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Review

A Survey on Microgrid Energy Management Considering Flexible Energy Sources

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Abstract: Aggregation of distributed generations (DGs) along with energy storage systems (ESSs) and controllable loads near power consumers has led to the concept of microgrids. However, the uncertain nature of renewable energy sources such as wind and photovoltaic generations, market prices and loads has led to difficulties in ensuring power quality and in balancing generation and consumption. To tackle these problems, microgrids should be managed by an energy management system (EMS) that facilitates the minimization of operational costs, emissions and peak loads while satisfying the microgrid technical constraints. Over the past years, microgrids' EMS have been studied from different perspectives and have recently attracted considerable attention of researchers. To this end, in this paper a classification and a survey of EMSs has been carried out from a new point of view. EMSs have been classified into four categories based on the kind of the reserve system being used, including non-renewable, ESS, demand-side management (DSM) and hybrid systems. Moreover, using recent literature, EMSs have been reviewed in terms of uncertainty modeling techniques, objective functions (OFs) and constraints, optimization techniques, and simulation and experimental results presented in the literature.

Keywords: microgrid; energy management system; demand-side management; uncertainty; energy storage; distributed generation

1. Introduction

There are strong incentives to utilize distributed generations (DGs) for reducing greenhouse gases, improving power system efficiency as well as its reliability, competitive energy policies and postponement of transmission and distribution system upgrading [1]. In fact, DGs are composed of renewable units such as wind turbines (WTs), photovoltaic (PV), fuel cells (FCs), biomass along with non-renewable ones such as micro-turbines (MTs), gas engines (GEs), diesel generators (DiGs), etc. [2]. DGs eliminate the need for the transmission system by being installed near the customers [3]. Integration and control of DGs along with storage devices and flexible loads can constitute a low voltage distribution network, called a microgrid, which can be operated in isolated or grid-connected mode [4]. The generic concept of a microgrid is shown in Figure 1.

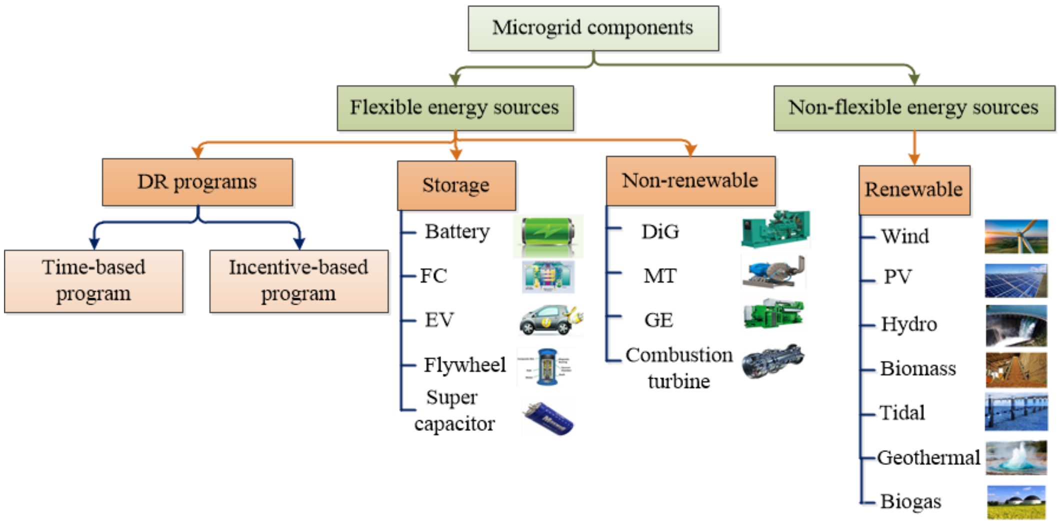


Figure 1. Microgrid components.

Microgrids often face difficulties in supplying demand due to the lack of sufficient energy generation sources. This obstacle is caused by intermittent nature of loads and renewable energy sources [5]. As a result an energy management system (EMS) is necessary to tackle this problem. EMS for a microgrid represent relatively new and popular topics that attracted lots of attention, recently. Existing review papers in literature have investigated microgrid EMSs from a different aspects, as summarized in Table 1 [6–13].

Table 1. A survey on the existing review papers of microgrid energy management system.

Ref.	Objective Function	Const.	Flexible Resources		Optimization Techniques	Microgrid Operational Mode	
			DR	ESS		Islanded	Grid-Connected
[6]	✓	✓		✓	✓	✓	
[7]	✓			✓	✓	✓	✓
[8]					✓	✓	✓
[9]				✓		✓	✓
[10]				✓	✓	✓	✓
[11]					✓	✓	✓
[12]			✓		✓	✓	
[13]	✓	✓			✓	✓	

The contributions of this review paper are:

- Microgrid EMSs have been classified into four categories based on the kind of the reserve system being used including non-renewable energy sources, energy storage system (ESS), demand-side management (DSM) and hybrid.
- Energy management modeling studies have been reviewed in terms of uncertainty modeling techniques, objective functions (OFs), constraints, and optimization techniques.
- The microgrids which are considered as the case study of different EMS papers have been reviewed in this paper.
- The scenarios of the simulation results section have been categorized.

The aim of an EMS is to determine the optimal use of DGs in order to feed the electrical loads [14]. An EMS can be operated in two modes, namely centralized and decentralize. In the centralized mode, the central controller aims to optimize the microgrid power exchanged based on the market prices and security constraints. In the decentralized mode, DGs and controllable loads have more degree of freedom [15]. As a result, the microgrid components are considered to be intelligent and try to maximize the revenue of the microgrid by communicating with each other [16]. The initial duty of EMS in both centralized and decentralized mode is to ensure the microgrid of providing load-generation balance [17]. The EMS fail in matching the generation and load, whenever the total load is higher than the maximum capacity of DGs [18] and no other additional actions are taken. A solution for this drawback is to trade power with the utility or other micro-sources, however, this solution leads to an increment of pollution, costs and the need to solve a more complex unit commitment problem as a result of the additional units [19]. Various supporting systems such as DiGs, ESSs and DSM are employed to overcome the supply-demand mismatch of a microgrids. This paper provides the literature review of microgrid EMSs by classifying the existing articles into four categories as follows:

(1) Non-renewable based EMS
(2) ESS-based EMS
(3) DSM-based EMS
(4) Hybrid systems based EMS

The remainder of the paper is organized as follows: in Section 2, the aforementioned categories are briefly introduced. A survey of uncertainty modeling techniques in EMSs is presented in Section 3. The mathematical formulation of objective functions along with constraints are presented in Section 4. The appropriate optimization techniques used by an EMS, microgrid test systems and obtained simulation results are reviewed in Sections 5–7, respectively. Finally, the conclusions are presented in Section 8.

2. Classification of EMS Literature

In this section, the necessity and utilization of the aforementioned categories are explained.

2.1. Category 1: Non-Renewable Based EMS

In case of failure or inaccessibility of ESSs, it is recommended to use non-renewable energy sources including diesel generators (DiGs), micro turbines (MTs), gas engines (GEs) or combustion turbines as a backup energy source in the microgrid. A DiG is made up of a combination of a diesel engine and an electric generator. The efficient selection of DiG depends on various factors such as load type, fuel cost, transportation cost, etc. [7].

