Energy Management of Microgrids for Smart Cities: A Review

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Abstract: Electric power reliability is one of the most important factors in the social and economic evolution of a smart city, whereas the key factors to make a city smart are smart energy sources and intelligent electricity networks. The development of cost-effective microgrids with the added functionality of energy storage and backup generation plans has resulted from the combined impact of high energy demands from consumers and environmental concerns, which push for minimizing the energy imbalance, reducing energy losses and CO2 emissions, and improving the overall security and reliability of a power system. It is now possible to tackle the problem of growing consumer load by utilizing the recent developments in modern types of renewable energy resources (RES) and current technology. These energy alternatives do not emit greenhouse gases (GHG) like fossil fuels do, and so help to mitigate climate change. They also have in socioeconomic advantages due to long-term sustainability. Variability and intermittency are the main drawbacks of renewable energy resources (RES), which affect the consistency of electric supply. Thus, utilizing multiple optimization approaches, the energy management system determines the optimum solution for renewable energy resources (RES) and transfers it to the microgrid. Microgrids maintain the continuity of power delivery, according to the energy management system settings. In a microgrid, an energy management system (EMS) is used to decrease the system's expenses and adverse consequences. As a result, a variety of strategies and approaches are employed in the development of an efficient energy management system. This article is intended to provide a comprehensive overview of a range of technologies and techniques, and their solutions, for managing the drawbacks of renewable energy supplies, such as variability and load fluctuations, while still matching energy demands for their integration in the microgrids of smart cities.

Keywords: microgrids; energy management; smart city; renewable energy sources; photo voltaic; energy storage; energy management system

1. Introduction

The terminology "smart city" refers to more efficient, equitable, and adaptable cities which will be created using socioeconomic, environmental, and technological systems [1]. In terms of power, the essential aspects of a smart city are a reliable electricity supply from renewable energy sources (RES) and the application of energy efficient techniques throughout the system; i.e., at least 80% of the city's structures should be energy efficient. Smartness is defined as the intelligent integration of all infrastructural and socioeconomic activities that pave the way for a brighter future, not simply technologically. We believe that only by intelligent use of human, financial, and technical resources, and in consideration of

environmental, demographic, social, infrastructural, and economic issues, can this ideal future can be realized.

Renewable energy resources (RES) such as wind, biomass, solar, tidal energy, and hydropower are examples of RES that can ameliorate the problem of the increasing greenhouse effect while emitting zero pollutants into the atmosphere [2–5]. RES have the potential to make a major contribution to the mitigation of fossil fuels and global climate change [6]. Renewable energy (RE) should be cost-effective, and come from clean energy source [7] which is also environmentally friendly [8]. In many papers ([9] and the references included there), several scholars explored the common concepts of renewable energy resources (RES), distributed generation (DG), and microgrids. To satisfy the ever-increasing energy demands, power plants are being built near major consumption points. Energy supply is becoming much more competitive, resulting in lower prices [10,11].

In terms of the power paradigm, smart energy and stable electricity networks are some of the most important aspects of smart cities; in fact, electricity grids and information and communication networks are the two technological features that primarily characterize smart cities. Smart energy and power networks are enabling microgrids to be integrated into smart cities, which not only facilitate the integration of renewable energy sources but also enable new energy-related value-added services [12]. A microgrid is defined as a collection of loads, energy storage facilities, and small-scale generating systems [13]. A microgrid is an electrically bound portion of a distribution network that collects locally in order to form a self-sufficient energy system. Distributed generating sources, energy storage devices, and controlled loads must all be integrated to produce a self-sufficient energy system [14,15]. Microgrids may provide a dependable source of electricity in remote regions where the development or expansion of electrical grids is physically and/or economically difficult. Although these systems are unable to make use of the main grid, they serve as valuable test beds for developing suitable control functions capable of maintaining a reliable supply of electricity [16–19]. Hybrid energy systems (HES) are frequently used to provide electrical power for a variety of uses, such as residences or farm land in outlying areas where there is no grid extension [20]. Hybrid energy systems offer high reliability and lower costs as compared to systems that have only one energy source [21].

Microgrids offer real-time energy management. Each has its own communication system that is necessary for managing the energy between generation and demand [22]. Microgrids play a major role in the transition of urban infrastructure into a smart city. Water, transportation, and other infrastructures rely on distribution grids for fundamental services; microgrids, equipped with modern information and communication technology, are grids that are suitable for smart cities. Microgrids operate in one of the two modes: isolation and grid [23,24]. As illustrated in Figure 1, microgrids can be classified by the types of energy source they use, such as renewable, nonrenewable, or hybrid.

