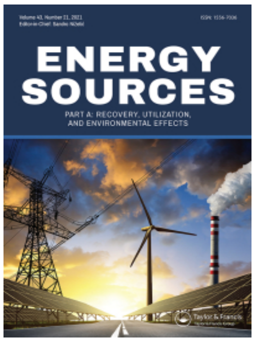

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Albert Paul Arunkumar[a], Selvakumar Kuppusamy[a*], Suresh Muthusamy[b*], Santhiya Pandiyan[c], Hitesh Panchal[d], and Pragash Nagaiyan[b]

[a]Department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Kattankulathur, Chennai, India; [b]Department of Electronics and Communication Engineering, Kongu Engineering College (Autonomous), Perundurai, Erode, India; [c]Department of Computer Science and Engineering, Kongu Engineering College (Autonomous), Perundurai, Erode, India; [d]Department of Mechanical Engineering, Government Engineering College, Patan, India

ABSTRACT

Microgrids, a scaled-down version of utility grids, are gaining attention in the last decades. The distinct features of microgrids such as the utilization of renewable energy resources and elimination of power transmission requirements made them an inevitable area of research in the power sector. The intermittent nature of the distributed generation resources and the need for improvising the economic feasibility of the microgrid made the energy management of microgrids as an inexorable research paradigm. Using recent literature, the Energy Management Systems (EMS) developed for microgrids is reviewed based on the aspects of EMS and the optimization techniques used in the EMS framework. An extensive analysis of literature on microgrid EMS based on four categorizations, namely, the optimization techniques used, type of grid considered, mode of microgrid operation (grid-connected or islanded), and software/solvers used as a platform for solving the EMS problems, is presented. The components of the microgrid test system considered such as energy resources and storage systems are also reviewed later. The meta-heuristic methods are found to be the mostly used (nearly 33% of literature) optimization technique. The objective of the optimization model majorly focusses on cost minimization (approx. 62% of literature) and is of multi-objective nature. For the purpose of distributed generation, the Photovoltaics (PV) (approx. 27%) and Wind turbine (WT) (approx. 19.5%) is the most preferred source whilst batteries (approx. 67%) are the most preferred for storing energy. This article addresses the methods and effective prospects to achieve energy management objectives of the microgrid and concludes with futuristic insights.

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Introduction

The largest engineered systems ever built are today's electrical grids. These massive systems are built so that they can deliver power wherever and whenever required. Such an electrical grid can be dissevered into a substantial transmission network and multitudinous distribution networks. The large-scale transmission network receives power from the centralized generators (ranging in MW) and transmits the power to substations, where the voltage is stepped down so that it can be made available for the end-users. These existing grids are facing evolutionary changes as a consequence of several factors. Due to the extreme centralization of the utility grid, numerous significant drawbacks such as existing networks expansion, limitations on the RES integration, transmission line congestion, monopoly of

CONTACT Selvakumar Kuppusamy selvakse@gmail.com Department of Electrical and Electronics Engineering SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu India; Suresh Muthusamy infostosuresh@gmail.com Department of Electronics and Communication Engineering, Kongu Engineering College (Autonomous), Perundurai, Erode, Tamil Nadu India

utility grid gradually mandated the need for alternative approaches against the vertically integrated main grids. Three Ds, namely, "decarbonize, decentralize, and democratize" have become a major focus (Green 2016) for the whole electrical system to reduce carbon emissions, to get rid of the utility grid's monopoly, to provide power even to remote communities by improving the infrastructure, and to focus more on resilience and reliability of the grid. The necessitous challenge of decreasing the carbon footprint caused by the excessive harnessing of fossil fuels paved the way for Renewable Energy Resources (RERs). India has set an ambitious target to achieve a capacity of 175 GW worth of renewable energy by the end of 2022, which expands to 500 GW by 2030 [2]. Norway aims at reducing carbon emissions by 40% by 2030. The UK government passed legislation, which codifies achieving net-zero emissions by 2050 (*Climate Change Report Card: These Countries Are Reaching Targets*, n.d.). The integration of intermittent power resources expedited the modernization of the electrical grid. On the other hand, the need of providing power to the remote community where the interconnection with the main utility cannot be achieved, mandated the need for diminutive autonomic grids. For many decades, such small autonomic grids have existed in a significant number of remote places like hill stations and very remote villages (Olivares et al. 2014). Such small-scale autonomous grids with distributed generations and a cluster of loads are collectively said to be known as a microgrid. The microgrids can also be operated in synergy with the utility grid to improve the reliability of the grid by providing power to it, in times of need. The microgrid can also get power from the utility grid when it runs out of generation and storage. This mode of operation is usually termed as grid-connected mode (Jadav, Karkar, and Trivedi 2017). On islanded mode, the microgrid serves its needs by its own generation and storage amenities. The evolution of microgrid brought drastic changes in the electrical power system domain. Whilst the need for framing standards for microgrid implementation, communication infrastructure requirements, legal barriers, and intermittent nature of the renewable energy resources were the hurdles in the path of Microgrid development. Despite these challenges, the benefits of microgrid from the economic, environmental, technical, and social points of view significantly aided the development of microgrids. Working Group C6.22 of The Conseil International des Grandes Réseaux Électriques (CIGRÉ) enumerates reduced carbon footprint, improved energy efficiency, improved reliability of power supply, network operational benefits, and minimization of overall energy consumption as the distinct benefits offered by microgrids (CIGRE WG C6.22 2015).

When microgrids became an inevitable sector of electrical power systems, their high capability of RES integration mandated the need for analyzing the Microgrid's interactions with the utility grid. The necessity of maintaining the stability of the utility grid in case of dynamic interactions of microgrid (Lasseter et al. 2002) mandated the need for Microgrid Energy Management Systems (M EMS). The EMS for microgrid aims at providing necessary functions like power quality control, energy market participation, and optimizing the system performance. The major focus of an M EMS is to arbitrate the optimal utilization of DG to supply the loads. In (Chandak and Rout 2021), the EMS for islanded microgrids are reviewed based on the objectives, constraints, energy storage systems, and optimization techniques used. For the same, a review on EMS based on the foresaid aspects excluding ESS and objective functions (but including DR) is presented in (Banerji et al. 2013) and (C.Lassetter et al., 2019), respectively. The EMS for islanded microgrids based on the flexible resources such as ESS and

Table 1. Classical methods.

Approach	Literature	Optimization Technique used
Classical Approach	(Chaouachi et al. 2013; Comodi et al. 2015; Jirdehi et al. 2020)	LP and MILP
	(Helal et al. 2019)	NLP and MIP
	(Jabari 2021; Střelec and Berka 2013; Sukumar et al. 2017)	MINLP
	(Gomes, Melicio, and Mendes 2021; Jalili, Sedighizadeh, and Fini 2021; Mosa and Ali 2021; Taha and Mohamed 2016)	MILP
	(Merabet et al. 2017)	Dynamic programming
	(Choudar et al. 2015; Singh, Muhammad, and Asghar 2021; Xiang et al. 2021)	Rule-based approach

Table 2. Meta-heuristic methods.

Approach	Literature	Optimization Technique used
Meta- Heuristic approach	(Li et al. 2017), (Mah et al. 2021; Chalise et al. 2016; Chiñas-Palacios et al. 2021; Kim, Kim, and Lee 2021; Hossain et al. 2021; Moghaddam et al. 2011; Perez-Flores et al. 2021; Wang et al. 2021; Wasilewski 2018)	PSO and its variants such as MPSO, APSO
	(Chalise et al. 2016)(Askarzadeh, 2018a) (Perez-Flores et al. 2021)	GA and its variants
	(Kumar and Saravanan 2019)	Artificial fish swarm optimization
	(Arefifar, Ordonez, and Mohamed 2017)	Tabu Search
	(Motevasel, Seifi, and Niknam 2013)	Bacterial foraging Algorithm
	(Marzband et al. 2017)	Artificial bee colony
	(Marzband et al. 2014)	Gravitational Search algorithm
	(Yu, Wang, and Li 2015)	Modified differential evolution
	(Ei-Bidairi et al. 2018), (Dey, Bhattacharyya, and Márquez 2021)	Grey Wolf optimization and its variants
	(Nan et al. 2021)	θ-modified krill herd approach
	(İpek and Tamyürek Mehmet 2021)	Harris Hawks Optimization
	(Hui, Fang, and Dihuang 2021)	Whale Optimization algorithm
	(Xing and Liang Hui 2021)	Distributed Neurodynamic Algorithm
	(Ahmed et al., 2021)	Equilibrium Optimizer Technique
	(Quynh et al. 2021)	Modified Shuffled Frog Leaping Algorithm
	(Veluchamy 2021)	Muddy Soil Fish Optimization Algorithm
	(Ali et al. 2021)	Modified Harmony Search
	(De, Das, and Mandal 2021)	Flower Pollination Algorithm

Table 3. AI based methods.