2.2. Category 2: ESS-Based EMS

Microgrid EMSs face difficulties in the management of renewable energy sources such as wind and solar energy. This problem is due to the uncertain nature of the available energy which is caused by the difference between real-time and forecasted power production [20]. One of the solutions to tackle this problem is to utilize ESSs [21]. In most cases, ESSs maintain the power balance between generation and consumption by storing power during inexpensive or off-peak hours and discharging it during high-price or peak hours [22]. Diverse studies have been focused on the utilization of ESSs in a microgrid [23]. Utilizing ANN (Artificial neural network) for prediction of wind power generation, multi-objective energy management of microgrid considering uncertainties of wind generation in presence of ESS is studied in [24]. Karavas et al. [25] have studied the microgrid EMS considering a battery as ESS and solved the optimization problem based on distributed intelligence and MAS. Alavi et al. [26] solved the microgrid energy management problem considering a battery as a reserve energy source. In order to cover wind and solar power uncertainties, PEM has been used. Chen and Duan [27] have solved the optimal management problem of DGs with ESS in a microgrid by a MRCGA. Simultaneous capacity optimization of DGs and storage devices by considering the effects of weather condition and non-dispatchable power sources have been introduced in [28]. The EMS problem for multi-microgrid is proposed by Logenthiran et al. in [29] while the ESS being used as a reserve energy source.

2.3. Category 3: DSM-Based EMS

Another way to cope with unbalances of microgrid production and consumption is to utilize DSM programs [1]. All activities aiming to match the supply and demand by modifying time and/or shape of customers' demand profile is called DSM [30]. After the liberalization of electricity market, DSM is divided into following two categories [31]:

- Energy efficiency: which reduces consumption of the demand side by improving the efficiency of products.
- Demand response (DR): which modifies the usage of end-users in comparison to their normal consumption in response to changes in electricity price or incentive payments which aim to reduce consumption during expensive hours or when system reliability is at risk [32].

DG uncertainties and electricity price fluctuations cannot be managed and coped with for energy efficiency. As a result, special attention is given to DR programs in a microgrid and it is therefore crucial to study the impacts of various DR programs on the EMS of a microgrid.

DR programs are categorized into two groups namely: price-based and incentive-based DR programs [33]. A more detailed explanation of these categories can be found in [34].

Microgrid EMS in a deterministic case and with a multi-objective problem is studied in [35] wherein a price-quantity based DR package is utilized to manage the random nature of DGs. Falsafi et al. [36] have utilized both price-based and incentive-based DR programs to provide reserve, and to cover the wind power uncertainties in a multi-objective formulation. Nejhad et al. [37] have studied the EMS problem of microgrid as a stochastic problem in presence of DR programs. In addition, microgrid EMS taking into account effects of DR program is formulated as a MILP in [38]. A security-constrained EMS problem is considered in [39], in which frequency management is studied along with energy management and DR is utilized as a reserve energy source. The optimal operation of microgrid in the presence of electrical vehicles and responsive loads are discussed in [40] by considering wind and PV uncertainties.

2.4. Category 4: Hybrid Systems Based EMS

In this category, a combination of the abovementioned categories, two by two or all together, are surveyed to overcome microgrid EMS problems. Similar to the previous categories, this topic has also attracted lots of attention in the literature. In [41], the probabilistic coordination of DGs, ESS and DR are presented in a microgrid by performing a load reduction in the presence of security risks. Simultaneous implementation of ESS and DR is studied as a multi-objective problem by Marzband et al. [18]. Microgrid EMS in a system containing PV and wind turbines as DGs, DiG and small hydro generator as reserve power sources, DR and battery storage system is modeled by Zhao et al. [42] by using multi-agent systems (MASs). Talari et al. [43] have studied stochastic scheduling of microgrid components in presence of ESSs and DR programs. Pourmousavi et al. [44] have solved the management problem of an islanded microgrid which is composed of various DG units, storage and DR as a multi-timescale problem. The authors of [45] have utilized a pumped-storage unit and DR program in a new stochastic optimization framework to cover existed uncertainties of microgrid EMS problem. An overview of recent technologies in application of storage and DR operation of microgrids is presented in [33].

Solving the EMS problem of a microgrid is composed of various steps, including predicting uncertain parameters, modeling uncertainties, mathematical formulation of objective functions and constraints, choosing the optimization technique to solve the problem and selecting the understudying microgrid as the case study. Classification of the abovementioned steps along with sub-category of each step is shown in Figure 2. For instance, the existed uncertain parameters in microgrid EMS problem can be predicted in different time horizons such as short-term, mid-term and long-term time period. Prediction in short-term period can be performed using classical and intelligent techniques. Classical methods include ARIMA (auto-regressive integrated moving average), GHARCH (Generalized auto-regressive conditional heteroskedasticity), DR and TF (Transfer function) while the intelligent ones are ANN, FNN (fuzzy neural network) and SVR (support vector regression). Theses explanations can be expanded for other steps, too.

3. Prediction of Uncertain Parameters

Lack of information which leads to a probability of a difference between real and forecasted values is defined as uncertainty [26]. The uncertain parameters in a microgrid EMS can be generally classified into the following two categories:

- Operational parameters: These parameters include the amount of generation and load in power systems.
- Economical parameters: Economic parameters have an effect on the economic aspects of the power system and include uncertainty in fuel supply, production cost, economic growth and interest rates [46].

The prediction of uncertain parameters can be performed over various time horizons ranging from minutes to a couple of days as a short-term prediction, from several weeks to months as mid- term prediction and from multiple months to several years as long-term prediction [47]. Since the microgrid EMS problem is accomplished at hourly intervals, short-term forecasting methods are suitable to be used for this purpose. Classification of these short-term forecasting methods is represented in Figure 2 which is broken down into two categories namely classical and intelligent methods [37]. Classical techniques include well-known methods such as auto-regressive integrated moving average (ARIMA) [48], generalized auto-regressive conditional heteroskedasticity (GARCH) [49], dynamic regression (DR) and transfer function [50].

Intelligent methods are based on training historical data by mapping them on input-output of data-driven structures [37]. Artificial neural network (ANN) [51], fuzzy neural network (FNN) [52] and support vector regression (SVR) based on ARIMA can be classified in this category [53].

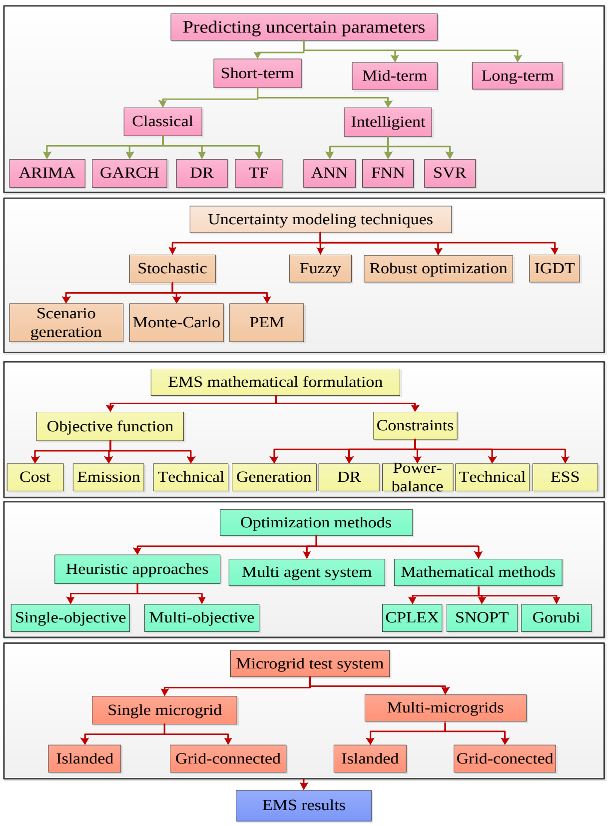


Figure 2. Overall EMS structure and underlying methods of each step.