Renewable energy resources (RES) such as wind and solar do not produce constant amounts of electricity. As a result, predicting and maintaining the generation from these resources is extremely challenging, which may result in fluctuations in the continuous power supply. The microgrid's reliability and the preservation of the energy supply–demand balance are both important. The latter problem becomes more prevalent in stand-alone mode when there are few sources available to satisfy demand [25–27].
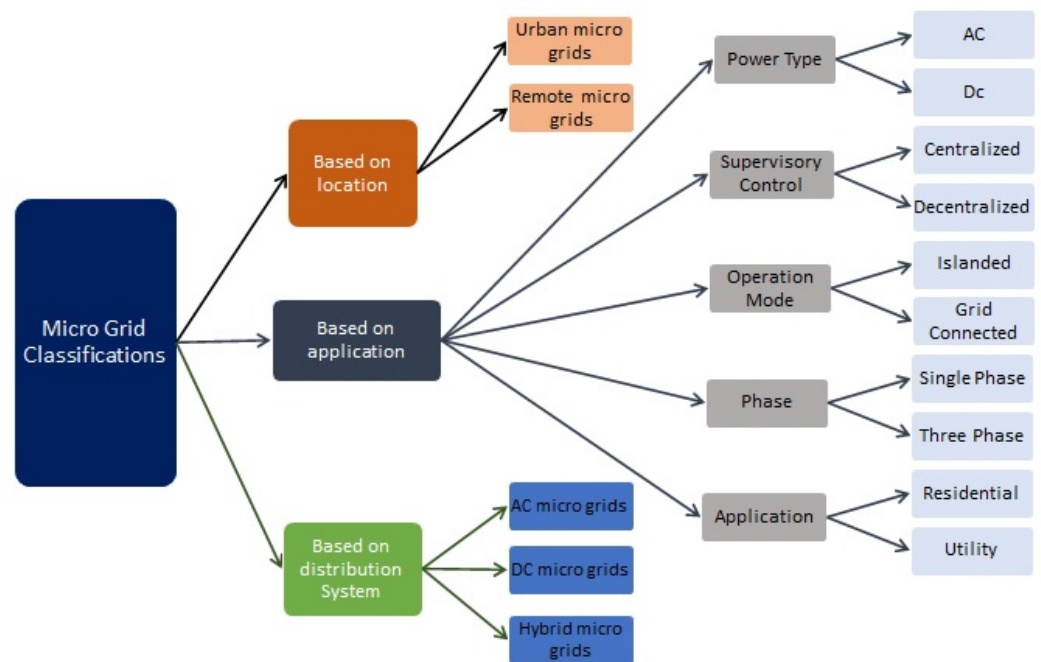
Figure 1. Classification of MGs.

2. Microgrid EMS-Based Network

Microgrids frequently experience trouble with supplying and consuming energy due to the shortcomings of renewable energy sources [28]. To deal with energy management systems, microgrids have their own communication networks (EMS). The energy management system provides optimum solutions to microgrids, which are developed from various mathematical techniques to discover optimal solutions. Using to these approaches, the microgrid can reduce the uncertainty and load varying issues of renewable energy resources [18]. The EMS of a microgrid operates in two modes, centralized and decentralized, ensuring that generation and load are matched [29–31]. Microgrids are also categorized based on their modes of operation, which include power type, supervisory control, phase, and application, as illustrated in Figure 1.

The intelligent communication module in the microgrids EMS uses the best decision making strategies, including human–machine interface modules (HMI), DERs for load forecasting, and a supervisory control and data acquisition module, which delivers the best decision and tries to increase the revenue of the microgrid by using communication network [32–35].

However, while the initial installation costs of renewable energy-based plants are higher than those of conventional plants, the maintenance and operating costs are lower and will continue to fall as technology advances. As the behavior of renewable sources is usually intermittent, it is better to employ several resources when they are accessible. Hybridization of renewable resources enhances the efficiency, reliability, and economics of the power system. These hybrid MGs, as illustrated in Figure 2, can be used as stand-alone units, grid-connected units, or in conjunction with traditional units [36–38].

The intermittent nature of an RES/microgrid is due to the fact that loads are connected to solar and wind energy sources rather than the grid, and these sources have a major influence on loads. When there is a shortage in these sources due to environmental factors, the loads stay connected without any supply. Frequency fluctuations, voltage fluctuations, and harmonic distortion are the primary concerns with power quality. The system will become unstable as a result of voltage fluctuations caused by changes in irradiation levels, which will have a direct impact on the solar and wing-based stand-alone systems' reliability. The same is applicable in the wind example, where variations in wind speed have an impact

on the whole hybrid system. Accurate forecasting and scheduling are necessary to minimize these effects [39–42].
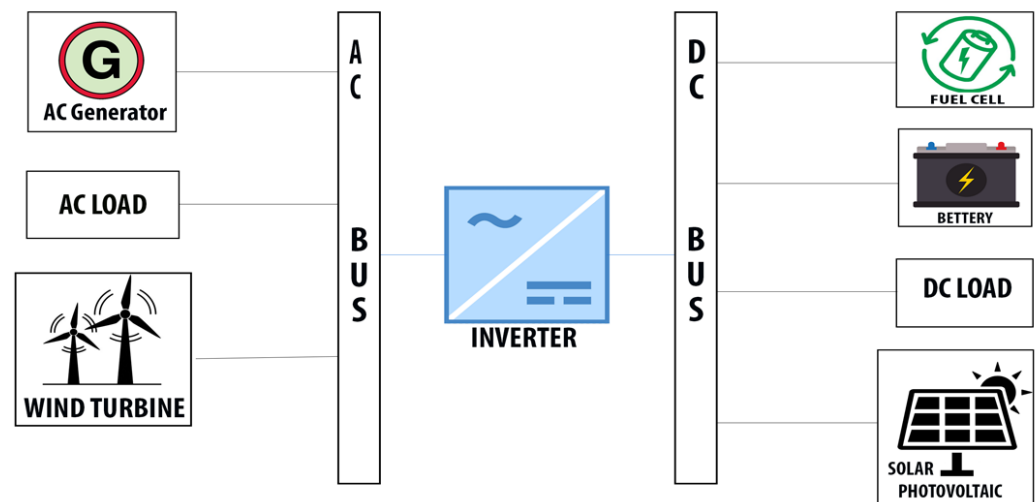

Figure 2. Hybrid microgrid.

