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Review

Towards Optimal Management in Microgrids: An Overview

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Abstract: A microgrid is a set of decentralized loads and electricity sources, mainly renewable. It can operate connected to and synchronized with a traditional wide-area synchronous grid, i.e., a macrogrid, but can also be disconnected to operate in "island mode" or "isolated mode". When this microgrid is able to manage its own resources and loads through the use of smart meters, smart appliances, control systems, and the like, it is referred to as a smart grid. Therefore, the management and the distribution of the energy inside the microgrid is an important issue, especially when operating in isolated mode. This work presents an overview of the different solutions that have been tested during the last few years to manage microgrids. The review shows the variety of mature and tested solutions for managing microgrids with different configurations and under several approaches.

Keywords: microgrid management; microgrid control; optimization

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1. Introduction

Over the past decades, the planet has experienced a deterioration in the weather conditions and an increase in natural disasters. The aforementioned problems have been discussed at climate conferences [1]. As the energy crisis and environment pollution arise from the great demand for electric energy, one of the solutions to reduce harmful emissions to the environment and demand for electric energy is to reduce the use of fossil energy sources (FESs) and accelerating the use of renewable energy resources (RESs), especially solar energy, which is useful in the production of electric energy through photovoltaic (PV) panels [1,2]. There is currently great worldwide interest in assessing: (i) the performance of a PV system, (ii) the price per PV module, (iii) the solar resource of the place of energy generation, etc. [3].

A microgrid (MG) is a small part of a power distribution system that interconnects distributed generation (DG) (mini wind turbine generators (MWTs), fuel cells, PV, etc.), energy storage systems, and controllable loads, which can turn into a self-sufficient energy system. An MG can connect to or disconnect from public grids and operate connected or in island mode [4–9]. An MG mostly operates in grid-connected mode, but sometimes, there is low energy demand or faults in the public grid and the MG must change to island mode. Under island mode, the renewable power systems operate with PV and/or MWT, whose production is uncertain. In order to manage this uncertainty, the MG employs energy storage systems (ESSs) for situations with low renewable generation [10]. This is an interesting solution for power generation; thus, it is under continuous research. The present research analyzes the MG's many characteristics, topology, energy management, or test beds around the world, among other targets [11–15].

Taking into account the topology of an MG, this can be classified into three groups: alternate current (AC), direct current (DC), and hybrid [11]. An AC MG is the most widely used configuration, as it connects directly from DG units in the public grids. However, its major disadvantage is the difficulty in controlling it, as it has four major components that must be taken into account: active power, reactive power, harmonics, and unbalanced components [11,12]. Most of the DC MGs are still in the research stage. The DC MGs advantage with respect to the AC MGs is the general performance, since fewer converters are used and there is no circulation of reactive current in the grid [11,13,14]. Finally, hybrid AC/DC MGs are having a great impact, as they combine the advantages of both AC and DC. The AC/DC MGs are a great solution for conventional public grids, although there are few articles about such a configuration [11]. These topologies need an energy management strategy, since their correct operation provides many benefits.

An MG must have an efficient energy management system (EMS) to monitor the operation of a complex system formed by electrical, thermal, and mechanical components with results in the short-term (adapt to the demand and production) and long-term (extending the lifespan of the most expensive and sensitive MG elements), resulting in a decrease in the costs of the system and an increase in the benefits. However, inappropriate decisions may lead to aging and early failure of the MG's elements [16–18]. Besides that, an efficient control system for managing the MG is useful when this operates in isolated mode since the control system is able to manage the energy source and loads in order for the MG to be self-sufficient. Hence, a control algorithm is essential for efficient energy management; some of these algorithms are available in [16–21]. It is often intended to minimize the operating cost, minimize pollution emissions, and maximize energy production through an objective function. A quadratic objective function model used in many EMSs is shown in Equation (1). Additionally, the net sum of all energy flows can be represented by an energy balance depending on the RESs, the ESSs, and the power of the grid, as shown in Equation (2).

$$J = \sum_{i=1}^{\infty}[\delta P_{sto}(t+j|t) - P_{sto,ref}(t+j)]^2 + \sum_{i=1}^{\infty}[\lambda \Delta P_{grid}(t+j-1)]^2 \tag{1}$$

subject to:

$$\sum_{i=1}^{\infty} P_{gen,i}(t) + \sum_{i=1}^{\infty} P_{grid,i}(t) + \sum_{i=1}^{\infty} P_{sto,i}(t) - \sum_{i=1}^{\infty} P_{load,i}(t) = 0 \tag{2}$$

where (i) P_{sto} is the storage power, (ii) $P_{sto,ref}$ is the setpoint for storage power, (iii) P_{gen} is the power generated, for example by renewable sources, (iv) P_{grid} is the power for the main grid, and (v) P_{load} is the power load.

On the other hand, the constraints can be of different types with the aim to minimize the operating cost, maximize energy production, maximize the useful life of the elements, etc., through the constraint equations expressed in Equations (3)–(6). Additionally, one of the most important constraints that is intended to be minimized is the greenhouse gas emissions through the constraints Equation (7).

$$P_{sto,min} \leq P_{sto}(t) \geq P_{sto,max} \tag{3}$$

$$P_{grid,min} \leq P_{grid}(t) \geq P_{grid,max} \tag{4}$$

$$P_{gen,min} \leq P_{gen}(t) \geq P_{gen,max} \tag{5}$$

$$SOC_{min} \leq SOC(t) \geq SOC_{max} \tag{6}$$

$$P_{gf,min} \leq P_{gf}(t) \geq P_{gf,max} \tag{7}$$

where (i) $P_{sto,max}$ and $P_{sto,min}$ are the storage power maximum and minimum, respectively, (ii) $P_{grid,max}$ and $P_{grid,min}$ are the maximum and minimum power for the main grid, respectively, (iii) $P_{gen,max}$ and $P_{gen,min}$ are the maximum and minimum power, respectively, generated by, for example, renewable sources, (iv) SOC_{max} and SOC_{min} are the maximum and minimum state-of-charge of the storage systems, respectively, for example batteries, flywheels, hydrogen tanks, and so on, and (v) $P_{gf,max}$ and $P_{gf,min}$ are the maximum and minimum power generated through nonrenewable energy, respectively.

The main innovative aspect of this work is to present a contemporary review of the main elements, architectures, advances in technology, and control algorithms for efficient energy management in MGs. To this aim, the main latest references that can be found in the literature about the current technologies in the research field of energy management in MGs are presented and summarized. The methodology of this review was a deep search of the main conference proceedings and scientific databases. From this search, the main recent references in the area of management in MG were selected. The search was focused in the EMSs of MGs, focusing on the new control trends (distributed, centralized, and cooperative control). The control strategies studied for this article are based on the control of devices or the planning methodologies that allow the MG users to optimize the use of resources. Additionally, the articles are classified by the optimization methodology that was used to minimize the objective function. The paper is organized as follows: The elements of an MG are described in Section 2, whereas in Section 3, the control algorithms used in the energy management of MGs are presented. Finally, the main conclusions are discussed in Section 4.

2. Elements of an MG

An MG is considered an energy distribution system that can be formed by PV panels, MWTs, fuel cells, process heat, natural gas, etc. It is also composed of an ESS, controllable loads, a control system, and planning methodologies for the optimization of resources. On the other hand, MGs can operate connected to or disconnected from the public grid [5,9]. The growth in the area of MGs in recent years has made it possible to combine different generation sources, and it is for this reason that MGs can be categorized as electric MGs (composed only of electric energy), combined heat and power MGs (composed of process heat and power), and multi-carrier MGs (composed of power and natural gas) [22,23]; on the other hand, it is important to mention that this review was based on the study of electric MGs.