4. Uncertainty Modeling

Uncertainty managing is one of the main difficulties decision makers have to deal with [46]. As a result, various methods have been employed in order to manage the uncertainty of the aforementioned parameters in Section 3 in microgrid energy management [46,54–57]. In this section, a review of all existing uncertainty modeling techniques used by an EMS are presented which are classified broadly into four categories as shown in Figure 2.

4.1. Stochastic Methods

Stochastic methods are used to approximate the PDF of random variables [58]. The first efforts in modeling uncertainties using stochastic methods was made by Dantzig [59]. These methods can be used, when the PDF of input parameters is known [60]. A brief introduction of three main stochastic technique are given below:

4.1.1. Scenario Generation

Modeling uncertainties through scenario generation methods needs to know the PDF. In these methods, by dividing the PDF in multiple parts, each part is assumed as a scenario with an occurrence probability proportional to the PDF value of the preferred selected section [61]. The scenario generation method is used in [40] in order to cover uncertainties related to upper, lower and expected values of wind and PV systems. As reported by Alharbi and Raahemifar [41], uncertainties of wind, solar power and load are represented by discrete probability distribution sets as scenarios. In [39], load, wind and PV power random scenarios are firstly generated using MCS and roulette wheel mechanism. Then, to improve the computational speed, a scenario reduction algorithm is employed. Various scenarios for modeling wind and PV output powers are generated by Monte Carlo simulation by Talari et al. [43].

4.1.2. MCS

In MCS-based methods, for each input parameter, a sample is generated using its PDF [62]. As MCS is a repetitive procedure, sample generation process is repeated for some iterations. Finally, histograms, statistic criteria or other approaches are used to analyze the outcome [63]. Caralis et al. [64] have used a Monte Carlo method to manage wind power uncertainties with the goal of earning profits from wind energy investment. Uncertainties related to solar radiation and load are investigated using MCS in [63] via optimization of the hybrid system.

4.1.3. Point Estimate Method (PEM)

PEM is one of the methods used to estimate the value of uncertain parameters with high computational accuracy and is based on the concept of uncertain input parameters moments [65]. This method covers uncertainties by establishing a connection between input and output variables whose main steps are explained by Hong [66]. In [26], PEM is utilized to model uncertainties of wind and solar power. Peik-Herfeh et al. [67] employed PEM to model the uncertainties of market price and generation sources via a probabilistic price-based unit commitment problem.

4.2. Fuzzy Method

Based on fuzzy theory, a degree of membership can be attributed to each uncertain parameter using membership functions. Then, an α-cut method [68] can be used to determine membership functions of output variables according to membership functions of input parameters. An effort has been made in [69] to review the application of fuzzy methods in renewable energy sources. A fuzzy method has been used by Sourodi et al. [70] to study the effects of uncertain power output of DGs on power losses in distribution networks.

4.3. Robust Optimization Method

The robust optimization method [71] was introduced to explain parameter uncertainties using uncertain boundaries. Robust optimization is suitable when there is a lack of information about PDF of parameters. This technique is used to cover load uncertainties by Alavi et al. in [26]. Robust optimization is employed for wind and load uncertainty in Ref. [72].

4.4. Information Gap Decision Theory (IGDT)

As a decision-making approach, IGDT makes minor assumptions on the structure of uncertainty [73]. This technique makes robust decisions against uncertainty of the input parameters. The optimal bidding strategy in day-ahead electricity market considering uncertainties of market price is performed by implementing IGDT in [74]. Nojavan et al. [75] proposed a method based on IGDT to evaluate procurement strategy of large consumers.

5. Mathematical Formulation of EMS

Microgrid energy management is an optimization problem which aims to properly schedule short-term operation of DGs, ESSs and controllable loads with respect to various objective functions and constraints [76]. In this section, a literature review of existing objective functions as well as constraints considered by an EMS have been elaborated. Furthermore, Figure 2 represents a classification of objective functions utilized by the EMSs along with their constraints.

5.1. Objective Functions

The EMS can manage a microgrid by solving various objective functions. Objective functions may include capital or operational costs of the microgrid. Costs related to fuel, maintenance, start-up and shut-down, degradation as well as procurement from the utility in case of power deficiency, are considered as operational costs [77]. Table 2 provides a collection of utilized EMS objective functions in literature. In this table, objective functions are reviewed from being single objective and multi-objective perspectives, too.

Table 2. Survey through collection of EMS objective functions.

Ref	OF Equation	Details	Single	Multi
[24]	$F = \sum_{t=1}^{T}\left\{\sum_{i=1}^{N_g}\left[u_i(t)P_{gi}(t)(B_{gi}(t)+K_{OM_i})+S_{gi}\lvert u_i(t-1)\rvert\right] + \sum_{j=1}^{N_{ES}}\left[u_j(t)P_{Sj}(t)B_{Sj}(t)\right]+P_{Grid}(t)B_{Grid}(t)\right\} + \sum_{t=1}^{T}\left\{\left(\sum_{i=1}^{T_E}\sum_{j=1}^{N}EF_{ij}P_{gi}(t)\right)+P_{Grid}(t)EF_{grid}\right\}$	$B_{gi}(t)$ and $B_{Sj}(t)$ represent bids of ith DG and jth storage device. EF_{ij} is the emission factor of jth DG. In addition, $P_{gi}(t)$ and $P_{Sj}(t)$ represent power generation of ith DG and jth storage device.		✓
[28]	$COE = \frac{C_{antot}}{E_{anserved}}$	COE is the cost of energy which is computed by the ratio of total annualized cost (C_{antot}) to total annual energy served ($E_{anserved}$).	✓	
[18]	$F = \sum_{t=1}^{m}(C_t^g + Cr_t^g + C_t^{ES-} - C_t^l - C_t^{ES+} + \Omega_t) \times \Delta t$	C_t^g, Cr_t^g are the cost of energy produced by renewable and non-renewable sources. C_t^{ES-}, C_t^{ES+} represent the cost of ESS charge and discharge. C_t^l, Ω_t are the DR cost and is the penalty of the energy not supplied.	✓	

