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Review

Survey of Sustainable Energy Sources for Microgrid Energy Management: A Review

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Abstract: Renewable energy sources are nowadays a viable choice to satisfy the rising energy consumption and promote the advancement of sustainable development. These systems are integrated into microgrids using a variety of technological solutions to ensure customer communication and distributed generation facilities in an optimal way. Energy management in microgrids refers to the information and control system that provides the necessary functionality to guarantee that the generating and distribution systems produce energy at the lowest expenses. This study analyzes the various optimization objectives, constraints, problem-solving techniques, and simulation tools used for connected and freestanding microgrids. It reviews the literature on energy control in microgrids powered by sustainable energy. Energy storage technology is also viewed as an intriguing alternative to managing the intermittent nature of renewable energy because of its advanced techniques, increased energy efficiency, and capacity to perform tasks such as frequency response. The final phase suggests future suggestions, particularly for the model-based prediction of energy storage systems.

Keywords: energy storage; microgrids; energy management; renewable energy

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1. Introduction

The diminishing supply of fossil fuels, such as carbon, oil, and petroleum, results from the world's exponentially increasing energy consumption. The result is the greenhouse gases that cause climate change by trapping heat, contributing to respiratory disease from smog and air pollution. To address the aforementioned global problems, renewable energy, such as sun, wind, biomass, and tidal energy, has been employed in both small and large-scale energy systems [1]. Global energy consumption will increase by over 25% by 2040 when renewable energy sources are expected to account for 40% of the world's energy mix. Energy demand and supply must be balanced, which presents significant challenges for renewable energy sources [2]. Because of the increasing demand for energy and the redesigning of power infrastructure, energy is now produced close to what is consumed. Renewable sources, particularly solar and wind power, have become less expensive and competitive to generate this electricity.

Several articles discuss microgrids (MG) [3–7], energy storage devices, and distributed generation (DG). A hybrid form of renewable energy battery power devices (and, in some situations, a diesel generator) is frequently the best option since it considers one or more renewable sources and is highly dependent on climatic and meteorological conditions [8–12]. Electricity is frequently provided via hybrid energy systems for several standalone uses, including homes or farms in remote locations without grid extensions, telecommunication antennae, and equipment devices [13–15]. Compared to systems that exclusively utilize one energy source, these hybrid solutions often indicate the highest reliability and lowest prices.

A microgrid comprises energy storage systems, various loads, and miniature power plants [16,17]. A medium- or low-density distribution system dispersed generation using hybrid systems that combine renewable and traditional energy sources to produce electricity for end-user customers might be used to characterize it in a broader sense. Storage increases the microgrid's dependability and is utilized to compensate for the PV's sporadic nature and wind output electricity [18,19].

Real-time management requires communication networks which these microgrids have [14]. Microgrids can also run independently and with a grid [15].

The injection of energy produced by decentralized power plants (wind and PV, . . .) to the grid, leads to the study of microgrids. DG distributed generators are also found in microgrids, which are based on converters and batteries. However, alternative systems are the most widely used, which encourages research in the field of DC and AC microgrids.

Hybrid, alternating current (AC), and direct current (DC) microgrids are the three types, depending on the source type they handle, as shown in Figure 1.

