian, "An adaptive particle swarm optimization algorithm based on directed weighted complex network," *Math. Problems Eng.*, vol. 2014, pp. 1–7, 2014, doi: 10.1155/2014/434972.

[114] X. Qian, Y. Yang, C. Li, and S.-C. Tan, "Operating cost reduction of DC microgrids under real-time pricing using adaptive differential evolution algorithm," *IEEE Access*, vol. 8, pp. 169247–169258, 2020, doi: 10.1109/ACCESS.2020.3024112.

[115] J. Sun, X. Liu, T. Bäck, and Z. Xu, "Learning adaptive differential evolution algorithm from optimization experiences by policy gradient," *IEEE Trans. Evol. Comput.*, vol. 25, no. 4, pp. 666–680, Aug. 2021.

[116] S. Puchalapalli, S. K. Tiwari, B. Singh, and P. K. Goel, "A microgrid based on wind-driven DFIG, DG, and solar PV array for optimal fuel consumption," *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 4689–4699, Sep. 2020, doi: 10.1109/TIA.2020.2999563.

[117] D. Pilakkat and S. Kanthalakshmi, "An improved P&O algorithm integrated with artificial bee colony for photovoltaic systems under partial shading conditions," *Sol. Energy*, vol. 178, pp. 37–47, Jan. 2019, doi: 10.1016/j.solener.2018.12.008.

[118] T. Adefarati, S. Potgieter, R. C. Bansal, R. Naidoo, R. Rizzo, and P. Sanjeevikumar, "Optimization of PV-wind-battery storage microgrid system utilizing d genetic algorithm," vol. 2, pp. 633–638, 2019.

[119] J. Yan, W. Daobo, B. Tingting, and Y. Zongyuan, "Multi-UAV objective assignment using Hungarian fusion genetic algorithm," *IEEE Access*, vol. 10, pp. 43013–43021, 2022, doi: 10.1109/ACCESS.2022.3168359.

[120] P. C. Nayak, B. P. Nayak, R. C. Prusty, and S. Panda, "Sunflower optimization based fractional order fuzzy PID controller for frequency regulation of solar-wind integrated power system with hydrogen Aqua equalizer-fuel cell unit," *Energy Sour., A, Recovery, Utilization, Environ. Effects*, pp. 1–19, Jul. 2021, doi: 10.1080/15567036.2021.1953636.

[121] A. M. Hussien, H. M. Hasanien, and S. F. Mekhamer, "Sunflower optimization algorithm-based optimal PI control for enhancing the performance of an autonomous operation of a microgrid," *Ain Shams Eng. J.*, vol. 12, no. 2, pp. 1883–1893, Jun. 2021, doi: 10.1016/j.asej.2020.10.020.

[122] Z. Yuan, W. Wang, H. Wang, and N. Razmjooy, "A new technique for optimal estimation of the circuit-based PEMFCs using developed sunflower optimization algorithm," *Energy Rep.*, vol. 6, pp. 662–671, Nov. 2020, doi: 10.1016/j.egyr.2020.03.010.

[123] O. V. G. Swathika, S. Mukhopadhyay, and Y. Gupta, "Modified cuckoo search algorithm for fittest relay identification in microgrid," in *Proc. 5th Int. Conf. Frontiers Intell. Comput.*, 2017, pp. 81–87, doi: 10.1007/978-981-10-3156-4.

[124] S. Mandal and K. K. Mandal, "A reliable energy management and generation scheduling model in microgrids using modified cuckoo search algorithm," in *Proc. Emerg. Trends Electron. Devices Comput. Techn. (EDCT)*, 2018, pp. 1–6.

[125] L. Liu, X. Liu, N. Wang, and P. Zou, "Modified cuckoo search algorithm with variational parameters and logistic map," *Algorithms*, vol. 11, no. 3, p. 30, Mar. 2018, doi: 10.3390/a11030030.

[126] H. Tao, F. W. Ahmed, H. Abdalqadir Kh Ahmed, M. Latifi, H. Nakamura, and Y. Li, "Hybrid whale optimization and pattern search algorithm for day-ahead operation of a microgrid in the presence of electric vehicles and renewable energies," *J. Cleaner Prod.*, vol. 308, Jul. 2021, Art. no. 127215, doi: 10.1016/j.jclepro.2021.127215.

[127] I. N. Trived, M. Bhoye, R. H. Bhesdadiya, P. Jangir, N. Jangir, and A. Kumar, "An emission constraint environment dispatch problem solution with microgrid using whale optimization algorithm," in *Proc. Nat. Power Syst. Conf. (NPSC)*, 2016, pp. 1–6.

[128] B. Cao, W. Dong, Z. Lv, Y. Gu, S. Singh, and P. Kumar, "Hybrid microgrid many-objective sizing optimization with fuzzy decision," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 11, pp. 2702–2710, Nov. 2020.