Several scholars have addressed these energy management techniques utilizing various solution methodologies in order to accomplish optimal and effective MG operation. The subsections that follow provide a comprehensive critical study of these techniques and solutions.

3. Classical Methods of EMS

3.1. Energy Management by Linear/Non Linear

E. Dursun and O. Kilic [43] investigated the behaviors of three methods on a standalone hybrid system, including PV/wind/PEMFC, where PV and wind were considered primary sources and PEMFC was considered a backup source. The author's main objective in this work was to increase the efficiency of the fuel cell (FC) and provide a continuous power supply in the hybrid system with no fluctuations. The researcher used established power management techniques to assess battery efficiency, taking into account the battery state-of-charge (SOC) and surplus power from the primary source in a Matlab/Simulink control algorithm (wind and PV).

J. Ahmad et al. [44] offered a cost-effective energy management technique based on mixed integer linear programming. Researchers are looking at the influences of hybrid systems on capital and operational expenses. One can reduce load peaks by keeping an eye on this kind of generation's intermittency and instability. The cost function is computed using linear programming, and the size of the microgrid is optimized using HOMER software through simulation. An energetic and economic analysis of three distinct solar assisted heat pump (SAHP) systems using the best operational approach was published in [45]. Three distinct types of SAHPs, and solar collectors and battery sizes, were discussed in this article. The mixed-integer linear programming (MILP) method lowered the heating system's running costs, and numerical analysis was carried out using TRNSYS and Refprop 9.1 software.

Moazeni and J. Khazaei [46] examined the convergence time and reduced the cost function of the water–energy microgrid by using two techniques, mixed-integer nonlinear programming (MINLP) and MILP. MILP was utilized in the first approach to minimize the cost function and achieve optimality in the MINLP formulation. In the second technique, MILP was used to simulate the nonlinear behavior of the cost function using MATLAB software. In [47], three alternative techniques were presented to investigate the performance of a hybrid system that included solar panels (PV) and battery storage devices. TRNSYS software was used for performance testing, and size was determined manually.

HOGA (also known as iHOGA) and HOMER software were used for genetic algorithm optimization, and the state of charge of the battery and the pressure in the hydrogen tank were studied.

M. Nemati, M. Braun [48] introduced two algorithms used for microgrid work scheduling, unit commitment and economic dispatch. The latter is a superior genetic algorithm (GA), and the former is an MILP that was enhanced. This study also introduced a unique technique for dealing with MILP restriction and a new lithium battery aging model. To evaluate the microgrid model and compare it to others in different situations, GA and MILP optimizers were used. In [49], the mix-mode energy management technique (MMEMS) was presented, which optimizes the cost-effectiveness microgrid operation and provides the optimal battery sizing for economic microgrid operation. The author solved economic dispatch problems by using three techniques, on/off mode, continuous mode, power-sharing mode. Linear programming (LP) was used to solve energy management problems such as power-sharing and continuous modes, whereas MILP was used to solve on/off mode (MILP). The size problem of the battery was solved by the particle swarm optimization technique.

Anglani and Braun [50] presented an economically optimized energy management system (OEMs) for a microgrid which minimized the fuel consumption of a remote temporary military base (FOB) featuring diesel generators. The linear programming method was used to optimize the cost-effectiveness of a diesel generator fuel consumption. The suggested semi-continuous optimization model was solved using two approaches. Only one generator was operational in the first approach, and both generators were operational in the second, but only one generator output was used at a time. Moreover, the rain flow method was used to deal with battery sizing and charging/discharging between operational and capital costs.

Helal and Hanna [51] examined the energy management system that deals with the optimal scheduling of a hybrid AC/DC microgrid for remote areas. The energy management problems were formulated by the MINLP and the goal was to keep the daily operating costs as low as possible. All the EMS simulations were done via MATLAB where the optimizer was modeled via the GAMS environment. For hybrid microgrids in remote locations, [52] employed a two-stage stochastic optimization method. The size and uncertainty problems in a hybrid microgrid were solved using LP and MILP optimization. The MILP optimization yielded the most stable system, but the LP model yielded the most cost-effective system. Python was used to implement the optimization algorithms. A summary of recent studies of EMS based linear/nonlinear has been compiled in Table 1.

Table 1. Summary of recent studies of EMS based on linear/nonlinear programming.

Reference	System Configuration	EMS Approach	Remarks
[43]	PV/wind/PEMFC	MILP via MATLAB/Simulink	To improve the fuel cell membrane's efficiency and ensure a continuous energy flow in the hybrid system, three strategies were examined in this paper.
[44]	Hybrid Micro grid	MILP via HOMER	Author Minimized operational cost, and reduce intermittency, instability, and load peaks of the hybrid system.
[45]	SAHP/PV/Thermal (PV/T) collectors	MILP via TRNSYS and Refprop 9.1	The researcher reduces the operational cost of the Heating system, battery sizes, and study SAHP operational strategy.
[46]	Water Energy micro gird	MILP and MINLP via MATLAB	The researcher applied two techniques and analyzed the convergence time, cost function, and nonlinear behavior of the model of a micro grid.
[47]	PV/ battery storage systems	MILP and GA via TRNSYS and HOMER	Three strategies were proposed in this paper to analyze the performance testing and SOC of the battery.