The autonomous and decentralized operation in an MG can introduce a cost-effective solution for future distribution systems. The advances in communication and control systems have grown in recent years, which has increased the research into the different elements of an MG [24]. The main elements of an MG are presented in the following subsections, in which a quick description of the technologies and a summary of their characteristics are provided.

2.1. Energy Generation System

An important part of energy systems is governed by the generation of centralized energy such as coal, natural gas, nuclear, and hydroelectric plants. These carry out the transmission of their high-voltage energy over long distances, in order to distribute it to their final users. However, the fast entry of RESs into the market is changing the landscape. In addition, the large centralized energy systems mentioned above are aging and may generate conflicts with the current large demand for energy [25]. Many countries have reacted to this problem with adjustments to their public policies, promoting the generation of distributed energy with low carbon emissions and high efficiency. The distributed energy resources involved in MGs promote solar and wind energy sources due to their sustainability and economic performance [25,26].

The technologies in an MG include new concepts such as combined heat and power (CHP), MWTs, PV, microturbines or fuel cells, as well as consolidated technologies (synchronous generators driven by DC engines, single-phase and three-phase induction generators, or small hydro). A detailed description of these can be found in [8,26–29].

2.2. Energy Storage System

The ESS is one of the main components of some MGs, which must be cost effective at energy generation. The ESS plays a key role in geographic areas with unstable weather conditions due to its capacity to preserve power, as well as balance energy demand and generation. These systems comprise three necessary functions for their correct operation [25,30]:

1. Ensure power balance in an MG under unfavorable conditions such as transients and load fluctuations, since DG, having a lower inertia, cannot manage to provide a fast response to these disturbances;
2. Ensure energy transport capacity when dynamic variations occur in intermittent energy sources, for which even DG can operate as dispatchable units;
3. Supply the initial power for the transition between network-connected and island mode operation in the MG.

Mature EES technologies and those in development were described in [31–36]. Batteries, supercapacitors, hydrogen storage, and flywheels are the most applicable storages in MGs [25,33,34,36]. Currently, there is an extensive variety of ESSs, which encourages MGs' development towards self-sufficiency.

2.3. Power Electronics

Microgrids usually use PV technologies (generating DC power) or MWTs (generating high-frequency AC power), which need an inverter interface, such as DC/AC or DC/AC/DC. This interface can consist of a single inverter or a converter and an inverter, to transform the energy generation of the MG into energy compatible with the loads and/or the public grid [15,25]. Additionally, it is important to mention the importance of inverters in MGs, since they control the frequency and voltage, such as black start strategies [29].

Most of the distributed energy resources (DERs) include solar PV, fuel cells, or batteries, which generate DC power, together with many loads such as fans, heating, lighting systems, and even power electronics systems, which operate on direct current. As a consequence, DC MGs [28,37–40] have been proposed to avoid waste in the DC/AC conversion stage, since this means a loss of between 5% and 15% of the total energy generated [30]. However, it is worth noting that the promising applications of DC MGs have been limited by the shortage of household DC loads, which has boosted the appearance of AC/DC hybrid MGs with applications such as data centers or maritime and remote MGs [39,41–45]. Some examples of the different generation, storage, and interface options along with their advantages and disadvantages are provided in Table 1.

The components of an MG previously described in this section are an important part of the operation of an MG. It is possible to see in Figure 1 a simplified representation of an MG with systems coupled to DC and AC. In systems coupled to a DC-link, the battery bank is connected before the DC/AC inverter through a charge regulator, whereas systems coupled to an AC-link are connected after the DC/AC inverter through a charge regulator and inverter; finally, the data of all the elements of the MG are sent to the cloud through an intelligent interconnection.

Table 1. Interface, advantages, and disadvantages of different MG configurations.

Category	Type	Typical Interface	Advantages	Disadvantages
RES	PV [46–50] MWT [46,50,51] Small hydro [40,52]	Converter (DC-DC-AC) Converter (AC-DC-AC) Synchronous or induction generation	Free fuel supply Zero greenhouse gas emissions	Depends on random weather conditions Not dispatchable without storage
	Fuel cell [37,53,54]	Converter (AC-DC-AC)	Zero pollution on-site CHP can be used Dispatchable	High cost Limited lifetime
FES	Internal combustion engine [51]	Synchronous or induction generator	Fast startup CHP can be used Dispatchable	Greenhouse gas emissions Noise generation Generates pollution particles
Storage	Battery [36]	Converter (DC-DC-AC)	Proven technology with many years of research	Generates waste Limited charge and discharge cycles The price of this technology is high
	Flywheel [55]	Converter (AC-DC-AC)	High efficiency	High losses Limited discharge time
	Supercapacitor [33]	Converter (AC-DC-AC)	High storage capability and power output Longer lifecycle compared to modem secondary batteries	Low energy density Continuous research for improvement
	Hydrogen from hydrolysis [53,54]	Fuel cell	Zero pollution	Low system efficiency Hydrogen storage under investigation

2.4. Loads

A load is considered as an energy-consuming device that needs a supply to operate. In the studies carried out in [56,57], the loads could be classified into noncontrollable, shiftable, controllable comfort-based loads, and controllable energy-based loads.

The controllable loads, also called smart loads, are considered as a fusion between a noncritical load that can withstand voltage/frequency variations in short periods of time and a power electronic interface that isolates the load from the power. The smart loads are a possible solution to obtain better efficiency and power quality in an MG, and they can be classified into two types: (i) smart static load and (ii) smart motor load. They also have the possibility of connecting to the smart assistants that have become so popular in home automation for the loads' operation planning [58,59].

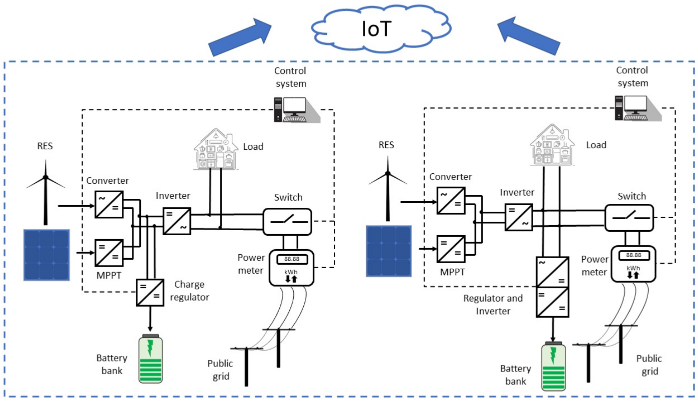

Figure 1. Simplified diagram of an MG with a DC-link (**left**) and a AC-link (**right**) of an ESS.

3. Microgrid Management

The integration of RESs, ESSs, and consumption carried out through MGs allows the users to exchange information with the distributed generation centers. Indeed, an EMS is necessary for the optimal operation of these DERs in an intelligent, secure, and coordinated way. Energy management in MGs is defined as a control and information system that aims to operate with the minimum possible costs both in the generation and distribution system and in the power supply [60–63].