[129] C. A. Rojas, J. R. Rodriguez, S. Kouro, and F. Villarroel, "Multiobjective fuzzy-decision-making predictive torque control for an induction motor drive," *IEEE Trans. Power Electron.*, vol. 32, no. 8, pp. 6245–6260, Aug. 2017, doi: 10.1109/TPEL.2016.2619378.

[130] M. Zeeshan and M. Jamil, "Adaptive moth flame optimization based load shifting technique for demand side management in smart grid," *IETE J. Res.*, vol. 68, no. 1, pp. 778–789, Jan. 2022, doi: 10.1080/03772063.2021.1886607.

[131] Y. Li, X. Zhu, and J. Liu, "An improved moth-flame optimization algorithm for engineering problems," *Symmetry*, vol. 12, no. 8, p. 1234, Jul. 2020, doi: 10.3390/sym12081234.

[132] A. Kumar, S. Das, and R. Mallipeddi, "An inversion-free robust power-flow algorithm for microgrids," *IEEE Trans. Smart Grid*, vol. 14, no. 8, 2015, doi: 10.1109/TSG.2021.3064656.

[133] J. Zhu, S. Huang, Y. Liu, H. Lei, and B. Sang, "Optimal energy management for grid-connected microgrids via expected-scenario-oriented robust optimization," *Energy*, vol. 216, Feb. 2020, Art. no. 119224, doi: 10.1016/jenergy.2020.119224.

[134] A. Najafi, M. Pourakbari-Kasmaei, M. Jasinski, M. Lehtonen, and Z. Leonowicz, "A medium-term hybrid IGDT-robust optimization model for optimal self scheduling of multi-carrier energy systems," *Energy*, vol. 238, Jan. 2022, Art. no. 121661, doi: 10.1016/j.energy.2021.121661.

[135] I. Ahamed and S. Mohammed, "Optimal microgrid battery scheduling using simulated annealing," in *Proc. Int. Conf. Power Electron. Renew. Energy Appl. (PEREA)*, Nov. 2020, pp. 1–6.

[136] R. Sridhar, C. Subramani, and S. Pathy, "A grasshopper optimization algorithm aided maximum power point tracking for partially shaded photovoltaic systems," *Comput. Electr. Eng.*, vol. 92, Jun. 2021, Art. no. 107124, doi: 10.1016/j.compeleceneng.2021.107124.

[137] S. Saremi, S. Mirjalili, and A. Lewis, "Grasshopper optimisation algorithm: Theory and application," *Adv. Eng. Softw.*, vol. 105, pp. 30–47, Mar. 2017, doi: 10.1016/j.advengsoft.2017.01.004.

[138] Z. Wang, Z. Hu, and X. Yang, "Multi-agent and ant colony optimization for ship integrated power system network reconfiguration," *J. Syst. Eng. Electron.*, vol. 33, no. 2, pp. 489–496, Apr. 2022, doi: 10.23919/JSEE.2022.000048.

[139] M. Z. Kreishan and A. F. Zobaa, "Allocation of dump load in islanded microgrid using the mixed-integer distributed ant colony optimization," *IEEE Syst. J.*, vol. 16, no. 2, pp. 2568–2579, Jun. 2022, doi: 10.1109/JSYST.2021.3100409.

[140] D. Chen, X. You, and S. Liu, "Ant colony algorithm with Stackelberg game and multi-strategy fusion," *Appl. Intell.*, vol. 52, pp. 6552–6574, Sep. 2022.

[141] H. U. R. Habib, A. Waqar, M. G. Hussien, A. K. Junejo, M. Jahangiri, R. M. Imran, Y.-S. Kim, and J.-H. Kim, "Analysis of microgrid's operation integrated to renewable energy and electric vehicles in view of multiple demand response programs," *IEEE Access*, vol. 10, pp. 7598–7638, 2022, doi: 10.1109/ACCESS.2022.3140587.

[142] H. U. R. Habib, U. Subramaniam, A. Waqar, B. S. Farhan, K. M. Kotb, and S. Wang, "Energy cost optimization of hybrid renewables based V2G microgrid considering multi objective function by using artificial bee colony optimization," *IEEE Access*, vol. 8, pp. 62076–62093, 2020, doi: 10.1109/ACCESS.2020.2984537.

[143] Y. Zhang, J. Li, and L. Li, "A reward population-based differential genetic harmony search algorithm," *Algorithms*, vol. 15, no. 1, p. 23, Jan. 2022.

[144] J. Zhang, Y. Wu, Y. Guo, B. Wang, H. Wang, and H. Liu, "A hybrid harmony search algorithm with differential evolution for day-ahead scheduling problem of a microgrid with consideration of power flow constraints," *Appl. Energy*, vol. 183, pp. 791–804, Dec. 2016, doi: 10.1016/j.apenergy.2016.09.035.