Table 2. *Cont.*

Ref	OF Equation	Details	Single	Multi
[25]	$F = NPC + \sum_{t=1}^{8760} P_b(t) + \sum_{t=1}^{8760} P_{H_2}(t) + \sum_{t=1}^{8760} P_w(t) + P_{wt} + P_{H_2T}$	NPC is the net present cost for 20 operating years. P_b, P_{H_2}, P_w, P_{wt}, P_{H_2T} are the battery, hydrogen, water, water tank and metal hydride tank penalty, respectively.	✓	
[26]	$F = CF_t^{OPR} + CF_t^{EMI} + CF_t^{RLB}$	CF_t^{OPR}, CF_t^{EMI} and CF_t^{RLB} represent the operation, emission and reliability cost of microgrid, respectively.	✓	
[27]	$F = C_{in}^{MG} + C_{op}^{MG}$ $C_{op}^{MG} = \sum_{i=1}^{L} (C_{Fi} + C_{OMi} + C_{Si} + C_{Ei}) + \sum_{j=1}^{M} C_{OMj}^{ESS} - C_G^{MG}$	The EMS cost composed of C_{in}^{MG} as investment cost and C_{op}^{MG} as operation cost.	✓	
[35]	$F = Cost^{Operating} + Cost^{Emission}$ $Cost^{Operating} = \sum_{t=1}^{T} (\cos t_{DG}(t) + ST_{DG}(t) + \cos t_s(t)$ $+ \cos t_{Grid}(t) + \cos t_{DR}(t))$ $Cost^{Emission} = \sum_{t=1}^{T} \{emission_{DG}(t) + emission_s(t)$ $+ emission_{Grid}(t)\}$	The objective function is considered as the operating and emission cost. $\cos t_{DG}(t)$, $ST_{DG}(t)$, $\cos t_s(t)$, $\cos t_{Grid}(t)$ and $\cos t_{DR}(t)$ represent DG cost, start-up and shut-down costs, reserve cost and cost of exchanged power with the grid, respectively.		✓
[36]	$F = F_{Cost}^{start-up} + F_{Cost}^{reserve} + F_{Cost}^{generation} + F_{Cost}^{DR} + F_{Emission}$	The objective function is composed of overall cost and emission functions.	✓	✓
[38]	$F = \sum_{t=1}^{ND} \left\{ \sum_{a=1}^{A} [(AT_{at}.ut_{at} + (MTC_a + BT_{at}).pt_{at}).H/ND \right.$ $+DT_a.yt_{at} + FT_a.zt_{at}] + \sum_{b=1}^{B} [((MFC_b + CF_b).pf_{bt} + \zeta_b.dpf_{bt})$ $.H/ND + EF_b.yf_{bf} + GF_b.zf_{bt}] + \sum_{c=1}^{C} [(CC_c.pdc_{ct}).H/ND]$ $\left. +[BP_t.pgb_t - SP_t.pgs_t + CD.pde_t + CE.pex_t].H/ND \right\}$	MTC_a and MTC_b represent maintenance cost of MT and FC while CC_cexpresses the incremental cost of load shedding.	✓	
[39]	$Frequency_{MG} = \sum_{s=1}^{Ns} \pi_s (\sum_{h=1}^{Nh} \sum_{l} \lvert \Delta f(s,l,h) \rvert)$	$Frequency_{MG}$ controls microgrid frequency as the EMS OF.	✓	
[40]	$F = \omega_1 \sum_{t=1}^{T} Cost^t + \omega_2 \sum_{t=1}^{T} Q_{r,i} Emission^t$	ω_1 and ω_2 represent non-negative coefficients for adjusting objective functions while $Q_{r,i}$ is ith price penalty factor.	✓	
[41]	$F = \sum_{s \in S} \lambda_s [\sum_{k \in K} \sum_{j \in J} (C_j(P_{j,k,s}) + SU_{j,k}) + \sum_{k \in K} C_{ES}.(V_{k,s}^{CH} + V_{k,s}^{DCH})$ $+ \sum_{k \in K} P_{k,s}^{Int,R-C-I}.C_k^{Int,R-C-I} + \sum_{k \in K} \Delta P_{k,s}^{do,R-C-I}.C_k^{DR,R-C-I}]$	The first term represents operating cost of DGs while the latter one is the operating cost of ESS. The expected cost of power interruption and responsive demand are computed by third and last terms, respectively.	✓	
[43]	$F = \sum_{t=1}^{T} \left\{ \sum_{n=1}^{N} (P_{n,t}B_{n,t} + SU_n \times y_{n,t} + SD_n \times z_{n,t} + c\pi_{n,t}^{U} SR_{n,t}^{U} \right.$ $\left. + c\pi_{n,t}^{D} SR_{n,t}^{D}) + \sum_{d=1}^{ND} CDR_{d,t} + \sum_{s=1}^{S} \mathrm{Pr}_{t,s} SC_{t,s} \right\}$	The cost function is composed of generation, trade-off, start-up and shut down costs of DGs as well as up and down reserves of demand response and security cost of the network.	✓	
[78]	$F = \sum_{t \in T} C_{t,money} + \sum_{t \in T} C_{t,money}^{startup} - \sum_{t \in T} P_{t,money} + \sum_{t \in T} \sum_{t \in T} \mu_{t,g}.\pi_g$	$C_{t,money}$, $C_{t,money}^{startup}$ denote the operation and start-up costs while $P_{t,money}$ is the total revenue. The last term represents penalty of the unmet load.	✓	
[79]	$F = \sum_{k_t} [(\sum_{g} a_g P_{g,k_t}^2 + b_g P_{g,k_t} + c_g w_{g,k_t} + C_{\mathrm{sup}} u_{g,k_t} + C_{sdn} v_{g,k_t})$ $+ d_s P_{shed,k_t} + d_c P_{curt,k_t}] \Delta t_{k_t}$	P_{g,k_t} is the generated power by DGs while P_{shed,k_t} and P_{curt,k_t} denote the amount of shedded and curtailed load, respectively.	✓	
[80,81]	$J = \sum J_{ij} \times x_{ij} \quad for\ 1 \le i \le j \le N_n$	J is the cost of transmission network, J_{ij} denotes the cost of interconnecting nodes.	✓	

5.2. Constraints

Different constraints can have an effect on energy management of a microgrid. For instance, maximum and minimum limits of power generation units must be satisfied to secure their safe and economic performance [82]. The balance between generation and consumption is another necessity of the system. The charge and discharge rates of ESS are also constrained. Violation of these constraints can lead to damaging effects on lifetime and efficiency of the ESS. Technical constraints of a microgrid include voltage at buses, feeder currents, frequency security aspects, start-up and shut-down reserve constraints, as well as ramping limits. In some of the studies which additionally consider responsive loads, constraints related to DR program must be satisfied. Table 3 provides a summary of the considered constraints used in the formulation of microgrid EMS.

Table 3. Survey through collection of EMS constraints.

Ref	Power Balance	Generation									ESS	DR	Technical
		DiG	GE	Biomass	MT	Wind	PV	FC	EV	Grid			
[24]	✓				✓	✓	✓	✓		✓	✓		
[28]	✓			✓		✓	✓				✓	✓	✓
[18]	✓				✓	✓	✓				✓	✓	
[25]	✓					✓	✓	✓			✓	✓	
[26]	✓	✓			✓	✓	✓				✓		✓
[27]	✓				✓		✓	✓		✓	✓		
[35]	✓				✓	✓	✓	✓		✓	✓	✓	
[36]	✓					✓						✓	
[38]	✓				✓			✓				✓	
[39]	✓		✓		✓			✓				✓	✓
[40]	✓				✓	✓	✓	✓	✓	✓		✓	
[41]	✓					✓	✓				✓	✓	
[43]	✓				✓	✓	✓	✓			✓	✓	✓
[78]	✓			✓		✓	✓				✓		✓
[79]	✓	✓			✓	✓					✓	✓	

6. Optimization Techniques of a Microgrid Performed by an EMS

The literature review reveals that various techniques have been utilized by researchers in order to solve the aforementioned optimization problems [17]. In this paper, these methods have been classified as follows:

6.1. Heuristic Approaches

Heuristic optimization techniques use exploratory approaches to solve the optimization problems while are unable to assure optimality of the obtained results [6]. A deterministic energy management problem is solved via multi-period gravitational search algorithm (MGSA) by Marzband and Ghadimi in [18]. In [35], the EMS optimization problem has been considered as a continuous multi-objective problem and is solved using multi-objective particle swarm optimization (MPSO) algorithm while it is solved by single-objective PSO in [26,40]. Motevasel and Seifi [24] have employed multi-objective Multi-objective Bacterial Foraging Optimization (MBFO) to solve complex and large-scale EMS problem. To deal with non-smooth cost functions, authors in [27,79] employed MRCGA. Implementation of multi-period ABC optimization algorithm to obtain an economic schedule of ESS and controllable loads of an islanded microgrid is studied in [83].