Table 1. *Cont.*

Reference	System Configuration	EMS Approach	Remarks
[48]	Multi cell grid structure/CEMS	MILP and GA via MATLAB	Two algorithms were proposed in this paper for scheduling the unit commitment and economic dispatch of micro grids.
[49]	Grid-tied MG	LP/MILP/PSO via MATLAB	The author analyzed the ON/OFF mode, continuous mode, power-sharing mode of grid-tied micro grid, and optimized the BES system.
[50]	FOB/BESS/PV	MILP/Rain flow method via MATLAB	The author minimized the fuel consumption of diesel generators and analyzed battery charging/discharging between operational and capital costs.
[51]	Hybrid AC/MG	MINLP via MATLAB an GAMS	The author presented a technique to deal with optimal scheduling of hybrid micro grids.
[52]	Isolated hybrid MGs	LP/MILP via python	Two-stage stochastic optimization technique is presented in this paper to solve sizing and uncertainty problems in the hybrid micro grids.

3.2. Energy Management Based on Rule Based and Dynamic Programming

Merabet and Ahmed [53] presented a real-time energy management system of a hybrid microgrid using wind, solar, and battery. An online rule-based optimization technique is introduced to manage the switching operation among battery charging/discharging, off mode of the PV system, and load shedding. In a laboratory based hybrid microgrid experiment, power converters and control algorithms provide efficient and stable operation of EM between different sources in microgrids. Testing and control of microgrids are performed in MATLAB/Simulink, and real-time monitoring is performed by integration with RT-LAB.

M. Jafari and Z. Malekjamshidi [54] provided an economic strategy for an energy management system that incorporates a set of PV panels, a fuel cell panel, and a battery in both grid-connected and off-grid modes of a hybrid microgrid. Dynamic programming (DP) deals with the off-line optimization, and real-time monitoring is done by the rule-based controller, which ensures the optimal control of power flow. MATLAB's graphical user interface was used to keep track of and record data from the proposed energy management system in both scenarios, sunny and cloudy PV generation. While [55] offered optimal distributed generation scheduling to accomplish economic and environmental output, and ensure power security and stability in microgrids. In this study, two primary objectives were considered: economic and environmental objectives. As a result, this work considered multi-objective and multi-parametric optimization, and the dynamic performance of battery problems. Multi-parametric dynamic programming was used to optimize the energy management of microgrids. Simulation results were used to assess the model's efficiency.

Shuai and Fang [56] proposed two optimal operations in microgrids for real-time energy management. The first one is MINLP in which Ac power flow and battery storage are considered. The second one is approximate dynamic programming (ADP), which was formulated for optimization problems. The microgrids are connected to the grid. The solution of the Bellman equation determines sequential decisions. The optimization algorithm's efficiency was tested numerically using a microgrid benchmark and MATLAB. In [28], they focused the economical energy management of real-time microgrids while considering load fluctuations and power flow constraints. The Markov decision process (MDP) was formulated for real-time scheduling. To achieve optimal real-time scheduling, approximate dynamic programming (ADP) with a recurrent neural network (RNN) was developed. To understand the optimal value function, an iterative method approximate policy iteration (API) is used. The simulation model was analyzed in MATLAB R2015a. A

summary of recent studies of EMS based on rule/dynamic programming is presented in Table 2.

Table 2. Summary of recent studies of EMS based on rule/dynamic programming.

Referenc	System Configuration	EMS Approach	Remarks
[53]	wind/solar/battery	Rule-based via MAT-LAB/Simulink/ RT-LAB	Author analyzed the switching operation among battery charging/discharging, off mode of the PV system, and load shedding of micro grids.
[54]	PV/FC/Battery	DP/Rule-based via MATLAB	Author proposed an optimal EM plan between off-grid and grid-connected modes of micro grids
[55]	Hybrid MG	Multi-parameter dynamic programming	Optimal scheduling of DGs and battery sizing problems are considered in this paper
[56]	Hybrid MG	ADP/MINLP via MATLAB	In this paper, real time EM of MG is proposed
[28]	Hybrid MG	MDP/ADP/RNN via MATLAB	The researcher proposed algorithms were derived to achieve optimal real time scheduling

4. Meta-Heuristic Approaches of EMS

Energy Management Based Particle Swarm Optimization

The PSO algorithm's basic elements are the swarm's population and the number of particles in the swarm. The PSO introduces a search space where these particles move according to a set of basic formulae. These particles define their own best positions and the swarm's overall best position in order to discover the optimal position in relation to each other. They arrive to control the growth of the swarm after they have discovered their optimal places. The process of determining the optimal place is ongoing, although it is not precise [57–61]. The population of birds is depicted in Figure 3, with birds seeking for food in a search area.