Optimization in MGs is directly linked with the maximization of the output power of the generators in a particular instant, the maximization of the ESS's lifetime, and the minimization of the environmental impacts and of the operating costs. It is necessary to establish limitations and a objective function that relates to the operative cost of an MG. Some variables for this are maintenance, fuel, startup and shutdown, degradation, and the purchase of energy from the public grid. The optimization techniques presented in this review for the control of MGs are classified according to the optimization method used and the objective function to minimize [60,63,64], as expressed in Figure 2.

- Optimal Microgrid Control
  - Optimization Objective
    - Economic/Environmental
      - Energy dispatch
      - Demand-side management
      - Economic dispatch
      - Carbon dioxide emissions
    - Power flow
      - Optimal power flow
      - Load shedding
  - Optimization Techniques
    - Metaheuristics
    - Linear and nonlinear programming
    - Dynamic programming
    - Stochastic and robust programming
    - Predictive control
    - Multiagent
    - Artificial intelligence
    - Other techniques

Figure 2. Classification of optimal control strategies for MGs' control.

3.1. EMS Based on Metaheuristic Methods

A metaheuristic method is a higher-level method or a heuristic one designed to find, generate, or select a partial search algorithm that may provide a sufficiently good solution, that is a local solution, not necessarily global, to an optimization problem. These methods are used with incomplete or imperfect information or limited computational capacity.

One of the most widely used techniques in the literature is particle swarm optimization (PSO). Optimization methods such as PSO are widely used in different areas, which allows developing variations of their operation to obtain better results. The literature shows some techniques that use these variants. For example, Aghajani and Ghadimi in [65] presented multi-objective PSO (MOPSO), considering an intelligent EMS for an MG aimed at minimizing both the operating costs and pollution emissions. The MG in this research case included generation resources such as MWTs, PV panels, battery units, a wind turbine (WT), and a fuel cell. The results obtained in this paper were analyzed in three cases: (i) basic operation, which represents the normal function of the grid, (ii) operation at maximum capacity with RESs, and (iii) operation when the energy is unlimited. The third case proved to be the most favorable, since the amounts of emission were reduced by 23% and the operating costs were reduced by 5%, concluding that renewable resources are important for minimizing pollution from MGs, whereas the costs increase in the short term. Another similar work was presented in [66], in which Indragandhi et al. used MOPSO as a technique for the energy management of a hybrid DC/AC MG. The MG was composed of a PV system with modules (Trina Solar TSM-250-PC), a wind system with WTs (Elsonic India Group), and a fuel cell (Horizon H-1000 PEM). This paper applied the MOPSO strategy by defining the objective functions for the power cost and energy loss probability so as to obtain significant benefits in terms of sustainability, efficiency, and reliability. On the other hand, Hossain et al. [67] presented a PSO algorithm for the real-time energy management of a community MG that could work in island or grid-connected mode. The community consisted of twenty homes with six wind systems (5 kW/generator), five PV generators with a nominal power of 4 kW each, and an ESS installed. The proposed objective function had the aim of reducing the electricity costs and increasing the benefits by exchanging the energy of the MG with the public grid. The results obtained by this objective function decreased the operational cost by 12% compared with the original objective function over a time horizon of 96h. An example for which a multiobjective problem was proposed and solved by PSO can be found in [68], in which a novel algorithm, called guaranteed convergence PSO with Gaussian mutation (GPSO-GM), aimed at minimizing the capital investment and fuel costs of the system. The GPSO-GM's energy management was used in an MG composed of a PV system, WTs, and an ESS including batteries and diesel generators. The wind speed and solar irradiance data were obtained from [69], which were used in the modeling stage. Finally, the results of GPSO-GM demonstrated precision and robustness. In addition, they showed that the economic evaluation of the proposed system was a more attractive investment compared to other alternatives. As a fifth example, in [70], the methods of regrouping PSO (RegPSO) and a genetic algorithm (GA) were compared to validate its performance. The MG considered in this document was a real industrial MG, referred to as "Goldwind Smart Microgrid System", located in Beijing (China). This MG was composed of three PV systems, a diesel generator, and an ESS, including a lithium-ion battery and a vanadium redox flow battery. The EMS was aimed at minimizing both the operation and energy costs, and RegPSO presented better results than the GA. Finally, Zeng and Berti [71] proposed a new PSO multiobjective optimization algorithm, which was based on a fuzzy mechanism to minimize the operating and emission costs in demand response. The algorithm was used with a grid-connected MG composed of several production and storage systems containing CHPs, fuel cells, ESSs, energy-only units, and heat buffertanks. The proposed algorithm could reduce the cost by about 10%.

As an alternative evolutionary algorithm, a new powerful optimizer was proposed in [72] based on a crow search algorithm (CSA) in a hybrid DC/AC MG. In order to obtain realistic solutions, the data for the forecast PV and WT output power, the reactive and active power values, and the market prices were used. The CSA optimization method followed the same principle as that of the survival of crows, since they steal food from other birds and hide it to then eat it. They predict the behavior of other crows, using their experience as thieves to avoid becoming victims. Each crow represents a possible solution and, at the same time, a vector that contains elements with a possible value/optimal state for each variable. In this problem, the optimal value and state of the GDs, the ESS, and the main network are each crow's elements. The CSA algorithm minimized the operating costs of the MG, choosing the best among the three previous test solutions, for which the best result was 22.58%, 10.90%, and 15.24%, obtaining a significant reduction compared to previous outcomes obtained with PSO and the GA.

On a different note, there were some papers in the literature that dealt with a rule-based EMS (REMS) to minimize or maximize several characteristics of the MG. In [47], Torres et al. proposed a rule-based controller (RBC) for optimal energy management in an AC MG located at the CIESOL bioclimatic building at the University of Almería (Spain). The system was composed of PV panels, battery systems, an electric vehicle (EV), and a relay board, which allowed or rejected the power fluxes according to certain rules aimed at minimizing the energy consumption from the public grid. Another similar work can be found in [73], in which an REMS with a nature-inspired grasshopper optimization algorithm (GOA) was presented. This optimization method was aimed at minimizing the cost of energy (COE) and the probability of the deficiency of energy supply. The MG used as a testbed incorporated a WT, PV modules (STP275S-20/Wem), a battery bank, and a diesel generator. It used meteorological data from the database of the Nigerian Meteorological Agency. The method that offered the minimum value for the objective function was REMS-GOA (USD0.3656/kWh), as compared to REMS-CSA and REMS-PSO, which had a COE of USD 0.3662/kWh and USD 0.3674/kWh, respectively.

Finally, Rana et al. [74] presented a novel consensus filter based on a dynamic state estimation algorithm to stabilize energy production and consumption in a grid-connected MG. This MG was composed of a PV system, a wind generation system, and loads. The results showed that the proposed method could estimate the system states in 0.00004 s. These states were estimated with good accuracy; therefore, they could be used to design control strategies to stabilize energy production and consumption with respect to the public grid.

3.2. EMS Based on Linear and Nonlinear Programming

Linear programming optimization is used in optimization problems in which the objective function and the constraints are linear mathematical expressions. On the other hand, if any of them are nonlinear, the problem is referred to as nonlinear programming. In recent years, some optimization linear problems have mixed discrete (integers) and continuous (real) variables. In this case, this is called a mixed-integer linear programming (MILP) problem, and its solution is more expensive, in computational terms, than a simple linear programming problem.