Approach	Literature	Optimization Technique used
AI based approach	(Kyriakarakos et al. 2012), (De Santis, Rizzi, and Sadeghian 2017), (Yu-Kai Chen et al. 2013), (Arcos-Aviles et al. 2021)	Fuzzy logic
	(Leonori et al. 2018)	Adaptive fuzzy neural inference system
	(Venayagamoorthy et al. 2016)(Gamez Urias, Sanchez, and Ricalde 2015) (Boujoudar et al. 2021)	Neural network and its variants like Recurrent NN
	(Ma et al. 2016) (Liu et al. 2017) (Asimakopoulou, Dimeas, and Hatziargyriou 2013) (Nwulu and Xia 2017)(Mondal et al. 2018)(Mohamed and Koivo 2011)	Game theory
	(Karavas et al. 2015)(Anvari-Moghaddam et al. 2017)(Nunna and Doolla 2013) (Arcos-Aviles et al. 2021)(Bogaraj and Kanakaraj 2016)(Dou and Liu 2013)	MAS
	(Moradzadeh et al. 2021)(Ji et al. 2021)	Deep-Learning
	(Zeinal-kheiri et al. 2021)	Lyapunov- Optimization

DR is presented in (Díaz et al. 2017). The energy management aspects of microgrid along with optimization techniques and evolutionary aspect of smart grids are presented in (Campagna et al., 2020) and (Jirdehi et al. 2020), respectively. Another review on EMS for islanded microgrid based on aforementioned aspects except flexible resources is presented in (Sukumar et al. 2017). This paper presents an extensive review on MEMS considering all the major aspects such as objective functions, mode of operation, software's/solvers used for optimization, type of microgrid considered, components of microgrids, and notably the optimization techniques used for optimizing the microgrid model.

Table 4. Stochastic and Robust methods.

Approach	Literature	Optimization Technique used
Stochastic and Robust methods	(Amrollahi and Bathaee 2017; Farzin et al. 2016, Farzin, Fotuhi-Firuzabad, and Moeini-Aghtaie 2017; Hajiamoosha et al. 2021; Rezaei and Kalantar 2015; Tabar, Jirdehi, and Hemmati 2017)(Azarhooshang, Sedighizadeh, and Sedighizadeh 2021; Hu, Lu, and Chen 2016; Naja et al. 2020; Nikkhah, Nasr, and Rabiee 2021; Roustaee and Kazemi 2021; Shen et al. 2016)	Stochastic method
	(Amin and Barati Ali Reza 2022; Babqi 2022; Bishwajit, Sheila, and Mahapatra Fausto Pedro 2022; Guo and C 2016; Lujano-Rojas et al. 2012; Madad, AminS, and Afari Majid 2022; Majumder, Dash, and Dhar 2021; Syed et al., 2022; Tsao and Thanh 2021; Xiang, Liu, and Liu 2016; Yang, Su, and Wang 2021; Zhang, Gatsis, and Giannakis 2013; Zografou-Barredo et al. 2021)	Robust programming

An integrative review is performed so as to probe the key aspects of the MEMS. Literature works from standard and reputed journals related to the theme are selected, and they are scrutinized based on the following keywords: energy management systems, optimization techniques, microgrid operation, renewable energy resources, grid connected, islanded microgrids, heuristic energy management systems, and robust microgrids. A tenure of eight years, i.e., from 2014 to 2022, is considered for the selection of literature. The objective of this article is to provide an extensive insight on the existing EMSs for microgrids on all their major aspects and to provide inferences on the advantages and limitations of them. The inferences in accordance with the objective is presented under each corresponding section. The paper is organized as follows: a brief note on microgrid and its architecture is presented in Section 2. The classification of microgrids and short notes on each classification is presented in Section 3. Section 4 introduces energy management in microgrids along with its operational modes. The EMS is categorized into six categories based on the optimization techniques and an extensive analysis of the approaches followed is presented in Section 5. Section 6 and section 7 present the analysis based on the nature of objective function of the EMS and the type of microgrid considered. The mode of operation of the microgrids considered for the analysis and the software's/tools used to perform the optimization is presented in sections 8 and 9, respectively. The components of the microgrids such as power generation sources and storage systems are analyzed and presented in sections 10 and 11, respectively. Section 12 concludes the paper with few futuristic insights.

Microgrid – definition and architecture

The definition for the microgrid is still under argumentation in technical forums. There is a surfeit of definitions available in the literature. However, a microgrid can be defined as a small autonomous grid (LV network) or a single controllable entity (Lasseter et al. 2002) of the entire electrical grid consisting of a cluster of loads, distributed generations (DGs), and Energy Storage Systems (ESS). In other words, the microgrids are nothing but an explicit part of the smart grid which operates at the distribution system level. It integrates the power resources and storage, close to the loads (Chandak and Rout 2021).

Distributed generation is the process of on-site power generation near the consumer's premises which will significantly reduce the necessitousness of transmission lines. Unlike conventional energy resources, renewable energy sources (non-flexible resources) can be installed anywhere for power production. Location independence is a good attribute of renewable energy resources which makes it more suitable for remote power grids. Solar Photovoltaics, Wind, Biomass, Tidal, Geothermal, Biogas, and Hydro energy can be used as CO_2-neutral resources for onsite power generation. As all these resources are intermittent in nature, few nonrenewable resources (flexible resources) like diesel gGenerator, microturbine, and combustion turbines can also be used as backup power-producing resources. Owing to the intermittent nature of the distributed generation resources and to ensure the availability of power throughout the entire time horizon, various energy storage systems such as

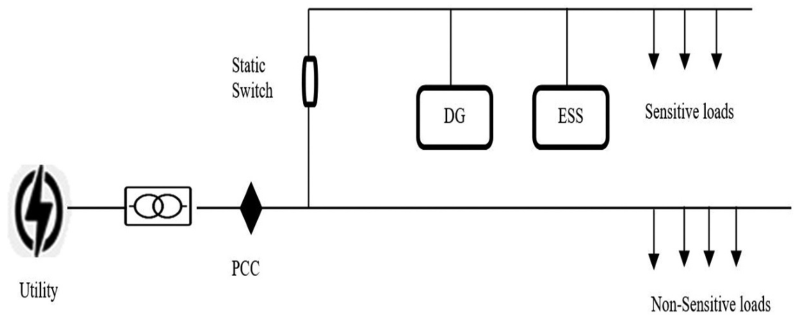


Figure 1. General architecture of the microgrid.

batteries, fuel cells, flywheels, and supercapacitors are used for storing energy when available in excess and to supply it back in times of need. There exists a plethora of papers on microgrid's architecture. To describe components of the microgrid, a lot of different models and layouts have been proposed in the literature. A generalized architecture of the microgrid can be reasoned using Figure 1. The schematic diagram shows that the microgrid is a single controllable entity (Banerji et al. 2013) when viewed from the utility grid's point of view. The PCC is located on the primary side of the transformer, which aids in the coupling and decoupling of the utility and microgrid. The sensitive and nonsensitive loads are connected to separate feeders so that during any fault/disturbance, the sensitive loads can be protected. The modern electronic loads which are more sensitive to power quality are termed sensitive loads. e.g., digital computers, variable frequency motor drives, etc. The static switch which is also known as a separation device (SD) is utilized for islanding the sensitive loads during a disturbance but allows the traditional loads to ride through the disturbance.

Microgrids – classification

The classification of microgrid is majorly based on its power supply architecture and its location. Based on the architecture, the microgrid is majorly classified into three categories, namely, AC, DC, and hybrid microgrids as shown in Figure 2. In simple words, a microgrid is said to be an AC microgrid if it has an AC main feeder. Similarly, if the main feeder is a DC feeder, it is a DC microgrid. If both the AC and DC sub-feeders are present along with an AC main feeder, then the microgrid is said to be known as a hybrid microgrid. In most of the literature, the microgrids are classified into AC and DC microgrids as a major classification. Also, authors in (Banerji et al. 2013) explained about a microgrid architecture with high-frequency AC (HFAC) link which is suitable for aerospace applications like aircraft and spacecraft based on HFAC power distribution system. As depicted in Figure 3, microgrids can be classified into urban and remote microgrids based on the location.

AC microgrid

The AC microgrids are grids that can be readily integrated with the existing main grids. The microgrids which supply and operate on AC power are termed AC microgrids (Chandak and Rout 2021). The ready integration of the AC microgrid with the utility becomes doable as the extant grid operates on AC power and the integration of AC microgrids requires less or no power electronic interfaces. On the other hand, to supply DC loads and to store energy in energy storage systems, there is a need for power electronic interfaces like AC/DC converters and bidirectional converters.

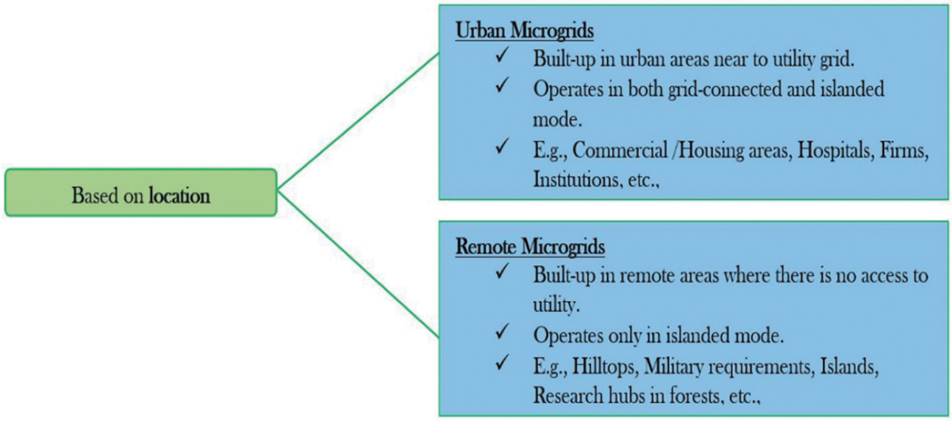


Figure 2. Microgrid classification based on location.