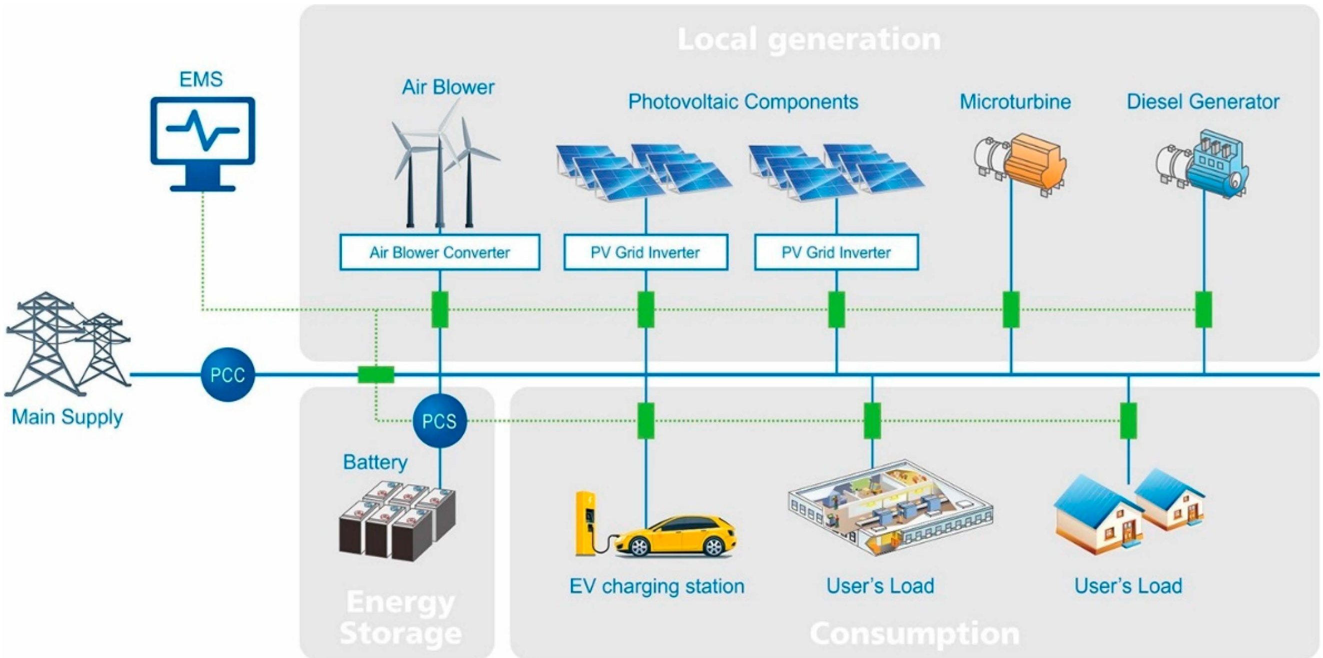

Figure 1. An integrated microgrid system [15].

Because power from variable distributed sources, such as solar and wind power systems, can fluctuate and is difficult to forecast dramatically to maintain stability in a microgrid, it is critical to conserve the balance of power supply and demand based on the accessibility of one of the main sources (solar irradiation and wind). The demand and supply equilibrium issue arises from the balance of power demand and supply, and there is just a small quantity of supply to balance the demand, which is much more crucial [16]. Mana Managing microgrid energy optimization is typically as a challenge for offline optimization [17].

Microgrids powered by renewable energy sources are classified as "smart grids", which provide various technology options for enabling communication between users and dispersed generations. When supported by a platform, an information system known as an energy management system (EMS) provides the necessary functionality to ensure that energy is produced, transmitted and distributed at the lowest possible cost [18]. Microgrid energy management requires the implementation of a control program that allows the system to operate as efficiently as possible [19]. This is accomplished by taking into account the two modes of operation for microgrids at the lowest possible cost (isolated and interconnected). When considering microgrids with renewable energy sources, it is critical to consider resource fluctuation, such as solar radiation [20].

In summary of the research on microgrid energy management, several authors have used various methods to resolve the energy management issue in an ideal microgrid setup. However, these systems must improve their solution strategies when distributed generating, storage components, and electric vehicles are integrated [21]. Other recent publications have analyzed different storage and demand-based integration strategies for renewable energy systems [22]. This latter focuses on two key areas: (1) maximizing storage use and (2) enhancing user involvement through responsiveness to demand systems and other cooperative techniques. In [23], the authors reviewed hybrid renewable energy management techniques, especially different hybrids that operate independently of the grid system topologies. Furthermore, various review articles have displayed the control goals of energy management systems (EMS) and microgrid supervisory controllers (MGSC) [24–26]. Authors in [27,28] propose control methods for a grid-connected inverter and synchronous generator.

The remainder of this paper is arranged as follows. Section 2 investigates the control of AC microgrid. Section 3 summarizes 3 the methods of microgrid optimization. Section 4 describes the benefits and drawbacks of various energy management strategies. Section 5 concludes the paper.

2. Control of AC Microgrid

Three tiers make up the proposed hierarchical control structure: the droop approach serves as the main control and includes a virtual output impedance loop; the backup control enables reversing the primary control's deviations; and the third control regulates the flow of electricity from the microgrid to the system for distributing power outside.

As seen in Figure 2, the microgrid control can be divided into three levels. We will explain each level in the following sections.

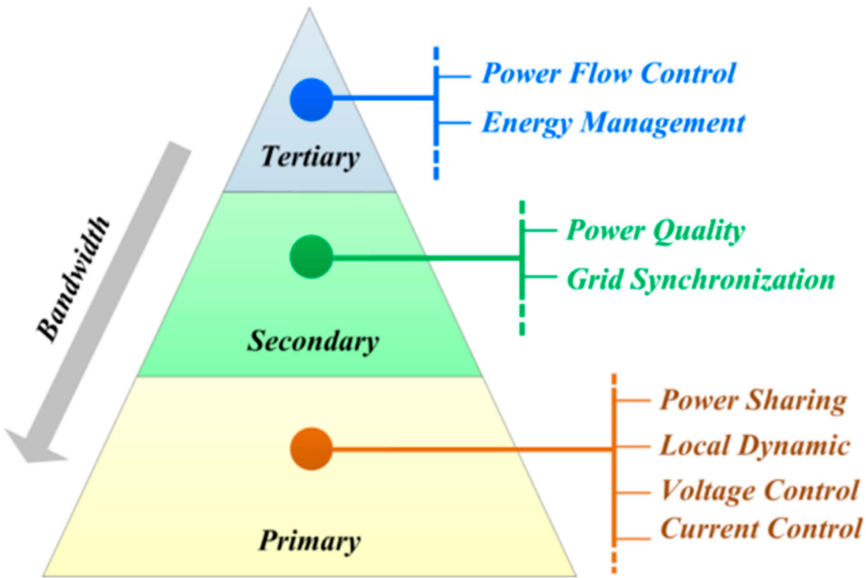

Figure 2. Hierarchy of the microgrid control.