[145] K. P. Kumar and B. Saravanan, "Day ahead scheduling of generation and storage sources in a microgrid using artificial fish swarm algorithm," in *Proc. 21st Century Energy Needs Mater., Syst. Appl. (ICTFCEN)*, 2016, pp. 1–6.

[146] L. Zhang, M. Fu, T. Fei, and J. Liang, "The artificial fish swarm algorithm optimized by RNA computing," *Autom. Control Comput. Sci.*, vol. 55, no. 4, pp. 346–357, Jul. 2021.

[147] M. O. Khan, S. Kirmani, M. Rihan, and A. K. Pandey, "Stochastic modelling and integration of electric vehicles in the distribution system using the Jaya algorithm," *IETE J. Res.*, pp. 1–16, Jan. 2024, doi: 10.1080/03772063.2023.2294874.

[148] M. Yazdanian and A. Mehrizi-Sani, "Distributed control techniques in microgrids," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2901–2909, Nov. 2014, doi: 10.1109/TSG.2014.2337838.

[149] C. Zhong, Y. Zhou, J. Chen, and Z. Liu, "DC-side synchronous active power control of two-stage photovoltaic generation for frequency support in islanded microgrids," *Energy Rep.*, vol. 8, pp. 8361–8371, Nov. 2022, doi: 10.1016/j.egyr.2022.06.030.

[150] P. Satapathy, S. Dhar, and P. K. Dash, "A new hybrid firefly optimized P-Q and V-f controller coordination for PV-DG-based microgrid stabilization," *Int. Trans. Electr. Energy Syst.*, vol. 28, no. 7, p. e2568, Jul. 2018, doi: 10.1002/etep.2568.

[151] A. M. Abdulmohsen and W. A. Omran, "Active/reactive power management in islanded microgrids via multi-agent systems," *Int. J. Electr. Power Energy Syst.*, vol. 135, Feb. 2022, Art. no. 107551, doi: 10.1016/j.ijepes.2021.107551.

[152] M. Z. Khan, E. M. Ahmed, S. Habib, and Z. M. Ali, "Multi-objective optimization technique for droop controlled distributed generators in AC islanded microgrid," *Electric Power Syst. Res.*, vol. 213, Dec. 2022, Art. no. 108671, doi: 10.1016/j.epsr.2022.108671.

[153] J. M. Rey, I. Jiménez-Vargas, P. P. Vergara, G. Osma-Pinto, and J. Solano, "Sizing of an autonomous microgrid considering droop control," *Int. J. Electr. Power Energy Syst.*, vol. 136, Mar. 2022, Art. no. 107634, doi: 10.1016/j.ijepes.2021.107634.

[154] V. F. Pires, A. Cordeiro, D. Foito, and J. F. Silva, "Control transition mode from voltage control to MPPT for PV generators in isolated DC microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 137, May 2022, Art. no. 107876, doi: 10.1016/j.ijepes.2021.107876.

[155] V. Subramanian, V. Indragandhi, R. Kuppusamy, and Y. Teekaraman, "Modeling and analysis of PV system with fuzzy logic MPPT technique for a DC microgrid under variable atmospheric conditions," *Electronics*, vol. 10, no. 20, p. 2541, Oct. 2021, doi: 10.3390/electronics10202541.

[156] R. Aazami, S. Esmaeilbeigi, M. Valizadeh, and M. S. Javadi, "Novel intelligent multi-agents system for hybrid adaptive protection of microgrid," *Sustain. Energy, Grids Netw.*, vol. 30, Jun. 2022, Art. no. 100682, doi: 10.1016/j.segan.2022.100682.

[157] E. Buraimoh, A. O. Aluko, O. E. Oni, and I. E. Davidson, "Decentralized virtual impedance-conventional droop control for power sharing for inverter-based distributed energy resources of a microgrid," *Energies*, vol. 15, no. 12, p. 4439, Jun. 2022, doi: 10.3390/en15124439.

[158] P. Buduma, M. K. Das, R. T. Naayagi, S. Mishra, and G. Panda, "Seamless operation of master–slave organized AC microgrid with robust control, islanding detection, and grid synchronization," *IEEE Trans. Ind. Appl.*, vol. 58, no. 5, pp. 6724–6738, Sep. 2022, doi: 10.1109/TIA.2022.3185575.

[159] R. Manojkumar, C. Kumar, S. Ganguly, H. B. Gooi, S. Mekhilef, and J. P. S. Catalão, "Rule-based peak shaving using master-slave level optimization in a diesel generator supplied microgrid," *IEEE Trans. Power Syst.*, vol. 38, no. 3, pp. 2177–2188, May 2023, doi: 10.1109/TPWRS.2022.3187069.

