Energy Management Strategies for Microgrids: A Review

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***Abstract* - The term "energy management" (EM) describes the steps taken to create a system that uses less energy, including monitoring, planning, optimising, and conserving. Despite being a sustainable energy system, a microgrid (MG) needs an efficient and effective energy management system (EMS) since renewable energy resources (RERs) and electricity demand are unpredictable. Making full use of distributed energy resources (DERs) in a safe and dependable manner is of the utmost importance. It is accomplished by incorporating an advanced decision-making approach into EMS. In an effort to create a microgrid that can maintain itself, several researchers have been working on improving electromagnetic (EM) approaches for microgrids recently. To fully understand the field of electromagnetic fields in MGs, a comparative research is necessary. The EM methods and demand response approaches created by the MG for effective decision-making are compared and evaluated in this paper. In addition to discussing the benefits and drawbacks of EMS, this article expands the definition to include supervisory control, operational time framework, and decision-making approach. The unpredictable nature of renewable energy sources and their associated loads necessitates novel approaches to uncertainty management and modelling. A variety of researchers have developed EM methods for MGs, and this publication summarises all of them in a thorough and current manner. Additionally, suggestions for future research are provided. If you're having trouble visualising the theoretical underpinnings of this area of study, this website should help.**

***Keywords:* Energy management, Microgrid, Distributed Energy Resources.**

I. INTRODUCTION

Conventional or fossil fuel generators (TGs) are responsible for half of the annual rise in energy demand, according to the International Energy Agency's (IEA) 2021 study. There is serious cause for alarm over the dramatic rise in GHG emissions and the steady decline in the usage of fossil fuels. A new way of thinking is taking place in the energy industry, with a focus on RERs and the rise of EVs over more conventional forms of transportation [2-6]. Renewable energy resources (RERs) primarily consist of solar photovoltaic (PV), wind (WTG), biomass, and hydro, which together reduce emissions of greenhouse gases (GHG) and provide clean energy for sustainable development [7-9]. Renewable energy sources will increase their power output at a rate of about 95% during the next five years, according to the International Energy Agency (IEA). From 2020–2026, the IEA predicts that renewable power production will increase by 60%. It is anticipated to exceed 4800 GW, which is about the same as the whole world's capacity for nuclear power and fossil fuels combined [1,10]. In addition, during the next five years, China is expected to continue leading the way in renewable energy capacity growth, with 43% of the world total. Europe, the US, and India will follow after [10]. Roughly 80% of the increase in renewable capacity globally has come from these four energy sectors [10]. As can be shown in Figure 1, the International Energy Agency (IEA) expects renewable energy capacity at the national level to rise throughout the next five years [10]. In addition, the IEA predicts rapid development across a range of renewable energy sources during the next five years, as shown in Fig. 2 [10]. Among the several types of on-site generators that fall under the umbrella term "distributed energy resources" (DERs) [12-14], RERs, TGs, and ESS are prime examples. In order to improve distribution network voltage stability and decrease line losses, these DERs are essential. Distributed energy resources (DERs) derived from renewable sources, which are often linked by inverters, need an efficient control plan to guarantee maximum utilisation [16]. Connecting several micro-scale distributed energy resources (DERs) and loads into a low-voltage electrical network is called a microgrid (MG).