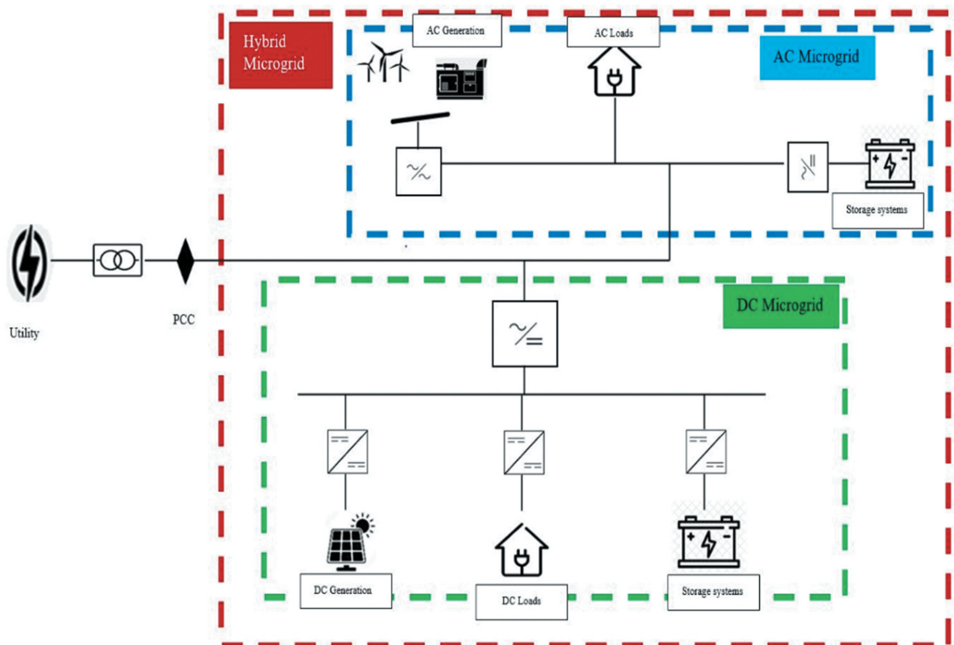


Figure 3. Schematic diagram of AC, DC and Hybrid microgrids.

DC microgrid

The concept of power generation and the ability to store the same in the form of DC piloted the concept of DC microgrids. Unlike the AC microgrid, DC microgrids require significant power electronic interfaces for integrating them with the utility grids. When compared to the AC microgrids, the DC microgrids possess a better efficiency when feeding the DC loads due to fewer conversion processes. The specific capability of DC microgrid is that it has its self-fault-ride through capability unlike AC microgrids. Although there are significant advantages like reduced conversion loss of inverters, own fault-ride through capability, zero reactive power compensation requirement, no need for synchronization (Banerji et al. 2013), it has a few disadvantages such as the need for separate DC distribution line and standard protection as there is no zero-point crossing in DC voltage.

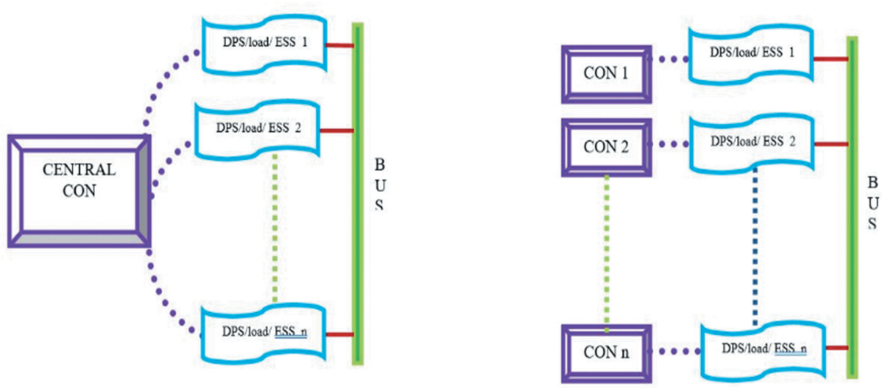
Hybrid microgrid

These microgrids are comprised of both AC and DC distribution systems. The number of power conversion levels and power electronic interfaces can be reduced with this hybrid MG architecture (Chandak and Rout 2021). This is because the AC and DC loads in the customer premises can be fed from the corresponding feeders with less/negligible conversion.

Energy management in microgrid

As discussed in section 1, the EMS is meant for optimizing the power supply to the loads at a minimal cost (Flexible and Sources 2019) and to ensure certain attributes such as power quality, participation in energy markets, and so on. The standard IEC 61970 delineates EMS as "a computer system comprising a software platform providing basic support services and a set of applications providing the functionality needed for the effective operation of electrical generation and transmission facilities so as to assure adequate security of energy supply at minimum cost" in the context of power systems management (IEC 61970, n.d.). MEMS can be operated in two modes, namely, centralized mode and decentralized mode (Flexible and Sources 2019). Microgrid management is a complex multi-objective control problem that controls and supervises various domains including load power sharing, regulation of power quality, voltage and frequency regulation, and overall system optimization. In centralized EMS, data are acquired from the utility as well as the components of MG, and based on the acquired data, optimization methods are executed to achieve sustainable and efficient operation. The major advantage of the centralized EMS is that it can function in an efficient manner and can provide strong supervision if designed properly.

The role of microgrid central controller (MGCC) is inevitable (Díaz et al. 2017) in centralized EMS control as shown in Figure 4(a). While on the other hand, the failure of the CC (Central Controller) may lead to an entire breakdown of the system. The major disadvantage of the centralized EMS control method, i.e., the single point failure, can be overcome by the decentralized EMS control which is depicted in the Figure 4(b). Also, the computational burden can be significantly reduced in



(a) (b)

Figure 4. (a) Centralized control architecture, (b) Decentralized control architecture.

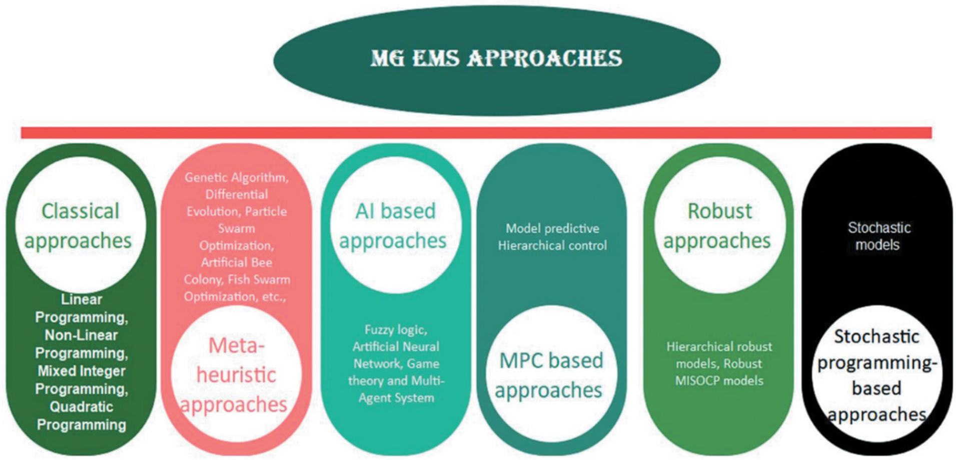


Figure 5. Classification of microgrid EMS approaches.

decentralized EMS control. Although the decentralized EMS has significant advantages over centralized EMS, improper synchronization among the units and communication infrastructure (Campagna et al. 2020) requirements can be a hindrance in the application of decentralized control.

Extensive analysis of mems optimization techniques

Although the selection of EMS method depends on the size of the system, the goal of optimization, the accuracy of energy management, this article provides an extensive analysis of the various available microgrid EMS strategies to provide a better understanding of the techniques and methodologies implemented for achieving the objectives. EMS for microgrids can be classified into six categories as shown in Figure 5 based on the approaches/techniques they implement to perform the optimization.

