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Review

Role of optimization techniques in microgrid energy management systems—A review

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ABSTRACT

Expeditious urbanization, population growth, and technological advancements in the past decade have significantly impacted the rise of energy demand across the world. Mitigation of environmental impacts and socio-economic benefits associated with the renewable energy systems advocate the higher integration of the distributed energy systems into the conventional electricity grids. However, the rise of renewable energy generation increases the intermittent and stochastic nature of the energy management problem significantly. Therefore, an optimal energy management technique is required to achieve a high level of system reliability and operational efficiency. A state-of-the-art systematic review of the different optimization techniques used to address the energy management problems in microgrids is presented in this article. The different optimization techniques used in energy management problems, particularly focusing on forecasting, demand management, economic dispatch, and unit commitment, are identified and critically analyzed in this review. The inferences from the review indicated that the mixed integer programming techniques were widely used, considering their simplicity and performance in solving the energy management problem in microgrids. The multi-agent-based techniques and meta-heuristics algorithms outperformed the other conventional techniques in terms of the efficiency of the system due to the decentralized nature of the EMS problem in microgrids and the capability of these techniques to act effectively in such scenarios. In addition, it was also evident that the use of advanced optimization techniques was limited in the scope of forecasting and demand management. Advocating the need for more accurate scheduling and forecasting algorithms to address the energy management problem in microgrids. Finally, the need for an end-to-end energy management solution for a microgrid system and a transactive/collaborative energy sharing functionality in a community microgrid is presented.

1. Introduction

Technological advancements, population growth and urbanization have rapidly increased the energy demand and rate of consumption of electricity [1,2]. Fossil fuel-based conventional energy generation resources are commonly used to address the energy demand caused by daily human activities. However, the use of conventional energy resources induces adverse environmental impacts such as climate change and global warming. Relying completely on conventional energy resources to meet the energy demand is considered an ineffective solution. Therefore, renewable energy resources such as solar, wind, tidal, biomass, hydro, geothermal, etc., are considered as a sustainable alternative to address the high energy demand [3]. In addition, it also reduces the adverse environmental, economic, and social impact, thereby making it a more viable choice.

The evolution of electricity grids from conventional to current and then to futuristic electricity grids are illustrated in Fig. 1. In the conventional electricity grids, the energy demand is primarily addressed only by the conventional energy sources (fossil fuels) obtained from the electricity grids or utility providers. The location of the generation units/ power plants are situated at the nearest proximity to the availability of the resources, increasing the complexity of the system in the transmission front. Therefore the conventional electricity grid has many drawbacks, like high transmission losses, high environmental

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Nomenclature

$\theta - KHA$	θ-Krill Herd Algorithm
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ADP	Approximate Dynamic Programming
AFS	Artificial Fish-Swarm Algorithm
AI	Artificial Intelligence
BA	Bat-inspired Algorithm
$BBBCA$	Big Bang Big Crunch Algorithm
$BEMS$	Building Energy Management System
$BESS$	Battery Energy storage systems
BFO	Bacterial Foraging Optimization
BHA	Black Hole Algorithm
BOA	Bayesian Optimal Algorithm
BP	Bi-Level Programming
BSA	Backtracking Search Algorithm
CCG	Column Constraint Generation
CCP	Chance-Constrained Programming
CHP	Combined Heat and Power
CMA	Congestion Management Approach
CRO	Coral Reefs Optimization
CSA	Cuckoo Search Algorithm
DE	Differential Evolution
DER	Distributed Energy Resources
DG	Distributed Generation
DM	Demand Management
DM	Dinkelbach Nethod
DP	Dynamic Programming
DS	Distributed Storage
DSM	Demand side Management
ED	Economic/Environmental Dispatch
EMS	Energy Management Systems
ESS	Energy storage systems
FA	Firefly Algorithm
FFO	Fruit Fly Optimization
FL	Fuzzy Logic
FW	Fire Works Optimization
GA	Genetic Algorithm
GSA	Gravitational Search Algorithm
GT	Game Theory
GWO	Grey Wolf Optimization
HA	Heuristic Approach
$HBB - BC$	Hybrid Big Bang Big Crunch
HS	Hierarchical Scheduling
HSA	Harmony Search Algorithm
ICA	Imperialist Competitive Algorithm
$IGDT$	Information Gap Decision Theory
IMA	Improved Memetic Algorithms
ISA	Interior Search Algorithm
$JADE$	Java Agent Development Environment
LH	Levy-Harmony
MAS	Multi Agent Systems
MG	Microgrids
MHO	Moving Horizon Optimization
MIP	Mixed Integer Programming
MPC	Model Predictive Control
NEA	Niching Evolutionary Algorithm
$NERL$	National Energy Research Laboratory
NN	Neural Network
$NSGA - II$	Non-Dominated Sorting Genetic Algorithm
PSO	Particle Swarm Optimization
PV	Photo Voltaic
RES	Renewable Energy Systems
RL	Reinforcement Learning
RNN	Recurrent neural network
RP	Robust Programming
SB	Scenario-Based
$SFLA$	Shuffled Frog Leaping Algorithm
SoC	State-of-Charge
SP	Stochastic Programming
TOU	Time-Of-Use
UC	Unit Commitment
$V2G$	Vehicle to Grid
VPP	Virtual Power Plants
WCA	Water-Cycle Algorithm
WoS	Web of Science

impact, etc., Over the past few decades, the integration of centralized renewable-based energy generation resources are substantially increasing in the power grids due to the technological improvements with respect to the efficiency and cost of renewable generation units and the importance given to a more sustainable solution. Alongside this, the concept of Microgrids (MG) is also rapidly increasing into the conventional power grids. Microgrids (MG) are low voltage, small scale electricity grids that comprises a wide variety of distributed energy resources (DER) that can operate in a controlled and coordinated manner to address the demand effectively. Microgrids can operate both in grid-connected (as part of the distribution grid) and islanded mode (disconnected from the primary grid and it is self-sufficient) as illustrated in Figs. 2 and 3. DER, in general, includes distributed generation (DG) units, distributed storage (DS) units, and controllable loads [4,5]. The MGs reduces the social and economic impact of fossil fuel-based energy generation by advocating the higher integration of renewable energy-based generation systems into the electricity grids. Operation and control of microgrids are envisaged to be done locally at the current state of development.

The concept of microgrids has been introduced in the current electricity grids envisioning the higher impact of renewable energy integration. Microgrids with excess renewable generation currently have the functionality of selling back to the conventional power grid which introduces the problem of over-generation. It is also clear that the increase in the use of renewable energy resources is evident in the current electricity grids considering the social impact of renewable energy generation. Recent advancements in the field of battery storage and highly efficient power electronic converters prove that the vision of replacing conventional fossil fuels with 100% renewable energy is feasible. However, renewable energy systems (RESs) have a drawback concerning the dependency of stochastic weather conditions, which must be considered when modeling the system. The conventional renewable energy systems (RES) consists of energy generation sources (solar and wind) along with appropriate AC/DC or DC/AC converters, power conditioning units, battery storage system, and fluctuating load.

Microgrids are expected to increase the power quality and bring a variety of economic, environmental and technical benefits to both society of consumers and the electric providers [5] ensuring that it is an efficient system. In grid-connected mode, the microgrid can acquire or supply the imbalance between local demand and generation via the primary grid. However, in islanded mode, the demand and generation should always be in a balanced state to ensure power quality and stability. The power imbalance within the microgrid is addressed by adjusting and increasing the generation power capacity of the alternative

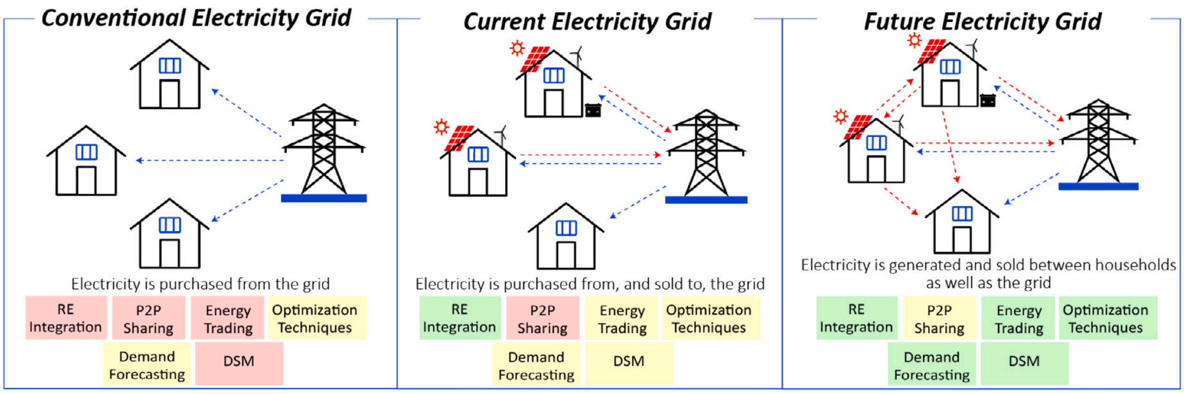

Fig. 1. Evolution of the electricity grid infrastructure.

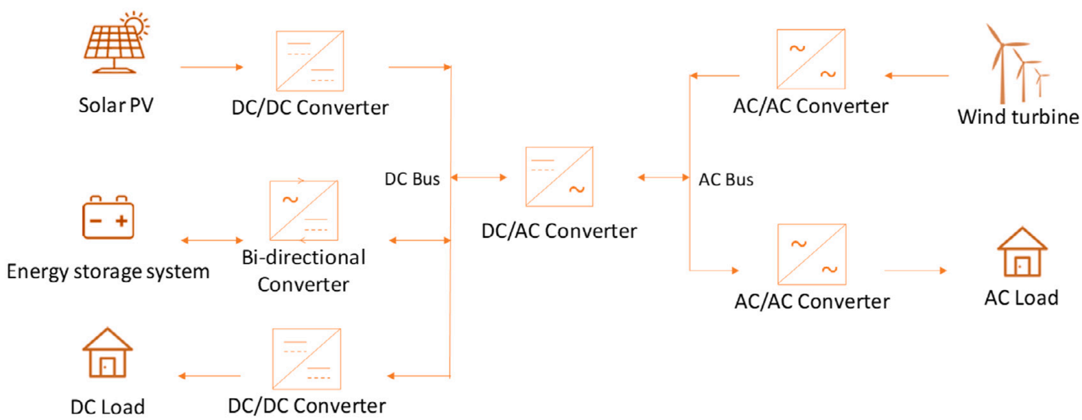

Fig. 2. Isolated Microgrids [6].

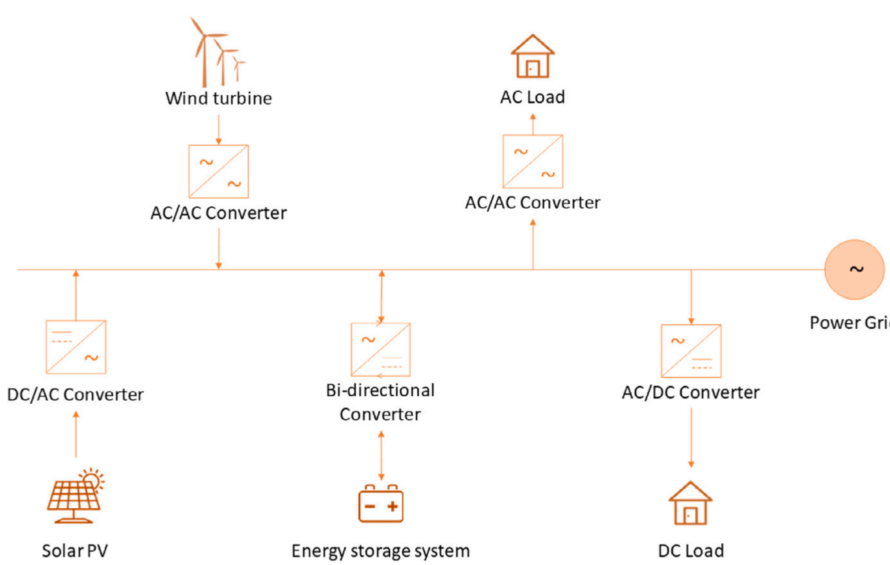

Fig. 3. Grid-Connected Microgrids [6].