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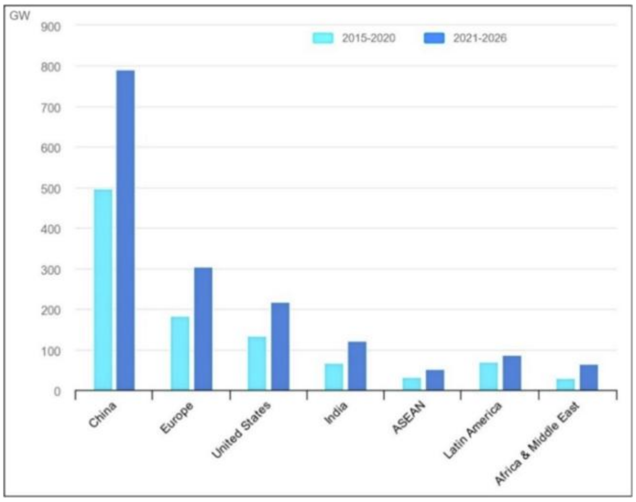
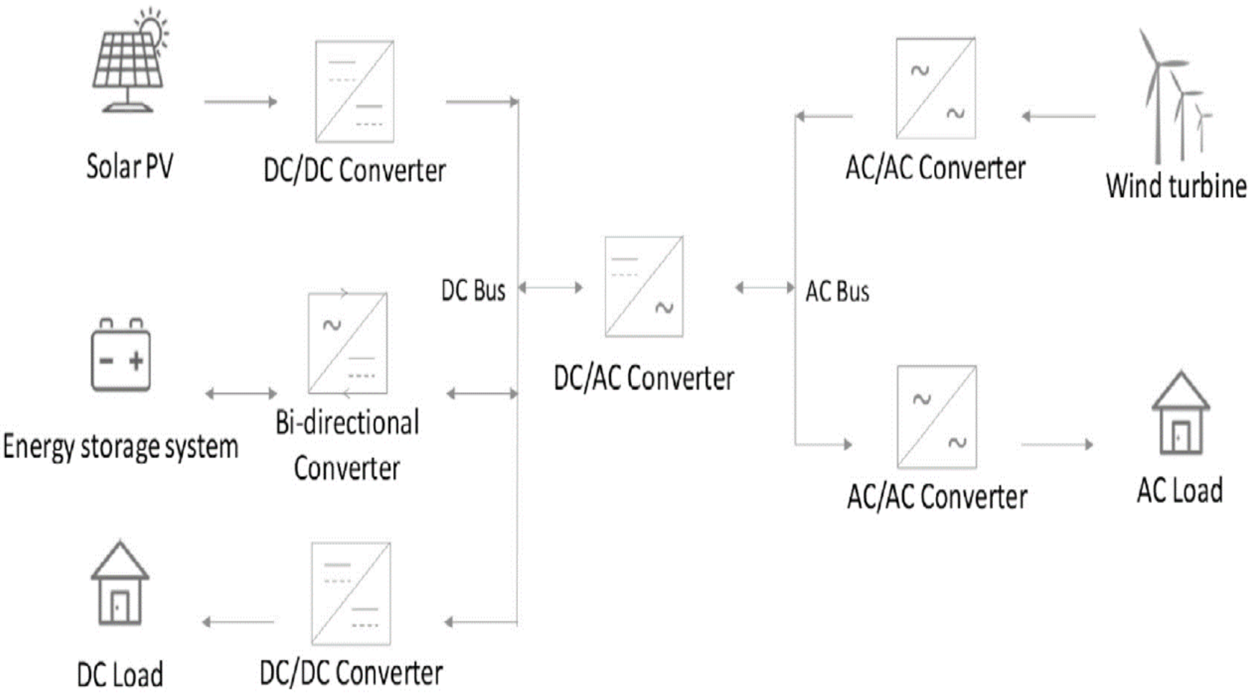


Fig. 1. Renewable energy capacity prediction

Electricity networks and utility companies can only meet the energy demands of conventional electrical systems by supplying traditional energy sources, which are fossil fuels. The location of the producing units and power plants in relation to the availability of resources makes the gearbox front of the system more complicated. As a result, there are a number of issues with the current electrical grid. These include high environmental costs associated with renewable production units, significant transmission losses, and a lack of effort to find a more sustainable replacement. Conventional electricity networks are quickly adopting the idea of microgrids (MG). Microgrids (MG) are networks of interconnected distributed energy resources (DER) that can meet demand efficiently through regulated and coordinated operation. Figures 2 and 3 show that microgrids may function in two modes: grid-connected and islanded. In the former, the microgrid is incorporated into the distribution grid, while in the latter, it is autonomous and separate from the main grid. Among the many parts that make up distributed energy resources (DER) are distributed generation (DG) units, distributed storage (DS) units, and controlled loads [18]. To lessen the economic and social toll of powering our homes and businesses with fossil fuels, the MGs facilitate better integration of renewable energy generating systems into power networks. The present iteration of microgrids is only capable of handling local control and operation.

