Optimal Allocation and Operation of Droop-Controlled Islanded Microgrids: A Review

Maen Z. Kreishan [ID] and Ahmed F. Zobaa *[ID]

Electronic and Electrical Engineering Department, Brunel University London, Uxbridge UB8 3PH, UK;
maen.kreishan@brunel.ac.uk
* Correspondence: azobaa@ieee.org

Abstract: This review paper provides a critical interpretation and analysis of almost 150 dedicated optimization research papers in the field of droop-controlled islanded microgrids. The significance of optimal microgrid allocation and operation studies comes from their importance for further deployment of renewable energy, reliable and stable autonomous operation on a larger scale, and the electrification of rural and isolated communities. Additionally, a comprehensive overview of islanded microgrids in terms of structure, type, and hierarchical control strategy was presented. Furthermore, a larger emphasis was given to the main optimization problems faced by droop-controlled islanded microgrids such as allocation, scheduling and dispatch, reconfiguration, control, and energy management systems. The main outcome of this review in relation to optimization problem components is the classification of objective functions, constraints, and decision variables into 10, 9 and 6 distinctive categories, respectively, taking into consideration the multi-criteria decision problems as well as the optimization with uncertainty problems in the classification criterion. Additionally, the optimization techniques used were investigated and identified as classical and artificial intelligence algorithms with the latter gaining popularity in recent years. Lastly, some future trends for research were put forward and explained based on the critical analysis of the selected papers.

Keywords: optimal allocation and operation; droop control; islanded microgrid; renewable energy; generation and load uncertainties; artificial intelligence; multi-objective optimization

1. Introduction

Over the last decade, a significant shift has occurred in research trends toward design and operation of decentralized electric distribution networks. This can be realized by the substantial focus on microgrid implementation, control, and optimization studies in several published literature reviews [1–23]. One of the main unique features of microgrids is the ability to operate in a decentralized manner without the supervision of the utility main grid. This unique characteristic of microgrids is fundamental to the deployment of renewable energy resources. A microgrid (MG) can be defined as a small-scale distribution network with multiple distributed generation (DG) units and electrical loads either connected to the utility main grid at the point of common coupling or isolated. Furthermore, depending on the type of DG installation, whether it was conventional (such as gas microturbines, biomass boilers, etc.), renewable (such as wind, solar, tidal, etc.), or a combination of both, a microgrid could have an energy storage system (ESS) embedded to harvest the intermittent energy for use at a later time. According to the state of connectivity to the main grid, two modes of operation exist for an MG: islanded or grid-connected.

The grid-connected mode of MG operation is desired when the integration of renewable resources and economic operation goals is required [19]. Furthermore, the existence of a large power grid facilitates voltage and frequency control in the MG, while the distributed energy resources are utilized as constant power sources regardless of demand

variations [3]. On the other hand, islanded operation of MG is usually desired to defer upgrade costs, conduct scheduled maintenance, and compensate for main grid failures in supply reliability [24]. Moreover, islanding is necessary for the electrification of isolated regions and distant communities where the cost of connecting such areas is high or impractical, while the main source of generation for such isolated grids is fossil fuel and recently renewables [14]. Despite the numerous economic and environmental benefits an islanded MG can bring, one major problem that arises is how to guarantee quality of supply.

To ensure adequate supply quality of islanded MG and thus provide sufficient voltage and frequency regulation, all or some of the distributed energy resources must cease the constant power operation and start to follow demand variations to accomplish voltage and frequency control as stated in international standards such as IEEE std. 1547.4 for islanded systems design and operation [25] and IEEE std.1547.7 for DG interconnection with islanded power grids [26]. This type of control can be achieved through two distinct philosophies: centralized and decentralized control [11]. The selection of the former control philosophy is highly dependent on the existence of expensive and wide bandwidth communication infrastructure in the MG. The master–slave method is one of the most prominent centralized control approaches for its accurate power-sharing ability and near nominal frequency and voltage regulation. However, this type of control is often too expensive or impractical for the majority of islanded microgrids across the globe as the cost barrier is often blamed for preventing further communication infrastructure upgrades. Additionally, if microgrids were to phase out centralized generation on a massive scale, a reliable control strategy would be mandatory to facilitate this transition. However, centralized control often has a single point of failure, which makes it impractical and less reliable for large-scale application [11,18]. Hence, decentralized control methods have gained significant popularity to operate islanded microgrids where the cost of extra-high bandwidth communication channels is not desired. The most implemented decentralized approach is the droop control, where the active and reactive power output of DG units is linearly related to the frequency and voltage of the MG, respectively. Furthermore, the acceptable power-sharing capability of droop control eliminates the need for communication channels between the units. This is due to the fact that DG units operated in droop control are only required to gather local measurements for voltage and frequency using pre-existing infrastructure. An islanded MG that adopts the droop control strategy is referred to as a droop-controlled islanded MG (DCIMG).