Classical methods

The works of literature in this section correspond to the EMS problems which use classical methods such as linear programming (LP), non-linear programming (NLP), mixed-integer programming (MIP), dynamic programming (DP) methods, rule-based methods, and predictive optimization methods. The pieces of literature corresponding to classical methods are tabulated as Table 1 which utilizes stochastic and robust approaches exist1. A system with linear constraints and a maximizing/minimizing objective function can be modeled using the linear programming technique. If the constraints are non-linear then non-linear programming can be utilized to model the system (Jirdehi et al. 2020). In (Sukumar et al. 2017), a multi-objective EMS for the microgrid operation at the lowest cost using LP and MILP (mixed integer linear programming) techniques is presented. Three modes were taken as objective functions and they are continuous run mode, power sharing mode and ON/OFF mode. The first two objective functions were solved using the LP method and the MILP method was used for the third objective function. A real-life residential microgrid study case is considered and MILP-based optimization techniques have been used for energy management in (Comodi et al. 2015). For the purpose of forecasting the output of solar thermal power systems and photovoltaic systems, the radial basis neural network method is utilized. The objective function is modeled in this work, not as a mere actual energy cost but as to model a policy for energy purchase and sale of surplus energy. A multi-objective MPC-based robust optimal EMS is proposed in (Taha and Mohamed 2016) for optimal power scheduling for various generators. Non-linear and mixed integer programming (MIP) techniques are used for the optimization process. But the demand and power losses are not considered in the modeling of the EMS. In (Helal et al. 2019), a single-objective EMS based on mixed integer non-linear programming for a standalone MG to reduce the overall operational costs and to ensure a secure MG operation is introduced. A multi-objective EMS for the purpose of integrating the linear programming technique with artificial-intelligence based techniques is presented in (Chaouachi et al. 2013).

Energy trade between utility and microgrid and power generation cost related to DG were taken as the objective functions. The major drawback of this model is its higher computational complexity. In (Daniel et al. 2013), a multi-objective centralized optimal MEMS model based on mixed integer non-linear programming technique for minimizing the fuel costs, startup/shutdown costs of generators and penalty costs of reactive power requirements is presented. An approximate dynamic programming approach-based EMS is proposed for a grid-connected MG (Střelec and Berka 2013). The approach shows better performance when compared with myopic optimization in terms of reduced operating cost and much lesser computational time with dynamic programming methods. Switching between different modes of operation such as normal mode, disconnection mode, battery charging/discharging mode, etc., based on rule-based techniques for real-time optimized operation of microgrid are found in (Choudar et al. 2015; Merabet et al. 2017). In residential microgrids, a rule-based EMS model is applied (Singh, Muhammad, and Asghar 2021) for achieving a reliable power supply considering irradiance, grid power supply and battery voltage as input parameters to the model. For electrifying the airports by means of microgrid, a multi-objective EMS model based on MILP is presented in (Xiang et al. 2021). The objective of the model is to minimize the overall investment costs, operation, and emission costs. The operation and emission costs were minimized for five different energy supply scenarios. A MILP based EMS for achieving maximum expected network profit is introduced in (Gomes, Melicio, and Mendes 2021). The developed model acts as a support management system for the microgrid to participate in energy markets. Another MILP-based MG optimal operation is found in (Jalili, Sedighizadeh, and Fini 2021) where the minimization of net cost is the objective. The net cost considered here is a representation of energy and gas purchasing costs and carbon emission costs. An effective energy hub architecture is also presented in the literature. To minimize the emission and generation costs an MINLP EMS problem is formulated and solved using BARON (branch and reduce optimization navigator) for a DC microgrid in (Mosa and Ali 2021). The modeling for generation cost is done appropriately so as to obtain effective outcomes on minimum cost scenario. An MINLP-based EMS to determine optimum fuel utilization and power generation schedules is presented in (Jabari 2021) for economic fuel dispatch for diesel generators which is used to electrify the oil rigs in tidal areas.

The extensive analysis of the MEMS based on classical optimization techniques provides the following inferences:

(a) Only centralized microgrids are considered in the EMS approaches based on LP and NLP. The emission minimization, integration of DR, and battery constraints could have been given more importance for effective optimization.
(b) Similarly, the emission minimization and integration of DR is not emphasized in EMS approaches based on dynamic programming. On the other hand, the exchange of power with the utility is considered in these approaches.

Meta-heuristic methods

The EMS for MG based on evolutionary algorithms, swarm optimization algorithms, and combination of these algorithms are categorized under meta-heuristic approaches in Table 2. For the operation of an industrial microgrid in both grid-connected and islanded mode, a PSO (Particle Swarm Optimization)-based multi-objective EMS is utilized in (Li et al. 2017). The proposed model takes less computational time when compared with GA (Genetic Algorithm). In (Azaza and Wallin 2017), a multi-objective PSO-based MEMS where reliability, operation cost, and minimization of impact on environment are the objectives was put forth. The major drawback of the EMS model is the cost of battery degradation being not included. In (Chalise et al. 2016), a multi-objective GA and rule-based EMS model are introduced for the optimal operation of an islanded MG. All the objective functions are combined and are framed as an mixed integer quadratic programming (MIQP) problem. The overall objective in this model is to minimize the combined operational cost. A memory-based GA for a grid-connected MG is introduced in (Askarzadeh 2018a) to minimize the DERs operation cost. The proposed framework performs better when compared with GA and PSO with constriction and inertia factor. A single-objective EMS for MG based on artificial fish swarm optimization is introduced in (Kumar and Saravanan 2019) for optimizing the MG energy management considering a whole day storage. Similar to (Askarzadeh 2018a), the cost of battery degradation is not considered in the problem. An asynchronous decentralized EMS based on PSO for achieving the lowest operational cost in daily basis is proposed in (Perez-Flores et al. 2021). The power balance and generation limits are considered as constraints for the EMS model. To establish the effectiveness of PSO algorithms in cases of small-scale optimization problems such as microgrids, a modified PSO-based EMS is presented in (Hossain et al. 2021). Considering both electrical and hydrogen loads, an EMS based on PSO is presented in (Mah et al. 2021) for a standalone MG. A Gaussian-based regularized PSO along with a fuzzy clustering technique is utilized for achieving optimal energy trading to ensure the economical microgrid operation (H.J Kim, Kim, and Lee 2021). For this strategy, a hybrid demand response is introduced in this model for load peak-shaving. Another PSO-based EMS for aiding the microgrid in electricity market participation with and without DR schemes have been analyzed in (Wang et al. 2021). The developed model also ensures voltage stability and basic load support.

Considering load shedding cost, energy purchase cost, active power reserve cost, DR (demand response) cost, reactive power support cost, switching cost of automatic controlled switches, and operating cost as elements of the objective function, a GA-based EMS is proposed (Management & Microgrids, 2016) by the authors for an MG operating in grid-connected mode. By hybridizing the fuzzy self-adaptive and chaotic PSO, an adaptive PSO approach is utilized in (Moghaddam et al. 2011) for optimizing the multi-objective grid-connected EMS model. The hybridized algorithm performed better in contrast with the individual algorithm and also with GA. In (Elsied et al. 2015), a GA-based approach for a single-objective MEMS model where a novel cost function which includes startup costs of DERs and buying and selling power costs is introduced. The major drawback of this model is not considering the uncertainties in generation and in customers usage pattern. An EMS model based on Tabu-search is proposed for a multi-MG system in (Arefifar, Ordonez, and Mohamed 2017). A novel index, known as energy management index, is deliberated as objective and the aim of the model is to minimize the MG operational cost. The uncertainties of electric vehicles and rnewable energy resources are included in the model. The control approach is of centralized type.Authors in (Motevasel, Seifi, and Niknam 2013) proposed an EMS model for a MG including wind energy resource uncertainties. The model is based on bacterial foraging algorithm and the problem is of multi-objective type. The major focus of the model is to optimize the power exchange between the utility and the grid. The approach was found to have a better and fast convergence. For residential MG, an EMS model based on Artificial Bee colony is proposed by the authors in (Marzband et al. 2017). The proposed model is of multi-period two-layered hierarchy. The first layer is concerned with day-ahead scheduling of RERs, CGs and battery to reduce the operational cost of MG. Whilst the second layer is concerned with real-time scheduling with an interval of five minutes and is concerned with the same elements of the first layer and energy trading in addition to it. This model is found to be more effective on comparison with PSO in aspects of providing optimal solutions and computational time. In (Wasilewski 2018), the authors proposed an EMS model for MG based on EA and PSO algorithms for optimizing a single-objective problem. The objective is to minimize the annual costs discounted for a MG in a period of N years. In addition to the EA and PSO algorithms, a novel module called "Verification of modules" is introduced utilized in this framework. To optimize the operating cost of an islanded MG along with the penalty cost for undelivered power, an EMS model based on Gravitational Search algorithm is utilized in (Marzband et al. 2014). The model overtopped the PSO when experimentally validated for three different scenarios, namely, normal operating scenario, plug and play feature and unexpected sudden high demand requirement by the loads. In (Yu, Wang, and Li 2015), a modified differential algorithm-based EMS model for a grid-connected MG is proposed for the optimal economic operation of the MG. The proposed model performs energy scheduling to achieve the objective of the model whose elements are cost of energy trading between the utility and MG, and cost of battery degradation and is found to be effective than rule-based economic operation of the MG. For an interconnected MG, a meta-heuristic approach called Grey Wolf Optimization approach-based EMS model is developed in (Ei-Bidairi et al. 2018) to reduce the MG operation costs by minimizing the costs of the power generating units. Similar to (Azaza and Wallin 2017) and (Kumar and Saravanan 2019), the degradation cost of battery is not included in the model. Another objective of the model is to diminish the emission levels of the conventional power resources, which consume fossil fuels for power production.