2.1. Primary Control

The goal of this control is to maintain friability by adjusting the internal control loops for the current and voltage reference frequency and amplitude.

It employs the well-known P/Q droop technique:

$$\omega = \omega^* - G_p(s).(P - P^*) \tag{1}$$

$$E = E^* - G_q(s).(Q - Q^*) \tag{2}$$

P and Q are the active and reactive powers with P^* and Q^* as references, as illustrated in Figure 3.

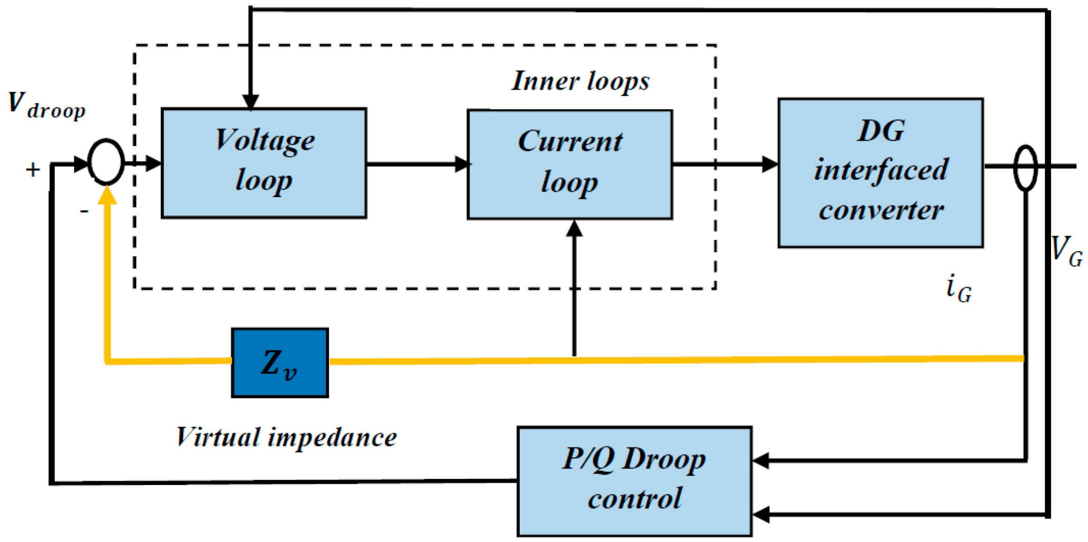

Figure 3. P/Q method visualization.

E and ω are the voltage amplitude and the frequency, with E^* and ω^* their references. $G_p(s)$ and $G_q(s)$ are linear transfer functions.

2.2. Secondary Control

Secondary control is proposed as a compensatory method for frequency and amplitude anomalies. To maintain the output voltage, the frequency and amplitude levels of the microgrid are measured and compared to MG and EMG references. Errors corrected by compensators are then transmitted to all MG units. The secondary control must reduce tolerable frequency variation to within 0.1 Hz in NE (north of Europe) or 0.2 Hz in UCTE (Union for the Coordination of Continental European Electricity Transmission [27,28]). The integrating grid requirements improves stability.

The frequency and amplitude restoration controllers for an AC microgrid can be obtained similarly, as shown below:

$$\delta\omega = K_p.(\omega - \omega^*) + K_i.\int (\omega - \omega^*)dt \tag{3}$$

$$\delta E = K_p^i.(E - E^*) + K_i'.\int (E - E^*)dt \tag{4}$$

K_p, K_i, K_p', and K_i' are the secondary control compensator's parameters. In this instance, $\delta\omega$ and δE must be constrained to stay within the range of permitted amplitude and frequency variations.

2.3. Third Control

Both reactive and active power fluxes can be exported or imported independently. The third control, energy management, aims to achieve this.

Control laws can be stated in the following expressions:

$$\delta\omega = K_p^i.(P - P^*) + K_i'.\int (P - P^*)dt \tag{5}$$

$$\delta E = K_p^i.(Q - Q^*) + K_i'.\int (Q - Q^*)dt \quad (6)$$

where the tertiary control compensator's control parameters are K_p, K_i, K_p', and K_i'. In this situation, they are saturated if δE and $\delta\omega$ are outside the permitted limits.

Notably, the reactive and active power fluxes depend on the Q' and P omens and can be exported or imported separately.

3. Methods of Microgrid Optimization

An extensive robotic system is used for energy management in microgrids to ensure resource efficiency [25–27]. Based on state-of-art information technology, it can optimize the administration of energy storage and decentralized energy source systems [28]. Microgrid optimization frequently includes the following goals: increasing generator output power, minimizing microgrid operating costs, extending the life of storing energy systems, and lowering environmental costs.

Figure 4 shows the microgrid's optimization methods.