The implementation of DCIMG control strategy often occurs in multiple or hierarchal stages referred to as primary, secondary, and tertiary control. Therefore, an energy management system (EMS) to supervise those control stages is required. This shall ensure adequate voltage and frequency regulation and near constant balance between supply and demand observing certain technical, economic, and environmental constraints for the MG [15]. Optimal planning and operation of DCIMG is vital for the successful EMS execution, which is necessary to yield the benefits of DG, in particular those of renewable energy resources. In one way, DG is fundamental for the sustainable development of future smart grids due to the many benefits it can offer, such as improved voltage profile, reduced network power losses, deferment in transmission and distribution infrastructure upgrades, diversity of generation portfolio, and reduction in emissions from fossil fuels [3,5]. On the other hand, the increased growth in renewables has brought forward various technical issues due to the uncertainty associated with their operation. Therefore, many researchers have undertaken different approaches to employ various classical and artificial intelligence (AI) optimization techniques to enhance and optimize the planning and operation of DCIMG.

Connection standards and legislation urge the use of protective devices with DG units connected at the distribution levels [25,26]. Furthermore, the adopted control strategy in those microgrids must integrate with these protective devices to be able to isolate the system from the main grid in case of faults. As is the case for islanding operations, these extra devices with DG units often act as an uninterrupted power supply (UPS) to guarantee the continuity of supply to the isolated MG. A major drawback for master–slave controlled

islanded microgrids is the single point of failure, where any persistent fault in those extra devices acting as the master unit will drive the MG toward the point of collapse. However, this issue is resolved in DCIMG as multiple units are actually acting similarly to the master unit objective, and this is another reliability advantage of DCIMG over centralized master–slave islanded microgrids.

According to the comprehensive survey of many review papers [1–23] illustrated in Table 1, it was concluded that some reviews have focused on the optimal planning of microgrids without an emphasis on the MG mode of operation [1,22], while others focused on the control strategy and optimal EMS without taking into consideration the other aspects of MG planning [3,15,18,19]. Furthermore, those MG surveys that addressed optimization techniques lacked a certain focus on the optimal planning and operation of DCIMG [5,13]. In light of the foregoing, and to the best of the authors' knowledge, no review work has been published previously that focused on DCIMG optimal operation and allocation and gathered all the aspects of the optimization problem in terms of objective functions, constraints, decision variables, and optimization algorithms. Therefore, this paper aims to fulfil the gaps and attempt to provide an insight to the current state of the art research in DCIMG and to suggest possible future trends.

Table 1. Overview of MG optimization-related subjects covered in previous literature reviews.