A large-scale MG optimization problem for minimizing the total cost subjected to both the system and assets' constraints is solved using θ-modified krill herd approach in (Nan et al. 2021). An autonomous AC microgrid is modeled and Harris Hawks optimization algorithm is applied to achieve a cost-effective and reliable microgrid model (İpek and Tamyürek Mehmet 2021). The proposed method was found to be efficient when compared with PSO, FA (Firefly algorithm), GWO (Grey-Wolf Optimization), and SSA (Salp Swarm Algorithm). Also, a hybrid modified GWO is utilized for modeling the EMS for achieving an efficient economic emission model of the microgrid (Dey, Bhattacharyya, and Márquez 2021). A hybrid PSO feed forward NN algorithm is used in (Chiñas-Palacios et al. 2021) to model the EMS for a rural Biomass Gasification plant. The objective of the model is to produce the required quantity of syngas for meeting up the energy demand requirement. Whale optimization along with long short-term memory (LSTM) algorithm is used for modeling EMS of a wind-driven DC microgrid for improving the accuracy of the wind power scheduling in (Hui, Fang, and Dihuang 2021). A multi-objective cost minimization problem subjected to local and global constraints such as ESS constraints, power balance constraints, etc., a distributed neurodynamic algorithm is proposed in (Xing and Liang Hui 2021) for an isolated microgrid. To improve the voltage profile and stability along with cost minimization of a grid-connected microgrid, equilibrium optimizer technique is applied to the MEMS model (Ahmed et al., 2021). Compared to whale optimization algorithm and sine cosine optimization algorithm, the results are found to be optimal. The efficient utilization of RES is assured by applying modified shuffled frog leaping algorithm (MSFLA) (Quynh et al. 2021) to MEMS. The objective of the proposed model is achieved by proper sizing of battery storage systems. A novel muddy soil fish optimization algorithm is proposed in (Veluchamy 2021) for modeling EMS to achieve optimal energy flow and to balance the generation-demand ratio in the network. Taking into account the behavior of PHEV (Plug-in Hybrid Vehicles) and uncertainties in the generation forecast, a modified harmony search based EMS is modeled in (Ali et al. 2021) for analyzing the impact of electric vehicle charging on optimal operation of microgrid. For the optimal operation of microgrid and to address the uncertainties of RES, an EMS based on flower pollination algorithm is proposed for a grid-connected MG in (De, Das, and Mandal 2021).

Following are the inferences obtained from the extensive analysis of MEMS approaches based on meta-heuristic approaches:

(a) The simultaneous minimization of operational and emission cost is considered in most of the approaches.
(b) In comparison with the classical approaches, the integration of DR is addressed in a better manner.
(c) The uncertainties are quantified using popular methods such as Scenario Generation and Reduction method and Point Estimation method which improvised the EMS performance.
(d) The computational complexity is not explained in some of the literature considered.

(e) Centralized architecture is considered in most of the works of literature.

Artificial intelligence-based methods

The EMS models based on artificial neural networks (ANN), fuzzy logic, multi agent system (MAS) approach and certain miscellaneous AI approaches are categorized under artificial intelligence methods in Table 3. An EMS based on fuzzy logic approach for isolated MG to reduce the net cost of the MG is introduced in (Kyriakarakos et al. 2012). The minimization of net cost is performed along with penalty costs on hydrogen storages, water storages, and SOC of the battery. The computation time taken by the algorithm is very small (typically 1s –2s). Economic dispatch and unit commitment in MG is performed by a Fuzzy logic-based EMS model considering GA for energy scheduling. To superintend the battery power allocation, Fuzzy expert system is utilized. To maximize the energy trading profit, an adaptive neural fuzzy inference system (FIS) is utilized in (Leonori et al. 2018). A Fuzzy logic EMS based on MAMDANI algorithm is modeled for an interconnected MG to manage the energy flow is proposed in (De Santis, Rizzi, and Sadeghian 2017). For the efficient utilization of the RERs and to maximize the life of the storage batteries, an EMS model based on Fuzzy logic approach is introduced and experimentally validated in (Chen et al. 2013). Evolutionary adaptive dynamic programming and reinforcement learning concepts-based EMS is put forth in (Venayagamoorthy et al. 2016) to ensure the maximum utilization of RERs and to reduce the carbon emissions. The proposed EMS model is solved by two NNs, namely, active NN and critical NN. The former solves the EMS strategy proposed in the framework and a performance index is calculated by the latter with respect to optimality. A Lagrange programming based NN approach is used by the authors in Wang et al. for modeling a MEMS to minimize the net cost of the MG. To forecast the RERs power generation and demand, radial basis NN is used. The proposed framework is found to be efficient than PSO-based approach. To maximize the power generation by RERs in order to minimize the energy import from utility, an EMS model based on recurrent NN approach is proposed in (Gamez Urias, Sanchez, and Ricalde 2015). To forecast the RERs power generation and demand, Kalman filter-based NN and hybrid wavelet functions is used. An EMS based on leaders-followers game theory for maximizing the active customer benefits is proposed in (Ma et al. 2016).The proposed framework also ensures the optimal distribution of benefits to the customers. Another leader-follower based game theory approach was utilized in (Liu et al. 2017), for optimal energy management and trading in grid-connected MG consisting of PV prosumers. Authors in (Asimakopoulou, Dimeas, and Hatziargyriou 2013) proposed a leader-follower game theory with two levels for energy management in MGs. The leader (upper level) deals with production cost minimization while the follower (lower level) focusses on net profit maximization. Game theory approach-based demand response EMS framework was developed in (Nwulu and Xia 2017). The DR is an Incentive-based DR scheme.

The framework minimized the fuel costs in order to maximize the grid operator’s benefit. An M EMS model using game theory approach is introduced in (Mondal et al. 2018) to maximize the benefits of the MG. The strategy selection for maximizing the MG benefit is selected based on cost and adequate use of energy. For optimizing the emission and operation costs of MG, the difference of Pareto objectives and Supercriterion is defined as an objective function. The proposed framework is optimized using a modified game theory-based approach (Mohamed and Koivo 2011).

In (Karavas et al. 2015), a multi-agent system approach based EMS to solve the optimization problem based on distribution intelligence is presented. The optimization problem is of multi-objective type whose objective is to optimize the net present cost (NPC) for a period of 20 years. The objective function includes NPC, battery penalty cost, hydrogen penalty, water and water tank penalty and metal hydride tank penalty (hydrogen storage tank) costs. The cost of battery degradation was not included. For coordinated energy and comfort management in MG and integrated buildings, a multi-agent control hierarchy was proposed in (Anvari-Moghaddam et al. 2017). The optimization problem is mathematically formulated as a multi-objective problem, and several cooperative agents were introduced to achieve global coordination and to accomplish the objectives of the system without the violation of the constraints. An optimal EMS based on MAS approach to minimize the peak demand and electricity cost in MG was introduced in (Nunna and Doolla 2013). Six agents, namely, generation agent, load agent, storage agent, DR agent, MG, and global intelligent agents, were introduced and trained to meet the system objectives. The framework also encourages customer participation by using an incentive-based DR approach. For a residential microgrid, a Fuzzy logic-based EMS of low complexity level is proposed in (Arcos-Aviles et al. 2021). The EMS is modeled so as to minimize the impact on grid power during RES integration to existing grid-connected appliances. An intelligent EMS for an islanded MG and a load shedding scheme is introduced in (Bogaraj and Kanakaraj 2016). Using PV system, wind turbine, battery, fuel cells, and load as agents, the proposed framework maintains energy balance by effective co-ordination of the aforementioned agents. A three-level multi-objective MAS-based decentralized EMS for a grid-connected MG is proposed by the authors in (Dou and Liu 2013). The three hierarchical layers are pertained with energy optimization, agent coordination, and control strategies for unit agents, respectively. The control strategies are based on V/f- and PQ-based approaches, and they are meant for the DERs. For the purpose of battery SOC estimation in M EMS model, a feed-forward neural network is utilized in (Boujoudar et al. 2021). A sustainable EMS for MG is modeled using a novel deep-learning-based method known as bidirectional long short-term memory for short-term load forecasting in (Moradzadeh et al. 2021). Considering the RES uncertainties, power demand and market prices, a gated recurrent unit based deep-learning method is introduced in (Ji et al. 2021). The proximal policy optimization method is used for training the neural-network. In order to reduce the real-time operating cost of the microgrid and to eliminate the need for dealing with prediction uncertainties, Lyapunov-optimization based real-time EMS is modeled in (Zeinal-kheiri et al. 2021).

The following inferences can be made from the analysis of MEMS based on Multi-Agent Systems:

(a) The computational complexity is not addressed in many literatures.
(b) The efficient and effective usage of uncertainty prediction and modeling methods is not emphasized with greater importance.
(c) Decentralized architecture is found to be utilized in majority of the literature.