[160] B. Sahoo, S. K. Routray, P. K. Rout, and M. M. Alhaider, "Power quality and stability assessment of hybrid microgrid and electric vehicle through a novel transformation technique," *Sustain. Energy Technol. Assessments*, vol. 51, Jun. 2022, Art. no. 101927, doi: 10.1016/j.seta.2021.101927.

[161] K. Zuo and L. Wu, "A review of decentralized and distributed control approaches for islanded microgrids: Novel designs, current trends, and emerging challenges," *Electr. J.*, vol. 35, no. 5, Jun. 2022, Art. no. 107138, doi: 10.1016/j.tej.2022.107138.

[162] E. Mohammadi, M. Alizadeh, M. Asgarimoghaddam, X. Wang, and M. G. Simões, "A review on application of artificial intelligence techniques in microgrids," *IEEE J. Emerg. Sel. Topics Ind. Electron.*, vol. 3, no. 4, pp. 878–890, Oct. 2022, doi: 10.1109/JESTIE.2022.3198504.

[163] S. Mohamed, M. Mokhtar, and M. I. Marei, "An adaptive control of remote hybrid microgrid based on the CMPN algorithm," *Electric Power Syst. Res.*, vol. 213, Dec. 2022, Art. no. 108793, doi: 10.1016/j.epsr.2022.108793.

[164] L. S. Araujo and D. I. Brandao, "Self-adaptive control for grid-forming converter with smooth transition between microgrid operating modes," *Int. J. Electr. Power Energy Syst.*, vol. 135, Feb. 2022, Art. no. 107479, doi: 10.1016/j.ijepes.2021.107479.

[165] F. R. Albogamy, M. Zakria, T. A. Khan, S. Murawwat, G. Hafeez, I. Khan, F. Ali, and S. Khan, "An optimal adaptive control strategy for energy balancing in smart microgrid using dynamic pricing," *IEEE Access*, vol. 10, pp. 37396–37411, 2022, doi: 10.1109/ACCESS.2022.3164809.

[166] P. Mansoorhoseini, B. Mozafari, and S. Mohammadi, "Islanded AC/DC microgrids supervisory control: A novel stochastic optimization approach," *Electric Power Syst. Res.*, vol. 209, Aug. 2022, Art. no. 108028, doi: 10.1016/j.epsr.2022.108028.

[167] T. Srikanth and S. Chitra Selvi, "A novel centralized supervisory with distributed control system-based microgrid," *Automatika*, vol. 63, no. 3, pp. 482–495, Jul. 2022, doi: 10.1080/00051144.2022.2052663.

[168] H. Yu, S. Niu, Z. Shao, and L. Jian, "A scalable and reconfigurable hybrid AC/DC microgrid clustering architecture with decentralized control for coordinated operation," *Int. J. Electr. Power Energy Syst.*, vol. 135, Feb. 2022, Art. no. 107476, doi: 10.1016/j.ijepes.2021.107476.

[169] D. Y. Yamashita, I. Vechiu, and J.-P. Gaubert, "A review of hierarchical control for building microgrids," *Renew. Sustain. Energy Rev.*, vol. 118, Feb. 2020, Art. no. 109523, doi: 10.1016/j.rser.2019.109523.

[170] Y. Yoo, S. Song, J. Suh, J.-H. Kim, R.-J. Park, and S. Jung, "Adaptive response method for communication failures of hierarchical reactive power control in wind farms," *IEEE Trans. Sustain. Energy*, vol. 13, no. 4, pp. 2343–2352, Oct. 2022, doi: 10.1109/TSTE.2022.3196939.

[171] T. M. E. Abou Saltouh, A. E.-S.-A. Nafeh, A. A. Abou El-Ela, F. H. Fahmy, and S. K. Nawar, "Control strategy for seamless transition between grid-connected and islanding modes in microgrid-based PV inverters," *Energy Syst.*, vol. 14, no. 4, pp. 1135–1162, Nov. 2023, doi: 10.1007/s12667-022-00528-1.

[172] F. Feng and P. Zhang, "Enhanced microgrid power flow incorporating hierarchical control," *IEEE Trans. Power Syst.*, vol. 35, no. 3, pp. 2463–2466, May 2020, doi: 10.1109/TPWRS.2020.2972131.

[173] M. Y. Worku, M. A. Hassan, and M. A. Abido, "Real time energy management and control of renewable energy based microgrid in grid connected and island modes," *Energies*, vol. 12, no. 2, p. 276, Jan. 2019, doi: 10.3390/en12020276.

[174] S. R. and M. Kowsalya, "HESS-based microgrid control techniques empowered by artificial intelligence: A systematic review of grid-connected and standalone systems," *J. Energy Storage*, vol. 84, Apr. 2024, Art. no. 111012, doi: 10.1016/j.est.2024.111012.