Reference	Optimization Elements					Mode of Operation		Optimization Problem						MG Type		Supervisory Control		Optimal DCIMG
	Ob	Co	Var	Alg	MO	Isd	GC	Al	Dis	Re	Cnt	EMS	Pro	AC	DC	Cen	Dec	
[1]	Y	Y	N	Y	Y	N	N	Y	N	N	N	Y	N	Y	N	N	N	N
[2]	Y	Y	Y	Y	Y	N	Y	Y	N	N	N	N	N	Y	N	N	N	N
[3]	N	N	N	N	N	Y	Y	N	N	N	Y	Y	Y	N	N	Y	Y	N
[4]	N	N	Y	Y	Y	N	Y	Y	Y	N	N	Y	N	Y	N	N	N	N
[5]	Y	Y	Y	Y	Y	N	Y	Y	N	N	N	N	N	Y	N	N	N	N
[6]	N	N	N	Y	Y	N	Y	N	Y	N	N	N	Y	Y	N	N	N	N
[7]	Y	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	N	Y	N	Y	Y	N
[8]	Y	Y	N	Y	Y	N	Y	Y	N	Y	N	N	N	Y	N	N	N	N
[9]	Y	Y	N	Y	Y	N	Y	Y	N	N	N	N	Y	Y	N	N	N	N
[10]	Y	N	N	Y	N	N	Y	Y	N	N	N	N	Y	Y	N	N	N	N
[11]	N	N	N	N	N	Y	Y	N	N	N	Y	N	N	Y	N	Y	Y	N
[12]	Y	N	N	N	Y	N	Y	N	Y	N	N	Y	Y	N	N	N	N	N
[13]	N	N	N	Y	N	Y	Y	N	N	N	N	N	N	Y	Y	N	N	N
[14]	N	N	N	N	N	Y	N	N	Y	N	N	Y	N	Y	N	N	N	N
[15]	N	N	N	Y	Y	Y	Y	N	N	N	N	Y	N	Y	Y	Y	Y	N
[16]	Y	N	N	Y	Y	N	Y	Y	Y	N	Y	Y	N	Y	N	N	N	N
[17]	Y	Y	Y	Y	Y	N	Y	Y	N	N	N	N	N	Y	Y	Y	Y	N
[18]	Y	Y	Y	Y	Y	N	Y	N	N	N	Y	Y	N	Y	N	N	N	N
[19]	N	N	N	N	N	Y	Y	N	N	N	Y	N	Y	Y	Y	Y	Y	N
[20]	N	N	N	Y	Y	N	Y	Y	N	N	N	Y	N	Y	N	N	N	N
[21]	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	Y	N	N	N	N
[22]	Y	N	Y	N	Y	N	N	Y	N	N	N	N	N	N	N	N	N	N
[23]	N	N	N	Y	Y	Y	Y	Y	N	N	N	N	N	Y	Y	N	N	N

Ob = objective function, Co = constraint, Var = decision variables, Alg = algorithm, MO = multi-objective, Isd = islanded, GC = grid-connected, Al = allocation, Dis = dispatch, Re = reconfiguration, Cnt = MG control, EMS = Energy management system, Pro = MG protection, Cen = centralized, Dec = decentralized, DCIMG = droop-controlled islanded microgrid, Y/N = yes/no.

This review paper is organized as follows: In Section I, the background of DCIMC is introduced. Section II, the main aspects of microgrid control and operation are explained while microgrid optimization is also described. In Section III, the optimization objectives, constraints, variables, and algorithms in DCIMG are explained in detail. The last three sections IV, V, and VI, demonstrate a discussion of the literature review, future trends, and the conclusion, respectively. A complete list of frequently used acronyms in this paper is illustrated in Table A1 (See Appendix A).