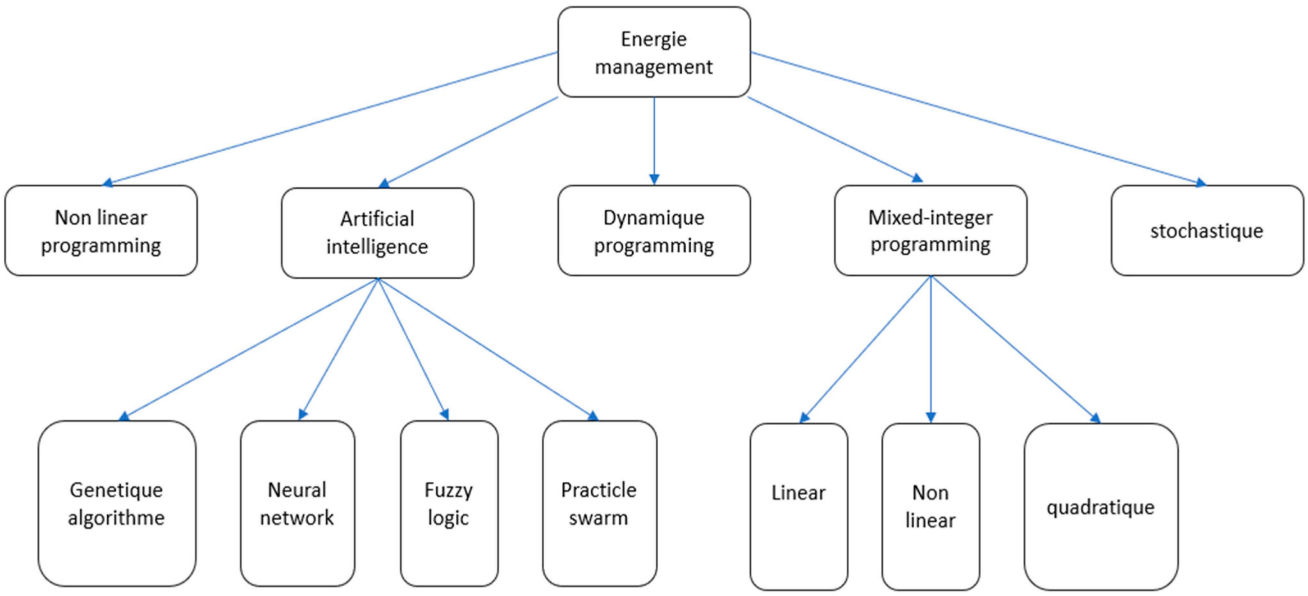

Figure 4. Energy management methods [29].

3.1. Stochastic Optimization Techniques

Stochastic optimization methods can be used to raise the value of an objective function even when random variables are described by probabilistic functions. In stochastic programming, optimization can happen in one, two, or more phases. In the event that there are two phases, the optimization is split into two. At the initial step of optimization, the optimal point of operation using predicted data is selected. A disturbance simply prompts the real-time operation to correct the optimization using the actual value at step two. Normally, the first step considers every situation whereas the second stage just considers a select few.

3.2. Dynamic Programming

Using the dynamic programming method, the multi-period optimization can be broken down into time-indexed sub-problems. As a result, Bellman's equation can be solved to identify the decision-making order. By breaking the problem down, the suggested solution resolves mixed-integer nonlinear programming brought on by practical considerations. This method may deal with stochasticity by incorporating empirical data with historical operational data. It reduces the dependency of optimality on forecast data by incorporating empirical knowledge into the real-time decision-making process.

3.3. Mixed Integer Programming and Non Linear Programming

When variables can be discrete or continuous, optimization problems are addressed using mixed integer programming techniques. The methods are so ideal for EMS applications within microgrids. The development of mathematical models for the microgrid's components aims to lower the cost function in MILP-based EMS. The MILP model evaluates wind speed, irradiation, load factors, and component cost parameters. The goal function and restrictions are non-linear rather than linear in mixed integer non-linear programming (MINLP) approaches. In order to create a linear model, MINLP models commonly require approximations. Continuous variables in MINLP models include the power produced by available generators, the electricity imported or exported at PCC, and the power injected by the ESS. When microgrids are taken into consideration, the power flow equation becomes more complex and nonlinear.

3.4. Artificial Intelligence

Moreover, microgrid optimization techniques based on multiagent systems enable decentralized administration of the microgrid and are made up of autonomously acting sections that carry out activities with predetermined goals. Communication between these agents also consists of loads, portable generators, and storage devices to achieve a low cost.

Specifically, in game theory, fuzzy logic, artificial neural networks, statistical techniques, and robust programming are employed to resolve optimization problems where the random variables are the parameters.

Combining the aforementioned techniques can lead to the development of additional methods, such as heuristic, stochastic, and enumeration algorithms.

4. Description of the Benefits and Drawbacks of Various Energy Management Strategies

4.1. Comparison of Some Common Energy Strategies and Principles

A microgrid is formed by combining various distributed generation resources and connecting them to the utility grid at a central location. Figure 5 depicts a microgrid energy management and several characteristics, such as control and data collection modules, load forecasting, optimization, and human-machine interfaces (HMIs) (Table 1).