Starting with the latter, an MILP problem was presented in [75] that minimized the power supplied by the public grid, which included continuous variables to model the power flow and binary variables for the state of the relays enabling or disabling certain power fluxes. The problem was solved for an MG located in the CIESOL bioclimatic building at the University of Almería, which was described in [47]. This MILP was able to reduce the electricity cost by 48.1%, since it took into account the hourly tariff to determine the consumption from the public grid. Another algorithm based on MILP was described in [76], in which the authors proposed an MILP with a new multi-objective solution that minimized the operating costs and pollution emissions in an MG composed of a PV system, a WT, a fuel cell, an MWT, a diesel generator, and a battery ESS (BESS). The operating cost, emission penalty, and power losses were reduced by 2.25%, 2.1%, and 3.56%, respectively. In addition, the results showed that carbon dioxide emissions were reduced by 51.60% per year with respect to the conventional grid. Another similar work can be found in [77], in which Hussain et al. proposed an EMS based on MILP, which had a function that minimized the operating cost of the MG network in grid-connected mode and maximized the service reliability in islanded mode. Each MG was a level of the MG network and was composed of controllable and renewable distributed generators, an ESS, and electric loads. The MILP algorithm obtained a reduction of 50% in the daily operating costs compared to hybrid EMSs. However, they were restricted to specific applications, this is not acceptable to many users. As a fifth example, in [78], Farsangi et al. presented a scenario with a reduction method based on MILP to minimize operational costs. The MG model was composed of a PV system, a WT, power-only units, CHP units, a heat-only unit, a heat buffer tank, plug-in EVs, and thermal and electric loads. The results showed that the operational cost was reduced by USD123.2819 (grid-disconnected) and USD246.4966 (grid-connected). Additionally, Farzin et al. [79] proposed a stochastic optimization problem that minimized the operating costs, which was formulated as an MILP model. The study of the MG was carried out in island mode and subsequently in grid-connected mode, which was composed of two dispatchable DG units, a WT, and one battery storage unit. The results showed that the MG's expected operating costs were minimized, through the proposed stochastic energy management strategy based on MILP, for which five cases with different time horizons were analyzed, obtaining the best result in the fifth case with an expected cost of reduction of 3.5% and reduction in the risk value of 3%. In [80], the problem was formulated using a parametric MILP (p-MILP) to operate seamlessly and in sync with a net cost minimization objective. The residential-level MG was located in Sarnia, Ontario, and was composed of a PV system, a WT, a BESS, a microturbine, and a utility grid connection. The results showed that the system made intelligent decisions under both external and internal uncertainties, without exceeding the operational limitations. As a final example, in [81], the authors formulated an optimization problem that was transferred into an MILP model. To evaluate the effectiveness of the proposed optimization model, an MG was considered, which was composed of a WT (250 kW), a PV system (150 kW), an aggregator EV unit, two WTs, two similar fuel cells, and a gas turbine. The maximal amount of power exchange with the main grid was 800 kW. The integration of EVs and renewable energies in the MG allowed the MILP to minimize the operating costs and pollution emissions in five different cases.

As regards linear programming, an iterative Newton–Raphson linear programming algorithm (NRLP) was proposed in [82], in which the objective function minimized the battery value loss and the power supply cost. A case study was used for an IEEE 34-bus distribution MG in Okinawa, Japan, to check the algorithm and analyze potential investments. The results of the NRLP reflected a high computational efficiency, which means that it may be a very useful tool for the long-term evaluation and optimization of complex power systems in the future. On the other hand, Tavakoli et al. [83] presented a linear optimization programming problem to maximize the resilience of an MG located in a commercial building with a peak load demand of 450 kW: it was composed of a PV system and a BESS connected to the power grid. In addition, the time horizon considered for the simulation was one week (168 h). The results showed that the operating costs increased slightly by 0.19%, while the resilience of the system increased by 41.1%.

Not only can linear problems be found when continuous and discrete variables are mixed, but nonlinear problems can as well. For example, in [84], Shuai et al. presented a stochastic mixed-integer nonlinear programming (MINLP) method, and then, the approximate dynamic programming decomposed the original MINLP to be implemented in an MG, which was composed of a PV system, a WT, a BESS, a gas microturbine, and a diesel generator. The simulation results of the energy management algorithm based on an approximate dynamic programming showed that the optimization cost of the MG was USD 97.17.

Lastly, it is important to highlight the work in [85], in which Wang et al. used a two-stage energy management strategy, based on Markowitz's theory of mean variance. The first stage used hierarchical optimization to minimize the operating cost of a networked

MG, with the grid-connected mode strategy, whereas the second stage employed a rolling horizon optimization strategy to minimize the imbalance cost between the day-ahead electricity and real-time electricity markets. The MGs of this paper were networks composed of community distribution generation units and a community ESS. The results were expressed in two cases to verify the effectiveness. In the first case, the mean operating cost was USD 226.70 and the standard deviation was 97.14, while in the second, the mean operating cost was USD 347.92 and the standard deviation was 93.35. The standard deviation in the former was less than in the latter with a confidence level of 95%.

3.3. EMS Based on Dynamic Programming

Dynamic programming methods are used to deal with highly difficult problems so as to reduce the execution time of an algorithm, which can be discretized and sequenced. The problem is transformed into subproblems, which are solved optimally. Finally, the solutions are superimposed to find the result for the original problem.

Recently, Jafari and Malekjamshidi [86] presented an ESS, which had an offline stage based on dynamic programming optimization and a real-time RBC to minimize the cost of energy received from the public network, the energy bill, and the benefits from sending energy to the network. The MG operated as a connected or disconnected network, located in a residential household with a maximum power of 4.5 kW and an average daily energy consumption of 22 kWh. It was composed of a PV system, a fuel cell, and a BESS. The results showed that the efficiency of the system increased by 4%; additionally, when the MG was connected to the network, the total energy cost was reduced by USD 2.13/day, while in disconnected mode, the reduction was only of USD 0.315/day. Another similar work can be found in [87], in which the authors proposed an optimal operation strategy using dynamic programming in a DC MG, comprising a PV system, a diesel generator (100 kW), a BESS with a nominal power of 100 kW, an EV, and constant output loads. The operation was based on dynamic programming developed to minimize the operational costs. This optimal operation allowed the MG to purchase energy from the public network at the lowest cost possible, with a price equivalent to KRW 60/kWh. In [88], a methodology based on dynamic programming was developed, with the objective of minimizing primary energy consumption over the simulation period. The hybrid MG used in this paper was located in a commercial building in the north of Italy. Additionally, it was designed for electric energy production, space heating, and hot water. It was composed of a PV panel, ground- and air-source heat pumps, a solar thermal collector, an auxiliary boiler, and a hot water storage. The results of this methodology based on dynamic programming were compared with a GA, showing an energy and computation time savings of over 5.4% and 41%, respectively. As a fourth example, in [89], Liu et al. presented an action-dependent heuristic dynamic programming method in a residential MG, which had the objective of finding a function that solved both the cost and energy transmission problems between dwellings. The MGs were distributed in *n* homes operating in grid-connected mode. Each of them was composed of a PV system, a BESS, and loads. The results of the method were compared with the PSO method, showing that the cost of buying energy from the public grid with the dynamic programming method was 75,569 centsover a whole month (30.7% saved), while the cost in the PSO algorithm was 80,476 centsover a whole month (26.2% saved). Thus, the dynamic programming method was able to reduce the economic cost of managing the MG more than the PSO method. As a last example, in [90], Jafari et al. presented a predictive 2D dynamic programming-based energy management method for a residential MG that could operate in either grid-connected or island mode, to minimize the energy costs. The MG was designed to supply a 4 kW residential load. It was composed of a PV system, a BESS, an electrolyzer, and a fuel cell stack that could operate as a load to generate the required hydrogen for the fuel cell, since it improved the storage capacity. The results of this algorithm showed a reduction of the energy cost by about 85% for a typical day, which implied a significant gain for RES users.