6.2. MAS

MAS is a smart system which is composed of multiple intelligent agents that are connected to each other within an environment [15]. The goal of MAS is to solve the optimization problems which are too complicated for a single agent. By assuming each member of microgrid as an agent, MAS has been used in [42] to find the optimal solution by the EMS problem. Optimal results of decentralized EMS problem have been studied using MAS approach by Karavas et al. [25]. A three-stage algorithm based on MAS is presented by Logenthiran et al. [29] to model the EMS problem in a multi-microgrid environment in which first stage schedules each microgrid to satisfy its load. The second and third stages determine microgrid bids and export power bids, respectively. Authors of Ref. [84] have utilized trust and reputation models to interconnect MAS effectively. In [85], a novel agent-based micro-storage management technique has been presented that allows all (individually-owned) storage devices in the system to converge a profitable and efficient behavior. A class of MAS technique is Distributed Constraint Optimization Problems (DCOP) in which a group of agents try to minimize the total cost related to a set of constraints. In a DCOP formulation the decision problem is translated to a set of constraints [86]. Long-term scheduling of microgrid is solved as an optimization problem using distributed constraint optimization (DCOP) by authors of [87]. Application of DCOP to solve large problems has difficulty as each agent can handle a single variable. So, a new multi-variable agent (MVA) DCOP decomposition method has been presented by athors of [88].

6.3. Mathematical Methods

Different kinds of software exist in order to solve microgrid EMS problems. Some of these solvers are mentioned below:

6.3.1. CPLEX Solver

CPLEX is a solver of GAMS package which can solve integer and linear problems [6]. In [39], the EMS problem is modeled as a MILP considering uncertainties and scenario generation process, and has been solved by the CPLEX solver of the GAMS environment. The multi-scenario MILP model has been utilized to mathematically formulate the EMS problem in [41], and is solved by CPLEX solver. CPLEX solver has been utilized to solve MIP scheduling problem of microgrid by Talari et al. [43]. A large-scale MILP problem in [36] is solved also by CPLEX solver. Another EMS problem is modeled as a MILP in GAMS software and solved via CPLEX solver [79].

6.3.2. SNOPT Solver

SNOPT is another software package of GAMS which is capable of solving nonlinear optimization problems [45]. The EMS mathematical formulation in [28] is a nonlinear programming problem, and has been solved by GAMS SNOPT solver.

6.3.3. Gurobi Optimizer

Gurobi optimizer is used to solve MILP problems [89]. In [78], the EMS problem is formulated as a MILP problem and has been solved using Gurobi optimizer. Tenfen and Finardi [38] have employed the same solver for computational purposes.

7. Microgrid Test Systems

For the sake of evaluating the performance of the aforementioned EMS algorithms, they have been applied on the majority of microgrids. There are some efforts to sum up the studied microgrid test systems in the area of EMS in the literature [20]. Reference [90] has proposed the classification of microgrids based on their topologies. A review of existing real-world microgrid test systems worldwide is presented in [20,91]. Evaluation of microgrids which are applied in real-life as well as laboratory test systems are surveyed in [92]. Nonetheless, in this section we will solely focus on the test systems which are exploited in EMS studies. Table 4 has classified these test systems from various panoramas including single-microgrid, multi-microgrid, islanded and grid-connected systems.

Table 4. Review of understudying microgrid test systems.

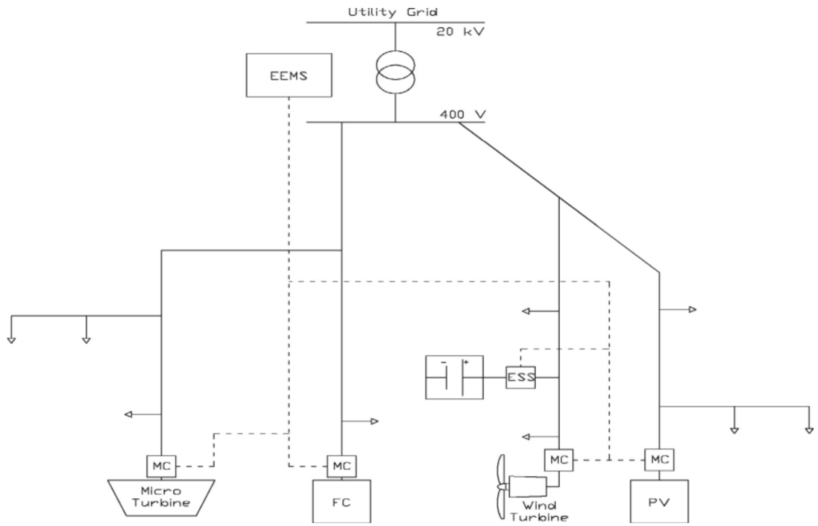
<table>
<tr><th></th><th></th><th colspan="2">Microgrid Mode</th><th colspan="3">Energy Source</th><th></th></tr>
<tr><th></th><th>Ref</th><th>Islanded</th><th>Grid-connected</th><th>Type</th><th>Min power (kW)</th><th>Max power (kW)</th><th>Schematic Diagram of Microgrid</th></tr>
<tr><td rowspan="6">Single Microgrid</td><td rowspan="6">[24]</td><td rowspan="6"></td><td rowspan="6">✓</td><td>WT</td><td>0</td><td>20</td><td rowspan="6">
</td></tr>
<tr><td>PV</td><td>0</td><td>25</td></tr>
<tr><td>MT</td><td>6</td><td>30</td></tr>
<tr><td>FC</td><td>3</td><td>30</td></tr>
<tr><td>ESS</td><td>−30</td><td>30</td></tr>
<tr><td>Grid</td><td>−90</td><td>90</td></tr>
</table>

Table 4. *Cont.*

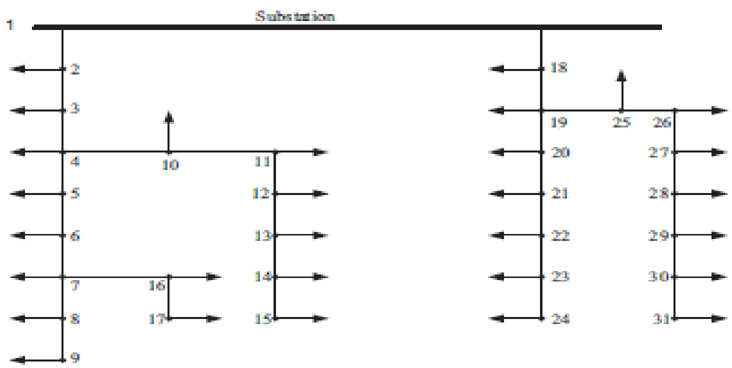
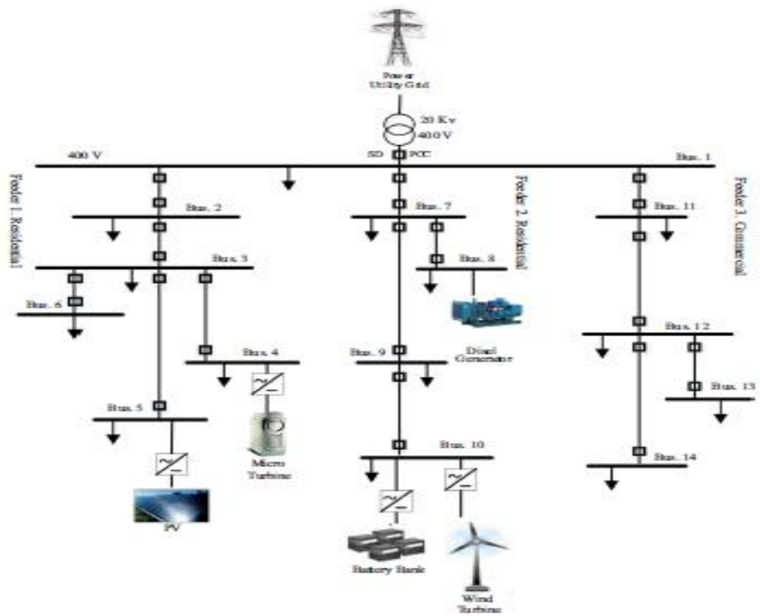
[28]	✓	WT PV Biomass Battery	0 0 0 −4500	250 250 1100 6500	
[26]	✓	WT PV MT DiG Battery	0 0 12.74 11.11 30	250 200 75 60 90	