2. Microgrid Overview

As previously mentioned in the introduction, an MG can be defined as a cluster or group of clusters of power distribution networks that has its own dispersed generation, energy storage facilities, adjustable smart demand, and a complete supervisory control and optimization strategy. As shown in Figure 1 [15], the aforementioned definition is illustrated by a generic MG architecture operated at the medium to low voltage levels. In the following subsections, further insight about the classification, type of operation, control, and optimization of DCIMG is introduced.
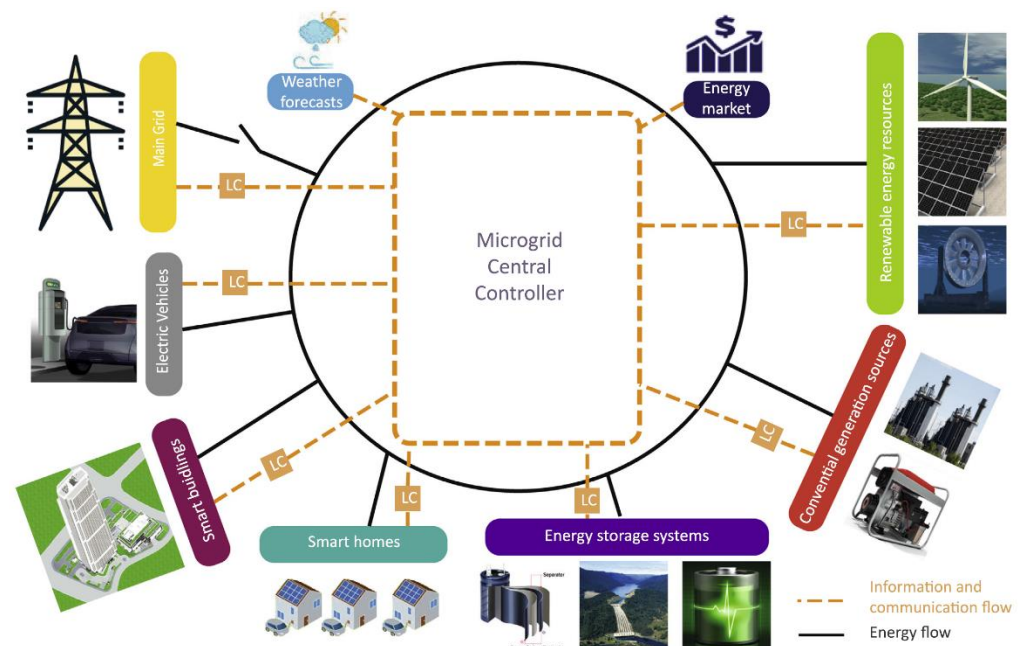

Figure 1. Microgrid general architecture.

2.1. Microgrid Classification and Structure

There exist different criteria to classify DCIMG into various categories based on the availability of grid connection as a grid-supported or sole remote application; the type of generation mix, whether it is conventional, renewable, or a mixture of both; distribution voltage level such as medium-voltage (MV) or low-voltage (LV) level; the type of electric current utilized in the system, as AC, DC, or hybrid AC/DC; the size of the electricity demand as small-scale or large-scale; type of load, such as residential, commercial, or industrial; and network topology, such as radial or meshed structure [4]. There is no standard structure or framework for DCIMG design and planning as it is merely reliant on the purpose of the MG application or the scale of the electricity demand it was intended to serve. According to [19], many existing microgrids, whether it was for testing or grid-support purposes, suffer from the high implementation costs due to the use of complex control systems and a high number of AC/DC and DC/DC converters. The article [19] adds that, despite the promising power quality solutions of these microgrids, they face greater reliability and feasibility problems that make them unsuitable for large-scale integration. Therefore, the adaptation of more planning- and optimization-oriented DCIMG studies is a promising option to expand renewable energy integration on a massive scale.

A general MG topology with both AC and DC operation for generation and loads is displayed in Figure 2 [17]. According to that mixture, an MG architecture can be classified based on the type of electric current used into three categories, which are explained in detail as follows:
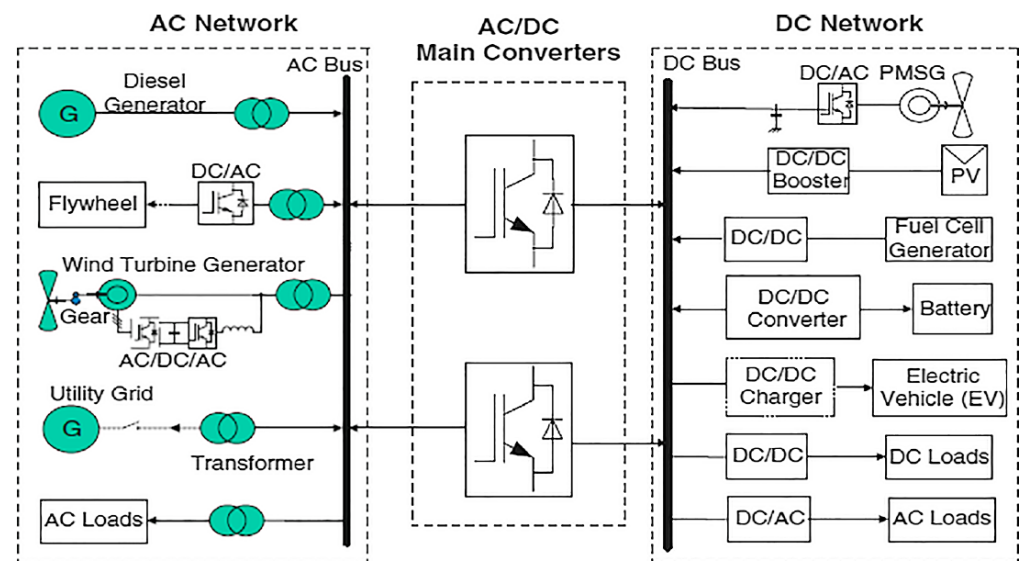
Figure 2. General hybrid AC/DC microgrid topology.