energy generation sources; this significantly increases the capital cost and environmental cost of the system. The consumption of electricity of every household in a microgrid is not uniform throughout the day, and if there is a renewable energy-based generation unit such as solar and wind, it is most likely non-linear as well. With the introduction of renewable energy sources like low-cost rooftop solars, residential buildings commonly known as nano-grids or smaller microgrids can address a share of the demand from the free/ carbon-free energy sources like solar and wind effectively. Advancements in the field of battery/ energy storage systems have contributed a lot to the high usage of renewable energy resources in modern power systems. The complexity of the energy management schemes increases exponentially with the rise in the number of households within the microgrid and the

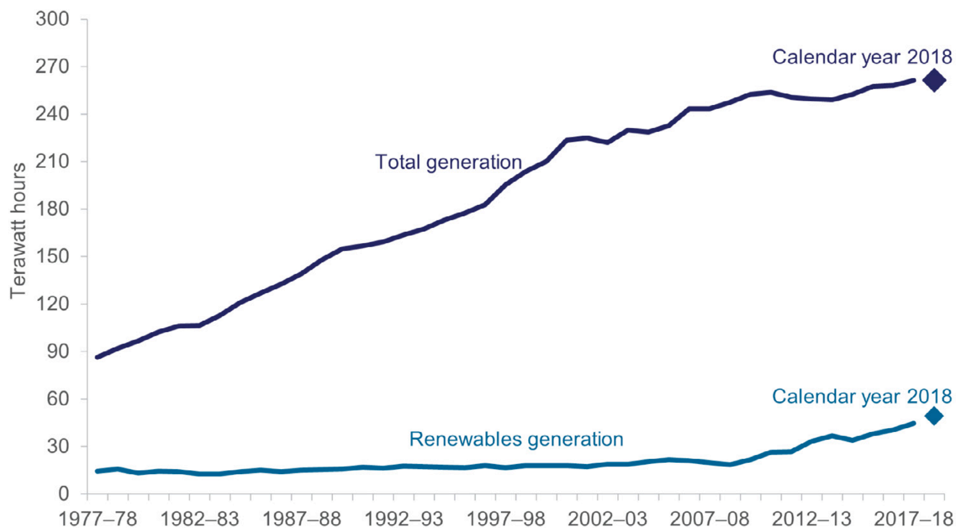

Fig. 4. Trend-line of the renewable generation capacity in Australia [7].

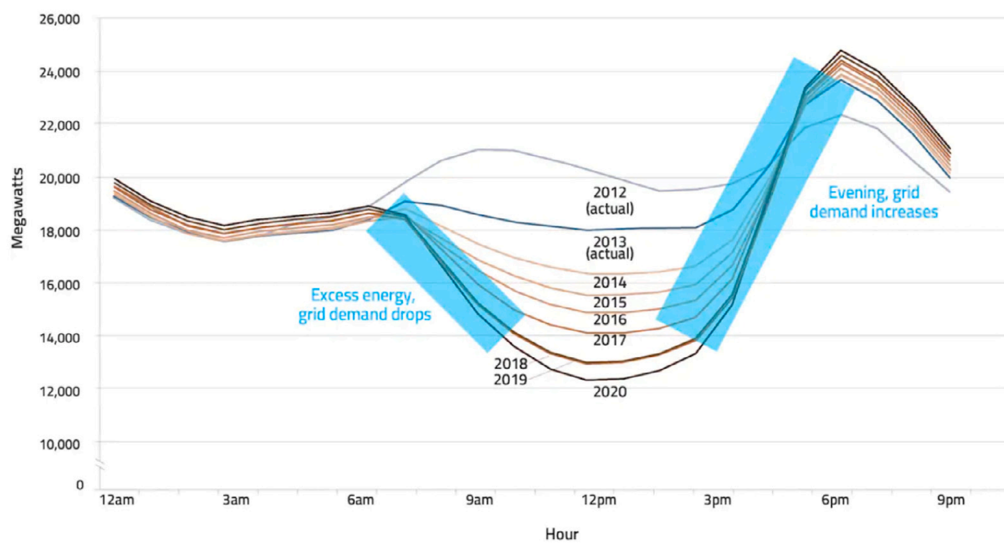

Fig. 5. Projected impact of the duck curve for the years 2020 [8].

high usage of renewable resources. Therefore, to address this issue, a proper, reliable, and smart energy management strategy is required.

Ensuring the energy sustainability of a power system is a multi-objective, multi-constraint problem, where the energy system requires the capability to make rapid and robust decisions regarding the dispatch of electrical power produced by generation assets. This process of control for energy system components is known as energy management. In the Australian context, the intervention of renewable energy resources is increasing consistently. The statistics provided by energy Australia update-2019 [7] illustrated that the capacity of renewable generation, including rooftop solar and the large scale solar farms, is increasing substantially as shown in Fig. 4. From an external perspective, microgrids with RES have a more significant chance of reducing their carbon footprints compared to fossil fuel generation. However, having in mind the stochastic nature of the solar generation, the concept of the duck curve was identified and the energy management system to address this from the utility providers or Distribution network supply providers (DNSPs) perspective. Moreover, this is considered a significant challenge for the utility companies for having an effective and efficient energy management strategy with the inclusion of renewables and microgrids into conventional power grids.

The article published by Carlos Waters, a researcher from the NERL explains the impact of electricity grid management in line with the increase in solar energy production in a deeper perspective [9]. With the raise in solar production, the complexity of the energy management systems is getting higher and here is a chart that explains the reason for the increase in complexity. Fig. 5 illustrates the demand for electricity at any given time of the day on the 31st of March 2012 in the state of California. The least amount of power is consumed by the consumers overnight and it is also clear from the demand curve that there is an increase in demand during the morning and at sun set where the demand shoots up to its peak. With the increase in new solar energy capacity every year, the midday or the off-peak hours demand dip lower and lower. This Drop in demand is commonly known as the duck curve. From the grid management perspective this drop in demand enables the distribution network service providers (DNSPs) or the distribution service operators (DSOs) should ramp up the energy generation to address the demand surge happening in the evening leading to issues like over generation and energy deficit. This also creates an issue with the increase in the complexity of the energy management algorithm. So, it is essential to have a proper energy management strategy that addresses this surge in peak demand adequately. In a nutshell, the combination of

Table 1
Review of the review articles focused on energy management systems in microgrids.

S.No.	Year of publications	No of citations	Highlights	Ref.
1	2018	209	A multi-disciplinary portrayal of current trends in microgrids alongside real-time applications and challenges in the energy management system of the microgrid is discussed in this review article.	[10]
2	2015	205	In this review the authors have presented a technical study on the different optimization techniques used in the microgrid planning scheme. The key focus was spread across the articles which were focused on the power and storage selection, sizing, siting and scheduling tasks.	[11]
3	2017	173	This review article highlights the different scheduling strategies incorporated in the microgrids systems with DERs. In addition, in this research, a detailed view of the VPPs scheduling highlights the importance of the concept of VPP.	[12]
4	2018	148	A detailed review of the energy management strategies used in microgrid energy management systems is presented. Alongside, the detailed study of the different optimization techniques and communication technologies used in order to achieve a low-cost EMS is discussed.	[13]
5	2016	107	A critical review of the current trends of microgrid systems with heterogeneous energy generation resources and energy storage systems is presented. The focus on the mathematical representation of the objective functions used in the energy management systems is the key contribution of this review.	[14]

different trends in power grids has evolved by addressing the following factors:

- Increasing energy demand
- Environmental Concerns
- Increasing Share of Stochastic Renewable Generation
- Increasing Share of Distributed Generation inducing stability issues
- Cost of Energy
- Security of Energy Supply
- Aging Infrastructure
- Information Technology Systems Security Concerns

Advancements in the field of MGs are encouraging the concept of a network of microgrids or commonly known as community microgrids that will assist the DSOs and DNSPs to accurately predict the demand during the above-mentioned surge and also effectively utilize the local generation by enabling the transactive energy sharing within the microgrids. The concept of Community microgrids or connected microgrids are considered as the future of power grids and with this type of system expansion, there is a need for an effective EMS to address the demand efficiently.

Therefore, in this review article, the main focus was given to the optimization techniques used in the EMS of Microgrids. This review article is organized as follows: In Section 2, a detailed overview of the existing review articles in the field of energy management and the proposed state-of-the-art systematic review paper is presented. Followed by which the classification of the different energy management approaches is presented, and a detailed analysis of the research articles using the classified techniques is discussed. After which, a detailed discussion of the analysis on the distribution of the identified articles is presented along with the type of optimization technique used in the energy management system. Finally, the future scope on the area of interest to the researchers in the field of the renewable energy grid is highlighted and the review article is concluded.

2. Methodology and scope

The review article presented in this manuscript highlights the observations obtained from the state-of-the-art systematic review undertaken on the published resources underlying the concept of EMS in MG from the year 2010 to 2020. Initially, a pilot study was carried out to understand the basic concepts of the EMS and to obtain a collective inference about the existing knowledge of reviews in the field. The inference from the analysis made on the existing review articles proved the need for a detailed study on the hybrid, meta-heuristic methods and the other non-conventional algorithms addressing the EMS problem. Therefore, the focus of the review highlighted in this manuscript was aimed at emphasizing more on the use of the above-mentioned optimization algorithms to improve the performance of the EMS. Table 1 highlights the overview of the existing review articles that are underlying the concept of EMS in MG's.

Followed by this, a set of keywords: energy management, microgrids, renewable energy, and optimization techniques were identified and used to filter the collection of references from the web of science (WoS). The retrieval of the documents where done twice during the phase of this critical review illustrating the advantage of the new systematic approach followed in this review process. A detailed flow chart of the step-by-step procedure of the critical analysis carried out in this review paper is illustrated in Fig. 6.

The systematic review process was initiated with a pilot study, that helped the authors get a basic idea of the advancement in the field of EMS in MGs. A list of keywords related to the optimization techniques in EMS was identified as a result of the case study conducted on the existing review articles published in the area of EMS in MGs. Initially, a collection of 877 articles was extracted from the web of science database, and an in-depth analysis of the different optimization techniques was carried out. Since the filtration was based on the type of optimization technique used and the citation score, it was important to re-access this list of identified articles in the course of the review. Therefore, to address the drawback that exists in the conventional systematic review process, a second level of the article extraction process was incorporated into the state-of-the-art review to include the perspective of the newly published articles and optimization techniques. After the second round of extraction from the web of science, another 137 articles were identified, making the total sum of 1014 articles. In the first level of filtration on the EMS systems, the techniques which use analytical solutions to address the EM problem were filtered (555 articles), and later an analysis of the citation score index was carried out to result in a total of 169 articles finally obtained. One of the main objectives of the review article is to highlight the use of novel optimization approaches addressing the EM problem in MGs. Therefore, initially out of the 555 articles identified, the optimization technique used was identified, and then later the top-cited articles from each technique were added into the final list of articles reviewed in this manuscript. The scope of the review was not limited to the application of optimization techniques in the management of the MG, it also included the optimization of the design of MG parameters. Fig. 7 illustrates the yearly distribution of the papers alongside the level of filtration highlighted in the review process.

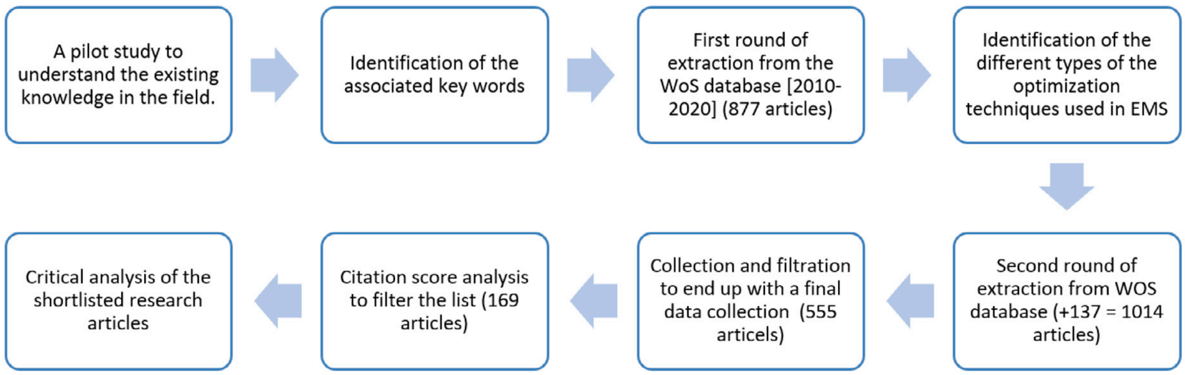

Fig. 6. The step-by-step procedure of the review process.