Table 4. *Cont.*

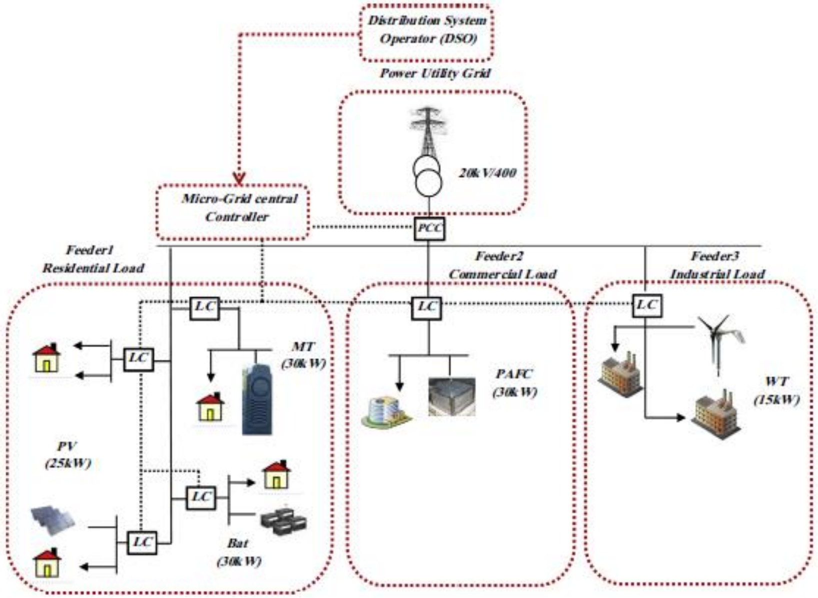
Ref.	Microgrid Mode: Islanded	Microgrid Mode: Grid-connected	Energy Source: Type	Energy Source: Min power (kW)	Energy Source: Max power (kW)	Schematic Diagram of Microgrid
[35]		✓	WT PV MT FC Battery Grid	0 0 6 3 −30 −30	15 25 30 30 30 30	

Table 4. *Cont.*

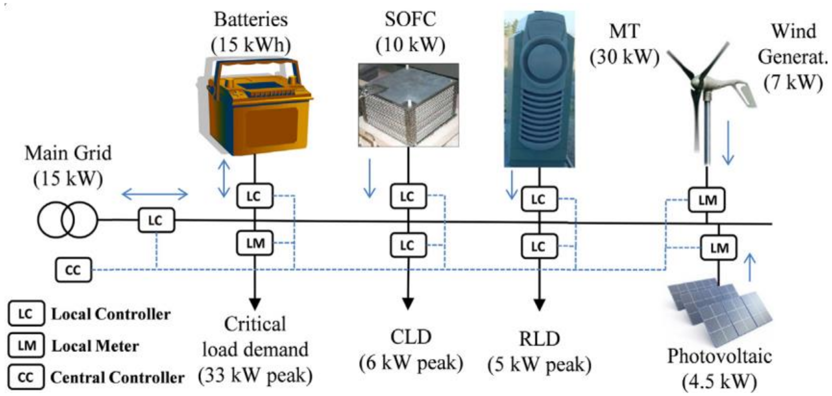
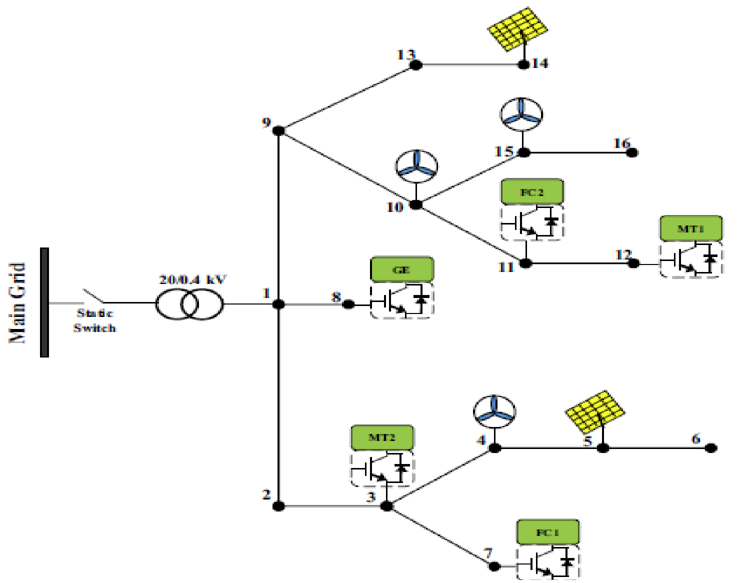
[38]		✓	WT PV MT FC Battery Grid	0 0 6 7 3 −15	7 4.5 30 10 15 15	
[39]	✓		WT PV MT FC GE	0 0 25 20 35	80 70 150 100 200	

Table 4. *Cont.*

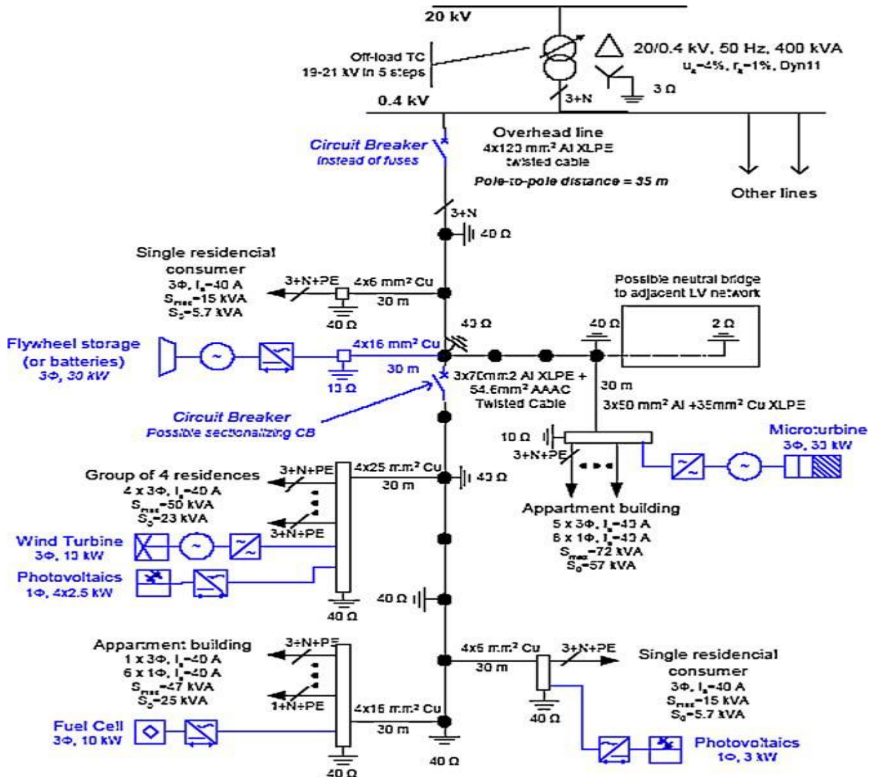
[40]	✓	WT PV MT FC DiG EV	0 0 6 3 2 0	15 30 30 30 50 1.5	