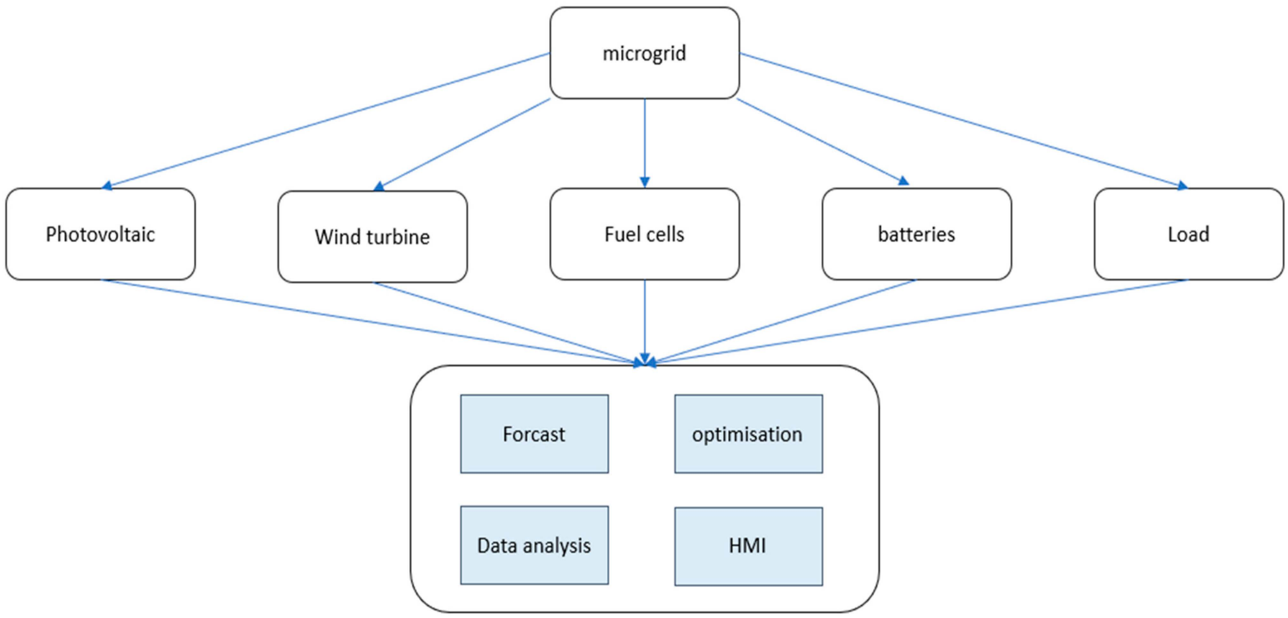

Figure 5. Management of a microgrid [29].

Table 1. Comparison of the optimization models.

Model	Advantages	Disadvantages
MILP	It resolves complicated issues with straightforward actions. It has a benefit compared to the MILP formulation in that it can obtain many optimal solutions.	Economic stochastic analysis and reliability. Restricted capabilities for applications with continuous or nondifferentiable objective functions.
MINLP	The mathematical function is nonlinear, or one of its parameters is non-linear.	Numerous iterations (high computational effort).
Dynamic programming (DP)	Dived to minor problems to solve a large one sequentially.	Complicated implementation due to numerous recursive methods.
Genetic algorithms (GA)	Population-based evolutionary algorithms search for the best answer using mutation, crossover, and selection. A sufficient convergence rate. Widely utilized throughout many industries.	Mutation and crossover parameters must be determined.
Particle swarm optimization (PSO)	Excellent brings about scattering and optimization challenges.	High complexity in computation.
Artificial bee colony	Easy to implement a population-based algorithm. A fast enough convergence.	Intricate formulation
Artificial Fish Swarm	Precision, rapid convergence, fewer parameters and flexibility	Maintains the benefits of GA but without its drawbacks (crossover and mutation)
Bacterial foraging algorithm	The problem's size and nonlinearity have less effects. Converge to the best solution compared to analytical techniques	Wide and complex search area

Figure 6 illustrates a classification of the different optimization strategies of microgrid energy management, and Table 2 discusses these models with their constraints, drawbacks, and contributions [30].