[175] M. Talaat, M. H. Elkholy, A. Alblawi, and T. Said, "Artificial intelligence applications for microgrids integration and management of hybrid renewable energy sources," *Artif. Intell. Rev.*, vol. 56, no. 9, pp. 10557–10611, Sep. 2023, doi: 10.1007/s10462-023-10410-w.

[176] S. Li, A. Oshnoei, F. Blaabjerg, and A. Anvari-Moghaddam, "Hierarchical control for microgrids: A survey on classical and machine learning-based methods," *Sustainability*, vol. 15, no. 11, p. 8952, 2023, doi: 10.3390/su15118952.

[177] M. Mohri, A. Rostamizadeh, and A. Talwalkar, *Foundations of Machine Learning*. Cambridge, MA, USA: MIT Press, 2018.

[178] M. Faccio, M. Gamberi, M. Bortolini, and M. Nedaei, "State-of-art review of the optimization methods to design the configuration of hybrid renewable energy systems (HRESs)," *Frontiers Energy*, vol. 12, no. 4, pp. 591–622, Dec. 2018, doi: 10.1007/s11708-018-0567-x.

[179] Y. Du and F. Li, "Intelligent multi-microgrid energy management based on deep neural network and model-free reinforcement learning," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1066–1076, Mar. 2020, doi: 10.1109/TSG.2019.2930299.

[180] M. N. Akhter, S. Mekhilef, H. Mokhlis, and N. M. Shah, "Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques," *IET Renew. Power Gener.*, vol. 13, no. 7, pp. 1009–1023, May 2019, doi: 10.1049/iet-rpg.2018.5649.

[181] Y. Ji, J. Wang, J. Xu, X. Fang, and H. Zhang, "Real-time energy management of a microgrid using deep reinforcement learning," *Energies*, vol. 12, no. 12, p. 2291, Jun. 2019, doi: 10.3390/en12122291.

[182] M. Lehna, B. Hoppmann, C. Scholz, and R. Heinrich, "A reinforcement learning approach for the continuous electricity market of Germany: Trading from the perspective of a wind park operator," *Energy AI*, vol. 8, May 2022, Art. no. 100139, doi: 10.1016/j.egyai.2022.100139.

[183] S. Rahman Fahim, S. K. Sarker, S. M. Muyeen, M. R. I. Sheikh, and S. K. Das, "Microgrid fault detection and classification: Machine learning based approach, comparison, and reviews," *Energies*, vol. 13, no. 13, p. 3460, Jul. 2020, doi: 10.3390/en13133460.

[184] L. Meng, E. R. Sanseverino, A. Luna, T. Dragicevic, J. C. Vasquez, and J. M. Guerrero, "Microgrid supervisory controllers and energy management systems: A literature review," *Renew. Sustain. Energy Rev.*, vol. 60, pp. 1263–1273, Jul. 2016.

[185] R. Li, C. Gu, F. Li, G. Shaddick, and M. Dale, "Development of low voltage network templates—Part II: Peak load estimation by clusterwise regression," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3045–3052, Nov. 2015, doi: 10.1109/TPWRS.2014.2371477.

[186] L. Yin and B. Zhang, "Time series generative adversarial network controller for long-term smart generation control of microgrids," *Appl. Energy*, vol. 281, Jan. 2021, Art. no. 116069, doi: 10.1016/j.apenergy.2020.116069.

[187] P. Zeng, H. Li, H. He, and S. Li, "Dynamic energy management of a microgrid using approximate dynamic programming and deep recurrent neural network learning," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 4435–4445, Jul. 2019, doi: 10.1109/TSG.2018.2859821.

[188] H. Hua, Z. Wei, Y. Qin, T. Wang, L. Li, and J. Cao, "Review of distributed control and optimization in energy internet: From traditional methods to artificial intelligence-based methods," *IET Cyber-Phys. Syst., Theory Appl.*, vol. 6, no. 2, pp. 63–79, Jun. 2021, doi: 10.1049/cps2.12007.

[189] Z. Shi, W. Yao, Z. Li, L. Zeng, Y. Zhao, R. Zhang, Y. Tang, and J. Wen, "Artificial intelligence techniques for stability analysis and control in smart grids: Methodologies, applications, challenges and future directions," *Appl. Energy*, vol. 278, Nov. 2020, Art. no. 115733, doi: 10.1016/j.apenergy.2020.115733.

[190] T. Wu and J. Wang, "Artificial intelligence for operation and control: The case of microgrids," *Electr. J.*, vol. 34, no. 1, Jan. 2021, Art. no. 106890, doi: 10.1016/j.tej.2020.106890.

[191] T. L. Oladosu, J. Pasupuleti, T. S. Kiong, S. P. J. Koh, and T. Yusaf, "Energy management strategies, control systems, and artificial intelligence-based algorithms development for hydrogen fuel cell-powered vehicles: A review," *Int. J. Hydrogen Energy*, vol. 61, pp. 1380–1404, Apr. 2024, doi: 10.1016/j.ijhydene.2024.02.284.