Table 4. *Cont.*

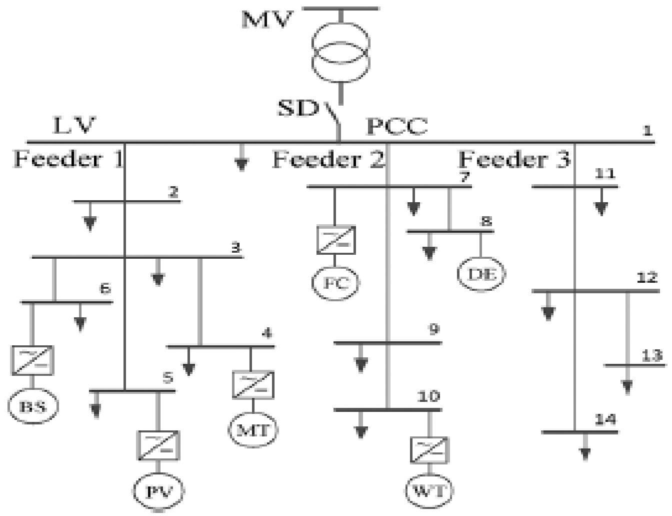
Ref.	Microgrid Mode: Islanded	Microgrid Mode: Grid-connected	Energy Source: Type	Energy Source: Min power (kW)	Energy Source: Max power (kW)	Schematic Diagram of Microgrid
[93]	✓	✓	WT PV MT DiG FC Battery	0 0 12.74 11.11 14 30	250 200 75 60 80 90	

Table 4. *Cont.*

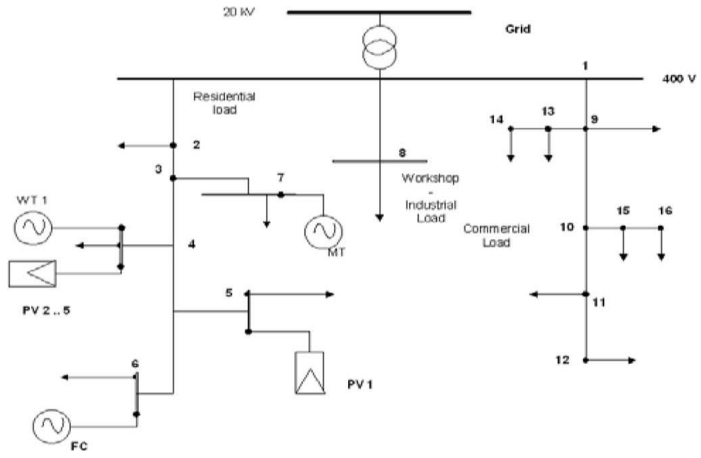
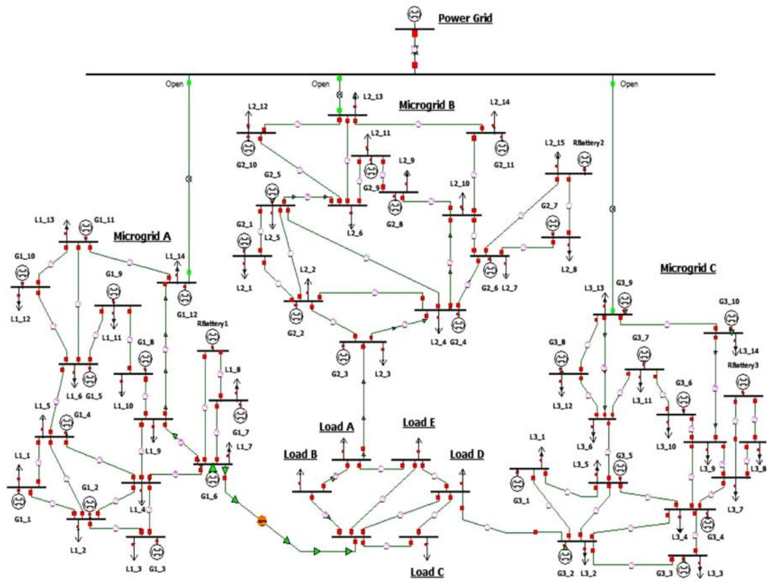
	[94]	✓		WT PV FC MT	0 0 3 6	15 2.5 30 30	
Multi-Microgrids	[29]	✓	A B C	Thermal PV WT Battery	10 0 0 0	45 360 140 500	

Table 4. *Cont.*

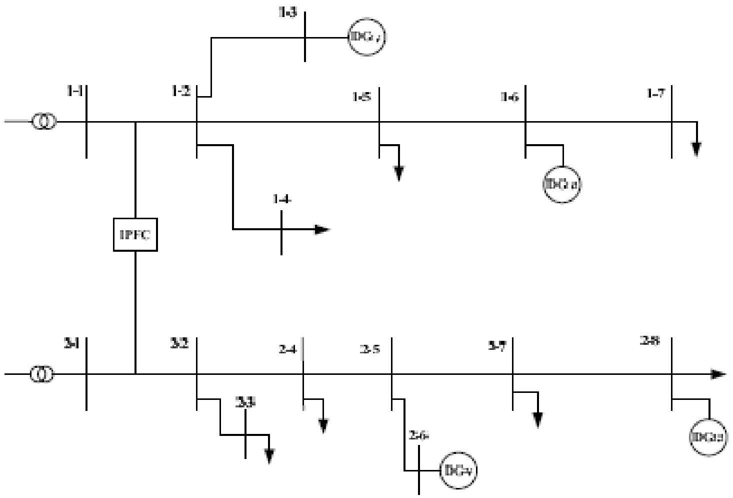
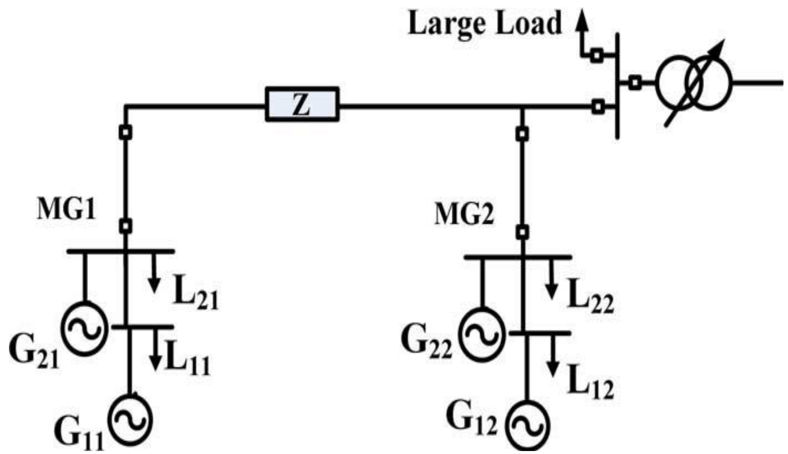
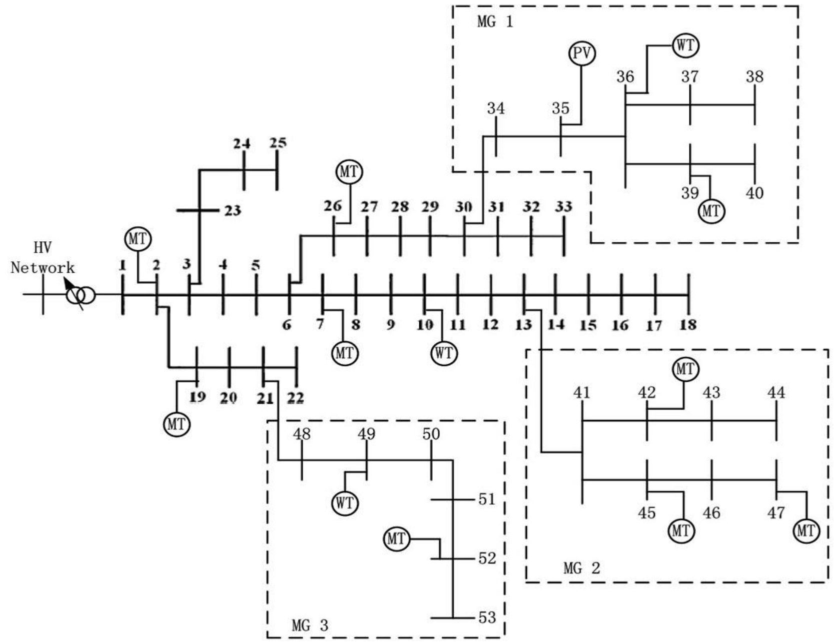
<table>
<tr><td rowspan="2">[95]</td><td rowspan="2">✓</td><td>1</td><td>$DG_{1,1}$
$DG_{1,2}$</td><td>0
0</td><td>5000
4000</td><td rowspan="2"></td></tr>
<tr><td>2</td><td>$DG_{2,1}$
$DG_{2,2}$</td><td>0
0</td><td>7000
6000</td></tr>
<tr><td rowspan="2">[96]</td><td rowspan="2">✓</td><td>1</td><td>$G_{1,1}$
$G_{2,1}$</td><td>0
0</td><td>100
100</td><td rowspan="2"></td></tr>
<tr><td>2</td><td>$G_{1,2}$
$G_{2,2}$</td><td>0
0</td><td>100
100</td></tr>
</table>