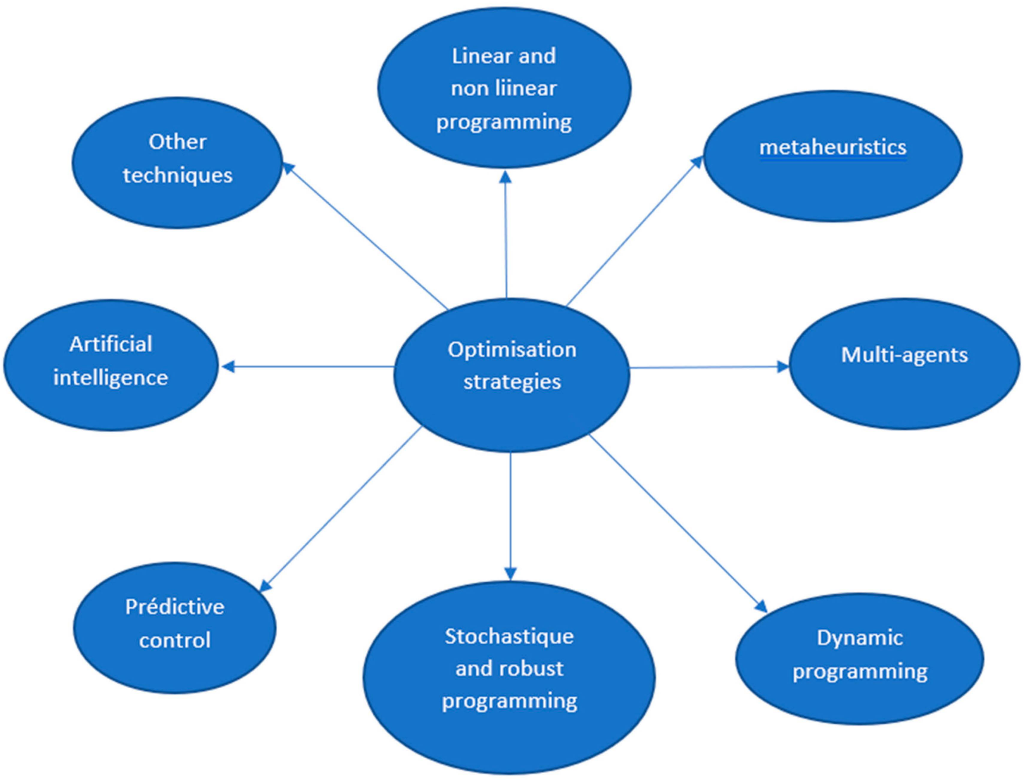

Figure 6. Some optimization strategies.

Table 2. An examination optimization of microgrid methods.

Reference	Optimization Strategy	Contributions	Constraints	Drawbacks	Multi/Single-Goal
[31]	mixed integer and non-linear	The Given each generator, includes dump and deferrable loads, the ideal power scheduling, is obtained using a robust optimal EMS MPC-based method.	Power ratio Battery Generator Renewable Sources Loads	Power losses and demand are not assessed	Multigoals
[32]	mixed integer and linear linear programming	an approach of energy management that combines three optional approaches (Power sharing, ON/OFF, and continuous run modes).	Battery Generation dispatch	Battery degradation costs are not taken into consideration	Multigoals
[33]	Non-linear programming	Decreased total operating expenses while preserving the safe operation of the standalone MG	AC power DC power Converter power Load Distributed generators power	Systematic battery storage is not examined. The cost of emissions for distributed biomass generation is not evaluated.	Mono-goal
[34]	Linear programming	Integration of AI-based linear programming techniques to solve multiobjective optimization	Limitations of dispersed generation in power balance	High computational complexity. Degradation of the battery is not assessed	Multigoals
[35]	Particle swarm algorithm (PSO)	Merge of two energy storage units that are ideals. less time for computation than GA	The generators' power Power transfer to the grid Charge/Discharge of the storage units Supply and demand balance	The traditional generator's emission costs are not evaluated.	Multigoals
[36]	Particle swarm algorithm (PSO) with Gaussian mutation	PSO variant new algorithm.	Active power Voltage Current	Power losses and Emissions of distributed generation are not assessed.	Mono-goal
[37]	Artificial bee colony	A two-layer control model is utilized to reduce a microgrid's operating expenses.	Power equilibrium Accessibility to resources Non-dispatchable resources Storing components	The formulation is difficult. The cost of emissions from a dispatchable microturbine is not calculated	Mono-goal
[38]	Fuzzy logic (Gray Wolf Optimization)	Optimization of the battery size, storage, and generation plan	Power balance Generators power Battery load	The cost of battery deterioration is not estimated	Mono-goal

