Energy Management System in Microgrids

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This entry gives a brief introduction to microgrids, their operations, and further, a review of different energy management approaches. In a microgrid control strategy, an energy management system (EMS) is the key component to maintain the balance between energy resources (CG, DG, ESS, and EVs) and loads available while contributing the profit to utility. This article classifies the methodologies used for EMS based on the structure, control, and technique used.

renewable energy sources | microgrid | energy management system | communication technologies | microgrid standards

1. Introduction

Over the last few decades, with an increasing population, the world has gone through an exponential consumption of energy which has led to the depletion of conventional resources like coal, crude oil, and natural gas. The exploitation of these resources has a severe impact on the environment with an increase in greenhouse gases [1][2]. To mitigate these effects, a policy has been adopted by different countries to introduce non-conventional/renewable sources to support the fields of electrification and transportation. In electrification, the existing power grid uses conventional sources for generation and lacks power quality. The poor power quality of supply leads to load shedding and blackouts, thereby interrupting the day-to-day activities of the consumers. The conventional grid uses one-third of the total generation fuel to convert into electricity and, with an eight percent loss in transmission lines of the generated electricity, is used to meet the peak demand that also has a five percent probability of occurring, with reduced reliability [3]. Conventional generation does not utilize the heat produced by itself for any application. These drawbacks of the conventional grid could be compensated with penetration of renewable sources at local areas or distributed generation (DG) there by reducing the transmission losses and maximum utilization of the output including heat generated [4][5][6]. Integration of dispatchable energy sources like wind and PV introduces the problem of intermittent power generation as they generally depend on climatic and meteorological conditions. A hybrid energy system consisting of storage elements and renewable energy sources is used for the continuous supply of power. The future power grid needs to be intelligent to maintain a reliable supply of economical and sustainable power for consumers [7][8][9][10]. To overcome the existing challenges in the grid, a smart grid needs to be adopted which controls the complex process of power exchange and plans as well for the growing energy demand. The future grid requires the support of communication technologies and local microgrids (MG) for efficient control of the system. The integration of renewable energy resources at the load side requires a two-way flow of power and data with the capability of adapting to management applications that can leverage the technology [11].

During a fault condition, the local microgrid isolates itself from the main grid, creating a standalone/islanding mode of supply to the consumers [12][13]. This feature is known as plug and play, which allows the local generation to meet the demand by balancing the energy available. The microgrid consists of a microgrid control center (MGCC) and local controllers (LCs) to balance the energy demand. The microgrid takes the inputs from forecasted parameters (weather, generation, and market prices) to meet the uncertain load demand and also participates in the energy market. The MGCC is supported by communication technologies and equipped with processing algorithms to overcome the challenges in the generation–demand balance [14][15][16][17]. The energy management in microgrids controls the power supply of storage elements, demand response, and local controllers/local generation sources. **Figure 1** shows a typical structure of a microgrid.