Table 4. *Cont.*

[97]	✓	1	WT	0	60	
			PV	0	60	
			MT	0	70	
		2	MT	0	30	
		3	WT	0	50	
			MT	0	60	
		DS	WT	0	30	
			MT	0	20	
			Grid	−260	260	

8. EMS Simulation Scenarios

The aforementioned EMS approaches are implemented on typical microgrid test systems in order to optimize the corresponding objective functions while considering various constraints in a 24-h time interval. Table 5 briefly summarizes the obtained simulation scenarios of reviewed papers to help researchers in directing their research efficiently. According to the first row of Table 5, three scenarios are considered in the results and simulation section of [24]. In the first scenario, all components of microgrid are operating within their limits and limited trade is available with the main grid. However, during the second scenario, WT operates at its maximum capacity while the third scenario studies effect of unlimited power exchange between microgrid and the upper utility. Same as the first row, remain rows of Table 5 explain the number and explanation corresponding to the simulation scenario of each reference.

Table 5. Scenarios of EMS optimization problem results.

Ref	Scenario Number	Details
[24]	1	All units operate within their limits and microgrid has limited trades with upper utility.
	2	WT operates at its maximum capacity while the rest are same as scenario 1.
	3	Unlimited energy is exchanged between microgrid and upper utility.
[28]	1	Microgrid losses are compared in islanded and grid-connected mode.
	2	The cost of energy for grid-connected and islanded microgrid are compared.
[18]	1	Normal operation.
	2	Sudden load increasing.
	3	Plug and play ability.
[26]	1	Microgrid supplies whole demand from utility grid while DGs and ESSs are neglected.
	2	DGs and ESSs have added to the microgrid while uncertain parameters are deterministic.
	3	Generated power of WT and PV are probabilistic while the load is deterministic.
	4	All of the uncertain parameters are probabilistic.
[27]	1,2	Microgrid can absorb power from utility grid in absence of ESS while the capacity of DG sources are fixed and variable.
	3,4	Microgrid can absorb power from utility grid in presence of ESS while the capacity of DG sources are fixed and variable.
	5,6	Microgrid exchanges power by utility grid in absence of ESS while the capacity of DG sources are fixed and variable.
	7,8	Microgrid exchanges power by utility grid in presence of ESS while the capacity of DG sources are fixed and variable.
[35]	1,2	Operating cost is minimized without and with DR program.
	3,4	Pollutant emission is minimized without and with DR program.
	5,6	Operating cost and pollutant emission are minimized simultaneously, without and with DR program.
[38]	1	The base case with the existing data.
	2	Extreme case by multiplying load demands by 2.
	3	Extreme case by multiplying PV and WT generation by 4 and 5.
	4	Base case along with classical modeling of MT and FC.
[39]	1	Microgrid EMS without DR.
	2	Microgrid EMS with DR.
[40]	1	Microgrid EMS without DR and EV.
	2	Microgrid EMS with DR but without EV.
	3	Microgrid EMS with DR and EV.
[41]	1	Base case without ESS and DR to focus on the generation and load uncertainty.
	2	Addition of ESS to scenario 1.
	3	Addition of DR to scenario 1.
	4	Addition of ESS and DR to scenario 1.
[43]	1	35% of peak load proportional to each hour is considered as deterministic reserve.
	2	Stochastic management of microgrid is performed without DR.
	3	DR is added to scenario 2.

9. Conclusions

This review paper has summarized energy management approaches for microgrids from a new perspective and classified it into four categories, namely non-renewable, ESS, DSM and hybrid- based EMS. This paper also provides a compendium on the modeling uncertainties associated with microgrid EMS, objective functions and constraints of microgrid formulation as well as many tools and techniques for solving this optimization problem. It is worth mentioning that considering various objective functions along with different technical and economic constraints has a large effect on the obtained EMS results. A brief review of test systems including single-microgrid and multi-microgrids is also described in this paper. A number of EMS simulation scenarios has been included while each one is an implemented simulation state. Furthermore, this work will help in identifying poorly researched areas in microgrid EMS for further investigation.

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Abbreviations

DG	Distributed Generation	ANN	Artificial Neural Network
ESS	Energy Storage System	FNN	Fuzzy Neural Network
EMS	Energy Management System	SVR	Support Vector Regression
DR	Demand Response	PDF	Probability Distribution Function
WT	Wind Turbine	PEM	Point Estimate Method
PV	Photo-Voltaic	MF	Membership Function
FC	Fuel Cell	IGDT	Information Gap Decision Theory
MT	Micro Turbine	MRCGA	Matrix Real-coded Genetic Algorithm
GE	Gas Engine	MAS	Multi-agent System
DiG	Diesel Generator	MILP	Mixed Integer Linear Programing
DSM	Demand-side Management	GARCH	Generalized Auto-regressive Conditional Heteroskedasticity
DR	Demand Response	ARIMA	Auto-regressive Integrated Moving Average
MCS	Monte Carlo Simulation	PEM	Point Estimate Method
MGSA	Multi-period Gravitational Search Algorithm	MPSO	Multi-objective Particle Swarm Optimization
MBFO	Multi-objective Bacterial Foraging Optimization	ABCO	Artificial Bee Colony
PSO	Particle Swarm Optimization	DCOP	Distributed Constraint Optimization Problems

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