Dynamic programming can be combined with other techniques such as robust programming. Thus, in [91], Shi et al. developed a novel multistage robust EMS model for a public network-connected MG composed of a WT, three diesel generators, uncertain loads, and an ESS, with a maximum capacity of 90 kWh and a minimum storage level of 20 kWh. To solve the multistage EMS problem, a robust version of the dual-dynamic programming method was used to minimize the generation costs. The results obtained were compared with stochastic dual-dynamic programming, sample average approximation (SAA), and a deterministic method. They concluded that the generation costs of the SAA method were the most economical.

In addition to those examples, some works that dealt with adaptive dynamic programming (ADP) have been published in recent years. For example, Wu and Wang [92] proposed a strategy of optimal management based on ADP deep learning. Additionally, the objective function was defined to optimize the cost of generating and supplying power in the MG. The MG used in this paper was composed of PV generation, wind generation, gas power, hydro power, and a BESS. From the data obtained with ADP deep learning, it was possible to see a reduction in the energy costs and, at the same time, a reduction in pollution emissions. In [93], the authors presented a method of optimization based on evolutionary ADP to minimize the operational costs and maximize the energy demand. The MG system was composed of PV generation (40 kW), wind generation (30 kW), a diesel generator (10 kW), a BESS, and loads. The results showed that the controllable load demand was 100% met and that its dispatch strategy extended the lifecycle of the battery. As a final example, a novel mixed iterative ADP algorithm on a residential MG was presented in [94], which had the objective of minimizing the finite electricity cost in each iteration. To validate the mixed-iterative ADP algorithm, the results were compared with a dual-iterative Q-learning algorithm, when the load was high, the electricity rate was expensive, and the BESS did not discharge its maximum power. In conclusion, the ADP method showed better results from an economic point of view, since with the ADP method, the electricity cost was 3451.55 cents, while the electricity cost with the dual iterative Q-learning algorithm was 5001.19 cents.

3.4. EMS Based on Stochastic and Robust Programming

Stochastic methods and robust programming are used to solve optimization functions, with random parameters and uncertainties that can vary over time. Both methodologies are different in the way in which they deal with uncertain parameters. In the stochastic programming approach, the uncertain parameters are captured by a discrete number of probabilistic scenarios, whereas in the robust optimization approach, their value ranges are defined by a continuous set [95]. Additionally, they have the ability to deal with errors while the algorithm is running.

An example of the use of stochastic methods in MGs is a hierarchical stochastic EMS in interconnected MGs to improve the cost and real-time power deviations of a multi-MG system [96]. The multi-MG system here was composed of three MGs with a total capacity of 3790 kW, 3700 kW, and 4150 kW, as well as a peak load of 2600 kW, 2700 kW, and 2750 kW for MGs 1, 2, and 3, respectively. According to the data shown in this paper, this optimization method had good performance in the energy exchange between the multi-MG system and the main grid throughout the optimization. Another example can be found in [97], in which the authors developed a stochastic optimization based on a two-stage stochastic programming model, which had the objective of finding a function to reduce the total installation cost of MG devices. The MG was located at the Institute of Nuclear Energy Research in Taiwan. It included a high-concentration PV generator (100 kW), two wind power generators (25 kW and 150 kW), a fuel cell (2 kW), and a BESS. The results obtained in this paper demonstrated the efficiency of the proposed system in improving the MGs' operation and investment under uncertainty. Another similar work can be found in [98], in which Zhang et al. proposed a method for stochastic nonconvex optimization programming based on a modified Lyapunov optimization technique to obtain the minimum MG operating cost in grid-connected mode. The MG was formed of wind generation, CHP, and energy storage for both electricity and heat. The results presented in this article showed that the modified Lyapunov optimization strategy reduced the operating cost of the MG. One last example of stochastic methods in MGs is [99], in which Reddy proposed an optimization technique for a hybrid MG using a multi-objective stochastic technique, in which the cost function tried to minimize the system losses and reduce the operating cost of the RES. The hybrid MG was modeled with renewable energy sources, PV generation and wind generation, and loads. Later, it was tested on the IEEE 37 node distribution system located in California. The results showed the efficiency of the proposed method, generating 9813.97 MW with a total generation cost of USD 30,995.13 during a time horizon of 24 h.

Additionally, to take robust optimization methods into account, a distributionally robust optimization (DRO) method was proposed by Shi et al. in [100] to minimize several objectives: (i) the generation cost, (ii) the ESS degradation, cost and (iii) the emission cost of diesel generators. The islanded MG model considered conventional generators, a wind generation system, an ESS, and load demand. The results of the DRO were compared with SAA and the stochastic optimization method, for which DRO showed its effectiveness and reliability versus the other methods compared. Another similar work was given in [101], in which Giraldo et al. presented a convex mixed-integer second-order cone programming model to minimize the costs of the energy imported from the public grid in grid-connected and island mode for single-phase or balanced three-phase MGs. The MG had a total peak demand of 18.31 MW and was composed of dispatchable DG units, PV, a WT, a BESS and loads. The results from this paper showed a compensation between the operating costs and the robustness level obtained for the MG. As a third example, in [102], Luo et al. proposed a robust optimization method incorporating a piecewise linear electrical and thermal efficiency curve to obtain the desired operating cost in a combined cooling, heating, and power (CCHP) MG located on a building in Shanghai, China. The CCHP MG was composed of a PV system (80 kW), a gas microturbine (200 kW), a boiler (258 kW), an absorption chiller (200 kW), a battery (200 kWh), an electric chiller (100 kW), a thermal storage tank (150 kWh), and a heat exchanger (200 kW). The results showed that the proposed optimization technique performed better than the deterministic optimization model with respect to the expected operating cost. Additionally, in [103], a two-stage robust optimization problem was proposed based on Internet-oriented MG energy management to maximize the benefits of energy production. The MG was located in China, Beijing Goldwind Industrial Park, and composed of PV panels, a WT, a BESS, CHP, heat pumps, EVs, and loads. The simulation results showed that by exporting the surplus generation with the operation of the robust optimization algorithm, the benefits of the MG increased compared to the traditional business mode. In [104], a robust energy management method accounting for the worst-case scenario was developed. It had an objective function aimed at maximizing the total exchange cost and obtaining the minimum social benefit cost. In addition, the Taguchi orthogonal array testing method was used to evaluate an MG in various possible testing scenarios, which was composed of PV panels, microturbines, fuel cells, diesel engines, and a BESS. The results showed a good balance in performance (economic benefits), showing positive results.

Finally, Dini et al. presented a strategy in [105], in which stochastic and robust methods were combined. Specifically, a hybrid stochastic/robust coordinated energy management strategy was presented to minimize the difference between the energy costs and reliability and between flexibility and security. The MG was composed of two WTs, a PV system, a CHP, two WTs, and a fuel cell. The results obtained by the proposed strategy showed the capabilities of the proposed hybrid method while, at the same time, improving the energy system adequacy indices.