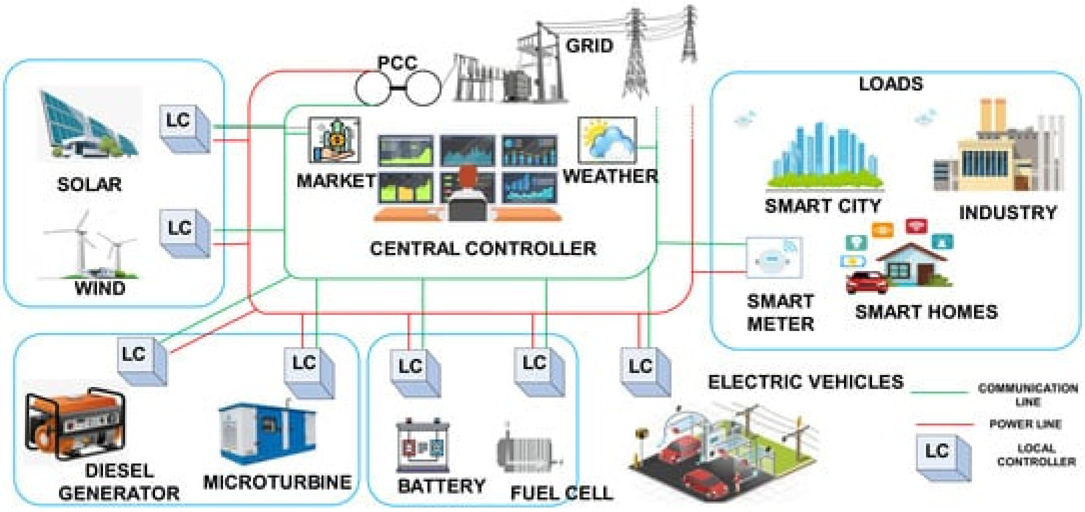

Figure 1. Structure of a typical microgrid.

The contributions of this paper are shown as below: This paper provides a brief introduction about the architecture of microgrids, different classifications in microgrids, components of a microgrid, communication technologies used, standards available for the implementation, and auxiliary services required. This paper provides a review of the recent analysis of the different energy management strategies consisting of classical, heuristic, and intelligent algorithms. The article analyzes each approach and its applications in that methodology. The paper addressed applications in energy management which include forecasting, demand response, data handling, and the control structure. This article provides insight on areas in which the scope of research and their contribution to energy management is in the nascent stage.

The energy management strategies proposed for the microgrid in the paper are structured into six sections. Section 1 is the introduction to microgrids and energy management. Section 2 provides a brief overview of microgrid elements, architecture, classification, and communication. Section 3 gives an overview of different control structures in energy management. Section 4 provides reviews on different numerical algorithms used in energy management strategies in microgrids based on the classification, control, and methods of approach. Remarks on each paper for different controls of the EMS application are given. Section 5 discusses the support infrastructure of microgrids for their efficient operation. Section 6 provides the conclusion of the paper.

2. Overview of Microgrid

A microgrid is a small or medium distribution system comprised of smart infrastructure capable of maintaining equilibrium in demand–supply while providing security, autonomy, reliability, and resilience. Sourced distributed generations (DGs) like photovoltaics (PV), wind turbines (WT), microturbine (MT), fuel cells (FC), and energy storage units (ESU) are expected to deliver electricity without interference from the main grid. This high penetration of DGs can cause challenges in the performance of power system stability in large areas. To minimize the risks, the concept of microgrids is proposed [18][19]. A microgrid is a small-scale low- or medium-level voltage distribution system consisting of distributed energy resources (DERs), intermittent storage, communication, protection, and control units that operate in coordination with each other to supply reliable electricity to end-users [20].

Conventional generation (CG), such as coal-based thermal power plants, hydro power plants, wind-generation farms, and large-scale solar and nuclear power plants, are centralized to supply electricity for long distances. A decentralized generation is energy generated by the end-users by using small-scale energy resources [21][22]. Local generation when compared with the conventional power system reduces the transmission losses and the cost associated with it. The generation could be from 1 kW to a few 100 MW; the generation units are mostly used to support the peak load of the demand. Distributed generation sources consist of both renewable and non-renewable sources, i.e., wind generators, PV panels, small hydro power plants, and diesel generators [23]. Combined heat and power (CHP) is where heating is added along with electricity in the application. The sources that are being used in CHP systems are Stirling engines, internal combustion engines, and micro-turbines (MT) using biogas, hydrogen, and natural gas [24]. CHP technology stores excess allowing optimum performance, thereby attaining efficiency of more than 80%, to that of about 35% for centralized power plants [25]. **Table 1** shows characteristics of distributed generation sources.

Table 1. Characteristics of distributed generation sources.