2.1.1. AC Microgrid

Due to the practical and efficient power transfer of AC voltage over a long distance, thanks to the AC step-up/step-down voltage transformers, AC-based microgrids gained an undisputed reputation for ease of renewable resource integration with minimal modification of existing utility grid infrastructure. Furthermore, due to the minimal power loss advantage of AC systems compared to DC transmission and distribution over radial network topology, AC microgrids have gained popularity for integration with main grids at the MV and LV power distribution levels. This efficient power transfer advantage was further strengthened by the minimum interference of AC systems with established protection schemes contrary to DC systems that require sophisticated protection mechanisms. Therefore, the existence of AC infrastructure makes it feasible and cost-efficient to expand the integration of AC-based renewable generation such as wind, tidal, and biomass energy. Moreover, the vast majority of loads in the distribution networks are of AC-based power, which makes it more sensible to adopt AC microgrids as bases for smart grids expansion [17,19].

Similarly, the advantage of the AC system in minimal power loss across longer distribution lines makes it more suitable for large-scale microgrid application that supports residential, commercial, and industrial loads with considerable numbers. Unlike the DC system, which is only suited for small-scale application of few DC loads connected to a common DC bus, the nature of DC current makes it inefficient to elect a sole DC system as a candidate for MG expansion to a large scale.

Despite the many advantages of the AC system over the DC system, the inherent issue of frequency synchronization for different DG units and the inaccurate reactive power sharing makes the planning and operating of AC microgrids a challenging task. The impact of improper reactive power sharing can be seen by increased thermal losses in distribution networks, while frequency regulation issues dictate the use of more AC/DC conversion systems. The reliance on conversion systems will further complicate the control and protection of these microgrids; this is due to the increase in non-linear loads and unwanted current and voltage harmonics. Moreover, the control and protection tasks become more complicated during islanded operation since minimal disturbances can cause large stability issues in the islanded MG [3,17].

2.1.2. DC Microgrid

The DC microgrids are defined as a group of DC-based generation units such as photovoltaic (PV) and fuel cells connected to a common DC bus serving DC loads. In this configuration, most of the DG units are connected to the common voltage regulated DC

bus via DC/DC converters or AC/DC rectifiers facilitated by power electronics. This type of MG is often adopted due to the existence of DC-only loads. However, it could also be connected to the main AC grid by DC/AC inverters. The main advantage of this type of microgrid is the higher efficiency in energy storage and minimized conversion losses due to less AC/DC/AC conversion. Moreover, the ease or elimination of frequency synchronization issues is also an advantage. The popularity of DC networks soon lost its appeal when considering the expansion of such microgrids to a large scale due to the inefficient transmission of power over a long distance. Furthermore, most of the available equipment in distribution networks is based on AC, and the cost of rolling out DC equipment becomes infeasible. Due to the cost and practicality challenges of DC microgrids, their applications are limited to small-scale and application-specific microgrids [17,19]. Moreover, common bus voltage regulation issues, load balancing, and coordination between different power converters are identified as major barriers in DC islanded microgrids expansion [27].