3.5. EMSs Based on Model-Based Predictive Control

Model predictive control (MPC) is a control methodology that uses a model of the system to predict its behavior. MPC is presented as a reliable, solid, and valid solution to counteract the uncertainties found in MGs, while it is able to guarantee effective energy management. Additionally, it is based on iterative and finite horizon optimization and uses the receding horizon strategy, that is, at each time, the optimal control sequence is calculated, the first control signal for that time instant is applied, while the remainder is discarded. Later, the horizon is displaced towards the future, and the control sequence is recalculated at the next time instant with new and updated information [106]. Typically, it combines stochastic programming and control.

As a first example, it is important to mention the work in [107] carried out by Dong et al. In this work, the authors replaced the voltage source inverter (VSI) with a dynamic matrix control (DMC) algorithm to maintain the energy stability control and improve the dynamic response performance of the VSI in a grid-connected MG located in Tianjin (China). DMC was the first MPC algorithm, introduced in the early 1980s and currently, it is available in almost all commercial industrial control software packages. The MG was composed of a PV system (2 MW), a BESS, and loads. The DMC results showed a considerable improvement in the response performance of the dynamic process.

Another application of the classical MPC strategy was presented in [108], in which a linear MPC model was presented that minimized the operating cost of the system and, at the same time, satisfied a set of constraints in a CCHP MG. The CCHP MG located in a building in Shanghai (China) was composed of a PV system (40 kW), a wind turbine (40 kW), an absorption chiller (200 kW), a gas microturbine (200 kW), a boiler (300 kW), a battery (150 kWh), an electric chiller (100 kW), a thermal storage tank (300 kWh), and a heat exchanger (200 kW). The results were divided into three cases for which the cost of the proposed linear MPC model was similar to the ideal cost in the three cases, which increased by 0.14%, 0.98%, and 2.64%, respectively. Another work in which the operating costs was minimized can be found in [109], in which Petrollese et al. presented a novel control strategy for the optimal energy management of MGs based on the integration of optimal generation scheduling with MPC. This strategy was tested in a laboratory-scale MG located at the University of Seville, which included an electronic power source that emulated a PV system, a BESS, a hydrogen production, and a storage system. The results showed that with the integration of MPC, the hydrogen storage, and the production storage system, the state-of-charge of the battery was far from its minimum value (40%). Additionally, the operating cost of the MG was reduced by 50%. On the other hand, Rigaut et al. [110] proposed an MPC strategy, for energy management in subway stations, with the aim to minimize the cost of consumed electricity in a thermo-electrical MG that connected regenerative braking energy sources, heating, ventilation, and air conditioning systems, specific profiles of electricity consumption, and a BESS (480 kWh). The proposed strategy was tested in a theoretical subway station, and the obtained results showed that a battery controlled for 20 h could save energy and economic cost by 32% and 34%, respectively, compared to the energy management of current stations.

Not only can the operation or economic costs be optimized in an MG through an MPC strategy, but other objectives may be achieved as well. For example, Bruni et al. [111] proposed a deterministic and stochastic MPC. The objective function of this EMS was aimed at maximizing the energy savings and improving the comfort conditions in a domestic DC MG. The MG was composed of PV panels, a fuel cell, a BESS, and the house load (mainly electric appliances and the thermal load of the heat pumps). The MPC results were compared to RBC, and the MPC test results were better than those of RBC, improving the comfort conditions. In addition, the energy savings were relevant, since they went from around 10% up to 30% or even more in the case of high RES availability. In [112], a horizon MPC was proposed to minimize the costs related to battery losses and depreciation. In this research, there were three types of prosumers (i.e., an element in the MG that both produced and consumed) in the distribution grid: (i) green prosumers (PV system and BESS), (ii) philanthropic prosumers, and (iii) low-income households. The results showed that if the owner and prosumers faced price competition, they could not improve the objective function. However, if there was no external competition, they could maximize their own benefits. On the other hand, the unscheduled power exchange level of the MGs with the main grid was minimized in [113], in which Bazmohammadi et al. proposed a hierarchical control structure of a multi-MG system, in which the second level adopted a two-stage stochastic MPC strategy. The simulated system was composed of three MGs that were equipped with a BEES of 350, 300, and 400 kWh, respectively. Then, the unscheduled power exchange level of the MGs with the main grid was evaluated in the AC Microgrid Research Laboratory at Aalborg University (Denmark). The results showed that adopting this energy management strategy could reduce the average unplanned daily energy exchange of the multi-MG by about 47%. The power losses in the islanded MG based on IEEE 13 were minimized by Morstyn et al. in [114], in which the authors developed a new convex MPC strategy. This islanded MG was composed of a PV system (100 kW) and four BESSs of 100 kWh each. The results of the convex MPC strategy provided a means of generating reasonable values based on the MG operating state.

If several MGs are considered with the aim to minimize a global objective MPC, this could be a good technique. It is possible to find in the literature some works that dealt with cooperative or distributive MPC, for which each MG had its own individual MPC and all of them exchanged information to try to minimize a shared objective. As examples, Kou et al. [115] proposed a new distributed economic MPC. The objectives of this method were: (i) to maintain the supply–demand balance, (ii) to obtain an optimal trajectory for the energy exchange, and (iii) to minimize the operating cost in a multi-MG. In this work, a distribution grid encompassing several MGs was considered, for which each MG was composed of several WTs, a gas microturbine, a BESS, and local loads. The results of the distributed economic MPC not only achieved the supply–demand balance in each MG, but also in all distribution grids. Another control algorithm based on distributed MPC was presented by Torres et al. in [116], in which the authors proposed a distributed MPC in a network of interconnected MGs, with a hybrid ESS, to improve the benefits of the exchange of energy with the public grid. The network of interconnected MGs was composed of four grid-connected MGs, which had one PV system each, a WT, an electrolyzer, a hydrogen tank, a fuel cell, a BESS, and an ultracapacitor. The results showed two procedures in both the daily market and the regulation service market. These procedures were compared to a single mode and a network of MGs, for which the networked operation of the MGs could improve the economic benefits in comparison with the single-mode operation. Lastly, in [117], a novel cooperative MPC was presented to minimize the energy exchanged with the distribution grid and the overall energy costs in urban districts, which could deal with multiple MGs. The system of multiple MGs was studied in three experiments: Experiments 1, 2, and 3 were composed of 5, 15, and 15 MGs, respectively. Each MG was connected to the distribution grid and equipped with a PV system (1 kWh/kWp), a micro-CHP (25 kW), a heat pump (2 kW), and a BESS (1 kWh). The results obtained by cooperative MPC showed a minimum cost saving of 10% with a prediction horizon of 24 h.

3.6. EMS Based on Multiple Agents

The optimization methods based on a multi-agent system (MAS) are applied to complex systems (systems that are composed of many interacting variables). These methods are used in MGs for the decentralized management of the MG and to operate the tasks with defined objectives.

Moghaddam et al. [118] proposed an MAS to reduce operating costs in a residential MG. The MG included different generation sources and ESSs, as well as controllable loads. Each residential building was equipped with a micro-CHP, a domestic hot water system, a heating/cooling system, and an ESS. The simulation results demonstrated that the proposed MAS was able to reduce the operating cost and, at the same time, ensure users' needs in any weather condition. On the other hand, Li et al. [119] presented a three-layer MAS model to promote the use of RESs and reduce the operating cost of an MG. The three-layer MAS for the MG was composed of a PV system, a WT, a BESS, a heat storage tank, an electric boiler, and a CHP. The results demonstrated that the MAS could reduce the operating cost by 1.84%, whereas the generation of the PV and WT increased by 14.67% and 11.86%, respectively.