[192] L. Meng, A. Luna, E. R. Díaz, B. Sun, T. Dragicevic, M. Savaghebi, J. C. Vasquez, J. M. Guerrero, M. Graells, and F. Andrade, "Flexible system integration and advanced hierarchical control architectures in the microgrid research laboratory of Aalborg university," *IEEE Trans. Ind. Appl.*, vol. 52, no. 2, pp. 1736–1749, Mar. 2016, doi: 10.1109/TIA.2015.2504472.

[193] M. Gržanić, T. Capuder, N. Zhang, and W. Huang, "Prosumers as active market participants: A systematic review of evolution of opportunities, models and challenges," *Renew. Sustain. Energy Rev.*, vol. 154, Feb. 2022, Art. no. 111859, doi: 10.1016/j.rser.2021.111859.

[194] S. Shokoohi, S. Golshannavaz, R. Khezri, and H. Bevrani, "Intelligent secondary control in smart microgrids: An on-line approach for islanded operations," *Optim. Eng.*, vol. 19, pp. 917–936, Dec. 2018.

[195] N. M. Dehkordi, H. R. Baghaee, N. Sadati, and J. M. Guerrero, "Distributed noise-resilient secondary voltage and frequency control for islanded microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3780–3790, Jul. 2019.

[196] M. Elsayed, M. Erol-Kantarci, B. Kantarci, L. Wu, and J. Li, "Low-latency communications for community resilience microgrids: A reinforcement learning approach," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1091–1099, Mar. 2020, doi: 10.1109/TSG.2019.2931753.

[197] Q. Chang, X. Ma, M. Chen, X. Gao, and M. Dehghani, "A deep learning based secured energy management framework within a smart island," *Sustain. Cities Soc.*, vol. 70, Jul. 2021, Art. no. 102938.

[198] S. Moayedi and A. Davoudi, "Distributed tertiary control of DC microgrid clusters," *IEEE Trans. Power Electron.*, vol. 31, no. 2, pp. 1717–1733, Feb. 2016, doi: 10.1109/TPEL.2015.2424672.

[199] G. Shahgholian, "A brief review on microgrids: Operation, applications, modeling, and control," *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 6, Jun. 2021, Art. no. e12885, doi: 10.1002/2050-7038.12885.

[200] J. M. Raya-Armenta, N. Bazmohammadi, J. G. Avina-Cervantes, D. Sáez, J. C. Vasquez, and J. M. Guerrero, "Energy management system optimization in islanded microgrids: An overview and future trends," *Renew. Sustain. Energy Rev.*, vol. 149, Oct. 2021, Art. no. 111327, doi: 10.1016/j.rser.2021.111327.

[201] Y. Wu, Y. Wu, J. M. Guerrero, J. C. Vasquez, and J. Li, "AC microgrid small-signal modeling: Hierarchical control structure challenges and solutions," *IEEE Electrific. Mag.*, vol. 7, no. 4, pp. 81–88, Dec. 2019, doi: 10.1109/MELE.2019.2943980.

[202] A. Abhishek, A. Ranjan, S. Devassy, B. K. Verma, S. K. Ram, and A. K. Dhakar, "Review of hierarchical control strategies for DC microgrid," *IET Renew. Power Gener.*, vol. 14, no. 10, pp. 1631–1640, Jul. 2020, doi: 10.1049/iet-rpg.2019.1136.

[203] A. Shaqour, T. Ono, A. Hagishima, and H. Farzaneh, "Electrical demand aggregation effects on the performance of deep learning-based short-term load forecasting of a residential building," *Energy AI*, vol. 8, May 2022, Art. no. 100141, doi: 10.1016/j.egyai.2022.100141.

[204] T. A. Nakabi and P. Toivanen, "Deep reinforcement learning for energy management in a microgrid with flexible demand," *Sustain. Energy, Grids Netw.*, vol. 25, Mar. 2021, Art. no. 100413, doi: 10.1016/j.segan.2020.100413.

[205] S. S. Madani, C. Kammer, and A. Karimi, "Data-driven distributed combined primary and secondary control in microgrids," *IEEE Trans. Control Syst. Technol.*, vol. 29, no. 3, pp. 1340–1347, May 2021, doi: 10.1109/TCST.2019.2958285.

[206] T. Vigneysh and N. Kumarappan, "Artificial neural network based droop-control technique for accurate power sharing in an islanded microgrid," *Int. J. Comput. Intell. Syst.*, vol. 9, no. 5, p. 827, 2016, doi: 10.1080/18756891.2016.1237183.

[207] I. Chakraborty, S. Sekaran, and S. K. Pradhan, "An enhanced DC–DC boost converter based stand-alone PV-battery OFF-grid system with voltage balancing capability for fluctuating environmental and load conditions," *Energy Sour., A, Recovery, Utilization, Environ. Effects*, vol. 44, no. 3, pp. 8247–8265, Sep. 2022, doi: 10.1080/15567036.2022.2120574.