Table 2. *Cont.*

Reference	Optimization Strategy	Contributions	Constraints	Drawbacks	Multi/Single-Goal
[39,40]	Evolutionary algorithm (EA) and PSO Algorithm	Application of an energy hub model for optimization of a multicarrier MG.	Power balance Voltage in the transformer	Deterministic condition is a limitation.	Multigoals
[41]	Artificial fish swarm optimization	A MG's energy management schedule, which considers storage for the entire day and dynamic pricing, is optimized	Power equilibrium traditional methods of generating power standard power generators	Battery degradation cost is not assessed	Mono-goal
[42]	Particle swarm algorithm (PSO)	It considers Three different objectives: Reliability, Operation cost, and Environmental impact.	Indefinite	Degradation cost of battery is not counted.	Multigoals
[43]	Bacterial foraging algorithm	Optimized the power exchange with the grid, the battery and the generator setpoints. Quick convergence.	Power balance Generation limits of distributed generators Storage limits	Power losses are not counted	Multigoals
[44]	Mixed-integer nonlinear programming (MINLP)	less reliance on forecast data. Various battery models compared.	Charge flow Dispatch generators Programming of the generator on/off Battery charge and discharge	Prediction of battery life is disregarded	Multigoals
[45]	Dynamic Rules	Different restrictions are used by the MG management system for the batteries bank state of charge (SOC).	Battery Power balance	Battery cost and degradation are not considered.	Mono-goal
[46]	Dynamic programming	Energy management strategy for PV. Batteries to stabilize and permit PV to run at a constant and stable output power	Charge/Discharge of batteries	Battery degradation and lifetime prediction are not evaluated	Multiobjective
[47–49]	Multiagents	Reliable technique for real-time energy storage management used to adjust power imbalance optimally. Control system with many layers and coordinated control. Battery energy storage system, optimization problem based on distributed intelligence, and a multiagent system	Battery charge and discharge Power Equilibrium and Load Scheduling	Battery lifetime and degradation are not assessed Complex control scheme	Multigoals

Table 2. *Cont.*

Reference	Optimization Strategy	Contributions	Constraints	Drawbacks	Multi/Single-Goal
[50]	Stochastic	A straightforward way to include the influence of stand-alone scheduling on the grid-connected operation.	Power balance Dispatchable Distributed generation Renewable power generation Load Charge/Discharge of batteries	The battery aging model and the cost of DG emissions are not evaluated	Multigoals
[51]	Robust programming	hybrid wind-battery-diesel system load management is optimized	Battery bank with wind turbine power source for the diesel generator	Shifting of controllable loads may be inefficient.	Mono-goal
[52]	Mixed Integer Quadratic Programming	Demand side management and unit commitment for generators are evaluated by an integrated stochastic energy management model.	Power balance Generation Demand Reserve capacity	The deterministic model requires more processing time. Costs associated with emissions from traditional generators and DG are not assessed	Mono-goal
[53]	Model predictive control	Automatic load shedding of noncritical loads when expected power imbalances threaten the MG's stability.	Power distributed generators	The battery's charging and discharging rates are not taken into account. Similarly, communication lags	Multigoal
[54]	Model predictive control	a detailed mathematical description of the ideal EMS for standalone microgrids considering restrictions of power flow and unit commitment	Power balance Reserve Unit commitment Energy storage Grid	High computational effort The cost of emissions for traditional sources is not assessed.	Mono-goal
[55]	Model predictive control	The main contribution of this work is daily optimizer that considered capacity losses while calculating the lead-acid battery's deterioration	Not specified	The model of the lithium battery is not evaluated	Multigoal

Table 2. *Cont.*

Reference	Optimization Strategy	Contributions	Constraints	Drawbacks	Multi/Single-Goal
[56]	Genetic algorithm	A unique cost function includes the startup costs of distributed resources as well as the costs of selling and purchasing power.	Balance of power emissions battery power generator start	Distributed sources and battery state of charge are not considered. Customers' uncertainty as well as the MGs' uncertainty in their energy generation are not taken into account.	Mono-goal
[57]	Game theory	Distributed energy management schedule in various MGs.	Energy transfer to the grid and the MG's generation capacity	Computational complexity is not counted.	Multigoal
[58]	Artificial Intelligence (Fuzzy logic)	easy implementation, enhanced power profile quality of the grid	discharge/charge of batteries	Only the battery charger/grid-connected inverter is controlled. Battery degradation is not evaluated.	Multigoal
[59]	Game theory	Reduce the cost of fuel and trading power.	Power balance DG Traditional generator power The power that can be transferred between the main grid and the MG is limited	The conventional generators' emission costs are not assessed	Multigoal
[60]	Markov decision process	Linear model to evaluate the MG lifetime cost.	Gas turbine capacity Gas turbine emissions	Limited number of sizes' possible combinations	Mono-goal
[61]	Rule-based	Study of the predictive expenses of hybrid system including battery degradation. After developing a hybrid-operating regime, a levelized cost of electricity study is conducted (LCOE). Accuracy of energy storage degradation costs	Power balance SOC battery	The capacity fade modeling of temperature is not considered Conditions for dynamic state-of-charge cycling are not counted	Multigoal

4.2. Tools and Modes of Microgrid Operating

Multiple operating modes for microgrids have been covered in numerous studies that examine linked microgrids. In contrast, several authors view the independent mode as a substitute supply control, particularly in rural regions or locations without traditional grids [62]. Therefore, operating on and off the grid is a viable option. The factors mentioned above are compiled in Table 3.

Table 3. Modes of microgrids operating.