C. Li, X. Jia, and Y. Zhou [62] presented an energy management technique to keep the load curve stable in microgrids. Three types of multi-agent models were investigated in this paper: the underlying case, the demand response case, and energy storage case. The authors described a solution to solve these three factors and compare the results by applying the metaheuristic approach that is particle swarm optimization. Moreover, the author combined two algorithms, adaptive search and the chaotic search method, to enhance the PSO to an ACPSO algorithm, which reduces the number of iterations using a Jade and MATLAB environment. In [63] was an improvement of the energy management of the solar-diesel hybrid generator. Two cases of optimum scheduling were investigated in this study. When the load was large in the first scenario, the amount of additional solar energy had to be raised in proportion. When the load was low in the second scenario, the diesel generator's efficiency had to be considered. The author created a multi-objective optimization model, which he solved numerically using the PSO optimization approach.
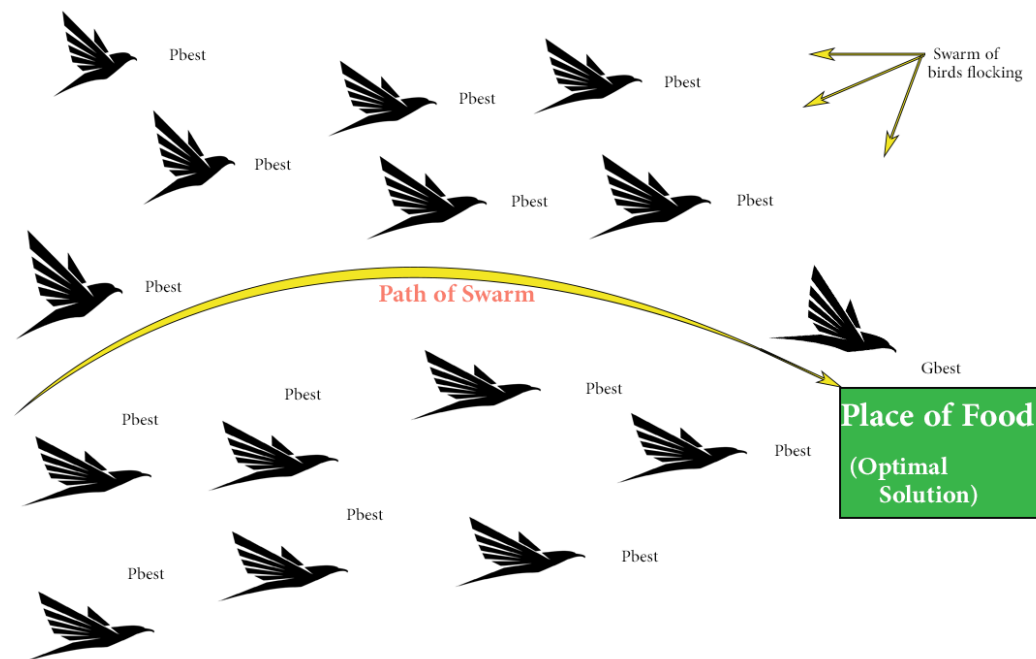
Figure 3. Particle swarm optimization.

Hossain and Pota [64] calculated real-time energy management and electricity pricing by using the meta-heuristic algorithm. In this article, a modified PSO was developed to cope with the cost function and battery charging and discharging activities. The cost function graph may be modified by the need for real-time energy management in the community using MATLAB, as shown in the simulation results. In [65], a multi-period power flow approach based on successive approximations (SA) and an energy management methodology that follows the master salve strategy to cope with the particle swarm optimization (PSO) were employed in tandem to determine the optimal solution of a Battery storage system (BSS). Simultaneous quadratic programming was used in MATLAB software to evaluate simulations.

T. Kerdphol and Y. Qudaih [66] proposed an EMS to prevent MGs from instability and system breakdown during extreme situations. The author derived PSO from the integration of demand response (DR) and evaluated the optimal size of the BESS system to boost the system's performance, safety, and stability. For the real-time energy management of standalone microgrids, particle swarm optimization (PSO) has been employed in [67,68]. A summary of recent studies of EMS based on rule/dynamic programming is presented in Table 2.

5. Energy Management Based on Genetic Algorithm

Charles Darwin's idea of natural evolution influenced genetic algorithms [69–71]. As part of the algorithm, the most appropriate individuals are selected for reproduction in order to create children in the following generation. The genetic algorithm is based on two main operations, crossover and mutation. Crossover shows the probability of a pair of parents mating [72–76]. The basic process of GA is shown in Figure 4.

Genetic algorithms (GAs) are one of the most popular population-based heuristic optimization approaches, and they are utilized to address a wide range of issues [41]. The ESS economic strategy and an actual matrix formatted GA-based smart EMS technique were developed by C. Chen and S. Duan [33] for grid-connected MGs. When it comes to predicting solar energy, the NN model is utilized. The net present cost of the ESS during its lifespan is considerably increased by an economic model based on its capital, operating, and maintenance expenses, and revenue from energy arbitration. Smart EMS includes

generator bids, storage bids, and electricity market revenue to reduce the MG's operating costs while satisfying the energy balance limitations and physical constraints of the DERs.
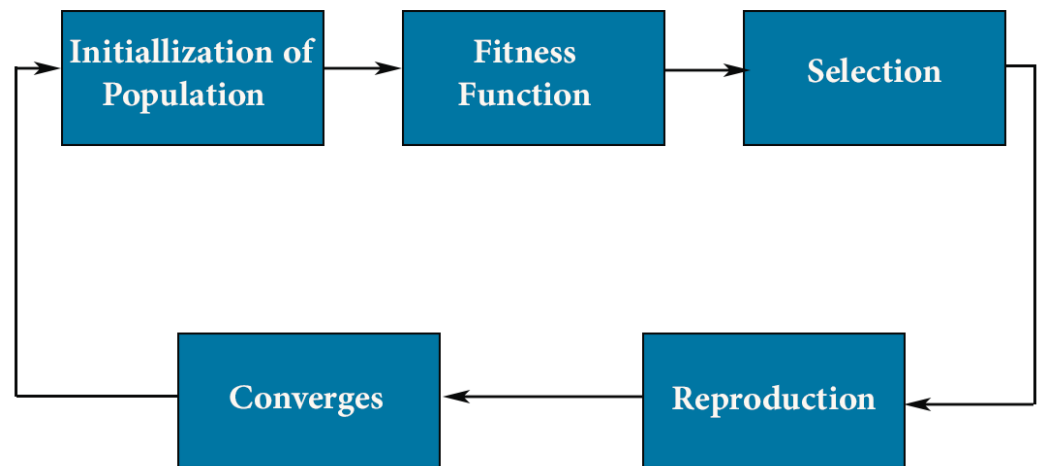
Figure 4. Architecture of the genetic algorithm.