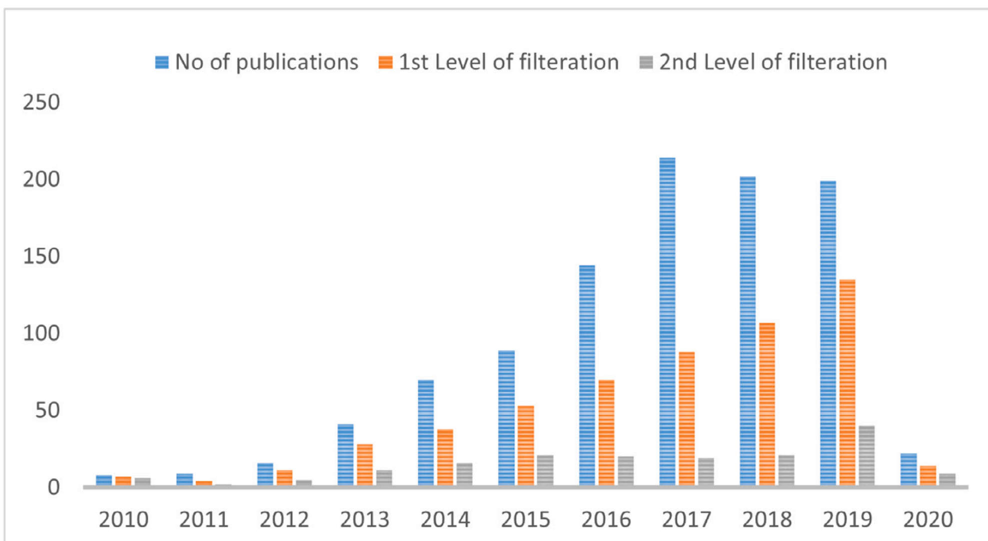

Fig. 7. Yearly distribution of the research articles across the different level of filtration in the review.

3. Microgrid energy management system

Due to the randomness or the intermittency characteristics of renewable energy generation the reliability and stability issues caused in the power system has induced a downside of the RES integration into smart grids. In order to address this downside of the MG, an efficient battery management system and a proper forecasting algorithm are required. Different optimization techniques have been proposed to address this issue by effectively scheduling the alternative energy resources or energy storage to maintain stability along with optimally dispatching the power generated to increase the economic benefit.

Energy management is one of the most used buzz words in the field of electrical engineering. In order to obtain a clear understanding of the different energy management strategies and get a detailed insight into the different optimization techniques used for energy management, a detailed review of the existing techniques was carried out. Fig. 8 highlights a basic microgrid model with the different renewable generation sources, loads, and energy management systems.

This review focuses on identifying the different optimization techniques used for addressing the EMS problem of the MG. Obtaining a better understanding of the microgrid models and the type of optimization technique used by the energy management system (EMS) in microgrids (MGs) is considered as one of the essential contributions of the review highlighted in the manuscript. Furthermore, a collective analysis was carried out by evaluating the type of supervisory control, power mode, operational mode, citation score, and the objective of the EM scheme. The objectives of the EM scheme are categorized into four major types, forecasting, economic/environmental dispatch (ED), unit commitment (UC), and demand management (DM) in this review article. The forecasting objective mainly covers the use of machine learning and AI techniques to predict the futuristic load/generation profiles. The ED mainly focuses on techniques that work towards improving the utilization of renewable resources to increase the environmental/economic benefit. Whereas, the unit commitment objective targets coordinating the different electricity generators to achieve a common target of fulfilling the demand at lower cost and increasing the revenue returns if fossil fuel-based generation sources are used alongside the RES. Finally, the demand management objective mainly targets the effective utilization of the load and scheduling of the usage patterns to increase the financial benefit.

4. Classification of optimization techniques in EMS

In general, the optimization techniques in EMS of MGs are classified into four major types, as highlighted in Fig. 9. Despite the conventional techniques being used frequently to address the EM problem, this review article focuses more on the non-conventional techniques and tries to cover the unexplored area of hybrid, meta-heuristics and non-conventional techniques. The following section presents a comprehensive review of the different types of optimization techniques used in addressing the EMS of MG's. A detailed overview of the topmost cited articles in the commonly used optimization techniques and novel techniques used to address this issue is presented in the following section.

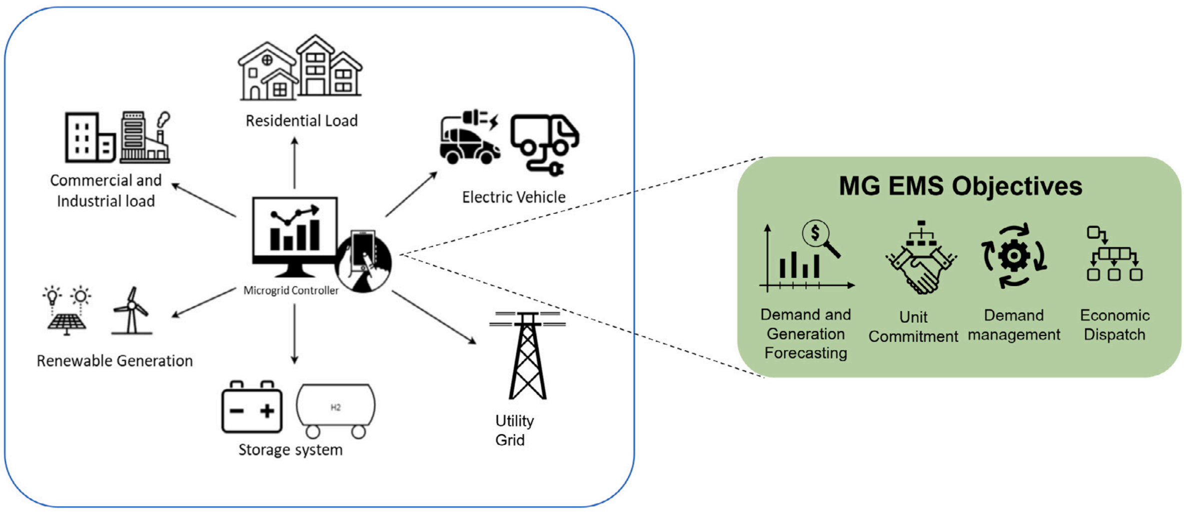

Fig. 8. Basic components of the Microgrid setup.

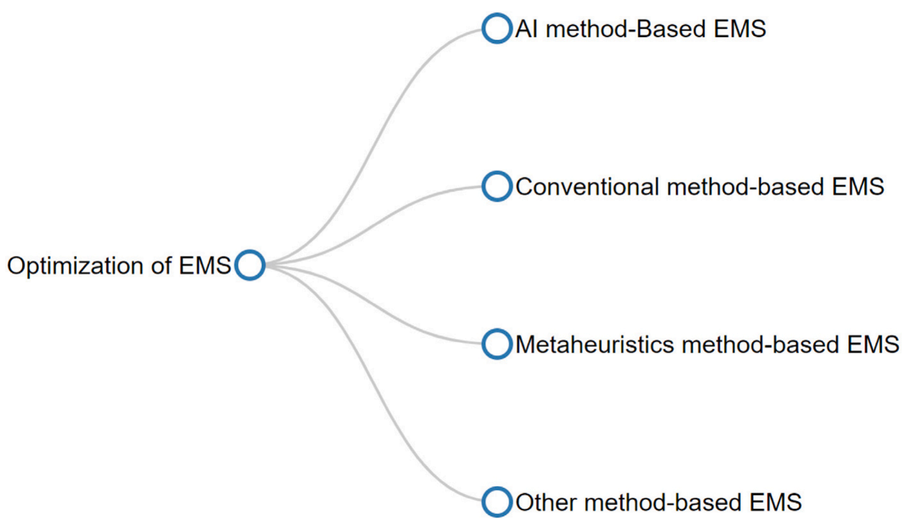

Fig. 9. Types of optimization techniques used in EMS.

4.1. AI-based EMS

Artificial intelligence-based EMS used in MG systems are mainly categorized into five major groups and Fig. 10 illustrated the pictorial representation of these types. A detailed overview of the use of specific techniques is presented in the following subsections. Table 2 illustrates the inference of the analysis carried out on the most cited articles in each type of AI-based EMS.

4.1.1. Fuzzy logic-based EMS

Chaouachi et al. formulated a multi-objective intelligent energy management control of a microgrid system that aims at minimizing the operational cost and carbon emission level [15]. A fuzzy logic (FL)-based battery management system aiming at optimizing the battery scheduling problem along with a novel neural network ensemble-based weather forecaster was proposed. The FL-based battery scheduling scheme significantly impacted the battery maintenance cost by increasing the lifetime of the energy storage system through a lower depth of battery discharge. Chen et al. proposed a fuzzy controller based EMS using LabVIEW to control and monitor a DC microgrid system [16]. Improving the life cycle of the battery based on the desired SoC was one of the main objectives of the proposed EMS, which also used RS-485/ZigBee network communication interface in real-time implementation of the system. A novel hourly energy management system of an islanded DC microgrid with hybrid distributed renewable energy sources and ESS was proposed in [17]. The proposed EMS considers optimizing the operational cost and the battery lifetime of the ESS. FL control establishes a buffer zone of logical segments within the range of zero and one to employ a predefined set of rules to achieve the objective of the system, and it is widely used for battery management optimization.

4.1.2. Game theory-based EMS

A mathematical theory formulated to study the rational behavior of a decision-maker to solve the conflicts and the cooperativeness of a system to achieve a common, well-defined goal is known as game theory (GT). Tushar et al. [18] proposed a real-time decentralized demand-side management system of a grid-connected residential microgrid with a new EV, ESS, and RES model. Each client interconnected in the microgrid predicts a day load demand and based on the forecasted value, the EMS plays a mixed strategy noncooperative game till it reaches a Nash equilibrium to modify the anticipated consumption pattern aiming at minimizing the total electricity cost. Earlier, in 2010 Mohamed et al. [19] presented a generalized GT based multi-objective optimal EMS approach that addresses the load demand and minimize

Table 2
Analysis on the AI based optimization techniques used in EMS.

Optimization technique	Ref.	Cite score	Supervisory control	Operation mode	Power mode	Objective			
						Forecasting	DM	ED	UC
	[15]	488	Centralized	Grid-Connected	AC	✓	✗	✓	✓
FL	[16]	256	Centralized	Grid-Connected	DC	✗	✗	✓	✓
	[17]	126	Centralized	Islanded	DC	✗	✗	✓	✓
	[18]	71	Decentralized	Grid-Connected	AC	✓	✓	✓	✗
GT	[19]	65	Centralized	Both	AC	✗	✗	✓	✓
	[20]	36	Decentralized	Islanded	AC	✗	✗	✓	✗
	[21]	365	Collective review on distributed control in MGs						
	[22]	233	Semi-Centralized	Grid-Connected	AC	✓	✓	✓	✗
MAS	[23]	173	Decentralized	Both	AC	✗	✗	✓	✓
	[24]	112	Decentralized	Grid-Connected	AC	✗	✓	✓	✓
	[25]	83	Decentralized	Grid-Connected	AC	✗	✗	✗	✓
	[26]	40	Decentralized	Both	AC	✗	✗	✗	✗
NN	[27]	39	Centralized	Grid-Connected	AC	✓	✓	✓	✗
	[28]	39	Centralized	Grid-Connected	AC	✓	✗	✗	✓
	[29]	113	Centralized	Both	AC	✗	✗	✓	✓
RL	[30]	81	Centralized	Grid-Connected	AC	✓	✗	✗	✓
	[31]	25	Centralized	Grid-Connected	AC	✗	✗	✓	✓

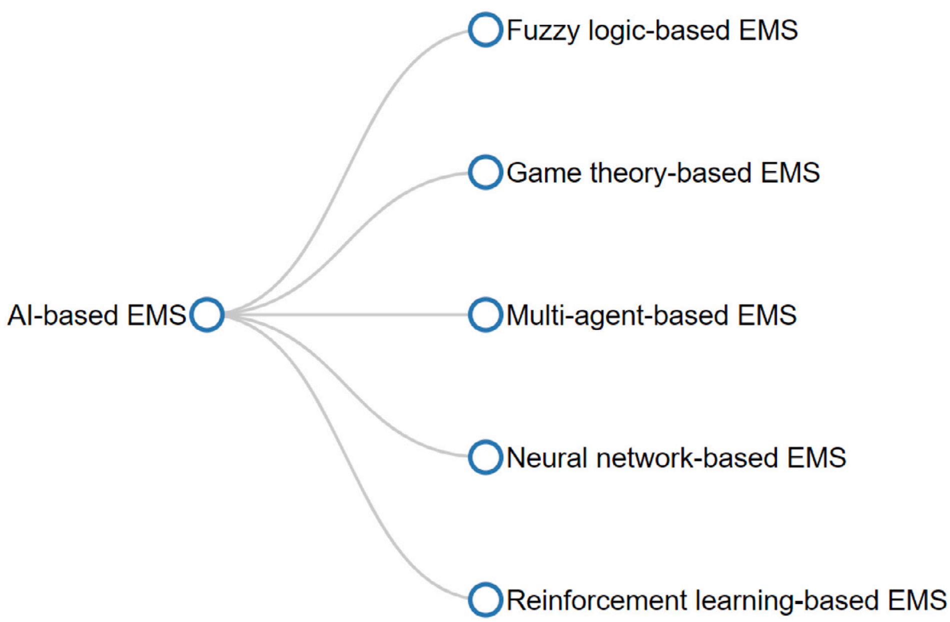

Fig. 10. Types of AI based optimization techniques used in EMS.

the cost and emission of the MG effectively and later in 2015 Belgana et al. [20] demonstrated a Stackelberg game approach considering interactions with the micro sources and consumers considered in the model. The decentralized nature of the MG EMS system benefits from the characteristics of the GT based algorithms and also the application of agent-based and GT based EM solutions for community MG has been identified as the most efficient solution addressing the issues of higher DER integration into MGs.