Reference	Microgrid Mode Operation
[11,20,30–33,36,39,45,49,51–53,55,56,58,59,63]	Grid-Connected
[9,31,34,40,42,44,47,48,50,54,57,60–64]	Off-Grid
[8,15,19,35,43,46,61,65]	Grid-Connected/Off-Grid

The most common simulation tools are summarized in Table 4, where MATPOWER and MATLAB/Simulink (MathWorks, Natick, MA, USA) are at the top of this list. MATLAB is a computing environment belonging to the fourth-generation programming language that can communicate with languages such as Python, Fortran, Java, C++, C#, and C. On the other hand, MATPOWER is a free-source program that simulates ideal power flows and evaluates MG performance using Monte Carlo. In addition, numerous authors have used GAMS as a programming language for optimization in linear, nonlinear, and mixed systems to address the problem of uncertain energy management and achieve the best microgrid sizing. Other tools, such as the optimizer-based CPLEX, have been used thanks to its compatibility with other programming languages.

Table 4. Tools and simulation software for managing microgrids.

References	Tools	Characteristics of Tools
[61]	PSCAD/EMTDC	HVDC, power electronics, power systems, FACTS, and control systems emulation software
[11,32,33,35,38,62]	MATLAB/Simulink MATPOWER	Engineers specialized in control, telecommunications, power electronics, and power systems use matrix based programming languages (C++, Java, and Fortran)
[30,63]	GAMS (GAMS Development Corp., Fairfax, VA, USA)	High-level programming mixed-integer nonlinear and linear optimization
[64]	C++	C++ development application for Windows environment
[40]	TRNSYS based in Madison, WI, USA (Thermal Energy System Specialists, LLC) based in Madison, WI, USA (Thermal Energy System Specialists, LLC) HOMER\sHOGA	Modeling hybrid energy production systems. Genetic Algorithm-Based Hybrid Optimization
[65]	RSCAD (RTDS Technologies Inc., Canada (Winnipeg, MA, USA) JADE (Jade, Christchurch, New Zealand)	Power systems simulator in real time
[61,66]	JADE	Multiagent platform in Java environment
[30]	HOMER	Simulation of energy hybrid system model
[36]	CPLEX (IBM, Armonk, NY, USA)	Optimization Compatible to C, C++, Java and Python

Simulink and PSCAD/EMTDC have been used to investigate microgrid modeling and simulation (Wigan, MB, Canada: Manitoba Hydro International Ltd.). In microgrids, power control and energy management are accomplished using these programs.

Other software is applied to enhance the performance and manage the energy in hybrid systems based on renewable energy sources, such as Homer Energy LLC, Boulder, CO, USA; HYBRID2 (University of Massachusetts; NREL/NWTC, Golden, CO, USA); or HOGA (or its modified version, iHOGA) (or its updated version, iHOGA).

5. Conclusions

Through a review of relevant literature, the centralization and decentralization approaches to microgrid energy management were discovered. Without a coordinated plan among the stakeholders in a microgrid, the first method optimizes by using the data that is already available. A computer center relays to each participant the perfect conditions.

In the second method, each microgrid component selects its ideal settings, and partial knowledge optimization is used. but metaheuristic techniques are typically used in centralized management. In various papers, centralized microgrid administration has been endorsed. However, the usage of distributed energy resources (DER) in a centralized information system may provide challenges for this type of management. If there is a lot of data, a high computing cost can be necessary. As an alternative approach, distributed energy management might be able to aid with this issue. By the use of distributed controllers, which manage data in real-time and necessitate communication equipment, data processing challenges are overcome and processing demands are reduced (e.g., Bluetooth, Wi-Fi, wireless networks, and IoT).

A microgrid's energy management model is made up of data acquisition systems, supervised control, human-machine interfaces (HMI), and climatic parameter monitoring and data analysis. The review of the literature was primarily concerned with management techniques based on foresight and quick preparation. To achieve a cost-benefit balance, the designer and operator of a microgrid might choose between centralized and decentralized administration. Choosing the most practical microgrid management strategy is now available. Decentralized administration provides more freedom, but a careful analysis is required to ensure the dependability and security of system functioning. When a single cost function is offered, the energy management problem or optimization control for a microgrid is transformed into a single-objective management/optimization model. The cost of running a microgrid is generally correlated with this function.

The problem becomes a multi-objective management/optimization model when it simultaneously addresses the technical, economic, and environmental issues. Based on the available literature, the authors have addressed the problem and proposed solutions utilizing techniques, such as linear and nonlinear programming, predictive control, dynamic programming, agent-based methods, and artificial intelligence. These solutions were selected based on their applicability, dependability, and availability of resources in the microgrid setting.

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Abbreviations

MG	Microgrid
AC	Alternating current line
ARMA	Autoregressive moving average model
CSA	Crow search algorithm
DC	Direct current line
DG	Distributed generation
DER	Distributed energy resources
EEMS	Expert system for energy management
EMS	Energy management system
GAMS	General algebraic modeling system
HMI	Human machine interfaces
HOGA	Hybrid optimization by genetic algorithms
HOMER	Hybrid optimization model for multiple energy resources

IHOGA	Improved hybrid optimization by genetic algorithms
JADE	Java platform for agent developers
MGSC	Microgrid supervisory controllers
MILP	Mixed integer linear programming
MO	Multiobjective
MPC	Model predictive control
PSO	Particle swarm optimization
PV	Photovoltaic
VPP	Virtual power plant

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