Fig. 2. Isolated Microgrids



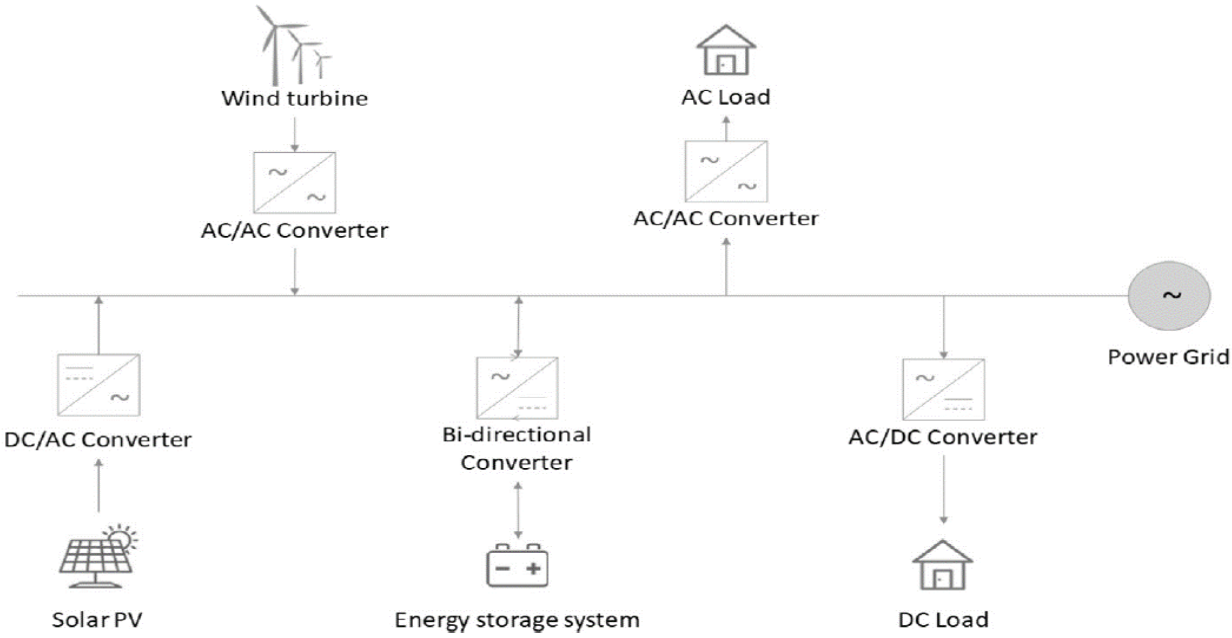


Fig. 3. Grid-Connected Microgrids

MG has many benefits, such as lowering CO2 emissions by using RERs, supporting the main grid with ancillary power, meeting local demand to cut transmission costs and distribution losses, and controlling internal loads to ensure enough generation, among other things. The most common way that MG is classified is seen in Table 1. Microgrids cannot function without Distributed Energy Resources (DERs) that are appropriately sized, efficiently administered, and deployed at the proper times. An energy management system (EMS) is necessary for MG to handle the uncertainties brought forth by renewable energy resources (RERs) and guarantee efficient and effective operation.

II. CLASSIFICATION OF MICROGRID

Table I: Typical microgrid classification.

Microgrid	Based on Architecture	DC Microgrid
		AC Microgrid
		Hybrid Microgrid
	Based on Operationn	Grid Connected
		Islanded
	Based on Scenario	Industrial
		Commercial
		Residential
	Based on Configuration	Radial
		Ring
		Mesh

III. CLASSIFICATION OF MICROGRID ENERGY MANAGEMENT SYSTEM

In order to accomplish efficient and optimal MG operation, there are three main types of EMS, as shown in Table II. These types are based on supervisory control, operating time framework, and decision-making technique. These categories are further examined in Section 3.

Table II: Categorisation of the energy management system.

EMS Classification	Based on Supervisory Control	Centralized
		Decentralized
		Distributed
	Based on Decision Making Approach	Optimization Based
		Power Control Based
	Based on Operating Time Platform	Real Time
		Offline

3.1 EMS Based on Supervisory Control

It is possible to refer to the thorough evaluation of various system-wide process operations as supervisory control.