Characteristics	Solar	Wind	Micro-Hydro	Diesel	CHP
Availability	Location-Based	Location-Based	Location-Based	Anywhere	Source-Based
Output	DC	AC	AC	AC	AC
Carbon emission	Nil	Nil	Nil	High	Source-Based
Interface	Converter	Converter + IG/SG	IG/SG	Generator	Generator
Flow control	MPPT/DC Voltage	MPPT/Torque and Pitch	Controllable	Controllable	AVR and Governor

Energy storage is a device that is capable of converting the electrical energy to a storable form and converting it back to electricity when it is needed. Based on the form of stored energy, there are four main categories for energy storage technologies: mechanical energy storage (MES), thermal energy storage (TES), chemical energy storage

(CES), and electrical energy storage (EES). The key components for the working of MG EMS are the energy storage units, which regulate the supply–demand balance during the operation of DGs. In [26][27][28], a conclusion is drawn that a system with several micro sources is modeled to support an island mode where storage systems are needed to maintain the balance of the intermittent sources. The energy storage devices that are included in microgrid systems that provide continuous power supply are batteries, flywheels, and supercapacitors [29]. In terms of the current economy, batteries are less expensive and have a high negative environmental effect compared to other storage devices. Storage in fuel cells is also another option that converts the fuel into electricity through a chemical process. These fuel cells require oxygen and hydrogen for continuous supply without discharge. A variety of fuels available for the fuel cell are propane, natural gas, anaerobic digester gas, methanol, and diesel hydrogen [30], while hydrogen has become prominent in recent years for its clean and safe operation. **Table 2** shows commonly used energy storage and their characteristics.

Table 2. Different energy storage systems in microgrids.

Characteristics	Charge/Discharge Rate (MW)	Discharge Duration	Response Time	Energy Density (Wh/kg)	Power Density (W/kg)	Environmental Impact	Service (Years)	Efficiency (%)
Battery	0–40	msec–hours	msec	10–250	70–300	High	5	70–90
Flywheel	0.001–0.005	msec–1 h	msec	0.005–5	500–10,000	Low	20	75–95
Supercapacitor	0.002–0.25	msec–15 min	instantaneous	5–130	400–1500	Low	>10	90–95
Fuel Cell	0.001–50	sec-day+	m sec	800–10,000	500–1000	Moderate	>15	20–90
CES	0.1–300	Hour–day+	min	3–60	-	Low	15	40–90
SMES	0.1–10	msec–10 sec	instantaneous	0.5–5	500–2000	Low	10	>95
Pumped storage	0.1–5000	Hour–day+	Sec–min	0.5–1.5	-	Low	25	>85

Loads can be categorized as residential, commercial, industrial, and others (agriculture and public offices) from the statistical data of feeder consumption in the distribution system. Measurement-based and component-based approaches are considered for load model identification [31]. The measurement-based approach needs the measured data from the smart meters or measuring devices which derives into load model structure. The capturing of data for load characteristics needs to be composed of different environmental conditions. The data obtained from the smart devices are used to form the load model structure as static, ZIP (constant impedance-resistive components or heating, constant current-street lighting, and constant power motors), and exponential [32][33]. Then, the structure is estimated and validated with field measurements by correcting the errors using intelligent detection techniques (artificial intelligence and pattern detection). The component-based approach aggregates the load model by combining the load consumption of individual components, acquired by the information or rating of each load in the load composition. This approach needs three different datasets: (i) individual component load model, (ii) percentage of each component's load consumption, and (iii) share of the load contribution from each load class—residential, commercial, and industrial. The individual component model parameters are obtained from experiments [34][35][36][37]. **Figure 2** has shown different loads classification is based on identification and control.