Due to the many advantages that the droop control strategy offers compared to the master–slave one, DCIMG has found its way in regulating DC microgrids as well. According to [28–30], the economic dispatch of DC-based dispatchable DG units was achieved based on linearized models of the MG, while an optimal control problem was formulated to enhance common bus voltage regulation by tuning controller parameters on one hand [27,31–33] and by achieving optimal storage cycle on the other [34,35]. The DC droop settings were selected based on the economic criteria in [36] and the environmentally oriented objectives in [37]. Conversely, the authors of [38], on the other hand, have aimed for more technical objectives to enhance the operation of DC-based DCIMG, taking the stochastic nature of demand in microgrids into account.

2.1.3. AC/DC Microgrid

This type of structure combines the advantages of both AC and DC microgrids, which helps the utilization of DC and AC loads in one microgrid. Since around 30% of loads in distribution networks are found to be of DC nature, it might be a cost-effective solution to adopt this hybrid MG to minimize conversion losses. Furthermore, the enhanced voltage transformation and better harmonic control are the main advantage of this type of configuration. Although a hybrid AC/DC structure of microgrids enhances energy storage and conversion efficiency, the increased complexity in design, stability, and protection of AC/DC networks act as main barriers against further expansion of this type of microgrids [17].

The adaptation of AC/DC hybrid microgrids is still a hot topic in the literature, since a number of promising studies have tackled the cost-related issues [39], efficient power transfer [40], and reduction in current sharing error [41,42]. The use of power electronic transformers (PET) has been proposed by [40] to facilitate efficient power transfer between multiple interconnected sub-grids in a hybrid AC/DC microgrid. In an attempt to minimize the current sharing error between dispersed generation units, an optimal selection of droop coefficients for DC and AC units was studied in the DCIMG framework using metaheuristic evolutionary computation technique in [41], while a sequential quadratic programming (SQP) approach was utilized in [42]. The cost-based analysis study of a remote hybrid AC/DC microgrid was introduced, taking into consideration the reliability assessment for power delivery during the selected days of operation [39].

2.2. Microgrid Droop Control Philosophy

The existence of proper islanding control strategy is fundamental to the successful operation of isolated microgrids. Therefore, islanding standards such as IEEE std. 1547.4 and IEEE std.1547.7 [25,26] dictate that islanding mode must be subjected to rigorous control mechanisms to enable adequate voltage and frequency support by DG units. This level of support becomes a necessity during generation and demand variations in light of different MG internal and external uncertainties. Furthermore, this adequate support is necessary to ensure autonomous operation of the microgrid without reliance on external

power supply and to minimize the impact of unpredictable system disturbances. To overcome the difference in size and technology among different DG units, power electronic converters are usually utilized to facilitate the connection of such units. Additionally, droop relations govern the way dispatchable DG units share active and reactive power between them based on load variations.

The increasing number of converter-interfaced units in isolated MG with low or no inertia has given rise to the concept of virtual inertia to provide frequency damping support [43,44]. Based on that, a converter unit control can be classified into either grid-following or grid-forming capability. As for grid-following control, the existence of communication between the utility grid and the converter is fundamental to pre-define voltage and frequency reference points. This concept is widely used with all non-dispatchable renewable units connected to the main grid via the inverter interface; hence, they operate in constant power control similar to slave units in the centralized control philosophy (i.e., a controlled current source with large parallel impedance), while in grid-following control, on the other hand, the converter units have the freedom to operate an AC microgrid without the need for synchronous generation reserve, where the virtual inertia concept can be implemented alongside droop control techniques (further grid-forming control techniques, which are beyond the scope of this paper, can be found in [44,45]). Hence, grid-following converters often belong to the decentralized control philosophy, wherein they operate in voltage and frequency control mode as dispatchable units (i.e., a controlled voltage source with small series impedance).

Despite the great advantage of the decentralized control approach over the centralized one in terms of reliability and cost effectiveness, decentralized control systems still suffer from the problem of high coupling between the elements of large-scale MG, which makes it near impossible to rely only on local measurements. Therefore, the combination of the two philosophies with a larger emphasis on droop control can happen in the hierarchal control schemes to facilitate successful control for large-sized microgrids. As described previously in the introduction, a complete droop control strategy is achieved in a hierarchal order; this is explained in detail in the next three sub-sections.