All of the controllers work together well. Figure 4 shows that there are three main kinds of EMS, which are dispersed, decentralised, and centralised, depending on the level of supervision. In order to schedule MGs properly, a central controller—an essential component of the centralised EMS—aggregates all relevant data on DERs, loads, the electricity market, and environmental conditions. The next step is to communicate the choices to the individual units' local controllers (LC). Multiple central controllers in a decentralised EMS communicate in real-time with their respective LCs and with each other. Every LC communicates with the master controller by sending demand requests for the current and future generations. In addition, it notifies the MG's LC of the results and arranges everything perfectly. This process will continue until the global and national goals are met. Distributed EMS, the third method, is an improved form of decentralised EMS that does away with the idea of centralisation altogether. All of the LC units in this system communicate with one another and the main controller via an internal bus, sharing information like as voltage and frequency. By connecting local and central controllers via a two-way communication channel, a worldwide solution may be more easily attained.

3.2 EMS based on operating time platform

When designing an efficient and effective EMS, the time required to implement a change or adaption is the most important factor to carefully consider. When making decisions, emergency medical services (EMS) mostly use either offline or real-time (RT) platforms.

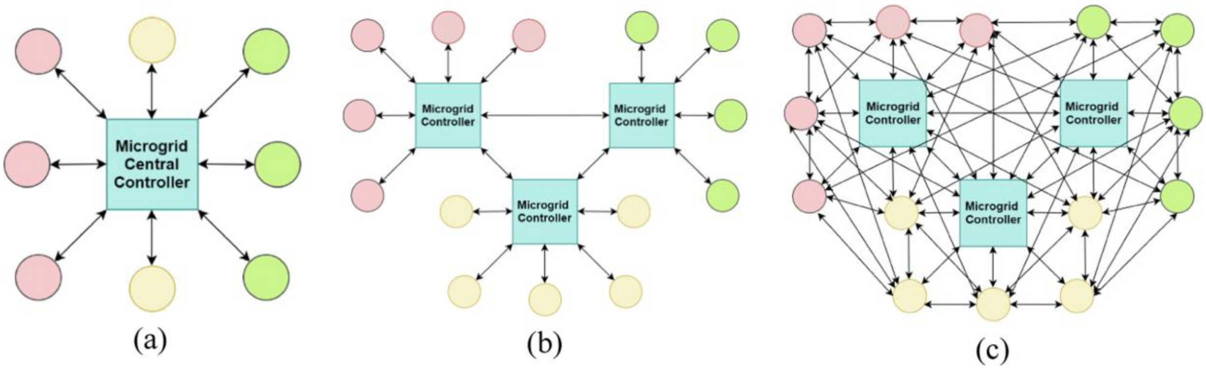


Fig. 4. Various supervisory control approaches for EMS in MG (a) Centralized (b) Decentralized (c) Distributed.

3.2.1. EMS based on the offline time platform

When expected characteristics, such as the output of renewable energy resources, the demand for loads, and market price, are known, day-ahead scheduling is commonly used. A perfect timetable for every part of the system is then generated by the offline EMS [19]. The offline energy management system does not take microgrid uncertainties into account, so to handle the uncertainty in renewable energy resources and load demand, commonly used probabilistic approaches for measuring uncertainty like Monte Carlo simulations and scenario reduction techniques are employed. You may then use a deterministic or random optimisation approach to find the best solution.

3.2.2. EMS based on the real-time platform

The inherent forecasting inaccuracies lead actual values to differ from anticipated values, making it harder to achieve the intended results—even when day-ahead scheduling may be the ideal choice. The highly unpredictable nature of RERs and load demand is the root cause of the complex EMS design. Many academics are concentrating on real-time (RT) scheduling as a means to reduce the effects of EMS uncertainty and simplify its design [20]. Microgrids that are linked to the grid should have their energy exchange with the grid optimised by real-time scheduling. In spite of its flaws, the offline EMS aids any MG's RT EMS in additional ways. The results of offline EMS are sent to RT EMS in order to confirm convergence. By breaking down the offline EMS goal into smaller subproblems, computing complexity may be reduced and distributed optimisation can be used to solve them.