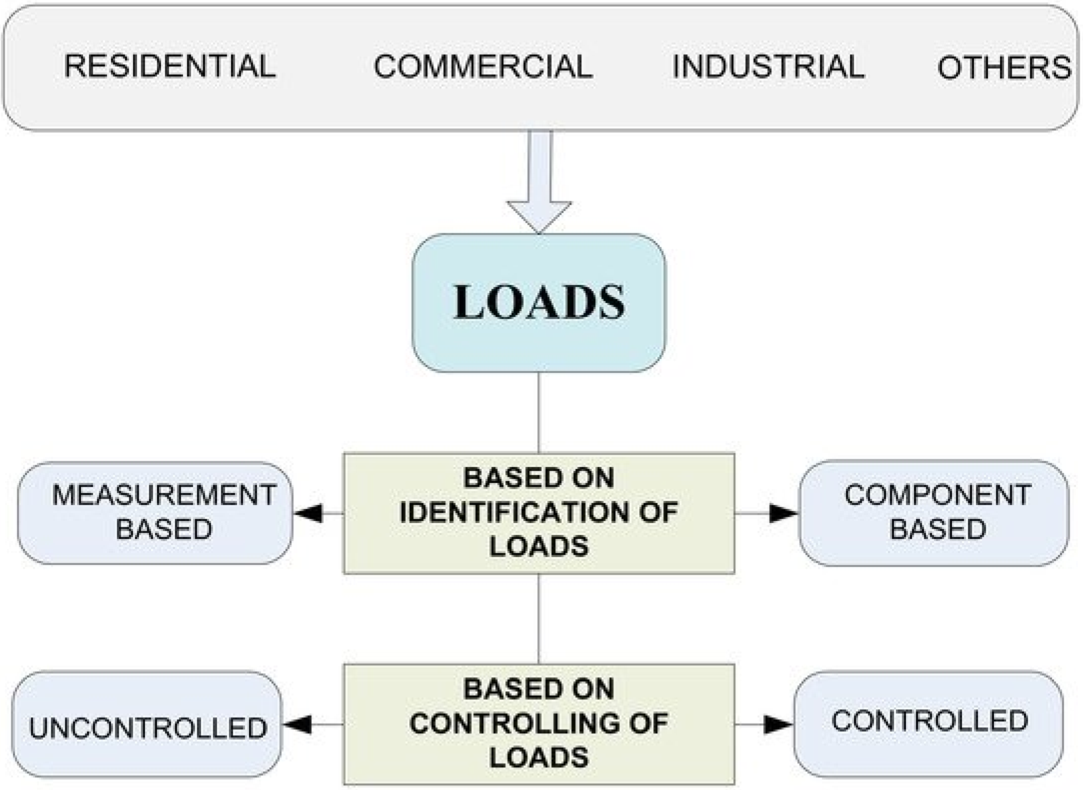

Figure 2. Loads classification is based on identification and control.

3. Energy Management System Control Structure

According to the International Electro-Technical Commission (IEC) standard application program about power systems, IEC-61,970 defines an energy management system 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 to assure adequate security of energy supply at minimum cost" [38].

Energy management in microgrids is a complex automated system that is aimed at optimal scheduling of available resources (CG, DGs, ESS) to meet the day-to-day demand while considering the meteorological data and market price. There are three control approaches in energy management of the microgrid which are: (i) centralized, (ii) decentralized, and (iii) distributed.

With an increase in the geographical area, the system control in centralized mode becomes difficult due to the delay or lag in the communication, which leads to delay control. This process is not feasible as well as not economical; hence, we choose the decentralized mode of control. In decentralized control, each unit has its own local controller that works in an autonomous state where it receives the voltage and frequency data [39]. Here, the decentralized control does not provide the all the information to the other local controllers, but rather exchanges the global information to make the decisions of the overall system. The exchange of information is allowed in a few controllers to take action spontaneously in a state of emergency. A third approach, obtained with a combination of the above two control approaches, is the distributed control [40]. This mode of control scheme provides control to both centralized as well to decentralized property up to a certain degree of control. In this control scheme, each local controller unit uses the local information like voltage and frequency from the neighbors, which helps to obtain a global solution by the central controller while using the two-way communication link by the local controllers. Characteristics of different types of controls in the energy management system are presented in **Table 3** .

Table 3. Characteristics of different types of controls in the energy management system.