Model predictive control methods

In (Garcia-Torres and Bordons 2015), an EMS for MG for the optimal economical scheduling of the MG is presented. The optimization problem is formulated, such that the degradation costs of ESS components are integrated along with the operational costs of MG. For great quantities of energy storage, the framework proposes hydrogen ESS as an effective ESS and on the other hand, batteries are found appropriate for small energy storage purposes. A single-objective MEMS (Microgrid Energy Management System) based on the MPC approach is presented in (Solanki et al. 2017). The objective function includes the costs of generation, startup, and shut down of the units and the load curtailment costs. An NN-based model is made use for the purpose of demand forecasting. A mathematical model for smart loads was also presented in the article. An MPC-based EMS (Dufo-López et al. 2017) for daily optimization of the MG taking corrosion losses, capacity losses, and degradation of the lead-acid batteries into account. The optimization problem is of multi-objective type. A two-level hierarchical structured EMS for grid-connected MG (Mendes et al. 2016) using two MPC controllers in which the first MPC controller is concerned with stable and secure operation of the MG and the second MPC controller focusses on the efficient economic operation of the MG. V2G operation is also included in the proposed framework and is controlled by the second MPC controller. For the safe scenario operation of microgrid and to mitigate the faults, an MPC-based EMS is utilized in (Marquez et al. 2021). A reliable MEMS based on MPC approach (Prodan and Zio 2014) in which the objective function is optimized using receding horizon control approach is found to achieve a better equilibrium among energy production, demand and grid integration. A novel two-stage MPC approach-based EMS is proposed in (Luo et al. 2017). The first stage is Economic dispatching stage (EDS) and the real-time adjusting stage (RTAS) is the second stage. The MPC approach is utilized in the EDS stage to schedule the operation based on the forecasted information. A robust EMS (Valencia et al. 2015) optimizes the operation cost of MG by efficiently dispatching the MG's using two MPC optimizers for the two hierarchical levels of the architecture. The upper and lower ranges of dispatch is determined using these two optimizers. Using a defined weighting factor, the final output is realized by a convex sum of the upper and lower ranges.

A multi-objective sustainable EMS (Solanki, Bhattacharya, and Canizares 2017) optimizes the operation and emission costs for an isolated MG under various operational schemes, namely, operation cost minimization, emission cost minimization, simultaneous reduction of emission and operation costs, pareto-optimality of operation and emission costs and minimization in deviation of both the costs. Two EMS approaches namely RBEMS (Rule-Based EMS) and OBEMS (Optimization-Based EMS) are applied to a microgrid testbed in (Mauricio et al. 2021) and the MPC-based OBEMS is utilized for minimization of generation and curtailment costs while the RBEMS is utilized for dispatching the generating units. For enhancing the power quality for a grid-connected MG, the MPC technique is applied to the three-phase inverter in (Akhtar and kirmani 2021). The outcome of the model is compared with outcomes of previously available models and found to be efficient. An industrial microgrid based on a sugarcane power plant is subjected to an OBEMS based on MPC technique (Emanuel et al., 2021) aiming at modeling of a "Fault-Tolerant Control System" (FTCS). The Moving Horizon fault estimation technique is utilized for estimating the faults. A nonlinear MPC-based EMS modeling for reducing the Total Operating Cost (TOC) by providing an optimal power dispatch strategy is introduced in (Jirapong and Maneeratpongsuk David 2021). The outcomes of the proposed model show a reduction of 1.72% of TOC in rainy season when compared to one-shot optimization methods. To minimize the load shedding cost, charging/discharging of ESS cost and cost of the uncertainties, a two-stage robust optimization technique is introduced in (Yang and Su 2021).

The extensive analysis of the MEMS based on model predictive control techniques provides the following inferences:

(a) The centralized architecture is considered in all these approaches.
(b) Much importance could have been given to reduction of emissions in these EMS models.
(c) The integration of DR and effective inclusion of constraints such as battery degradation could be effectively addressed so as to improvise the performance of EMS.
(d) For addressing the uncertainties, the forecasted data of DG's are made use in all of this work of literature.

Stochastic control methods

A single-objective EMS model for a standalone operation mode of a grid-connected MG based on stochastic approach (Farzin, Fotuhi-Firuzabad, and Moeini-Aghtaie 2017) optimizes the objective which consists of two functions which represent the expected operation and conditional VaR (CVaR) of the candidate solutions. To ensure the stability of MG, using frequency of MG as a control variable an EMS based on stochastic optimization approach is used (Rezaei and Kalantar 2015). A framework consisting of two-stage stochastic optimization was proposed in the article. The first stage focusses on scenario generation and reduction and the second stage performs MILP-based optimization.

A multi-objective EMS based on stochastic optimization is utilized for optimizing two objectives, namely, minimization of operational costs and environmental pollution (Tabar, Jirdehi, and Hemmati 2017). Scenario generation and reduction technique is implemented in the framework. A novel M EMS framework based on stochastic scheduling problem (Farzin et al. 2016). The function of the stochastic scheduling program in the proposed framework is to determine dispatchable RERs commitment, and based on the RERs commitment the program schedules energy for different load and RES scenarios. Finally, the program evaluates the expected cost and risk measures. The proposed framework was tested with a test microgrid and found to effectively deal with uncertainties during unscheduled islanded operations. For a grid-connected MG, a stochastic EMS is applied to minimize the total cost of the system along with reducing the emissions (Hajiamoosha et al. 2021). The total cost considered in this model is a function of fuel costs, operation, and maintenance costs. For minimizing the energy losses and renewable energy source generation costs in a hybrid PV/Wind microgrid, stochastic EMS is modeled and utilized in (Amrollahi and Bathaee 2017). A two-stage stochastic approach-based EMS for MG (Hu, Lu, and Chen 2016) is utilized to analyze the MG systems in the electricity market. The first stage is concerned with the determination of the decision for investing in MG devices. The EMS strategies are focused on the second stage of the model. Similar to (Farzin et al. 2016), a two-stage scenario-based stochastic approach is developed in (Shen et al. 2016) for the EMS of an MG under an electricity market environment. In this model, stochastic electricity prices are also considered. The proposed framework benefits both the MG and the customers. To ensure the reliability of the microgrid along with the energy management, a stochastic EMS is utilized in (Naja et al. 2020). To model the uncertainties of the load, energy price, distributed power generation, energy demand of some active loads, and availability of MGs equipment in order to minimize the expected MG operating cost emission level, and voltage deviations function a stochastic programming based on the combined Monte-Carlo Simulation (MCS) method and Kantorovich technique is utilized in (Roustaee and Kazemi 2021). A novel stochastic EMS with voltage stability as a constraint is proposed in (Nikkhah, Nasr, and Rabiee 2021) to ensure the system security and to improvise the energy management in microgrid in the presence of Plug-in Electric Vehicles. To minimize the overall cost for the operation and to the total of expected operation and risk costs of the microgrid community, a two-stage hierarchical stochastic EMS is modeled by combining Monte-Carlo Simulation (MCS) and fast backward/forward approach in (Azarhooshang, Sedighizadeh, and Sedighizadeh 2021).

The inferences made from the analysis of EMS approaches based on stochastic approaches are as follows:

(a) Complex problem formulation is the major drawback in these approaches.
(b) Few approaches are found to be effective than greedy planning methods and scenario-based optimization methods in terms of economic feasibility.

Robust programming-based methods

A single-objective load management strategy for MG based on robust programming is proposed in (Lujano-Rojas et al. 2012) for a hybrid system with wind energy, battery storage, and diesel generator. Based on the user's behavior and duty cycle of the appliances, the constraints were considered for the optimization problem. In (Xiang, Liu, and Liu 2016), a robust EMS for minimizing the operational cost for a grid-connected MG is proposed. The worst-case energy trading cost is included as a novel part of the framework. The dual decomposition method was utilized to decompose the actual problem into subproblems, which are then solved to obtain optimal results. To minimize the social cost of MG i.e., the cost which includes operating cost, DR costs, and worst case power trading cost a robust optimization technique is implemented in (Zhang, Gatsis, and Giannakis 2013). A two-stage hierarchical robust EMS is presented in (Guo and C 2016) in which the first stage is concerned with day-ahead UC operation of CGs and the second stage focuses on real-time DR and energy trading between MG and utility grid. In (Zografou-Barredo et al. 2021), a robust mixed-integer second-order cone programming (R-MISOCP) model for optimal scheduling of MG is proposed. The major advantage of the proposed model is that it allows trade-offs between the uncertainties. This is because the uncertainties are modeled using a robust approach. A robust type-2 fuzzy program was developed in (Tsao and Thanh 2021) for determining the number of location of RES along with utilization of block-chain technology to maximize the system profit. Through effective compensation of RES intermittency using robust random vector functional link network, the model proposed in (Majumder, Dash, and Dhar 2021) achieves continuous power supply based on numerous DGs. Economic and secure operation of RES

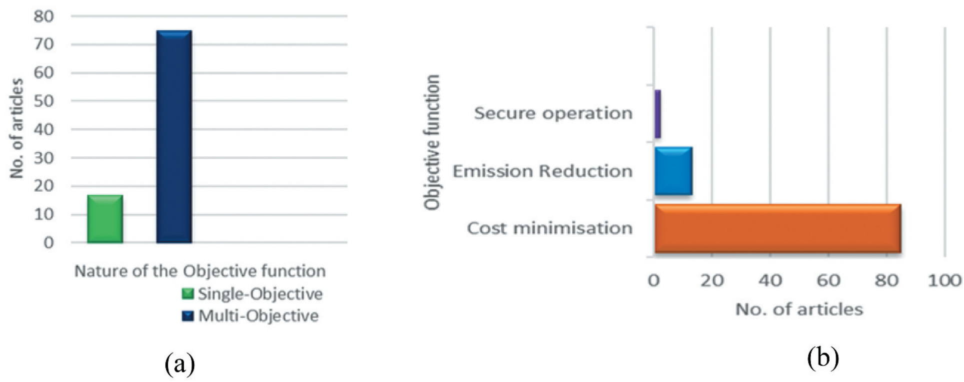


Figure 6. Comparison between (a) nature of objective function and (b) goal of objective function considered in EMS problems.