3.3 EMS based on decision-making approaches

To make sure the MG works well, reliably, and efficiently, decision-making processes are used. On the basis of these techniques, optimisation methods and power control strategies are the two main branches of

EMS. Included in the optimization-based strategy are tactics based on artificial intelligence, stochastic and resilient programming, classical programming techniques, meta-heuristic methodologies, and more. The power control-based approach encompasses model predictive control approaches as well as a variety of power control techniques, including as droop control, hierarchical control, peer-to-peer (P2P) control, and voltage-frequency control.

IV. ROLE OF OPTIMIZATION IN MICROGRID ENERGY MANAGEMENT SYSTEM

The four primary optimisation processes used by Microgrids' Energy Management Systems (EMS) are often illustrated in Figure 5. Despite the prevalence of conventional techniques, this review research places an emphasis on non-traditional approaches to the EM issue, delving into the unexplored territories of hybrid, meta-heuristic, and alternative methodology. The next section provides an in-depth analysis of the various optimisation techniques used by microgrids' Energy Management System. The most cited works on this topic, including both new and old optimisation methods, are summarised in this section.

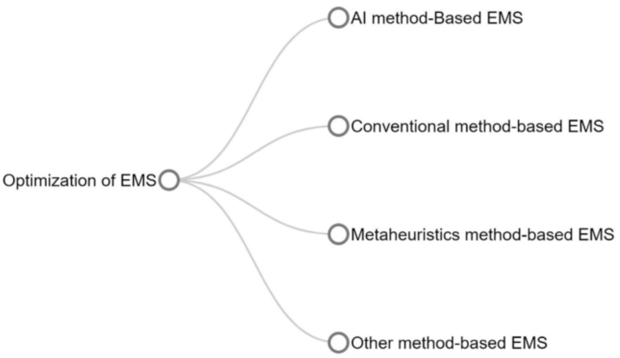


Fig. 5. Types of optimization techniques used in EMS.

4.1 AI Based EMS

As shown in Figure 6, the EMS used in MG systems that is based on artificial intelligence has five basic properties. Several approaches are thoroughly examined in the following subsections. To reduce operating expenses and carbon emissions, Chaouachi et al. developed an intelligent energy management control system for microgrids with several objectives. An innovative weather forecaster using ensemble neural networks and a battery management system based on fuzzy logic were suggested to tackle the issue of battery scheduling. By reducing the depth of discharge and therefore increasing the lifespan of the energy storage system, the FL-based battery scheduling method greatly affected the expenses of battery maintenance. In order to monitor and operate a DC microgrid system using LabVIEW, Chen et al. presented an Energy Management System (EMS) based on fuzzy controllers [21].