	Centralized	Decentralized	Distributed
Information Accessed	Micrografids pass information to the central controller	Independent control is provided with data from the other local controllers	Interoperability and data exchange between every device
Communication Information	Synchronized information from the device to the central controller	Information among local controllers is asynchronized	Communication is both locally and globally asynchronized
Function in real-time	Complex	Acceptable	Easy
Feature of Plug and play	The central controller needs to be instructed	Can be accessed by central controller	Available by the peers
Expenditure	More	Less	Less
Structure of Grid	Centrally controlled	Locally controlled	Both centrally and locally controlled
Tolerance during fault	Less tolerance capability	One router fault—tolerated N router fault—expensive	N router fault—tolerated, Possible self-healing feature
Infrastructure	Needs suggestion integrating DERs	Integration is modular and possible	No change while integration
Size (Number of nodes)	Less	IPv4-2^{12} IPv6-2^{128}	>2^{128}
Final Nodes	No identification	Unique identification IP	Global unique identifier

	Centralized	Decentralized	Distributed
Operation Flexibility	Very less	Available	Very much needed
Bandwidth & Latencies	Low and high	Both are great	High and low
QoS	Not allowed	Allowed	Inherent
Connectivity	EPA (Physical)	TCP/IP (Physical)	TCP/IP (Virtual)
Safety measures	Less	Available	High
Individuality	No	No	Possible

Load balance acts as a constraint between generation and demand. Load demand balance problems can be categorized in two ways: the supply-side and the demand-side [41]. Supply-side balance can be obtained by using the hierarchical control scheme for the economic scheduling for consumption by the end-users. Load control can be categorized as: (i) controllable loads, which are the loads that are managed according to the price, and (ii) shiftable loads, also known as deferrable loads, such as charging of electric vehicles, washing machines, dryers, which can provide scheduling flexibility for demand response.

4. Numerical Methodologies of EMS

Different EMS techniques are differentiated according to the numerical methods used for controlling the energy management system. These methods are broadly classified into three categories: (i) classical methods, (ii) metaheuristic methods, and (iii) intelligent methods.

Classical methods are the mathematical programming or classical programming methods that choose certain variables to maximize or minimize a given function subject to a given set of constraints. Branch and bound are the classic components that are used for solving the classical method approach to find the optimal solution in an iterative process without integer constraints. Classical methods use both linear and nonlinear optimization models to solve the problem. The classical methods are divided into certainty- and uncertainty-constrained problems.

An optimal solution can be found in the distinct search space as used in combinatorial optimization. Metaheuristic method is an iterative method that is unlikely to guarantee a global optimum solution due to its convergence properties. This can be compensated with finding the mean of the solutions; the use of Monte Carlo simulation improves the convergence of the solution. Stochastic implementation of optimization is dependent on the random variables created [42]. The metaheuristic approach works on two concepts, namely intensification and diversification. Intensification is searching a local area to find an optimal solution when we know that solution could be found in the prescribed region. The diversification process is searching the space on a global scale with no limits in the search pattern using the randomly generated variables, while randomization increases the diversity of solution when the search space exceeds the local optima. To find the global optimal or the best solution, both the intensification and diversification processes need to be in proper balance, which increases the rate of convergence in the algorithm [43][44][45][46][47]. A few metaheuristic algorithms are particle swarm optimization (PSO), genetic algorithm (GA), modified PSO (MOPSO), non-dominated sorting genetic algorithm II (NSGA-II), enhanced velocity differential evolutionary PSO (EVDEPSO), priority PSO, multi-voxel pattern analysis (MVPA), grey wolf optimization (GWO), artificial bee colony (ABC), adaptive differential evaluation (ADE), crow search algorithm (CSA), rule-based bat optimization (BO), gravitational search algorithm (GSA), alternating direction method of multipliers (ADMM) using modified firefly algorithm (MFA), teaching–learning optimization (TLA), social spider algorithm (SSO), and whale optimization algorithm (WOA). **Table 4** provides a critical review of the metaheuristic methods used in EMS.

Table 4. A review of metaheuristic methods used in EMS.