were considered as objectives and an robust EMS was modeled in (Yang, Su, and Wang 2021) and the model is solved using Bender's Algorithm. Power flow and ESS constraints are considered in the EMS modeling. An evident reduction in generation costs is obtained along with 47% of reduction in dynamic grid participation in (Bishwajit, Sheila, and Mahapatra Fausto Pedro 2022) using the robust EMS model based on a novel hybrid optimization method. An effective power management system which tracks the desired power values with very minimal amount of tracking errors is introduced in (Syed Shafi et al., 2022) for DC microgrids and is compared with existing approaches to establish the effectiveness of the robust model. A robust EMS model based on a novel MPC for small scale microgrid is introduced in (Babqi 2022). The proposed approach effectively optimizes the energy flow between each DG and utility grid and also enables Plug and Play of the DG sources. Information gap decision theory-based robust EMS model is developed for optimal scheduling in CHP-based microgrids in (Madad, AminS, and Afari Majid 2022). The proposed model is a single level model and achieves a better global optimum. Better solutions and fast convergence are achieved by the robust EMS model developed in (Amin and Barati Ali Reza 2022) based on novel inertia-weight local-search-based teaching-learning-based optimization method. Apart from the literatures mentioned here, a lot of research articles that utilize stochastic and robust approaches exist. The pieces of literature corresponding to robust and stochastic methods are tabulated as Table 4.

The inferences made from the analysis of EMS approaches based on robust approaches are as follows:

(a) Similar to stochastic approaches, complex problem formulation is the noteworthy drawback in these approaches.
(b) Few approaches are found to not emphasize the reduction of emissions and battery constraints.

Nature of objective function

The EMS model can be classified into two categories based on the objectives considered for optimization namely, single-objective and multi-objective EMS problems. In most of the literatures, the EMS model is of multi-objective type as shown in the chart (Figure 6(a)). The comparison between the goal of the objective function (in %) is depicted in the bar chart (Figure 6(b)). Three categorizations were done to put forth the importance of consideration of objective function. They are cost minimization, emission reduction, and secure operation. Cost minimization is the majorly focused on objective function that includes costs such as initial investment costs for installation of microgrids, operation

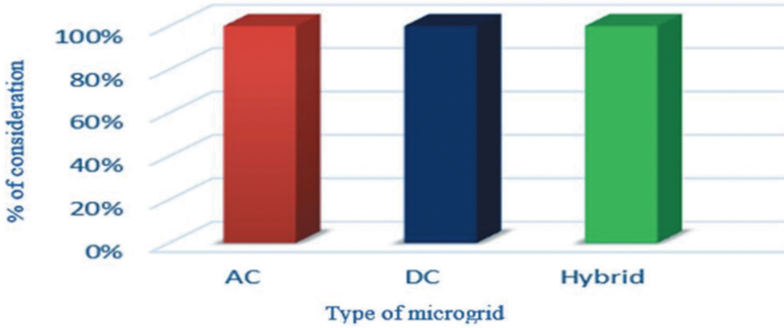


Figure 7. Comparison between type of microgrid considered for EMS problems.

costs for power generation, energy storage system operation costs, maintenance costs, and so on. Although the emission reduction also comes under the cost minimization category, it is categorized separately to put forth its importance.

The objectives like fault mitigation, power quality enhancement, resilience against critical loads, ensuring voltage and frequency stability, comes under the secure operation category.

Type of microgrid considered

Figure 7 summarizes the type of microgrid considered. The works of literature were scrupulously chosen such that equal importance was given to all three types of microgrids. Approximately, 36 articles on each category are chosen for the extensive analysis of the EMS models. As discussed in Section 3, AC microgrids were found to be easily integrated with the utility grid while DC microgrids mandate the power electronic interfaces. The predominant benefit of AC microgrids is that they can be stepped up/down easily for distribution over long distances and for supplying the load respectively. Complexity in the control and operation of microgrids is significant in the case of AC microgrids rather than DC microgrids (Shahgholian 2021).

Similarly, the integration of renewable energy resources and connecting the battery storage systems is doable in the case of a DC microgrid. On the other hand, the hybrid microgrid aids in connecting various non-flexible sources and loads to the utility grid. Despite this, the unpredictability of RES leads to difficulty in stabilizing the hybrid microgrids (Barik, Jaiswal, and Das 2021).

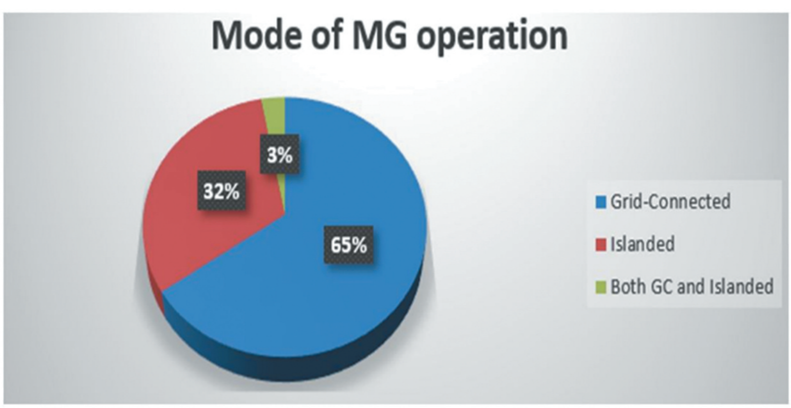


Figure 8. Comparison between mode of MG operation considered for EMS problems.

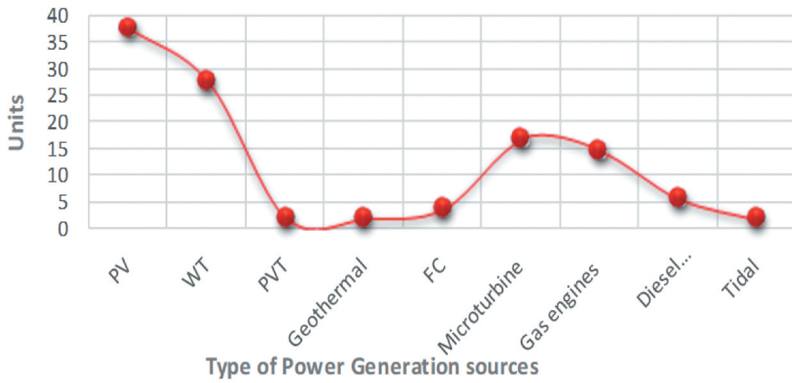


Figure 9. Comparison between power generation resources considered in EMS problems.

Mode of grid operation

The microgrid can be operated in both the grid-connected or islanded mode. The authors in the considered literature have given importance to both the grid-connected mode and the islanded mode of operation (Figure 8). But more focus has to be given to the islanded type microgrids as the number of works of literature corresponding to its energy management is less when compared to the grid-connected type. Thus, the grids operating in both the grid-connected or islanded modes are a feasible alternative.

Softwares/solvers used

Numerous software/solvers are used for solving the MEMS optimization problem. Of them all, MATLAB is found to be the most used tool. The user-friendly modeling makes MATLAB an indispensable platform for microgrid problems (*Small Scale Microgrid Model Using MATLAB*, n.d.). Among the solvers, CPLEX solver (a solver based on C language from MATLAB) (Fahad, Elbouchikhi, and Benbouzid 2018) is also used by many authors. The MATLAB in combination with LabVIEW is also found in a few literatures. Apart from the literature considered, HOMER software is a tool found to be utilized for modeling microgrids (*Homer Pro*, n.d.). The IBM ILOG CPLEX models of MATLAB got attention due to the fact that the optimization models can be developed and deployed immediately (*IBM ILOG CPLEX SOLVERS*, n.d.) and a comparison of outcomes can be made in an easy manner. Yalmip toolbox from MATLAB is used for expeditious prototyping of optimization problems (Löfberg 2004). On the other hand, GAMS (General Algebraic Modeling System) platform (*GAMS – A High Level Modeling System for Mathematical Programming*, 2021) is found to be used majorly in recent times. The versatile nature of the platform along with solvers like CPLEX (C-Simplex) and DICOPT ((DIscrete and Continuous OPTimizer) (DICOPT – GAMS 2021) proves to be effective for solving all non-linear optimization problems.

Sources of power generation

Power generation sources are an inevitable part of any kind of electrical network. In the case of microgrids, as discussed in Section 2, various flexible and non-flexible power resources can be used for on-site power generation i.e., distributed generation. As decreasing the carbon footprint caused by the exploitation of fossil fuels for power generation was the major cause for the Microgrid evolution, renewable energy resources are considered for distributed generation. These resources are abundant in nature and are clean green resources.