Relevant results can be obtained if an MAS is used in a distributed or in a decentralized manner. A distributed EMS architecture based on MAS was proposed in [120] by Khan et al. with the aim to improve efficiency and minimize power losses. The MG comprised PV systems, WTs, micro-hydropower systems, diesel generators, BESSs, and grid loads. The results were based on a case study located on Tioman Island (Malaysia), using meteorological data from the Malaysian Meteorological Department. These results of the MAS were compared with a centralized EMS, for which the proposed architecture obtained a higher performance with respect to the centralized EMS. Another similar work can be found in [121], in which Samadi et al. proposed an MAS-based decentralized EMS to optimize the behavior and the operating costs of an MG connected to the grid. The MG comprised a PV system, a wind and a diesel generator, a microturbine, a fuel cell, and an ESS. The operating costs of the MG were reduced by about 44% and 48% in comparison with MILP optimization and the nonlinearcondition, respectively. As a third example, in [122], a distributed peer-to-peer multi-agent framework was proposed to maintain a balance between generation and demand in a grid-connected DC MG. The MG was composed of six PV systems with a total nominal capacity of 14 kW, six residential loads with a total demand of 24 kW, and six EV units. Specifically, these EVs were three Ford Escapes and three Nissan Leafs equipped with 12 kWh batteries and three of with 24 kWh, respectively. The results of the proposed scheme guaranteed a faster performance, as well as ensured the energy supply.

In addition to the aforementioned examples, it is possible to find some papers in the literature that combined MAS with other techniques in order to obtain better results for the MGs' management than those using MAS exclusively. For example, Jin et al. [123] presented the structure of an MG based on MAS together with a game-theory-based optimization model to improve the stability of the power grid and reduce the operating costs. The MG was composed of several generation agents such as: a PV agent, a gas turbine agent, and a WT agent. The benefits of the WT, PV, and gas microturbines accounted for an increment of 6%, 19%, and 88%, respectively, when compared to a noncooperative game optimization. As a second example, in [124], Kofinas et al. presented a cooperative MAS for the energy management of a stand-alone MG, through a distributed, collaborative reinforcement learning method called fuzzy Q-learning, to guarantee electricity supply and increase the reliability of the MG. The MG was composed of an energy production group including a PV source, a diesel generator, and a fuel cell. On the other hand, the energy consumption group included a desalination plant, an electrolyzer, and a variable electric load, which simulated the energy consumption of a building. The MAS results presented energy production and consumption for two consecutive days in both winter and summer seasons. Lastly, in [125], an MAS based on deep neural networks and the alternating direction method of multipliers was presented to minimize the energy and operation losses' cost of agents in an MG operated in a multi-agent structure. This MG was composed of a conventional distributed generator, WTs, PV systems, and BESSs. This proposed EMS allowed forecasting the prices of the daily market, for which the results demonstrated that the highest possible curtailment was 35%.

3.7. EMS Based on Artificial Intelligence

Optimization methods based on artificial intelligence try to solve an optimization problem, usually a nonlinear one, using a method that replicates human behavior and/or its nature. Examples of these techniques are artificial neural networks (ANN), which are vaguely inspired by the biological neural networks that constitute the human brain, or GAs, which are inspired by the process of natural selection (only the phenotypes of the individuals that are the best adapted ones to the environment are passed from one generation to the next).

Cruz et al. [126] presented a dynamic ANN to minimize both the operating costs and the costs of energy purchase from the public grid, in a grid-connected MG. This MG was located in the Engineering Faculty at the Autonomous University of Yucatan (Mexico). The MG was composed of a PV system, a wind generation system, electric loads, and a BESS. The results of the ANN showed a prediction of the energetic variables presented in the MG with good estimation results.

On the other hand, there are several works in literature that dealt with GAs to minimize several features of the MG. In [127], an optimization problem was presented that was solved through GA to minimize the operating cost of an MG located in China and to make full use of clean energy. The MG had generation units such as a PV system, a CCHP, and an ESS. The results showed that the monthly system operating cost savings rate was between 1.38% and 1.68% after the demand response. Aldaouab et al. [128] proposed a GA approach to minimize the total annual cost of the system in an MG composed of a PV system, wind microturbines, a backup diesel generator, and a BESS, with a total residential consumption for a year of 73,492 kWh. The simulation results showed that using a backup power source to support the RES reduced the overall costs of the MG. As a third example, in [129], different strategies were developed for the synthesis of a fuzzy inference system EMS, by means of a hierarchical GA. The main aim of the proposed strategy in this work was to maximize the benefits generated by the energy exchange with the public grid in a residential MG composed of a PV system, a BESS, and loads. The results showed that the performances were 10% below the ideal reference solution.

Another artificial intelligence-based methodology that has been widely used in MG management is fuzzy logic. Fuzzy logic is based on the observation that humans make decisions based on imprecise and nonnumerical information. Fuzzy logic is a form of many-valued logic in which the true values of variables may be any real number between zero and one, both inclusive, unlike Boolean logic, for which the true values of variables may only be the integer values of zero or one. In [130], an EMS was proposed based on a fuzzy logic controller (FLC) to improve the MG's performance from both a technical (to prolong the device's lifespan) and an economic (to have the highest profitability and efficiency) point of view. The proposed controller was tested in a residential MG found at the Spanish Institute of Aerospace Technology. The MG was composed of a monocrystalline technology PV field (5 kWp), a fuel cell, an EV, and a hybrid hydrogen ESS together with batteries. Specifically, the batteries were made up of both a Li-ion battery bank (43.2 kWh) and a lead-acid battery bank (36 kWh). The simulation was carried out with data from Huelva, southwestern Spain. The results showed that the EMS based on the FLC guaranteed the residential demand and, at the same time, allowed for savings of up to EUR 630/year on the electric energy bill. Another similar work can be found in [131], in which Al-Sakkaf et al. proposed an EMS based on a low-complexity FLC to maximize the energy savings and, at the same time, minimize the cost in an autonomous DC MG for a residential house. The MG consisted of a PV system, a WT, a fuel cell, a diesel generator, and a BESS. The simulation was carried out in Dhahran City located in the eastern part of Saudi Arabia. The simulation results were compared with the PSO, GA, and artificial bee colony methodologies. The proposed method showed an energy savings of 10.79% and a reduction in the generation cost of 11.19%, with respect to conventional methods. In [132], the design of a low-complexity FLC was presented to minimize the grid power fluctuations while keeping the battery state-of-charge. This method was tested on a real residential MG located at the Public University of Navarre (Spain). The MG included a domestic AC load (7 kW), a PV system (4 kW), a small WT (6 kW), and a BESS made up of a lead-acid battery bank (72 kWh). The simulation was performed with the aim to make a comparison with other approaches seeking the same objective using real data, for which the improvements of the proposed design were evidenced. On the other hand, Ulutas et al. [133] developed an EMS based on a neuro-fuzzy inference system to reduce the energy exchange with the public grid in a grid-connected MG composed of a PV system, a BESS, and loads. The results of the neuro-fuzzy inference system verified that the EMS predicted the load and generation with high accuracy. Additionally, the public grid usage was reduced, which ensured that the electric bills would be lower.