Mohammed and Amirat presented [77] an intelligence-based evolutionary algorithm (GA) for optimizing the EMS and design of a freestanding hybrid microgrid that includes wind, PV, tidal, and batteries. This proposed GA approach was generated to lower the hybrid system's cost. Using the genetic algorithm approach, [78] investigated the energy management of a freestanding hybrid microgrid that included a wind turbine, solar panels, a diesel generator, and a battery. The GA was used to solve size difficulties, reduce costs, and alleviate pollution emission concerns. Furthermore, utilizing HOMER, GA was utilized to solve optimal meet load demand problems in order to increase the relevance of RES.

A summary of recent studies of EMS based on particle swarm optimization is presented in Table 3.

**Table 3.** A summary of recent studies of EMS based on particle swarm optimization.

Reference	System Configuration	EMS Approach	Remarks
[62]	Multi agent MG	PSO/ACPSO via Jade and MATLAB	Author proposed three methods to stabilize the load curve and compare it with each other.
[63]	Solar/Diesel hybrid Generator	PSO via MATLAB	Author studied two cases of optimal scheduling of hybrid generator.
[64]	Grid-connected MGs	PSO via MATLAB	Author proposed modified algorithm to deal with cost function and battery charging discharging modes.
[65]	DC-DGs	PSO/SA via MATLAB/sequential programming	The researcher proposed master salve strategy to find the solution of optimal BSS.
[66]	Hybrid MGs	PSO	The Research evaluated optimal BESS system to enhance the performance of MGs.

6. Artificial Intelligence Approaches in EMS

6.1. Energy Management Based on Neural Networks

The requirements of modern industries are not fulfilled through conventional control techniques, so it is time to deal with problems with artificial intelligence methods, such as ANN, whose basic structure is shown in Figure 5. The proposed control technique can also handle nonlinear systems [79]. Similarly to human beings, ANNs learn through examples. ANN is designed for specific applications, such as pattern recognition and classification of

data through a learning process. In a biological system, learning requires adjustments to the synaptic connections between neurons, just like ANN. It has numerous capabilities for complex systems, such as prediction, modeling, and control of performance [80–82].
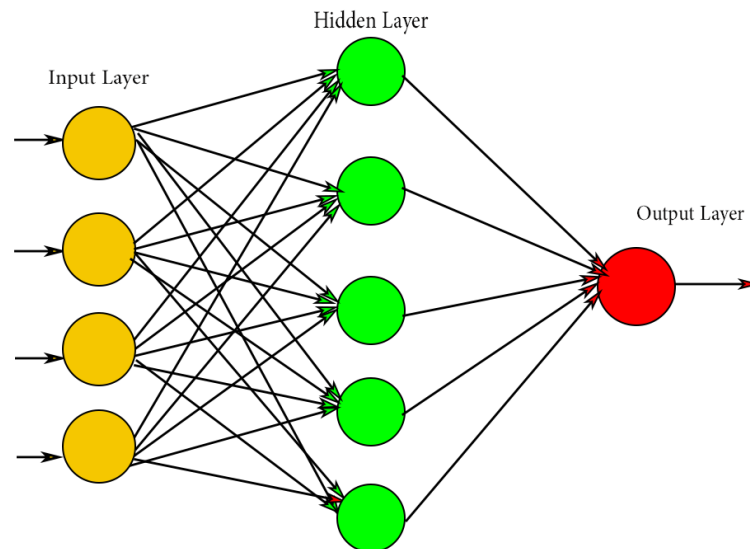
**Figure 5.** The architecture of an exemplary artificial neural network.

K. Roy and K. K. Mandal [83] presented a cost-effective EM model of a hybrid microgrid including a PV/WT/storage system. In this paper, real-time optimal scheduling of the microgrid was introduced to decrease the cost of electricity production. Using MATLAB/Simulink, the author developed a recurrent neural network (RNN) to assess demand response and an ant–lion optimizer (ALO) algorithm to address economic dispatch issues, and the results were compared to some existing methods. Jaganmohan Reddy and Pavan Kumar [84] developed a load forecasting EMS model of a microgrid that predicted short, medium, and long-term forecasts. The artificial neural network (ANN) was used in this study to assess real-time statistical forecasting of microgrids in various situations, such as daily, seasonal, and annual. The Levenberg–Marquardt back propagation algorithm was used to train the layers of the ANN, which enhanced coordination between microgrids in various places. MATLAB/Simulink was used to create this model. Another study [85] suggested a cost-effective EEMS for optimal wind turbine (WT) scheduling, an energy storage system (ESS), and an optimization module in interconnected microgrids. In this study, an artificial neural network (ANN) was developed to anticipate wind speed, and an ESS was utilized to decrease wind turbine fluctuation. Bacterial foraging optimization (MBFO) was used to address multi-objective problems. In terms of economic and environmental efficiency, this study showed that the EEMS can successfully coordinate the power generation of DERs and ESS.