4.1.3. Multi-agent-based EMS

A multi-agent system (MAS) is generally a computerized system that consists of multiple interactive, intelligent agents. The distributed nature of the agent architecture will enable the use of this optimization technique as a distributed control strategy used in the EMS of microgrids. A critical overview of the distributed control strategies using MAS was presented by Yazdanian et al. [21]. Zhao et al. [22] highlighted a MAS based semi-centralized building energy management system (BEMS) that optimizes the energy generation and distribution of the building cooling, heating, and power (BCHP) system. A MAS-based hierarchical control of an autonomous microgrid aiming at maintaining a fixed voltage with maximizing economic and environmental benefits is proposed by Dou et al. [23]. Nunna et al. [24] proposed an energy management model using a MAS-based system developed with the Java agent development framework (JADE) to reduce system peak and integrated demand response with distributed storage. Xu et al. [25] in their work highlighted that the high utilization of RES induces a supply–demand imbalance into a system and a distributed sub-gradient-based energy management algorithm was proposed to address this imbalance.

4.1.4. Neural network-based EMS

Baghaee et al. presented a novel decentralized robust power-sharing strategy under unbalanced non-linear load conditions in both isolated and grid-connected mode [26]. Experimental validation of the proposed energy management strategy using the OPAL-RT real-time digital simulator was a highlight of this work. Chaudhary et al. presented a smart energy management system based on a general neural network (NN) and wavelet transform method focusing on the demand response schemes consisting of flexible, static loads and pumped hydro storage system [27]. In general, the NN-based forecasting algorithm for predicting stochastic renewable energy output is widely used. Whereas, energy management algorithms based on NNs are also dependent on

Table 3
Analysis on the conventional-based optimization techniques used in EMS.

Optimization technique	Ref.	Cite score	Supervisory control	Operation mode	Power mode	Objective Forecasting	DM	ED	UC
	[32]	51	Centralized	Islanded	AC	✗	✗	✗	✓
BP	[33]	16	Centralized	Grid-Connected	AC	✗	✗	✓	✗
	[34]	10	Centralized	Grid-Connected	AC	✗	✗	✗	✓
	[35]	227	Centralized	Grid-Connected	AC	✗	✗	✓	✓
DP	[36]	134	Centralized	Grid-Connected	AC	✗	✗	✓	✗
	[37]	48	Centralized	Grid-Connected	AC	✗	✗	✓	✗
	[38]	898	Centralized	Islanded	AC	✓	✗	✓	✓
	[39]	153	Centralized	Grid-Connected	AC	✓	✓	✓	✓
MIP	[40]	151	Centralized	Grid-Connected	AC	✗	✓	✗	✓
	[41]	144	Centralized	Grid-Connected	AC	✗	✓	✓	✗
	[42]	108	Centralized	Islanded	AC	✓	✓	✓	✓
	[43]	391	Centralized	Islanded	AC	✓	✗	✗	✓
MPC	[44]	183	Centralized	Grid-Connected	AC	✗	✓	✗	✗
	[45]	138	Centralized	Grid-Connected	AC	✗	✗	✗	✓
	[46]	176	Centralized	Grid-Connected	AC	✓	✗	✗	✓
RP	[47]	155	Decentralized	Grid-Connected	AC	✓	✗	✗	✓
	[48]	106	Centralized	Islanded	AC	✓	✗	✓	✓
	[49]	465	Centralized	Both	AC	✓	✗	✓	✓
SP	[50]	168	Centralized	Islanded	AC	✗	✓	✓	✓
	[51]	166	Decentralized	Both	AC	✗	✗	✓	✓

the forecasting component in planning power-sharing and load response models. Besides, NNs are also used at EMS schemes focusing on economic dispatch and optimal operation of renewable energy integration [28]. In [28], the authors proposed an RNN based energy management system along with a multiagent based weather forecasting technique which is considered as a unique contribution of the presented research.

4.1.5. Reinforcement learning-based EMS

Venayagamoorthy et al. presented an intelligent dynamic energy management system based on the action-dependent heuristic dynamic programming-based controller. The performance of the proposed approach was compared with the decision tree-based dynamic energy management strategy underseen and unseen conditions, and results indicated that the proposed novel strategy is more reliable, environmentally friendly, and efficient [29]. Kuznetsova et al. proposed a two-step ahead reinforcement learning (RL) algorithm using a Markov chain model to plan for battery scheduling in a microgrid concerning the forecasted wind power output [30]. RL algorithm has also been used to optimize the coordination of different ESSs in a microgrid considering an interconnected topology [31].

4.2. Conventional-based EMS

Conventional-based EMS used in MG systems are mainly categorized into six major groups, and Fig. 11 illustrates the pictorial representation of this categorical distribution. A detailed overview of the use of the specific technique is presented in the following subsections, and Table 3 illustrates the inference of the analysis observed on the most cited articles in each type of conventional based EMS.

4.2.1. Bi-level programming-based EMS

Zhang et al. presented bi-level programming (BP)-based EMS to effectively address the unit commitment problem in the isolated MG model along with a novel compressed air energy storage (CAES) system [32]. The need for the development of advanced economic/numerical models to analyze the impact of policies devised to control the carbon emission along with the rise in the RE integration into MG was illustrated by Feijoo et al. [33]. A robust bi-level energy planning model was developed by formulating a mixed-integer second-order conic programming (MISOCP) problem that was solved by a two-stage robust column constraint generation (CCG) algorithm as this is presented in [34].

4.2.2. Dynamic programming-based EMS

In [35], a convex optimization problem was solved using the dynamic programming (DP) solution that was proposed to minimize the total operational cost of the microgrid. In addition to this DP-based scheduling algorithm, which acted as an off-line optimization problem, a sliding window-based real-time online energy management system was also presented. Xiaoping et al. illustrated a DP-based economic dispatch solution of an MG with RES [36]. The proposed DP-based control strategy for the discrete-time system proved its effectiveness over the static dispatch solutions. Followed by this, a practical battery/energy storage management system using the dynamic programming algorithm was presented in [37]. The novel battery/energy storage system models and the constraint-based cost model was the highlight of this work.

4.2.3. Mixed integer programming-based EMS

Mixed integer programming (MIP) techniques is a widely used conventional method used for EMS of an MG. This is mainly because of the simplicity of the technique and the low computational requirements of this approach. Kanchev et al. presented a deterministic EMS of an isolated MG architecture with a PV, storage system and gas microturbine units [38]. An individualized prosumer model with PV, ESS and ultra-capacitor was also considered in this research. A central energy management system using the MIP model is considered along with local power management units at the customer side acting as the prosumer in the microgrid. In [39], mixed-integer linear programming (MILP) was used to manage the energy production and demand alongside rolling horizon-based forecasting of load. Appropriate sizing and analysis of the RES and energy storage system along with a demand-side management system of the MG using a MILP method was investigated in the residential MG setup in Okinawa [40]. Stochastic scheduling of RES along with combined heat and power (CHP) system using MIP with a 24 h schedule is proposed in [41]. An end to end EMS of an MG with a forecasting system along with a unit commitment (size optimization) and a demand response scheme is presented clearly by Amrollahi et al. [42]. In addition to this, a provisional MG model was highlighted by Khodaei in [48], where the optimal scheduling problem was addressed by using a blenders decomposition method.

4.2.4. Model predictive control-based EMS

Model predictive control (MPC) is one of the other commonly used EMS techniques that address the unit commitment issue in MG's. In [43], The EMS problem was decomposed as a UC, and an optimal power flow problem. A model predictive solution was proposed

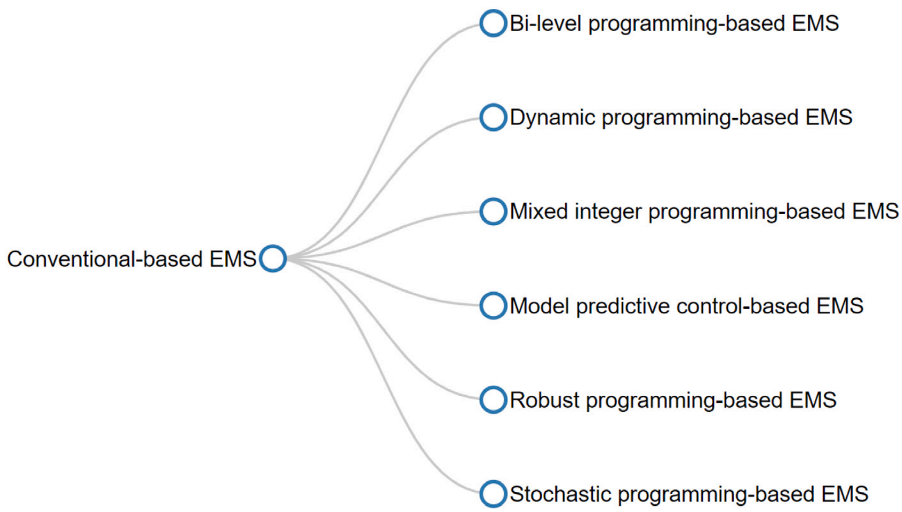

Fig. 11. Types of conventional-based optimization techniques used in EMS.

to solve the mixed-integer non-linear problem. The CIGRE medium-voltage benchmark was used to evaluate the performance of the proposed model in the research article presented. A receding horizon control-based model for optimal scheduling of the battery was presented by Prodan et al. in [44]. Followed by this, the use of MPC control for addressing the demand side management problem in MG was illustrated by Wu et al. [45].

4.2.5. Robust programming-based EMS

In [46], Malysz et al. proposes a robust counterpart formulation to address the peak demand and load smoothing of the uncertainties in the energy generation/demand of an MG using robust programming (RP) approach. A rolling horizon window-based MILP method is used to predict the energy usage and RE generation in this presented model. The computational complexities are reduced by relaxing the binary constraints and employing variable time steps to address the problem. Agent-based modeling is used to model the decentralized MG in which an RP-based optimization for the MG EMS is implemented and evaluated in [47].

4.2.6. Stochastic programming-based EMS

A stochastic energy scheduling system of an MG with RES was evaluated along with a case study on a modified IEEE-37 bus test feeder setup. Inferences from this study highlighted the effectiveness and accuracy of the proposed stochastic programming (SP)-based MG energy scheduling algorithm [49]. Another example of the smart MG EMS that aims at balancing the supply and demand of energy systems, ensuring the quality of service in electricity (QoSE), was obtained using a Lyapunov optimization technique in [50,51].

4.3. Metaheuristics-based EMS

Metaheuristics method-based EMS used in MG systems are mainly categorized into three major groups, and Fig. 12 illustrated the pictorial representation of these categorical representation. A detailed overview of the use of the individual technique is presented in the following subsections, and Table 4, Table 5, and Table 6 illustrate the inference of the analysis observed on the most cited articles in each type of evolutionary, swarm-based, and other metaheuristic algorithms used in EMS.