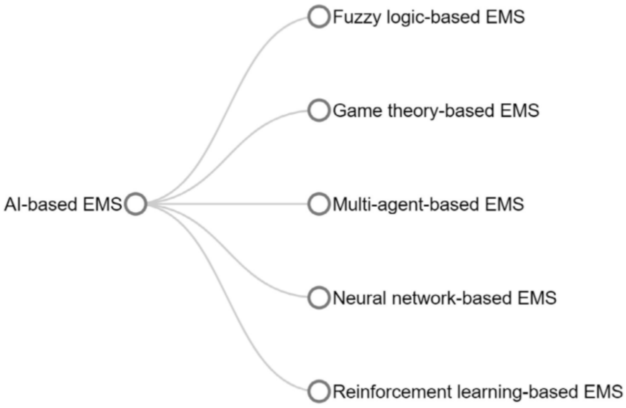


Fig. 6. Types of AI based optimization techniques used in EMS

The mathematical framework of game theory (GT) examines the rational behaviour of decision-makers in dispute resolution and the collaboration of systems in achieving a certain, stated objective. In a residential microgrid that is linked to the grid, Tushar et al. [22] presented a new model for a decentralised demand-side management system that takes into account electric vehicles (EVs), energy storage systems (ESS), and renewable energy sources (RES). This model operates in real-time. With the goal of lowering overall power expenditure, the EMS uses a mixed-strategy noncooperative game to adjust the projected consumption pattern until it finds a Nash equilibrium. Daily load demand predictions are made by every client connected to the microgrid. In light of the expected benefit. A computerised framework that incorporates several interacting intelligent agents is known as a multi-agent system (MAS). Because the agents are dispersed, this optimisation approach may be used as a distributed control technique in microgrids' Energy Management Systems (EMS). Extensive research on distributed control systems using MAS was carried out by Yazdanian et al. [23]. To optimise the production and distribution of energy for the building's cooling, heating, and power system, Zhao et al. [24] highlighted a semi-centralized BEMS that uses multi-agent systems (MAS). To maintain a constant voltage and increase economic and environmental advantages, Dou et al. [25] provide a hierarchical control for an autonomous microgrid based on multi-agent systems (MAS). The authors Chaudhary et al. [26] showcased a state-of-the-art energy management system that made use of wavelet transform technology and generic neural networks (NN). Flexible and static loads, as well as pumped hydro storage systems, were the focus of demand response activities. The output of renewable energy sources that are stochastic is often predicted using the neural network-based forecasting approach. Forecasting is a crucial component in the creation of models for power-sharing and load response, and it is also vital for energy management algorithms that use neural networks. In addition, designs of energy management systems that prioritise efficient dispatch and the optimal integration of renewable energy sources include neural networks [27].

4.2 Conventional based EMS

As seen in Figure 7, the majority of conventional EMS used in MG systems fall into one of six broad groups. Table 3 shows the results of a study of the most referenced articles for each form of conventional-based EMS, while the following subsections provide a thorough examination of the specific technique's utilisation..

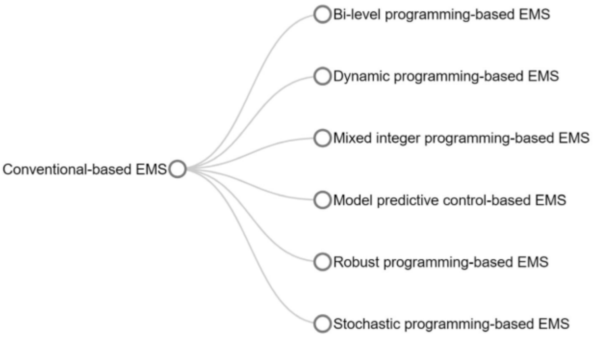


Fig. 7: Types of conventional-based optimization techniques used in EMS

In their study, Zhang et al. proposed a cutting-edge compressed air energy storage (CAES) technology and an energy management system (EMS) based on bi-level programming (BP) to solve the unit commitment problem in the isolated microgrid model [28]. In order to assess the effects of policies that seek to decrease carbon emissions while improving the integration of renewable energy into microgrids, it is necessary to construct advanced economic and numerical models, as demonstrated by Feijoo et al. [29]. As described in [30], a resilient bi-level energy planning model was developed by using a robust column constraint generation (CCG) technique to solve a two-stage mixed-integer second-order conic programming (MISOCP) issue.

The EMS of a microgrid (MG) often makes use of mixed integer programming (MIP) techniques. The approach's minimal computational needs and the technique's simplicity are largely responsible for this. The isolated Microgrid (MG) design that was suggested by Kanchev et al. [31] has gas microturbine units, solar (PV) panels, and a storage system. The EMS is deterministic. A customised prosumer model that includes solar systems, energy storage devices, and ultra-capacitors was also explored in this research. We investigate a centralised system for managing energy using the MIP model, with client-side local power management devices acting as microgrid prosumers.

4.3 Metaheuristic based EMS

Figure 8 shows the three main kinds of Energy Management Systems used in microgrids, which are based on metaheuristic methods. Following a thorough overview of the implementation of each method, Tables 4, 5, and 6 provide an analysis of the most cited works concerning evolutionary, swarm-based, and other metaheuristic algorithms used in EMS.