Although there are many advantages, the intermittency of these RES mandates certain conventional generators such as diesel generators, microturbines, and fuel cells. Figure 9 delineates that PV and WT are the most considered RES in the case of on-site power generation. Among these two PV is the widely used non-flexible resource. PV thermal system and tidal energy resources are the least considered power resources. On the other hand, the microturbines and diesel generators were the flexible power resources prepended for distributed generation purposes.

Storage systems

Apart from the power generation resources, the energy storage systems are also an ineluctable part of microgrids. The intermittency and uncertainty of the RES demanded energy storage facilities. The sustainable utilization of energy resources requires environmental-friendly and economic operation of the whole system (Meng et al. 2016). From the literature, the energy storage systems such as batteries, thermal storage systems, flywheels, and supercapacitors are found to be utilized for microgrid applications. From Figure 10, it can be inferred that the batteries were the eminently used ESS. Lead-acid or Li-ion batteries are the most used battery types. On the other hand, the energy storage devices like flywheels and supercapacitors for microgrid applications are gaining attention in the past few years.

Conclusion

A compendium of EMS architecture, optimization models along with the techniques used to solve those models, and the solvers used are provided in this article. Few notorious outcomes of this review are as follows:

(a) The EMS models proposed are majorly focusing on grid-connected systems and centralized EMS architecture is emphasized in all those models.
(b) More investigations are necessitous for islanded autonomic microgrid energy management strategies as there are considerably few literatures available for them.

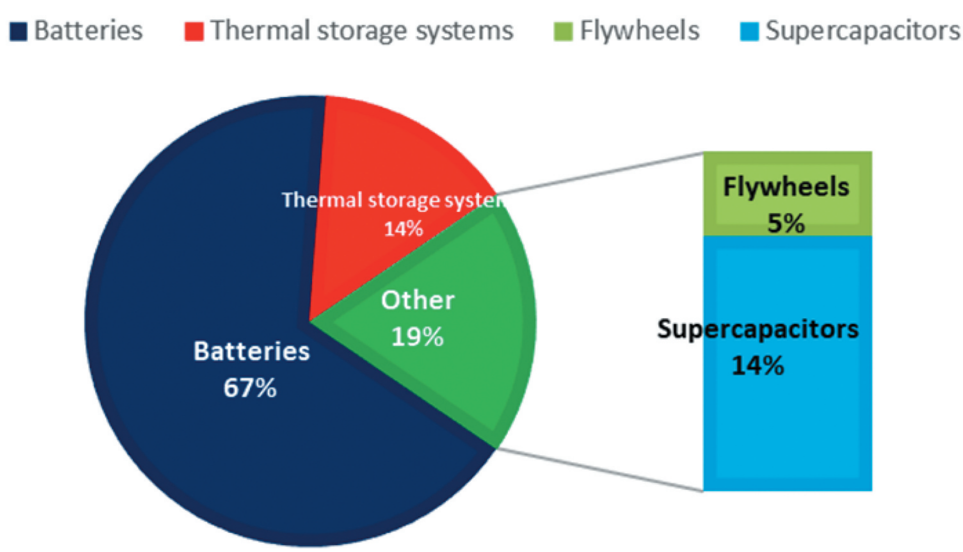


Figure 10. Comparison between ESS considered in microgrids.

(c) Both the centralized and decentralized type of EM systems are analyzed and it is found that MAS technique is the mostly used approach for decentralized microgrids, whilst the metaheuristic techniques and other approaches are majorly focused on the centralized ones.
(d) Cost minimization is the major objective considered in most of the MEMS models.
(e) Effective inclusion of technical and economical constraints (like battery degradation) and formulation of proper multi-objective functions will have a greater impact on the EMS results.

This article aids in exploring the poorly researched areas of microgrids in the important aspects of its energy management strategies. In future, the communication infrastructure and the privacy issues concerned with the infrastructure can be addressed in a more effective manner. As there are only few approaches which emphasize the decentralized architecture are available, more importance has to be given toward decentralized architectures. The complexities such as computational complexity and problem formulation complexity have to be addressed effectively. Addressing these areas will aid in formulation of a better EMS model with more desirable outcomes.

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No potential conflict of interest was reported by the author(s).

Notes on contributors

Albert Paul Arunkumar received his bachelor's degree in Electrical and Electronics Engineering and the master's degree in Power Systems Engineering during the year 2017 and 2020 from Anna University, Chennai. Currently, he is working towards the Ph. D degree in Electrical Engineering at SRM University, Chennai, in the area of Microgrid Energy Management Systems. His areas of interest include Microgrids, renewable energy systems, energy management systems, and deregulated power systems.

Selvakumar Kuppusamy received his B.E degree in Electrical and Electronics Engineering from Anna University, Chennai, India in the year 2010. He obtained his M.E degree in Power Systems in the year 2012 from K.S. Rangasamy College of Technology under Anna University, Chennai, India and Ph.d, in SRM Institute of Science and Technology, Kattankulathur, Chennai. He is currently working as a Assistant Professor in the department of Electrical and Electronics Engineering, SRM Institute of Science and Technology, Chennai, India. He has published 75 research papers in international journals. He has presented 20 papers in international conferences. His research interests are generation scheduling, power system operation, power flow analysis, and soft computing techniques in microgrids. He is life member of ISTE, MIE, IAENG, IACSIT, IRED, and member of IEEE.

Suresh Muthusamy received the bachelor's degree in Electrical and Electronics Engineering and the master's degree in Power Electronics and Drives during the year 2009 and 2011 from Anna University, Chennai and Anna University, Coimbatore, respectively. Currently, he is working toward the Ph.D. degree in Electrical Engineering at Anna University, Chennai, in the area of Hybrid Renewable Energy Systems. Since 2011, he has been working as an Assistant Professor Senior Grade in the Department of Electronics and Communication Engineering at Kongu Engineering College (Autonomous), Perundurai, Erode. He published more than 75 research articles in the reputed international journal publications like Elsevier, Springer, Taylor & Francis, SAGE, ASME, etc. & indexed in SCI, SCIE, Scopus, and Web of Science with good impact factor and also presented many papers in national and international conferences. His areas of interest include hybrid renewable energy systems, power electronic converters, hybrid electric vehicles, and battery management systems.

Santhiya Pandiyan received the bachelor's degree in Computer Science and Engineering and the master's degree in Computer Science and Engineering during the year 2013 and 2015 from Anna University, Coimbatore and Anna University, Chennai, respectively. Currently, she is working toward the Ph.D. degree in Computer Science and Engineering at Anna University, Chennai, in the area of Machine Learning. She worked as an Assistant Professor in the Department of Computer Science and Engineering at Paavai Engineering College (Autonomous), Namakkal from 2016 to 2021 for a period of about 5 years 7 months. Since August 2021, she has been working as an Assistant Professor in the Department of Computer Science and Engineering at Kongu Engineering College (Autonomous), Perundurai, Erode. She published eight research articles in various international journal publications like Taylor & Francis, Elsevier, etc. and presented four papers in national/international conferences. Her areas of interest include machine learning, deep learning, Internet of things, data structures, etc.

Hitesh Panchal received the bachelor's degree in Mechanical Engineering from Government Engineering College, Modasa, Gujarat during the year 2004 and the master's degree in Internal Combustion Engines and Automobile from L. D. College of Engineering, Ahmedabad, Gujarat during the year 2006. He then received the Ph.D degree in Mechanical Engineering in the area of Solar Thermal Engineering from K.S.V. University, Gandhinagar, Gujarat in 2015. Dr. Panchal has published more than 150 research articles in reputed National and International Journal publications like Taylor and Francis, Springer, Elsevier, ASME, SAGE, etc. and also received 5000+ Google Scholar citations with h-index of 47 and i-10 index of 113. Dr.Panchal received many prestigious awards like Best Ph.D Thesis Award, Bharat Excellence Award, Young Scientist Award, Bright Researchers Award, and many more from various organizations. Dr. Panchal has completed two Research projects from GUJCOST, DST of 15 lakhs and currently working on one Research project from DTE. Dr.Panchal has filed 24 full patents and 10 Industrial designs and among them two patents and seven industrial designs have been granted. Dr.Panchal has been selected in "Top 2% Indian Scientist under the energy category" published by Stanford University for the years 2020 and 2021.

Pragash Nagaiyan received the bachelor's degree in Electronics and Communication Engineering from Anna university, Chennai and the master's degree in Optical Communication & Signal Processing and currently he is working toward the Ph.D. degree in Information and Communication Engineering at Anna University, Chennai in the area of digital communication. Since 2015, he has been working as an Associate Professor in the Department of Electronics and Communication Engineering at Kongu Engineering College (Autonomous), Perundurai, Erode. He published four research articles in the reputed international journal publications and presented two papers in international conferences. His areas of interest include optical communication, signal processing, antennas, etc.

ORCID

Albert Paul Arunkumar http://orcid.org/0000-0002-9486-2036
Selvakumar Kuppusamy http://orcid.org/0000-0003-0580-158X
Suresh Muthusamy http://orcid.org/0000-0002-9156-2054
Santhiya Pandiyan http://orcid.org/0000-0002-7815-0821
Hitesh Panchal http://orcid.org/0000-0002-3787-9712

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