4.3.1. Evolutionary algorithm-based EMS

Algorithms inspired by the mechanism of the biological evolutions such as reproduction, mutation recombination and selection are commonly known as evolutionary algorithms. Applications of the evolutionary algorithms are well diversified, and a handful of evolutionary algorithm-based energy management solutions are critically reviewed in the following section. Significantly increasing distributed energy generation from RES in smart grids has introduced stochastic intermittence to the MG system. Accurate forecasting of the weather information and load patterns is an essential component of the EMS. In [52], a bilevel short term load forecasting algorithm using differential evolution (DE) algorithm is presented. Short-term load forecasting is a complex forecasting task, considering the high nonlinearity in the time series data. In addition to this, DE is used in optimizing the generation scheduling of the unit commitment problem in [53] and a battery scheduling problem in [54]. Battery scheduling optimization problem is one of the general drawbacks of MG-EMS, a coral reefs optimization (CRO) algorithm based solution was presented by Salcedo-Sanz et al. in [55]. The CRO algorithm stands out from the other optimization techniques as the promotion of the co-evolution in different exploration models within the unique population is distinct and helps significantly in addressing the scheduling problem.

Conti et al. proposed a novel niching evolutionary algorithm (NEA) to optimize the dispatching of the distributed generators and ESS in an isolated MG in [59]. Genetic algorithm (GA) is the most commonly used evolutionary algorithm, Chen et al. illustrated the performance evaluation of the smart EMS using GA deployed for optimal economic dispatch [60]. Similarly, Zhao et al. presented a complete investigation of reliable EMS in a standalone MG situated in Dong-fushan Island in China. The optimization of the battery life loss cost, $O\&M$ cost, fuel cost, and environmental cost is considered in this work, and results indicated that the proposed nondominated sorting genetic algorithm (NSGA-II) performs optimal system operations to obtain an optimum schedule under different scenarios [61]. An active EMS with DSM operations is evaluated on a 23-bus 11 kV microgrid setup using fuzzy clustering, and neuron-by-neuron algorithm, which is later optimized by the GA ensemble are illustrated in [62]. Li et al. presented a novel demand-side response (DSR) EMS scheme of an MG considering time-of-use (TOU) price using improved memetic algorithms (IMA) [65] and spinning reserve using θ -dominance-based evolutionary algorithm [67]. Operation management of an MG system with distributed generation units and ESS using the water-cycle algorithm to optimize the operation cost and emission cost was presented in [66].

Novel evolutionary computation algorithms inspired by the physical phenomenon's like the black hole algorithm (BHA), backtracking search algorithm (BSA), big bang big crunch algorithm (BBBCA),

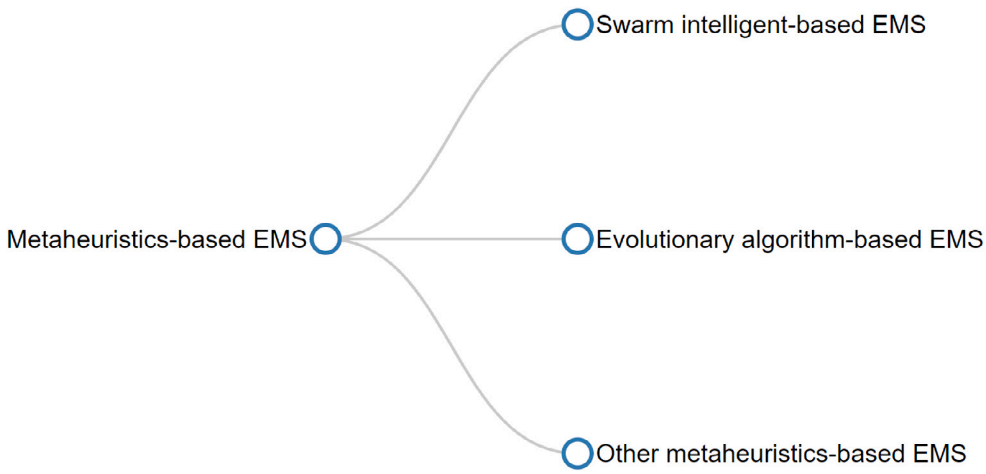

Fig. 12. Types of metaheuristics-based optimization techniques used in EMS.

Table 4
Analysis on the evolutionary algorithm-based metaheuristics techniques used in EMS.

Optimization technique	Ref.	Cite score	Supervisory control	Operation mode	Power mode	Objective			
						Forecasting	DM	ED	UC
BHA	[9]	49	Centralized	Islanded	AC	✗	✗	✗	✓
BSA	[56]	19	Decentralized	Grid-Connected	AC	✗	✗	✓	✓
	[57]	05	Centralized	Grid-Connected	AC	✓	✗	✗	✓
BBBCA	[58]	04	Centralized	Grid-Connected	AC	✓	✓	✓	✗
CRO	[55]	18	Centralized	Grid-Connected	AC	✗	✗	✓	✗
	[52]	229	Short term load forecasting						
DE	[53]	19	Centralized	Grid-Connected	AC	✗	✗	✓	✓
	[54]	07	Centralized	Grid-Connected	AC	✗	✗	✗	✓
EA	[59]	197	Decentralized	Islanded	AC	✗	✗	✓	✓
	[60]	780	Centralized	Grid-Connected	AC	✓	✗	✓	✗
GA	[61]	359	Centralized	Islanded	AC	✗	✗	✓	✓
	[62]	189	Centralized	Grid-Connected	AC	✗	✓	✗	✗
ICA	[63]	64	Centralized	Islanded	AC	✓	✓	✗	✓
	[64]	51	Decentralized	Grid-Connected	AC	✗	✗	✓	✓
IMA	[65]	–	Centralized	Grid-Connected	Both	✗	✓	✗	✗
WCA	[66]	37	Centralized	Grid-Connected	AC	✓	✗	✓	✗
θ-dominance EA	[67]	23	Centralized	Islanded	AC	✗	✗	✓	✓

and imperialist competitive algorithm (ICA) are also used to address the diversified problems of microgrid energy management. In [9] an adaptive fractional-order fuzzy-based proportional–integral–derivative (PID) controller using a modified black hole optimization algorithm was proposed for load frequency control of an islanded microgrid. In addition, The novel consideration of the concept of the vehicle to grid (V2G) for frequency support of microgrids using the proposed algorithm was evaluated using the hardware-in-the-loop (OPAL-RT) system.

A binary backtracking search algorithm based optimal scheduling controller using an IEEE 14 bus system was simulated and experimentally verified by Abdolrasol et al. [56]. Alongside, Li et al. [57] presented a two-stage model predictive control strategy using as backtracking search algorithm and a stochastic programming-based forecaster for effectively scheduling the load based on the demand. Sedighizadeh et al. [58] developed a two-stage energy management optimization technique to ideally schedule power generation and implement a demand response problem using approximate dynamic programming (ADP) and hybrid big bang big crunch (HBB-BC) algorithm. A multi-period ICA algorithm was proposed by Marzband et al. [63] to formulate the optimal operation of an isolated microgrid with objectives of cost optimization and demand response regulation. Alongside, in [64] a decentralized grid-connected EV logistic service distribution system that uses ICA to optimize the operation planning, balancing generation dispatch (wind), and load fluctuations are presented.

4.3.2. *Swarm intelligent-based EMS*

Swarm intelligence is inspired by natural swarm systems, which consist of collective behavior of decentralized agents aiming to automatically solve complex problems such as ant colonies, bird flocking, animal herding, hawks hunting, fish schooling, etc. One of the most commonly used swarm-based algorithms is the particle swarm optimization (PSO) algorithm, Moghaddam et al. illustrated the use of the PSO to address the multi-objective EM algorithm to optimize the scheduling of BESS to solve the power mismatch problem [93]. The fast convergence rate and low computation requirement of the PSO technique have encouraged many researchers across the world to utilize this technique to address diversified EM problems.

The top three cited research articles are considered in this critical review illustrating the widespread application of the proposed technique. In [94], a droop control technique addressing the frequency drop of the MG system with the intermittent DERs is optimized by effective scheduling of the resources using the PSO technique. As highlighted in the previous sections, the introduction of ESS in the MG system introduces uncertainty in the EM scheme, which is adequately addressed by the use of PSO based optimization techniques [95].

Marzband et al. presented a multi-layer ant colony-based EM scheme for finding the optimal day-ahead hourly scheduling of an MG [68]. The proposed optimization technique proved to be flexible and rapid in reacting to any intermittency that occurred in the system to achieve the global objective of reducing the operational cost. A combined economic and environmental dispatch problem was investigated using an ACO based EM scheme to address a generation dispatch

Table 5
Analysis on the swarm-based metaheuristic techniques used in EMS.

Optimization technique	Ref.	Cite score	Supervisory control	Operation mode	Power mode	Objective Forecasting	DM	ED	UC
ACO	[68]	170	Centralized	Islanded	AC	✗	✓	✓	✓
	[69]	24	Centralized	Grid-Connected	AC	✗	✗	✓	✗
	[70]	22	Centralized	Islanded	AC	✗	✗	✓	✓
ABC	[71]	159	Centralized	Grid-Connected	AC	✓	✓	✓	✓
	[72]	92	Centralized	Islanded	AC	✗	✗	✓	✗
	[73]	41	Centralized	Grid-Connected	AC	✗	✗	✓	✗
AFS	[74]	06	Centralized	Grid-Connected	AC	✓	✗	✗	✓
BFO	[75]	139	Centralized	Grid-Connected	AC	✓	✗	✓	✗
	[76]	137	Centralized	Grid-Connected	AC	✗	✗	✓	✓
BA	[77]	–	Centralized	Islanded	AC	✗	✗	✗	✓
CSA	[78]	44	Centralized	Grid-Connected	Both	✗	✗	✓	✓
	[79]	13	Centralized	Grid-Connected	AC	✓	✗	✓	✗
	[80]	12	Centralized	Grid-Connected	DC	✗	✗	✓	✗
EMFA	[81]	01	Centralized	Both	AC	✗	✗	✓	✗
FA	[82]	255	Centralized	Grid-Connected	AC	✗	✗	✓	✓
	[83]	34	Centralized	Grid-Connected	AC	✗	✗	✓	✗
FFO	[84]	03	A point prediction model using a fruit fly optimization technique.						
FW	[85]	09	Centralized	Grid-Connected	AC	✗	✗	✓	✓
GHO	[86]	12	Centralized	Both	AC	✗	✗	✗	✓
	[87]	06	Centralized	Grid-Connected	AC	✗	✗	✗	✓
GWO	[88]	31	Centralized	Grid-Connected	AC	✗	✗	✓	✓
	[89]	23	Centralized	Islanded	AC	✗	✗	✓	✗
	[90]	23	Decentralized	Grid-Connected	AC	✗	✗	✓	✓
SFLA	[91]	06	Centralized	Grid-Connected	AC	✗	✗	✓	✗
NMHA	[92]	10	Centralized	Grid-Connected	AC	✗	✗	✗	✓
PSO	[93]	369	Centralized	Grid-Connected	AC	✗	✗	✓	✓
	[94]	310	A droop control of a multiple DG coordinated system.						
	[95]	180	Centralized	Grid-Connected	AC	✗	✗	✓	✓
$\theta - KHA$	[96]	77	Centralized	Grid-Connected	Both	✗	✗	✗	✓
	[97]	07	Centralized	Grid-Connected	Both	✗	✗	✓	✓

problem by Trivedi et al. [69]. MATLAB was used for implementing the above-mentioned EM technique, and observations from the study encouraged the investment in RES, highlighting the advantage of reduced operational cost and the net revenue of the MG system.

An experimental case study of three isolated MG situated at Kharga, Saint Katherine, and Qussair in Egypt using the ACO algorithm-based EMS for the economic feasibility study was carried out by Abo-Elyousr et al. [70]. Followed by the investigation highlighted in [68], Marzband et al. extended their evaluation of the proposed MG system using the ABC algorithm in [71,72]. Besides, an artificial neural network-Markov chain (ANN-MC) based power generation prediction algorithm was also introduced, and it proved to be more reliable, flexible and extendable in [71,72] a central EMS with day-ahead scheduling and with real-time scheduling for single side auction of a local energy market was presented. Lin et al. discussed the use of ABC optimization in the economic dispatch operation of MG to address the time-of-use (TOU) constraint [73]. The use of a similar algorithm called a modified artificial fish school (MAFSA) algorithm in an EMS of a DC MG with the objectives of power balance and unit commitment was deliberately evaluated by Huang et al. [74].