K. Roy and K. Krishna Manda presented [86] a hybrid strategy to reduce the cost of producing renewable energy resources. A hybrid microgrid consisting of a PV/WT/storage system was considered in this paper. The ANN and BFOA techniques were used to control power flow between the sources and the grid. The proposed techniques were implemented via MATLAB/Simulink, and they compared the results with GA and ABC algorithms. In [87], optimized scheduling of a MG solved the uncertainty of wind power/MT/FC/ESS. A probabilistic concept, APCCI, was applied to investigate the problems in the MG. To increase the accuracy of the wind turbine, wavelet decomposition was applied and results were sent to an ANN. The ANN provided optimal scheduling and enhanced the performance of MG. In [88], the authors presented an AI technique to reduce the demand for energy in peak hours and maximize the use of renewable energy sources such as PV/WT.

ANN and GA were used to provide optimal scheduling and manage the real-time energy demand in the domestic sector.

6.2. Energy Management Based on Fuzzy Logic

Many hybrid renewable energy systems have successfully employed fuzzy controllers as energy control and management units (EMU) [89–94]. Many logic values dealing with reality make up fuzzy logic. Fuzzy logic deals with Boolean values, such as 0 and 1 logics, which are both totally true and completely false. Figure 6 depicts the basic architecture of fuzzy logic.
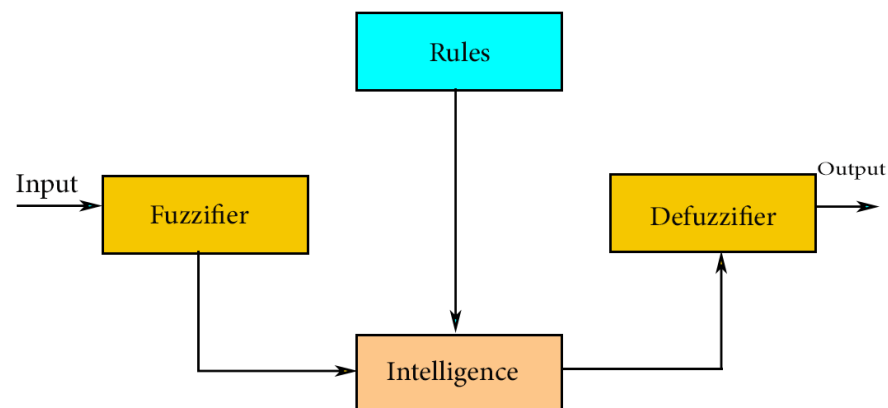
Figure 6. The architecture of fuzzy logic.

I. Abadlia proposed [95] the power management of renewable energy sources (RES) of a standalone hybrid microgrid. In this system, PV/FC/BES and PEMFC are used to ensure the continuous supply of power. Fuzzy logic energy management (FLPMS) was used in this paper to achieve the power management goals. FLPMS maximized the hydrogen production and continuous charging/discharging of the battery to meet the deficit power demands. In [96], the authors presented the energy management of a grid connected microgrid using a renewable energy source. The goals of minimizing the power fluctuations and keeping the battery SOC under a secure limit were achieved by the low complexity fuzzy logic controller.

L. Ciabattoni [97] used the fuzzy logic inference method to create a high-resolution model for household power usage. The aim of this research was to investigate the real-world economic advantages of altering load behavior using a novel fuzzy model and economic impact analysis. In [98], DSM was controlled by a fuzzy controller and a smart home scheduler. Costs and energy usage were minimized via fuzzy logic. The paper [99] describes a microgrid energy management system that incorporates PV/FC/battery with numerous grid-connected and off-grid modes. In the EM unit, fuzzy logic is utilized to identify the appropriate modes of operation for real-time and long-term anticipated energy generation data. Moreover synchronized bus-voltage balance is used to increase microgrid performance. The authors performed energy distribution and cost analysis.

A peak hour energy demand solution for an HVAC residential system was presented in [100]. Two methods were derived in this paper. The first one is supervised fuzzy logic learning (SFLL) to deal with electrical pricing, and the second one is an adaptive fuzzy logic model (AFLM) proposed in order to sense, understand, and adjust to new user preferences. In addition, a "house energy simulator" with an HVAC system, thermostat, and a smart meter was built in MATLAB-GUI to emulate an adjustable residential building. Fuzzy based dynamic EM was presented in [101] to increase the efficiency of a DC microgrid; fuzzy logic was implemented to improve the optimal charging and discharging of HESS .

7. EMS Based on Other Approaches

To improve the power output of each individual source, minimize the cost of energy, or maximize storage systems, several optimization methods are employed in general. The most commonly utilized optimization techniques and algorithms addressed in the literature study are shown in Figure 7, and a comparative analysis of optimization techniques is listed in Table 4.
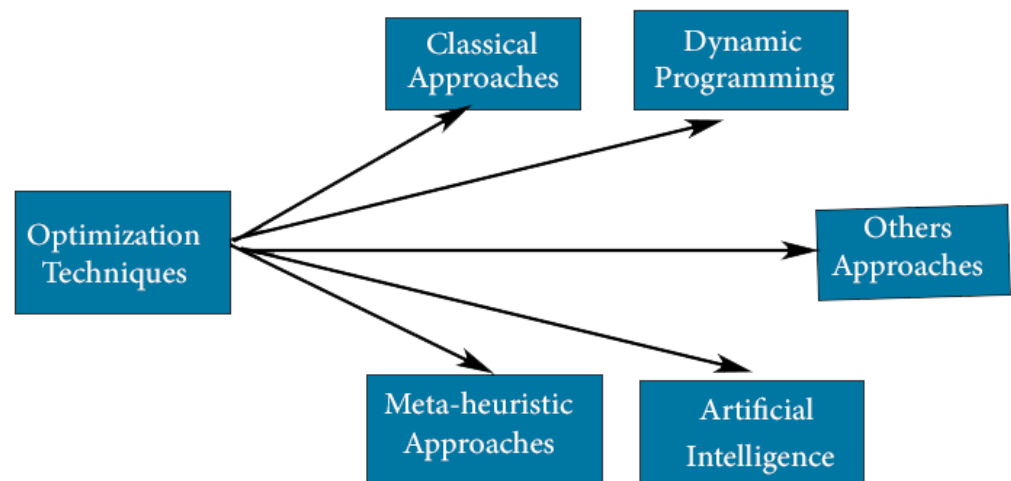