[208] X. Ding, R. Yao, X. Zhai, C. Li, and H. Dong, "An adaptive compensation droop control strategy for reactive power sharing in islanded microgrid," *Electr. Eng.*, vol. 102, no. 1, pp. 267–278, Mar. 2020, doi: 10.1007/s00202-019-00870-1.

[209] D. A. Martínez, E. Mojica-Nava, A. S. Al-Sumaiti, and S. Rivera, "A distortion-based potential game for secondary voltage control in micro-grids," *IEEE Access*, vol. 8, pp. 110611–110622, 2020, doi: 10.1109/ACCESS.2020.3002713.

[210] Z. Liu, Y. Luo, R. Zhuo, and X. Jin, "Distributed reinforcement learning to coordinate current sharing and voltage restoration for islanded DC microgrid," *J. Modern Power Syst. Clean Energy*, vol. 6, no. 2, pp. 364–374, Mar. 2018, doi: 10.1007/s40565-017-0323-y.

[211] S.-W. Lin, C.-C. Chu, and C.-F. Tung, "Distributed Q-learning droop control for frequency synchronization and voltage restoration in isolated AC micro-grids," in *Proc. IEEE Ind. Appl. Soc. Annu. Meeting (IAS)*, Oct. 2022, pp. 1–8, doi: 10.1109/IAS54023.2022.9939855.

[212] D.-D. Zheng, S. S. Madani, and A. Karimi, "Data-driven distributed online learning control for islanded microgrids," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 12, no. 1, pp. 194–204, Mar. 2022, doi: 10.1109/JETCAS.2022.3152938.

[213] M. S. O. Yeganeh, A. Oshnoei, N. Mijatovic, T. Dragicevic, and F. Blaabjerg, "Intelligent secondary control of islanded AC microgrids: A brain emotional learning-based approach," *IEEE Trans. Ind. Electron.*, vol. 70, no. 7, pp. 6711–6723, Jul. 2023, doi: 10.1109/TIE.2022.3203677.

[214] H. Karimi, M. T. H. Beheshti, A. Ramezani, and H. Zareipour, "Intelligent control of islanded AC microgrids based on adaptive neuro-fuzzy inference system," *Int. J. Electr. Power Energy Syst.*, vol. 133, Dec. 2021, Art. no. 107161, doi: 10.1016/j.ijepes.2021.107161.

[215] Z. Zhang, C. Dou, D. Yue, B. Zhang, and F. Li, "Neighbor-prediction-based networked hierarchical control in islanded microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 104, pp. 734–743, Jan. 2019, doi: 10.1016/j.ijepes.2018.07.057.

[216] N. Chettibi, A. Mellit, G. Sulligoi, and A. Massi Pavan, "Adaptive neural network-based control of a hybrid AC/DC microgrid," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1667–1679, May 2018, doi: 10.1109/TSG.2016.2597006.

[217] Y. Xia, Y. Xu, Y. Wang, and S. Dasgupta, "A distributed control in islanded DC microgrid based on multi-agent deep reinforcement learning," in *Proc. IECON 46th Annu. Conf. IEEE Ind. Electron. Soc.*, Oct. 2020, pp. 2359–2363, doi: 10.1109/IECON43393.2020.9254716.

[218] S. Bera, S. Chakraborty, D. Kumar, N. Ali, and M. Lehtonen, "Optimal deep learning based aggregation of TCLs in an inverter fed stand-alone microgrid for voltage unbalance mitigation," *Electric Power Syst. Res.*, vol. 210, Sep. 2022, Art. no. 108178, doi: 10.1016/j.epsr.2022.108178.

[219] S. Totaro, I. Boukas, A. Jonsson, and B. Cornélusse, "Lifelong control of off-grid microgrid with model-based reinforcement learning," *Energy*, vol. 232, Oct. 2021, Art. no. 121035, doi: 10.1016/j.energy.2021.121035.

[220] S. Karagiannopoulos, P. Aristidou, and G. Hug, "Data-driven local control design for active distribution grids using off-line optimal power flow and machine learning techniques," *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6461–6471, Nov. 2019, doi: 10.1109/TSG.2019.2905348.

[221] J. Duan, Z. Yi, D. Shi, C. Lin, X. Lu, and Z. Wang, "Reinforcement-learning-based optimal control of hybrid energy storage systems in hybrid AC–DC microgrids," *IEEE Trans. Ind. Informat.*, vol. 15, no. 9, pp. 5355–5364, Sep. 2019, doi: 10.1109/TII.2019.2896618.