Motevasel et al. presented an EMS of a wind-powered MG considering the optimal scheduling of the RE sources along with the ESS. A novel ANN-based stochastic forecaster was used in this model along with the modified bacterial foraging optimization (MBFO) based multi-objective EM scheme focused on reducing the cost and emission of the overall system [75]. A similar intelligent EM scheme was formulated using the MBFO algorithm to evaluate a combined heat and power-based MG, results indicated that the proposed algorithm proactively considered both the heat and electric load along with optimally scheduling the dispatch for achieving the economic and environmental targets [76]. Shivaie et al. formulated an optimal sizing model of an autonomous hybrid RES with solar, wind, diesel and BESS using a modified discrete bat search algorithm. In addition, a Monte Carlo simulation was used in this proposed model to handle the intermittent characteristics of the load demand and RES [77]. Avoiding premature convergence is one of the significant drawbacks of swarm-based metaheuristic algorithms and crow search algorithms (CSA) proves to address this issue in an effective manner. Papari et al. proposed a stochastic EM framework with hybrid AC–DC [78] and a DC [80] MG for optimally scheduling of operation and management of the RESs. Moazzami et al. studied an economic optimization EM model of an MG integrated with wind farms and an advanced rail energy storage system using the CSA. The novel storage technology using rail energy storage system was a standout of this research work [79]. The inferences from the above-mentioned studies indicated that the CSA performed better in terms of avoiding getting trapped in the local minimum and enhanced the search capability of the optimization technique.

Elsakaan et al. formulated an EMS addressing the non-linear economic-emission dispatch problem of MG's. The effectiveness, robustness, and global convergence rate of the proposed enhanced moth-flame optimization (EMFO) algorithm illustrated notable benefits when solving the scheduling problem under intermittency [81]. Firefly algorithm (FA) is one of the other population-based optimization techniques which is used for addressing the issues within the field of power engineering. Mohammadi et al. proposed an adaptive modified firefly algorithm (AMFA) based EMS of an MG model to solve the intermittencies in the deterministic MG scheduling problem scenarios synthetically generated using a probability distribution function (PDF) [82]. In [83], FA was used to address the optimal scheduling problem of a more complex MG system with combined heat and power — proton exchange membrane fuel cell-combined (CHP-PEMFC), WT, PV and novel hydrogen storage system considering the reliability enhancement factors were incorporated into the EMS. Accurate forecasting of the wind and solar generation is considered as one of the key constituents of the EMS of the MG and a multi-objective modified fruit fly optimization technique was used alongside a group method of data handling neural network [84].

Wang et al. used the firework algorithm as a novel hybrid multi-objective EM algorithm of a microgrid along with a gravitational search operator to optimize the economic/environmental objectives [85]. In a hybrid RES integrated MG configuration reducing the total harmonic distortion at the point of coupling is one of the major influencing

Table 6
Analysis on the other metaheuristic techniques used in EMS.

Optimization technique	Ref.	Cite score	Supervisory control	Operation mode	Power mode	Objective Forecasting	DM	ED	UC
GSA	[98]	218	Centralized	Grid-Connected	AC	✓	✗	✓	✗
	[99]	171	Centralized	Islanded	AC	✗	✓	✓	✗
	[100]	30	Centralized	Islanded	AC	✗	✗	✗	✓
HSA	[101]	3	Centralized	Islanded	AC	✗	✗	✓	✓
HA	[102]	62	Centralized	Grid-Connected	AC	✗	✗	✓	✗
	[103]	40	Centralized	Grid-Connected	AC	✗	✗	✗	✓
ISA	[104]	18	Centralized	Grid-Connected	AC	✗	✗	✓	✓
	[105]	11	Centralized	Grid-Connected	AC	✗	✗	✓	✗
LH	[106]	35	Centralized	Islanded	AC	✗	✗	✗	✓
SB	[107]	132	Centralized	Islanded	AC	✓	✗	✓	✓
	[108]	4	A two-stage scenario-based coordinated scheduling model.						
TS	[109]	29	Centralized	Both	AC	✗	✗	✗	✓
TLBO	[110]	37	Centralized	Grid-Connected	AC	✗	✓	✓	✗
	[111]	15	Centralized	Grid-Connected	AC	✗	✗	✓	✗

factors of maintaining the load demand. A multi-objective grasshopper optimization algorithm was used to address this issue by Elkholy et al. [86] and Jumani et al. [87]. A day ahead power scheduling EM algorithm to formulate the minimization of the operational, emission, and power loss cost in an MG system using a grey wolf optimization (GWO) algorithm was studied using an IEEE 33-bus distribution network by Gazijahani et al. [88]. A case study conducted on battery sizing optimization addressing the unit commitment problem in a standalone microgrid situated at flinders island, Australia, also used the GWO algorithm to increase the performance of the proposed EM algorithm [89]. Shamshirband et al. proposed an optimal EMS scheme of an MG with plug-in electric vehicles integrated with an IEEE 69-bus system, and the use of GWO proved to handle the multi-objective issues in an effective manner [90].

AnEMS of an MG integrated with a fuel cell, WT, PV, gas-fired microturbine, and BESS was considered in [91], which was later solved by using a modified shuffled frog leaping algorithm (MSFLA) to reduce the environmental and economic cost of the system. The consideration of multiple constraints like the power balance constraint, generation capacity constraint, spinning reserve constraint along with the specific battery energy storage constraints proved to play a vital role in the EMS. The sizing optimization of an MG system with a vehicle to grid (V2G) parking docks was examined using a Nelder Mead heuristic algorithm (NMHA) in [92]. With the introduction of hybrid EVs into the grid, the complexity of the charging and discharging sequences considered in the EM scheme of the MG gets more non-linear and complex. Kavousi-fard et al. suggested a θ-krill herd algorithm ($\theta - KHA$) to address this non-linear problem and inferences from the study indicated that the proposed technique was more stable and faster in converging to the optimal solution [96]. With the fast convergence rate of the $\theta - KHA$ it was more efficient in addressing the multi-objective problems in an MG setup, Kamankesh et al. presented a stochastic framework addressing the economic/environmental dispatch and unit commitment problems [97].

4.3.3. Other metaheuristics-based EMS

Besides, the swarm optimization and evolutionary algorithm-based metaheuristics techniques there are few other metaheuristics algorithms used for optimizing the EMS of the MG. Niknam et al. presented an MG configuration with the cluster electric and/or thermal load along with RES. A gravitational search algorithm (GSA) is used to determine the optimal energy management of the MG with a probabilistic approach aiming at addressing the energy and operation management problems in the MG [98]. Marzband et al. presented an experimental validation of a real-time EM of an islanded MG using GSA which considered some variations in load consumption patterns, appropriate unit commitment of the ESS and demand response schemes [99].

GSA was also utilized in another case study that highlighted the optimal design and management of an ocean renewable energy storage system at Kish island in Iran [100]. Lazar et al. presented a harmony search algorithm (HSA) based EMS to address the day-ahead scheduling problem in an isolated MG. The use of a novel and an innovative graphical user interface (GUI) to present the results was a standout of the research presented in [101]. A state-of-the-art optimization technique aiming at reducing the fuel consumption and emission cost using a heuristic approach (HA) presented in [102] show better performance in terms of stabilizing the use of micro sources and optimizing global cost. Mallol-poyato et al. presents an EMS targeting at discharge scheduling of energy storage systems problems in an MG using hyper-heuristics [103].

El-Hendawi et al. investigated a real case study of an MG situated in Oshawa (Ontario, Canada) with variable load models using an interior search algorithm (ISA) for optimizing hour-by-hour scheduling of a day ahead power scheduling problem [104]. ISA was also used by Trivedi et al. to address the economic load dispatch and combined economic, emission dispatch problems of an MG's EMS [105], results illustrated that the ISA performed more effective in cost reduction when compared to ant colony optimization, cuckoo search algorithm. Sizing optimization is one of the other prime EM optimizations that is observed in the initial stages of the MG. A levy-harmony (LH) optimization-based sizing optimization of the EMS in an MG is presented in [106], proving the high accuracy and the search speed. Cau et al. presented a short-term generation scheduling concerning an economic dispatch scheme of an EMS in MG with a hydrogen storage system using a scenario-based (SB) approach [107]. The scenario-based optimization approach is used for forecasting in a two-stage SB coordinated scheduling model in [108]. A probabilistic reactive power planning of a distributed RES system using a tabu search (TS) algorithm aiming at real and reactive power adequacy was investigated in the paper presented by Arefifar et al. [109]. Teaching and learning-based optimization (TLBO) is one other metaheuristics algorithm that is used in EMS systems addressing demand-side management [110] and optimal scheduling problems [111] of an MGs. Many novel optimization techniques have been developed to address the energy management problem and it is clear that the swarm-based and evolutionary algorithms have been explored a lot in the literature. The main drawback of all these techniques are most of the work is limited to the simulation studies and the real-time application of these systems are very limited in the current literature and it is encouraged to work on the experimental evaluation of the techniques to utilize the real impact of these power full algorithms to address the energy management problem in MGs.

4.4. Other novel EMS approaches

In addition to the above-mentioned categorization on different optimization techniques used for addressing the energy management problem in microgrids, there are a few other novel energy management strategies that are not being critically analyzed in the existing review

Table 7
Analysis on the other novel techniques used in EMS—Part 1.

Optimization technique	Ref.	Supervisory control	Operation mode	Power mode	Objective			
					Forecasting	DM	ED	UC
APCL	[112]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
AHP	[113]	A multi-criteria decision analysis for integrated assessment of a sustainable MG for a remote village in the hilly region.						
BOA	[114]	Centralized	Grid-Connected	AC	✗	✗	✓	✗
Blenders decomposition	[115]	Centralized	Both	AC	✗	✗	✓	✓
	[116]	Centralized	Islanded	AC	✗	✗	✓	✓
CCP	[117]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
	[118]	Centralized	Grid-Connected	AC	✗	✓	✗	✗
Compromise programming	[119]	Centralized	Grid-Connected	AC	✗	✗	✓	✗
CMA	[120]	Centralized	Both	AC	✗	✗	✓	✗
Consensus algorithm	[121]	Centralized	Both	AC	✗	✗	✓	✓
Convex optimization	[122]	Decentralized	Grid-Connected	AC	✗	✗	✓	✗
Cooperative optimization	[123]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
DM	[124]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
DOA	[125]	Centralized	Grid-Connected	AC	✗	✗	✓	✗
Decomposition-coordination optimization	[126]	Centralized	Islanded	AC	✗	✗	✓	✓
EBIOA	[127]	Centralized	Islanded	AC	✗	✗	✗	✓
EMA	[128]	Centralized	Grid-Connected	AC	✗	✗	✓	✗
FBSA	[129]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
	[130]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
HS	[131]	Centralized	Grid-Connected	AC	✓	✓	✓	✓
Hong's point estimate method	[132]	Centralized	Grid-Connected	AC	✓	✗	✓	✓
	[133]	Centralized	Grid-Connected	AC	✓	✗	✗	✓
IGDT	[134]	Centralized	Grid-Connected	AC	✗	✓	✗	✗
	[135]	Centralized	Islanded	AC	✗	✗	✓	✓
Incentive-based programs	[136]	Centralized	Grid-Connected	AC	✗	✓	✓	✗
KFBO	[137]	Centralized	Grid-Connected	AC	✗	✓	✓	✗
Lagrangian primal-dual sub-gradient algorithm	[138]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
	[139]	Centralized	Grid-Connected	DC	✗	✗	✗	✓
LM	[140]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
Markov decision process	[141]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
	[142]	Centralized	Islanded	AC	✗	✗	✓	✓
Mesh adaptive direct search	[143]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
MST	[144]	Centralized	Islanded	AC	✗	✗	✓	✓
MMMOS	[145]	Centralized	Grid-Connected	AC	✗	✗	✓	✗
Monte carlo simulation	[146]	Centralized	Islanded	AC	✗	✗	✗	✓
	[147]	Centralized	Grid-Connected	AC	✗	✓	✗	✗

articles, therefore a detailed insight on these new novel techniques are added to the review presented in the manuscript in the following section. Tables 7 and 8 present a detailed observation of the use of these other novel techniques in EMS of MG's. Conventional unit commitment algorithms use historical information about the load demand and the renewable energy generation, which makes it impractical for situations where prior data is not available. In [112], Lee et al. presented an adaptively partitioned contextual learning algorithm (APCLA) for UC, which learns to schedule the optimal UC scheme and minimizing total operational cost without the use of past data. Kumar et al. proposed a bi-level decision analysis framework for integrating the optimization design tool of the rural microgrid using the analytical hierarchy process (AHP) developed using HOMER PRO [113]. Mohamed et al. [143] present a mesh adaptive direct search algorithm based optimal energy management system of a microgrid. In this research, the authors aim at optimizing the cost function of the system by considering emission cost which is a standout of this work. Parvizimosaed et al. [148] and Ross et al. [149] in their work highlight the use of a Pareto-optimal solutions approach to handle demand response of a microgrid system with plug-in hybrid electric vehicles and economic dispatch with renewable energy penetration. A Lagrangian primal–dual sub-gradient algorithm was used by Hamad et al. to address the convex optimization problem under global constraints to formulate an EMS of a DC distribution system in 2014 [139] and later they presented a novel control scheme for voltage regulation in a DC microgrid [138].