Figure 7. EMS optimization techniques.

Table 4. Comparative analysis of optimization techniques.

Optimization Techniques	Advantage	Disadvantage
MILP	Linear programming (LP) is a quick way to solve problems because the linear constraints lead to a convex feasible region, ensuring that the global optimal solution is achieved in many scenarios.	It shows limited abilities while dealing with non-differentiateable and continuous objective functions
MINLP	MINLP provides multiple optimal solutions of complex models which is an edge over MILP approach.	A large number of iterations are required (high computational power).
Dynamic programming (DP)	It can reduce the problem into sub problems, optimize each one, and moreover resolve sequential problems	Due to the large number of recursive functions, the implementation is complex
Genetic algorithms (GA)	To identify the best solution, population-based evolutionary algorithms employ operations like as crossover, mutation, and selection. An acceptable convergence speed. It is widely employed in a variety of fields.	Parameters for crossover and mutation, and population and stopping, must be defined.
Particle swarm optimization (PSO)	Good results in scattering and optimization problems.	Complicated computational requirements.
Neural Networks	It is utilized in situations where a quick evaluation of the learned target function is necessary.	High computational power Required
Fuzzy logic (FL)	To analysis the decision of the system FL provides best solution.	Don't have the capability of learning which neural networks have.

In [102], Roshandel devised an optimization method for finding the best cost-effective design for a stand-alone MG with a lithium battery storage system while taking into account various energy management control methods. To assess the battery's stability and longevity,

a complex model based on electrochemistry is used to assume the lifetime of lithium batteries. The results of a comparison of optimization techniques for the management of stand-alone MGs were published in reference [103]. Linear programming and genetic algorithms are typically used in this method. The findings show that managing regulated loads can save money by lowering operating costs and increasing the usage of renewable energy sources.

In [104], a series of approaches such as mixed integer programming for energy management optimization and the probabilistic Markov model to reflect PV generation uncertainty were used to study the development and MG optimization. A linear model was used to calculate the MG's lifetime. The authors of [105] presented an energy management system for a hybrid system that included wind, PV, and diesel. The service works both on and off the grid. Transitions between micro and utility grids are also controlled by a mechanism built within the inverter.

There are other factors that are not included in this paper that are required to identify the most suitable communication systems for microgrids, focusing on overall microgrid operations such as the transient response of distributed resources. When it comes to sensitive data transfer, such as protective relays, switches, and fault detectors, it is necessary to improve dependability and minimize delay problems. It is also important to optimize communications technology in order to improve control system functions such as reactive power regulation and power quality improvement control [32].

Moreover, in [106] a microgrid energy management system, research comparing Wi-Fi-based servers against wired connectivity was carried out. The wireless infrastructure provides a dependable, easy-to-build, and scalable infrastructure for a small-scale microgrid control system, although it has larger communication delays than cable LAN. Data from wireless communications experiments show that Wi-Fi is a viable choice for WAN infrastructure [107]. The energy efficiency of Li-ion batteries as energy storage devices in microgrids is being studied. The energy efficiency of a Li-ion battery is determined by its energy efficiency during charging and discharging scenarios [108,109].

8. Conclusions and Future Trends

Distributed energy resources, demand response, electric cars, and local controllers are the main building blocks of microgrids to be applied for smart cities. A central controller and communication devices are used to manage energy in a microgrid. This article presented a critical and comprehensive review of microgrid energy management issues and possible solutions. The fundamental goal of the EMS is to provide grid-connected and off-grid microgrids with minimal operating costs, optimal scheduling, and uninterrupted power delivery. As a result, the microgrid energy management framework is a multi-objective subject that addresses economic, technological, and environmental concerns of the smart city.

Various optimization approaches were explored in this study to find optimal solutions for microgrid operators' coordination. The assessment was mostly based on smart city requirements, particularly in terms of electricity consumption and management. Through the use of a variety of effective methods, these strategies explore alternatives, opportunities, and challenges to achieve energy management objectives. Then using a computer system, each microgrid operator receives the most cost-effective, least interrupted in terms of power flow, solution.

These approaches are chosen on the basis of their adequacy, practicability, and usability for optimal growth of microgrids. MG EMS also takes into account environmental concerns of conventional generators, the life expectancy of batteries, efficient DR integration, power loss and robustness, and the privacy of the customer. Some of these objectives have been the subject of studies. To achieve efficient operation of microgrids, there is still much work to be done, including improving customer privacy issues, analyzing the reliability of efficient communications systems, and managing costs. From the perspective of the energy system, effective energy management for lithium batteries is necessary. Thus, more

accurate degradation models to accurately estimate battery lifespan in real-time operating scenarios need to be created.

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