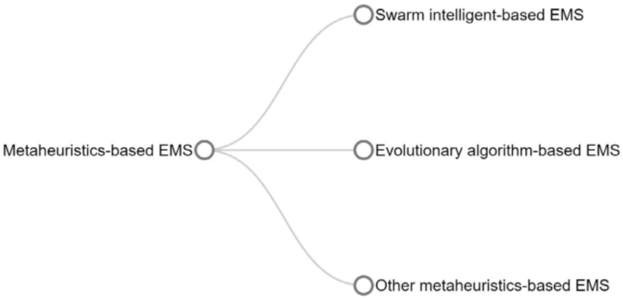


Fig 8: Types of metaheuristics-based optimization techniques used in EMS

A common definition of an evolutionary algorithm is one that takes its cues from natural selection, mutation, recombination, and reproduction. Several evolutionary algorithm-based energy management approaches are evaluated critically in the next section. There are several applications for evolutionary algorithms. As a result of smart grids' dramatic increase in the output of distributed renewable energy sources, stochastic intermittent has been added to the MG system. An essential part of the EMS is the ability to accurately forecast weather conditions and load patterns. In [32], a bilevel differential evolution (DE) algorithm-based method for short-term load forecasting is presented. Time series data is quite nonlinear, making it very difficult to predict demand in the near future. Generation scheduling using DE optimises both the unit commitment problem and the battery scheduling issue. Optimising the battery schedule is a common challenge with MG-EMS. In order to address this issue, Salcedo-Sanz et al. [33] suggested a coral reefs optimisation (CRO) approach. An important differentiator in the CRO approach to solving the scheduling problem is its promotion of the co-evolution of many exploratory models within a single population. This sets it apart from other optimisation strategies. A new niching evolutionary algorithm (NEA) was suggested by Conti et al. in [34] to improve the control of energy storage devices and distributed generators in a standalone microgrid. To demonstrate the smart EMS's effectiveness in attaining optimal economic dispatch through GA application, Chen et al. [35] used the genetic algorithm (GA), the most popular evolutionary method. A similar thorough assessment of dependable EMS in an independent MG located on China's Dong-fushan Island was carried out by Zhao et al. Optimal system operations yield an optimal schedule in a variety of contexts, as shown by the results obtained using the suggested nondominated sorting genetic algorithm (NSGA-II). The optimisation of operating and maintenance costs, fuel costs, environmental costs, and the cost of battery life loss are all taken into account in this work. The number 36. Innovative evolutionary computation algorithms, such as the black hole algorithm (BHA), backtracking search algorithm (BSA), big bang big crunch algorithm (BBBCA), and imperialist competitive algorithm (ICA), are used to address various challenges in microgrid energy management that are based on physical phenomena. An adaptive fractional-order fuzzy-based proportional-integral-derivative (PID) controller using a modified black hole optimisation approach was presented by [37] for load frequency management of an island microgrid. In addition, the suggested method was used to assess the innovative idea of vehicle-to-grid (V2G) for microgrid frequency support in the hardware-in-the-loop (OPAL-RT) system.

By using a binary backtracking search algorithm to an IEEE 14 bus system, Abdolrasol et al. [38] were able to simulate and experimentally validate an ideal scheduling controller. In addition, a two-stage model predictive control approach was suggested by Li et al. [39] for optimising demand-based load scheduling. This technique would use a stochastic programming-based forecaster in conjunction with a backtracking search algorithm. To efficiently plan power generation and meet demand response difficulties, Sedighizadeh et al. [40] devised a two-stage energy management optimisation technique using approximation dynamic programming (ADP) and the hybrid big bang big crunch (HBB-BC) algorithm. With an emphasis on cost optimisation and demand response management objectives, Marzband et al. [41] introduced a multiperiod ICA approach to describe the optimal functioning of an isolated microgrid. In addition, ICA is used to improve operational planning in [42], which presents a decentralised grid-connected electric car logistics service distribution system that equalises demand variations and generator allocation (wind). .

IV. CONCLUSION

An extensive literature evaluation covering all aspects of energy management systems is carried out in this study. Because of the need of efficient, dependable, and cost-effective operation in hybrid renewable energy systems, research into energy management is ongoing. Distributed generating unit designs are displayed, including energy management, control methods, optimisation approaches, and most importantly, the study's limitations or neglected areas. Microgrids (MGs) include intermittent renewable energy sources and face rising energy demands, making an effective Energy Management System (EMS) a crucial component of MG design. As the use of RES continues to grow rapidly, it is crucial to choose the best EMS approach. Whether or not an EMS is effective and dependable depends heavily on the energy management strategy and forecasting algorithm used. In order to control peak demand and save system costs, the EMS aims to precisely measure load and renewable generation. When deciding on an EM scheme to use, it is important to take into account not only the operational efficacy and system dependability levels, but also the scheme's complexity and flexibility.

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