Ref No	Method	Power Sources	Ev	Dr	Grid/Island	Ems	Remarks
[48]	NSGA-II	PV, WT, BT			G/I	C	A multi-objective optimization problem is proposed to maximize the economy. Intelligent power marketing is adapted to improve the economic dispatch of the microgrid.
[49]	NSGA-II	PV, WT, BT	*		G/I	C	This paper establishes an integral objective function considering the demand response and user satisfaction constraints, which has an effect on the economy and operation of the system with the DR strategy.
[50]	PSO	PV, MT, BT, TES			G/I	C	An optimal energy planning is proposed for the recently modeled energy hub. An efficient microgrid structure is discussed along with technical and economic prospects with optimization.
[51]	CVCPSO	PV, WT, DE	*		G/I	C	Minimizing the operating costs while maximizing the utility benefit using the CVCPSO algorithm, which yielded the Pareto-optimal set for each objective, and the fuzzy-clustering technique was adopted to find the best compromise solution.
[52]	MPVA	PV, WT, MT, BT			G/I	C	A sports metaheuristic algorithm to minimize the overall running cost of MG while studying four different MG scenarios.
[53]	GWO	PV, WT			G/I	C	A sine cosine optimizer is used to optimally participate in the trading of energy, i.e., selling or buying the power while bringing the capital cost of the microgrid.
[54]	ABC	PV, WT, DE, BT, FC	*		G/I	C	An EMS application of the V2G economic dispatch problem is optimized in the MG while converting

Ref No	Method	Power Sources	Ev	Dr	Grid/Island	Ems	Remarks
							the multi-objective problem to a single objective using the judgment matrix methodology.
[55]	EBC	PV, WT, MT, BT			G/I	C	Different TOUs are evaluated to minimize MG operational costs and to analyze the efficiency of a typical distribution system, considering all relevant technical constraints.
[56]	ADE	DG, BT			G	C	An ADE-based optimization is proposed for the DC microgrid modeling the active power sources under real-time pricing to minimize the total operating cost.
[57]	MOPSO	PV, MT, BT, TES		*	G/I	C	EMS application is proposed to reduce the carbon dioxide emissions and payback period of the microgrid structure.
[58]	EVDEPSO	PV, BT	*	*	G/I	C	A day-ahead planning schedule is determined to improve the energy market trading while managing the resources available. Includes the electric vehicles participating in the energy market, G2V and V2G.
[59]	Rule base BO	PV, WT, MT, FC, BT		*	G	C	A bat algorithm is used to optimize the MG operation by forecasting the load power and uncertainties in RES using probabilistic methods. The weight factors are taken for tuning.
[60]	CSA	PV, FC, DE, HY		*	G/I	C	The Pareto front is considered to investigate the operating cost, solar power uncertainty, carbon emission, and the cost of the parameters. Hydrogen fuel is considered in reducing operating costs.
[61]	GSA	PV, WT, BT	*	*	G/I	C	Optimization of the overall cost considering the carbon emission and weekly generation scheduling for the small dispatchable systems.
[62]	ADMM-MFA	PV, WT, MT, FC, BT		*	G/I	C	EMS is modeled for the MG to optimize the electricity price by considering the load profile, PV irradiance, and market prices with certain constraints.
[63]	TLA	PV, WT, MT, FC	*	*	G/I	C	Hybrid MG reducing the operating cost considering thermal power recovery and hydrogen generation; V2G technology helps to convert the PEVs into active storage.
[64]	SSO	PV, WT, DE, FC		*	I	C	Optimal sizing of the renewable energy sources with conventional sources to minimize the cost of

Ref No	Method	Power Sources	Ev	Dr	Grid/Island	Ems	Remarks
							energy (COE) and power loss supply probability while analyzing the reliability.
[65]	WOA	PV, WT, DE, BT		*	I	C	EMS is proposed to optimize the load demand of the MG by minimizing the operating cost with improved reliability of the power.

PV—Photo voltaic; WT—Wind Turbine; MT—Micro Turbine; TES—Thermal energy storage; DE—Diesel; FC—Fuel Cell; HY—Hydro; C—Centralized, DC—Decentralized, DT—Distributed, *—Availability.

Neuro-fuzzy is a combination of fuzzy approach and neural network, where fuzzy inference system (FIS) is adjusted by the data provided to NN learning rules. Improved speed, accuracy, and strong learning skills along with simple execution are the advantages of this approach [66].

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