[222] W. Ali, A. Ulasyar, M. U. Mehmood, A. Khattak, K. Imran, H. S. Zad, and S. Nisar, "Hierarchical control of microgrid using IoT and machine learning based islanding detection," *IEEE Access*, vol. 9, pp. 103019–103031, 2021, doi: 10.1109/ACCESS.2021.3098163.

[223] Y. Yoldas, S. Goren, and A. Onen, "Optimal control of microgrids with multi-stage mixed-integer nonlinear programming guided *Q*-learning algorithm," *J. Modern Power Syst. Clean Energy*, vol. 8, no. 6, pp. 1151–1159, Nov. 2020, doi: 10.35833/MPCE.2020.000506.

[224] M. Al-Saffar and P. Musilek, "Distributed optimization for distribution grids with stochastic DER using multi-agent deep reinforcement learning," *IEEE Access*, vol. 9, pp. 63059–63072, 2021.

[225] F. Guo, B. Xu, W.-A. Zhang, C. Wen, D. Zhang, and L. Yu, "Training deep neural network for optimal power allocation in islanded microgrid systems: A distributed learning-based approach," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 5, pp. 2057–2069, May 2022, doi: 10.1109/TNNLS.2021.3054778.

[226] S. Karagiannopoulos, R. Dobbe, P. Aristidou, D. Callaway, and G. Hug, "Data-driven control design schemes in active distribution grids: Capabilities and challenges," in *Proc. IEEE Milan PowerTech*, Jun. 2019, pp. 1–6, doi: 10.1109/PTC.2019.8810586.

**MOHD BILAL** received the B.Tech. degree in electrical engineering and the M.Tech. degree in electrical engineering with specialization in instrumentation and control from Zakir Husain College of Engineering and Technology (ZHCET), Aligarh Muslim University (AMU), Aligarh, India, in 2015 and 2019, respectively.

He is a dedicated Researcher in electrical engineering. Currently, he is a Research Scholar with the Department of Electrical Engineering, AMU. His primary interests include energy management for microgrids, where he explores the application of artificial intelligence to enhance microgrid energy management systems. He has actively contributed to the academic community through his research.

**ABDULLAH A. ALGETHAMI** (Member, IEEE) received the B.S. and M.S. degrees in mechanical systems production and design from King Abdulaziz University, Jeddah, Saudi Arabia, in 2002 and 2009, respectively, and the Ph.D. degree in mechanical engineering from Texas A&M University, College Station, TX, USA, in December 2017. In January 2018, he joined the Department of Mechanical Engineering, Taif University, where he is currently an Associate Professor. He joined Saudi Aramco as a Student Trainee, from 2000 to 2001. Additionally, he was with the Industrial Support Establishment (ISE) for eight years. His teaching and research interests focus on analysis, design, real-time control of mechatronic systems, and control engineering and technology. He is a member of ASME.

**IMDADULLAH** (Senior Member, IEEE) received the B.Tech. degree in electrical engineering, the M.Tech. degree in power systems and drives, and the Ph.D. degree in electrical engineering from Zakir Husain College of Engineering and Technology (ZHCET), Aligarh Muslim University (AMU), Aligarh, India in 2003, 2006, and 2020, respectively. He joined the Department of Electrical and Electronics Engineering, Anand Engineering College, Sharda Group of Institutions, Agra, India, from July 2006 to December 2007, as a Lecturer. He has been an Assistant Professor of electrical engineering with the University Polytechnic, AMU, since December 2007. He holds a patent on the FASAL system, "A concept of flexible asynchronous AC link." He has published several research papers in IEEE Transactions/Journals and IEEE conference proceedings. He has visited the Kingdom of Saudi Arabia (KSA) and United States of America (USA) for attending the conferences. His research interests include renewable energy systems, power systems and drives, and instrumentation and measurement.

**SALMAN HAMEED** received the B.Sc.Engg. degree in electrical and M.Sc.Engg. degree in power system and drives from the Department of Electrical Engineering, Aligarh Muslim University (AMU), Aligarh, in 1988 and 1991, respectively, and the Ph.D. degree in power system (FACTS controllers) from IIT Roorkee, in 2008. Currently, he is a Professor with the Department of Electrical Engineering, AMU. His teaching and research lies mainly in the area of power systems, applications of AI techniques in power systems, fuzzy logic controller, and application of nano technology in solar PV cells. He has delivered many invited talks at various institutes outside Aligarh. He has published several research papers in international journals, such as *International Journal of Electrical Power and Energy Systems* (Elsevier), *Electric Power Systems Research* (Elsevier), *International Journal of Energy Research* (Wiley), *International Journal of Energy Storage* (Wiley), and International *Journal of Modelling and Simulation* (Taylor and Francis), and in various international and national conference proceedings in India and abroad. He is the Gold Medalist and a recipient of the University Merit Scholarship from AMU. He is also a recipient of the QIP Research Fellowship from IIT Roorkee.