Zhao et al. proposed a duality-based approach that uses the principle of "probability of self-sufficiency" for short-term scheduling of renewable incorporated microgrid system [160]. An enumeration-based iterative optimization algorithm (EBIOA) was used by Bhuiyan et al. to address the optimal sizing of an islanded microgrid, ensuring a minimized loss of power supply probability and demand–supply balance of both real and reactive power [127]. The use of Kalman filtering based optimization (KFBO) technique in EMS of microgrids was examined by Comodi et al. (residential microgrid) [137]. Markov decision process was used by Lan et al. [141] to address the scheduling problem using real-time data, and Yan et al. highlighted the application of the Markov design principle to optimize the design of the Renewable integrated microgrid systems [142]. In a vehicle to grid (V2G) integrated microgrid setup a metropolis-hasting algorithm was used to undertake operational planning in an MG [117]. Information gap decision theory (IGDT) was used by Rezaei et al. to stabilize the frequency of the microgrid [135] and Mehdizadeh et al. to implement a demand response program [134]. In addition to the above mentioned techniques, techniques like forward–backward sweep algorithm (FBSA) [129], minimum spanning tree (MST) [144], optimal automatic generation control (OAGC) [157], congestion management approach (CMA) [120], Dinkelbach method (DM) [124], Laplacian matrix (LM) [140], Exchange market algorithm (EMA) [128], min–max multi-objective scheduling (MMMOS) [145], moving horizon optimization (MHO) [151], online learning-aided management (OLAM) [156],

Table 8
Analysis on the other novel techniques used in EMS-Part 2.

Optimization technique	Ref.	Supervisory control	Operation mode	Power mode	Objective			
					Forecasting	DM	ED	UC
Most valuable player algorithm	[150]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
MHO	[151]	Centralized	Both	AC	✗	✗	✓	✓
MIU	[152]	Centralized	Islanded	AC	✗	✗	✓	✓
Group search optimization	[153]	Centralized	Grid-Connected	AC	✓	✗	✓	✗
Non-convex optimization	[154]	Centralized	Grid-Connected	AC	✓	✗	✓	✓
OLAM	[155]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
	[156]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
OAGC	[157]	Centralized	Islanded	AC	✗	✗	✓	✗
Parametric cost function	[158]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
Pareto-optimal	[149]	Centralized	Grid-Connected	AC	✓	✓	✗	✗
	[148]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
PCPM	[159]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
Probabilistic approach	[160]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
	[161]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
PDA	[162]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
Rule-based optimization	[163]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
SSC	[164]	Centralized	Grid-Connected	AC	✓	✓	✗	✗
Taguchi's orthogonal array	[165]	Centralized	Grid-Connected	AC	✗	✗	✓	✗
Voluntary demand participation	[166]	Centralized	Grid-Connected	AC	✗	✓	✗	✗

Table 9
Analysis on the hybrid techniques used in EMS.

Optimization technique	Ref.	Supervisory control	Operation mode	Power mode	Objective			
					Forecasting	DM	ED	UC
AAA	[167]	Centralized	Grid-Connected	AC	✓	✗	✓	✓
ANFMDA	[168]	Centralized	Grid-Connected	AC	✗	✗	✓	✓
EMD+PSO+ANFIS	[169]	Centralized	Grid-Connected	AC	✓	✗	✗	✗
FL+MAS	[170]	Decentralized	Islanded	AC	✗	✗	✓	✓
GOAPSNN	[171]	Centralized	Grid-Connected	AC	✓	✗	✓	✓
HAS+GA	[172]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
HGSO	[173]	Centralized	Grid-Connected	AC	✗	✓	✓	✗
MEHO+TS	[174]	Centralized	Grid-Connected	DC	✗	✗	✗	✓
PSO+OGSA	[175]	Centralized	Grid-Connected	AC	✓	✗	✓	✗
QOCSOS+RF	[176]	Centralized	Grid-Connected	AC	✓	✗	✓	✓
SSA+CS	[177]	Centralized	Grid-Connected	AC	✓	✗	✓	✗
SA+PSO	[178]	Centralized	Grid-Connected	AC	✗	✗	✓	✗
SSA+WOA	[179]	Centralized	Grid-Connected	AC	✗	✗	✗	✓
RP+SP	[180]	Centralized	Islanded	AC	✗	✗	✓	✗
WOANN	[181]	Centralized	Grid-Connected	Both	✗	✗	✗	✓
VNS+DEEPSO	[182]	Centralized	Grid-Connected	AC	✗	✓	✓	✓

Table 10
Analysis of the top five EMS optimization techniques.

Optimization technique	Simplicity	Efficiency	Reliability	Adaptability	Forecasting	ED	UC	DM
MIP	G	B	M	G	M	M	B	M
SP	B	B	B	B	B	B	B	B
GA	M	M	M	M	G	G	M	M
PSO	G	M	M	M	VG	G	M	M
MAS	M	G	G	G	M	M	G	VG

procedural decision algorithm (PDA) [162], distributed optimization algorithm (DOA) [125], multi-interval-uncertainty (MIU) method [152], state space control (SSC) [164], hierarchical scheduling (HS) [131], Bayesian optimal algorithm (BOA) [114] and chance-constrained programming (CCP) [116–118] were utilized as the energy management schemes within microgrids.

4.5. Hybrid EMS

The combination of the existing algorithms in the form of hybrid EMS techniques proves to be more efficient and perform better in many cases. The results of the analysis carried out on the hybrid techniques are listed in Table 9 and the critical review of individual methods are presented in the following section. In [167], Elkazaz et al. presented a two-layer EMS aiming at minimizing the operational cost of the MG by maximizing the use of RES and optimal real-time battery scheduling using an adaptive autoregression algorithm (AAA). The two-layer architecture of the proposed model used a convex optimization technique to find the optimized power that must be drawn from the primary grid every 15 min in the upper layer. In the lower layer of the EMS, a rolling horizon predictive controller and a model predictive controller were used to optimizing the battery scheduling of the novel energy storage system was considered. Murugaperumal et al. [168] proposed an efficient system modeling and energy management tool aiming to reduce the operational cost of the MG. An adaptive neuro-fuzzy interference system (ANFIS), along with a modified dragonfly algorithm (MDA), was used to solve the multi-objective problem in the proposed MG. The ANFMDA algorithm optimizes the configuration of the MG setup to effectively address the load demand along with reducing the fuel cost of the system, whereas the ANFIS learning model

Table 11
Analysis of the top cited research articles.

S. No	Ref	Year of Publication	Optimization technique	No of Citations	Mathematical Model				
					Battery	WT	PV	MT	Load
1	[38]	2011	MIP	898	✓	✗	✓	✓	✓
2	[60]	2010	GA	780	✓	✓	✓	✗	✗
3	[15]	2013	FL	488	✓	✓	✓	✓	✓
4	[49]	2014	SP	465	✓	✗	✗	✗	✓
5	[43]	2014	MPC	391	✓	✓	✓	✓	✓
6	[93]	2011	PSO	369	✓	✓	✓	✓	✓
7	[21]	2014	MAS	365	Connected MG setup				
8	[61]	2013	GA	359	✓	✓	✓	✗	✓
9	[143]	2010	MADS	320	✓	✓	✓	✓	✗
10	[94]	2010	PSO	310	Inverter based droop control				

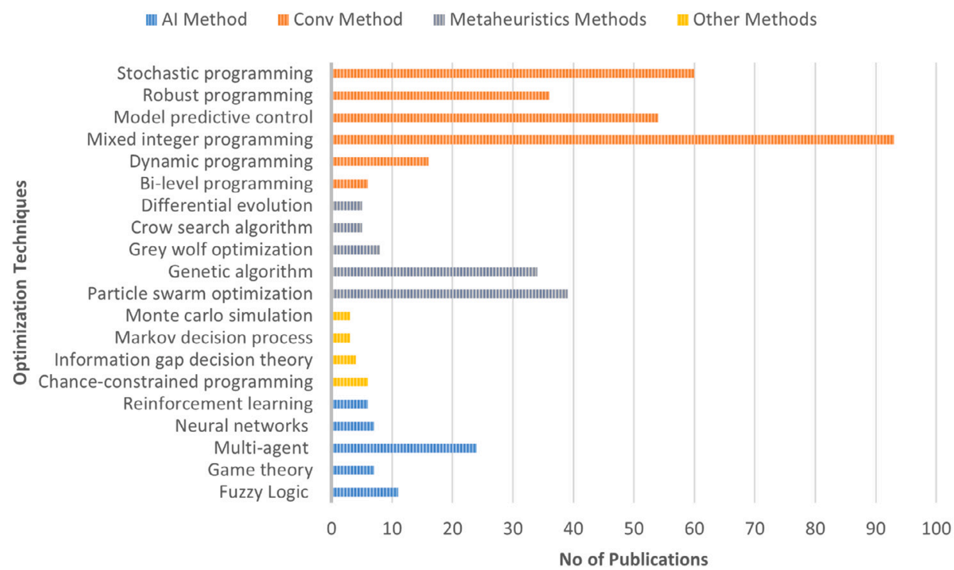

Fig. 13. Analysis of different optimization techniques based on the number of publications during 2010–2020.

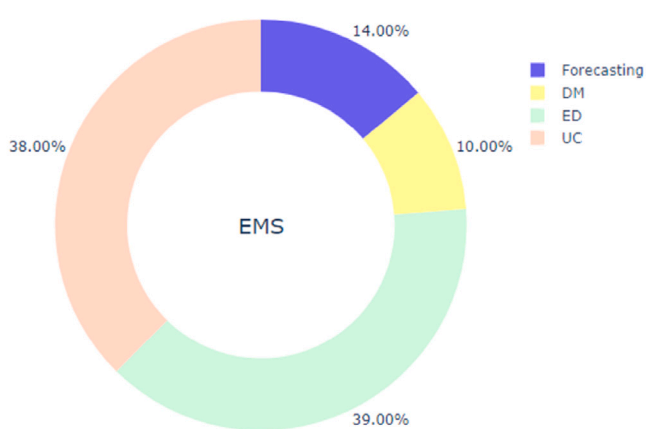

Fig. 14. Distribution of the objective of the EMS in the reviewed articles.

is used to predict the load demand accurately. Gajula et al. investigated the performance of a hybrid galactic swarm optimization (HGSO) technique in a residential MG with hybrid wind–solar energy [173]. Along with the GSO algorithm used for scheduling supplementary generation, an ant-lion optimization algorithm was used for shifting the peak load.

Accurate forecasting of renewable energy generation and the load demand is considered as an essential constituent of an MG's EMS system. Semero et al. [169] in their work proposed a hybrid short term load forecasting algorithm that combines an empirical mode decomposition (EMD) technique along with a PSO and an ANFIS model. The EMD initially decomposes the load data into a set of intrinsic mode functions and residues. Later the PSO algorithm is used to optimize the ANFIS model of each intrinsic set considered in the optimization problem. Hybrid EMS models have the advantage of mathematically optimizing two or more objective functions, which helps the EMS of an MG to address multi-objective problems effectively. In [171], a GOAPSNN (grasshopper optimization algorithm-particle swarm optimization-artificial neural network) technique was used to optimize the power flow and minimize the production cost of the MG system. The PSO-ANN technique was used to predict the load demand and the GOA technique was used to predict the optimal configuration of the MG to address the predicted load demand.