As a last example of artificial intelligence use in MGs, Mondal et al. [134] developed a solution for the problem of scheduling and energy exchange between MGs. The problem was studied as a multileader multifollower noncooperative Stackelberg game to maximize energy supply benefits by strategically choosing the optimal value in an MG that predicted the maximum amount of energy required by the load. The results of the simulation showed that the benefits of the energy supply increased.

3.8. EMS Based on Other Techniques

The methods described in this subsection cannot be classified into the previous ones since their characteristics do not fit well with those previously described. Hence, this section was created to present new algorithms that have been found in literature, developed for the optimization of EMS in MGs.

In the literature, it is possible to find dozens, even hundreds, of different optimization methods that have been tested in MGs, most of them in simulation mode. To name just a few examples, in [135], an EMS was proposed based on a rolling time horizon to maximize the benefits generated by the energy trade and, at the same time, to minimize the energy oscillations with the main grid. The method was tested in a grid-connected MG composed of a PV system, system loads, and a BESS. The results showed that the EMS based on a rolling time horizon provided better performance even in the presence of uncertainty in the predictions.

On the other hand, in [136], a fitted Q-iteration algorithm was developed based on Markov's decision process to minimize the energy cost and, therefore, maximize the self-consumption of local PV production in a residential grid-connected MG. This MG was composed of a PV system, a BESS, a residential load, and a transformer that connected the MG to the public grid. The developed method was compared with a model-based strategy, and the simulation results showed a performance difference of 19%.

An optimization method based on a generalized reduced-gradient algorithm to minimize the operating cost in a grid-connected MG was presented in [137] by Jordehi et al. The MG was composed of a PV system, a wind generation system, and a BESS serving a fleet of EVs. The results showed that the operating cost of the MG was significantly reduced.

The work presented in [138] must not be forgotten, in which the authors proposed an improved differential evolution algorithm to minimize the operating and maintenance cost, while at the same time reducing the energy losses. The method was tested in a grid-connected DC MG that was composed of a PV system, a WT, and an ESS made up of batteries and ultracapacitors. The simulation results of the proposed algorithm demonstrated its feasibility and effectiveness.

To close this subsection, MGs stand out in the area of smart grids, and for this reason, every day, new methods are emerging to improve their performance; one of these methods is the reconfiguration of MGs. It is important to mention that this method has become very prominent in recent years, and its operating principle is based on the correct change of the closed/open state of the switches, which results in a radial network or in a mesh, with the aim to improve the efficiency and sustainability of the distribution grid. In addition, this method minimizes losses and maximizes load balance at the network level [139–141]. However, this article was focused on the optimization methods described in Figure 2.

3.9. Summary

This study selected, from the most important conference proceedings and scientific databases, the most relevant works on energy management in MGs and tried to classify the selected works depending on the optimization method used to solve the cost function to optimize the energy management in MGs.

The results are summarized in Tables 2 and 3, which show both the number of references according to the optimization method implemented in the work and according to the addressed problem, respectively.

Table 2. Summary of the optimization methods for energy management in MGs.

Optimization Method	Reference	Number of References
Metaheuristic	[47,65–74]	11
Linear and nonlinear programming	[75–85]	11
Dynamic programming	[86–94]	9
Stochastic and robust programming	[96–105]	10
Model-based predictive control	[107–117]	11
Multi-agents	[118–125]	8
Artificial intelligence	[126–134]	9
Other techniques	[135–138]	4

Table 3. Summary of the addressed problems in energy management in MGs.

Addressed Problems	Reference	Number of References
Operative cost	[65,68,70–72,76–79,81,85,87, 91,93,97–99,108,109,115,117–119,121,123,127,137,138]	28
CO_2 reduction	[65,71,92,104]	4
Public grid consumption	[47,66,67,70,73–76,81,88,90,92–94,101,105,110,113,115,116,126, 129,136]	23
Balance generation and demand	[91,92,100,103,118,122,124,130, 131,133–135]	12
Others	[80,82–84,86,89,96,100,102,107, 111,112,114,120,125,128,132]	17

As can be seen, although there is no predominant optimization method and its choice depends on the problem addressed or the authors' knowledge in the optimization field, the cost functions most used when addressing the energy management in an MG deal with the operating cost and consumption from the public network.

4. Conclusions

In this work, the most relevant optimization techniques for MG management and operation were presented and briefly discussed. Among others, we discussed: MILP and MINLP, predictive control, heuristic methods, artificial intelligence, multi-agent based methods, and dynamic programming or stochastic and robust programming. Some of these techniques are classic ones and have been widely used in the management of MGs for several years. However, other techniques cannot be classified into known methods, since they are still under development, as was shown previously in Figure 2, but they have obtained promising results in this research field.

As pointed out previously, several optimization procedures to manage MGs were presented, but no particular one can be chosen as the "best" since this election depends on the features of the MG, that is it depends on the different elements that make up the MG or the objective to be maximized or minimized. The main idea that may be deduced from this review is that an energy management technique is mandatory at the time of operating an MG. Regardless of whether the objective is to maximize the MG production, reduce the CO_2 emissions, increase the benefits of the MG, or any other, a good EMS can increase the stability and efficiency of the MG while being able to extend the service life of its components. Not only can one objective be optimized at a time, but several ones can be at the same time, as has been pointed out in several works of this review, as in [71,76,99]. In this case, the EMS has multiple objectives since it can simultaneously present a response to economic, environmental, and technical problems.

With the creation and development of more and more MGs in the next few years and the need for them to interact so as to reach shared objectives, the optimization techniques to solve big problems for which several MGs are involved are of great interest due to the increase in this kind of system's complexity. The works [89,115–117,124,134] should be highlighted, in which distributed or cooperative optimization techniques were presented and tested with good results when it comes to managing the energy flows through several MGs. These techniques are most suitable to deal with this kind of problem, instead of using a centralized optimizer, due to the complexity of the optimization problem and the computational time needed to solve it. Distributed or cooperative techniques are able to reach solutions almost as good as if a centralized optimizer were used, but spending much less computational time.

Finally, other similar papers to this work can be found in [60,63]. These works have many interesting references. In this paper, we tried to update and complement the information related to managing the EMS of an MG from the authors' perspective.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating current
ADP	Approximate dynamic programming
BESS	Battery ESS
CCHP	Combined cooling, heating, and power
CHP	Combined heat and power
COE	Cost of energy
CSA	Crow search algorithm
DC	Direct current
DER	Distributed energy resource
DG	Distributed generation
DRO	Distributionally robust optimization
DMC	Dynamic matrix control
EV	Electric vehicle
EMS	Energy management system
ESS	Energy storage system
FES	Fossil energy source
FLC	Fuzzy logic controller

GA	Genetic algorithm
GOA	Grasshopper optimization algorithm
GPSO-GM	Guaranteed convergence PSO
MG	Microgrid
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear programming
MPC	Model predictive control
MAS	Multi-agent system
MOPSO	Multi-objective PSO
NRLP	Newton–Raphson linear programming algorithm
P_{gen}	Renewable power generated
P_{gf}	Power from a fossil generator
P_{grid}	Public grid power
P_{load}	Demanded power
PSO	Particle swarm optimization
P_{sto}	ESS power
PV	Photovoltaics
RegPSO	Regrouping PSO
RegPSO	Regrouping PSO
RES	Renewable energy source
RBC	Rule-based controller
REMS	Rule-based EMS
SAA	Sample average approximation
SOC	State-of-charge
VSI	Voltage source inverter
WT	Wind turbine

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