Karavas et al. evaluated the technical performance of the decentralized multi-agent-based EMS of an autonomous polygeneration MG [170]. The advantage of using a decentralized architecture of independently running different parts of the MG even under minor malfunctions without a complete system breakdown was critically evaluated in the proposed system. In [172], a combination of harmony search and a genetic algorithm (HS-GA) was used to address the unit commitment objectives of the MG alongside improving the voltage profile and stabilizing operational and security constraints. Similarly, a modified elephant herding optimization algorithm with tabu search algorithm (MEHO+TS) was used to optimize a multi-objective problem that shaped the active and reactive power to address the power flow management of the MG [174]. Durairasan et al. introduced a hybrid power flow management algorithm using squirrel search algorithm (SSA) with whale optimization algorithm (WOA) for a hybrid renewable energy sources (HRES) connected MG [179]. Similar to the above-mentioned

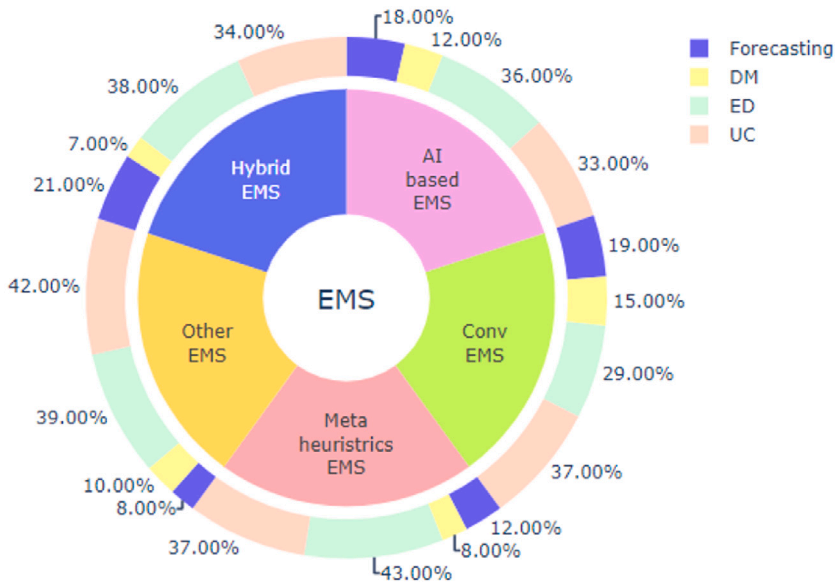

Fig. 15. Distribution of the objective of the EMS with respect to the type of optimization techniques.

method, another optimal power flow control algorithm using a hybrid WOA and ANN technique was considered in [181].

Metaheuristics algorithms are like PSO are commonly known to work alongside the other algorithms with higher efficiency. In [175], a hybrid particle swarm optimization and opposition-based learning gravitational search algorithm (PSO-OGSA) was used to address the two-stage dispatch problem of practical MG based on a day-ahead scheduling and real-time scheduling. Similarly, in [178] simulated annealing and particle swarm optimization (SA+PSO) based hybrid heuristic optimization technique was proposed to solve the generation dispatch problem. A slap swarm optimization algorithm with a cuckoo search algorithm was used to examine the performance of the EM system proposed with the objective of cost minimization [177]. Alongside this, a variable-neighborhood search differential evolutionary particle swarm optimization (VNS-DEEPSO) algorithm was proposed to solve multi-objective stochastic control models [182]. This novel algorithm was the winner of the IEEE congress on evolutionary computation/the genetic and evolutionary computation conference (IEEE-CED/GECCO 2019) 2019 smart grid competition and IEEE world congress on computational intelligence (IEEE-WCCI) 2018 smart grid competition. In addition to the metaheuristic algorithms, few conventional algorithms were also used as hybrid optimization techniques in EMS of MG's. For example, a two-stage coupled robust and stochastic optimal (CRSO) dispatching model with mixed-integer programming-based EMS of an islanded hybrid AC/DC MG was presented by Qiu et al. [180]. A consolidated model to reduce operational cost and enhanced power flow using random forest (RF) and quasi-oppositional-chaotic symbiotic organisms search algorithm (QOCSOS-RF) [176].

5. Discussions and future recommendations

The application of the specific optimization techniques in the EMS of MGs is critically reviewed in the above-mentioned sections of the manuscript. In this section, a deeper insightful analysis of these articles is presented based on the factors of the number of publications, distribution of the EMS based on the application and category of the technique. The distribution of the number of published research articles in relevance to the top optimization techniques is presented in Fig. 13. This analysis resulted in the observation that the MILP is the most commonly used optimization technique to address the EM problem in MGs. In addition to this, it was evident that the PSO and GA are

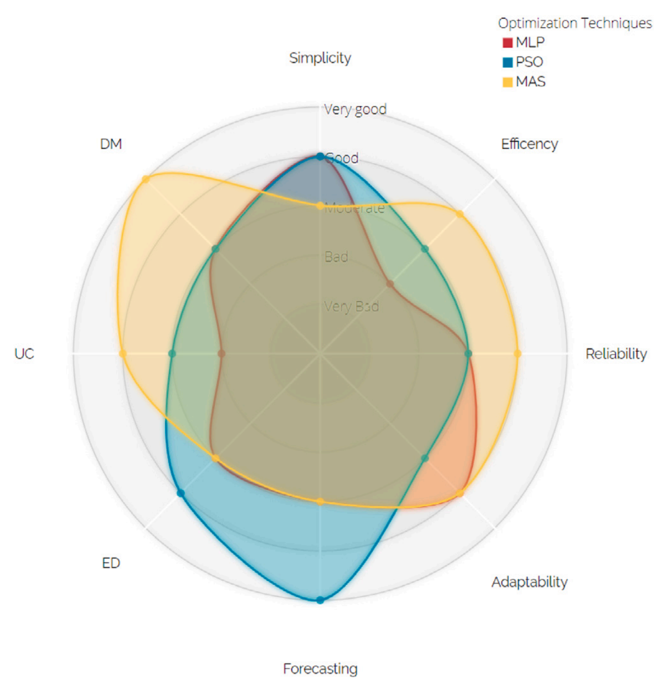

Fig. 16. Pictorial representation of the analysis on top three Techniques.

the commonly used meta-heuristics algorithms and the use of multi-agent and Game-theoretic algorithms are starting to increase with the introduction of a more decentralized system. The multi-agent-based systems prove to be more beneficial in a decentralized environment and the need for an end-to-end solution of a decentralized simulation tool for simulation the behavior of EMS in MGs is also identified in this review. Followed by which the distribution of the objectives in the EMS is expressed in Fig. 14, proving the need for a focus on the objectives of forecasting and demand management in the coming years. Also, the problems of unit commitment and economic dispatch have been explored to a greater potential considering the impact of the results on the efficiency and cost of the system. Fig. 15 illustrated the distribution of the objectives with respect to the type of optimization technique used in EMS of MG's. The increased share of the ED and UC problems

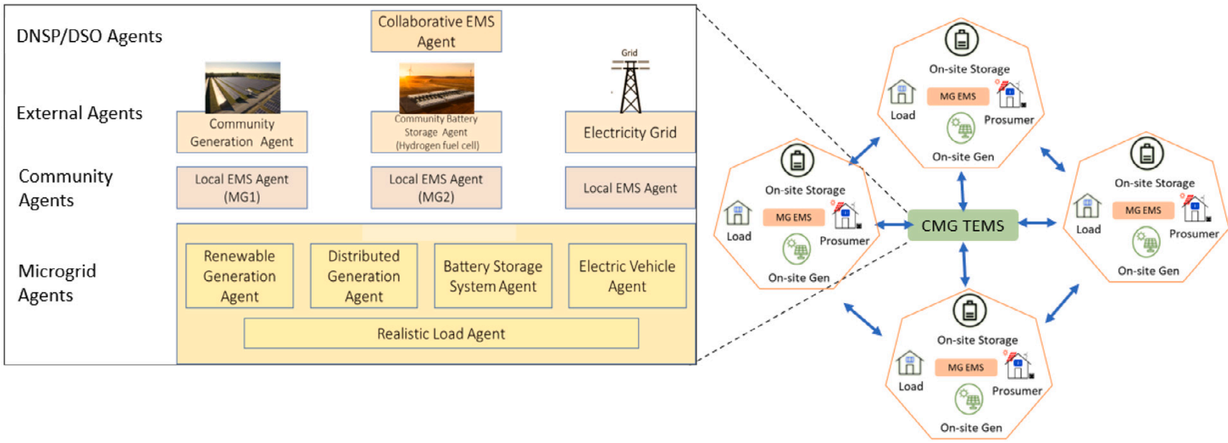

Fig. 17. Proposed Community based MG model with an hierarchical Multi-agent based EMS.

being addressed by the hybrid techniques revealed the fact that the application of hybrid techniques to address the different aspects of the EMS problem will be the solution to go forward and future research directions of the researchers should be targeted towards achieving higher efficiency by using the advantages of individual techniques to collectively achieve better results. Inferences also indicated that the Forecasting and Demand response are the areas to look forward to in the area of EMS in MGs as the importance of having optimal scheduling of demand and accurate forecasting of load and generation is identified. But there is still a lot more scope of improvement in this area of EMS in MGs.

Later, the top five optimization techniques used in the literature were analyzed based on the factors of simplicity, efficiency, reliability, adaptability, and capability to perform forecasting, ED, UC, and DM. The scores were given on the scale of good to bad indicating the performances of the optimization technique (G—Good, VG—Very Good, M—Moderate, and B—Bad). Table 10 illustrates the performance index of the top five-technique, and Fig. 16 shows the pictorial representation of the top three types. The MAS based systems would be most ideal in solving the complex problem of UC and DM and meta-heuristic algorithms like PSO and machine learning approaches like neural networks are better for forecasting and ED-based applications. The scores were obtained on the number of articles published from the total collected article pool considered for the review (555 articles) and also the indication of the factors of the simplicity and the results obtained by using the different optimization techniques.

Results from the review indicated that there is a need of developing a detailed mathematical model of the components of the MG and it was analyzed using the top 10 most cited research articles considered for EMS of MGs. Inference from the analysis is presented in Table 11. It is clear that the most commonly used component of the EMS is the battery, and the inclusion of RES adds another layer of complexity to the problem and the need for an optimal mathematical model. The electricity power grids are over a century-year-old, and this field of study has witnessed a relatively smaller number of ground-breaking innovations since its creation. Also, fellow researchers around the world are insisting a substantial focus of the researchers to work towards driving the change in the infrastructure of the electricity grids, which lead to the invention of the concept called community microgrids or connected microgrids are considered as an alternative of the conventional electricity grids. The main drawback of this breakthrough research innovation of connected microgrids is its adaptability and the requirement of the change in infrastructure to equip the P2P energy sharing capabilities. Alongside this, the need for an accurate and secure communication infrastructure ensuring an end-to-end communication platform that connects all the smart meters and other IoT devices.

Also, with the increase in renewable energy generation sources in the distributed network of microgrids, it is essential to have an efficient energy management strategy to forecast the amount of energy generated from renewable sources accurately. The complexity of the forecasting algorithms increases because of the stochastic nature of the renewable energy resources as they are intermittently related or dependent on the weather parameters specific to the location of the DERs. So, this is also considered a significant scope of the research for the future. The accurate forecasting of the generation capacity and the load profiling will lead towards obtaining the optimal energy management strategy. In addition to this, the need for the application of optimization techniques to effectively schedule the demand and increasing the economic and environmental dispatch of the available local renewable resources is considered an area to work for the future. It is also encouraged that the fellow researchers aim towards investigating the aspect of community microgrids with more optimal EMS for transactive energy sharing within the peers. Fig. 17 shows the functional overview of the proposed futuristic work of a community MG EMS.

6. Conclusion

An efficient EMS is an essential component of the MG configuration, considering the increasing energy demand and the integration of intermittent renewable energy generation. With the level of penetration of RES widely increasing, the need to find an optimal EMS technique is proven to be essential. The efficiency and reliability of the EMS depend majorly on the type of the forecasting algorithm and the energy management scheme used. In general, the EMS targets to accurately predict the renewable generation and the load to effectively manage the peak demand and reduce the total cost of the system. However, the selection of the type of EM scheme used is also dependent on factors like the complexity and adaptability of the EM scheme that is used to achieve a high level of system reliability and operational efficiency. The review presented on the different EMS techniques revealed that the use of MIP based EM solutions was the most common and MAS based systems would be most ideal in solving the complex problem of UC and DM and meta-heuristic algorithms like PSO and machine learning approaches like neural networks is better for forecasting and ED-based applications. Observations from the study also indicated that the meta-heuristics algorithms and multi-agent-based algorithms are computationally less expensive to address the complex EMS problem and resulted in better efficiency. Finally, the authors also highlight the need for futuristic EMS to focus more on the collaborative community MG set up and develop more accurate forecasting and scheduling algorithms to increase the economic and computational benefits.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Research ethics

No Ethics required.

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