2.2.1. Primary Control

This is the initial stage of MG control where droop control is undertaken instantly in response to load changes. The basic principle of droop control follows the behavior of the voltage source inverter separated from an AC bus by a power line, as shown in a typical inverter equivalent circuit in Figure 3.
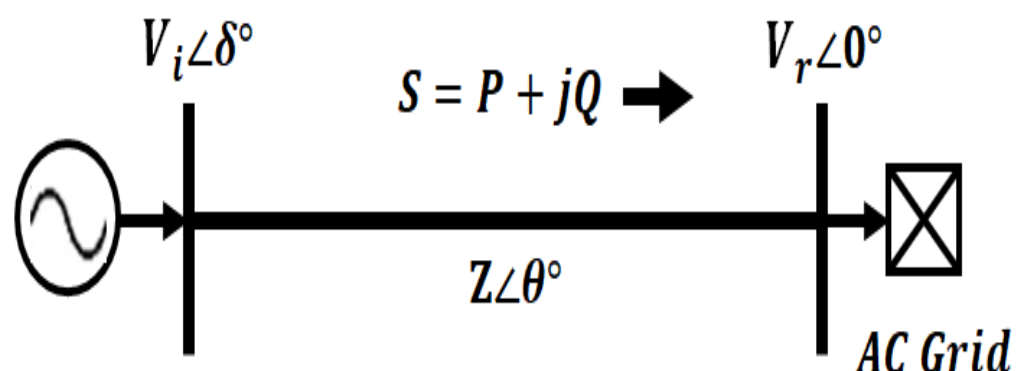

Figure 3. Inverter-based DG equivalent circuit.

Assuming Z as the equivalent impedance of the line and the inverter, then the output apparent power of the inverter can be written as:

$$S_i = V_r \left(\frac{V_i \angle \delta - V_r \angle 0}{Z \angle \theta^\circ} \right)^* \tag{1}$$

In practice, the impedance Z, as seen from the inverter side, is highly inductive, and the phase difference δ between the inverter output voltage and the AC bus voltage is negligible [11]; hence, Equation (1) can be rewritten to obtain the active and reactive output power of an inverter as follows:

$$P_i = \frac{V_r \, V_i \sin \delta}{X} \tag{2}$$

$$Q_i = \frac{\left(V_r \, V_i \cos \delta - V_r^2\right)}{X} \tag{3}$$

where X is the reactance part of the equivalent impedance; P_i and Q_i are the operating active and reactive output power of the inverter, respectively. Based on Equations (2) and (3), the frequency and voltage of an inverter-based dispatchable DG unit can be written as a function of the active and reactive power, respectively. The following droop Equations (4) and (5) describe the behavior of DG units during load variations:

$$\omega_i = \omega_o - m_p(P_i - P_o) \tag{4}$$

$$|V_i| = |V_o| - n_q(Q_i - Q_o) \tag{5}$$

where ω_o and $|V_o|$ are the no-load rated frequency and voltage of the inverter, respectively; m_p and n_q are the active and reactive droop coefficients, respectively; P_o and Q_o are the pre-set reference active and reactive output power of the inverter. Proper selection of the droop coefficients as well as voltage and frequency reference points is of great importance to improve the performance of conventional droop methods, especially during islanding mode. Hence, the use of classical and heuristic optimization techniques has been employed to optimize the performance of DCIMG; this will be covered in more detail in the next section.

Figure 4 depicts the *P–f* and *Q–V* droop characteristics of a typical inverter-based DG (IBDG) unit in the over- and under-generation scenarios. In an over-generation situation, the frequency and voltage of the system will increase due to a sudden drop in load. However, because of the droop response (the slope in *P–f* and *Q–V* curves), the IBDG will respond to the sudden load drop by decreasing the active and reactive power output, and that will bring down the frequency and voltage of the system within an acceptable level, while, on the other hand, in the under-generation situation, the IBDG droop response will increase the active and reactive power output to compensate for load rise, and this shall bring the frequency and voltage up to an acceptable level, as instructed by IEEE std. 1547.4 [25].
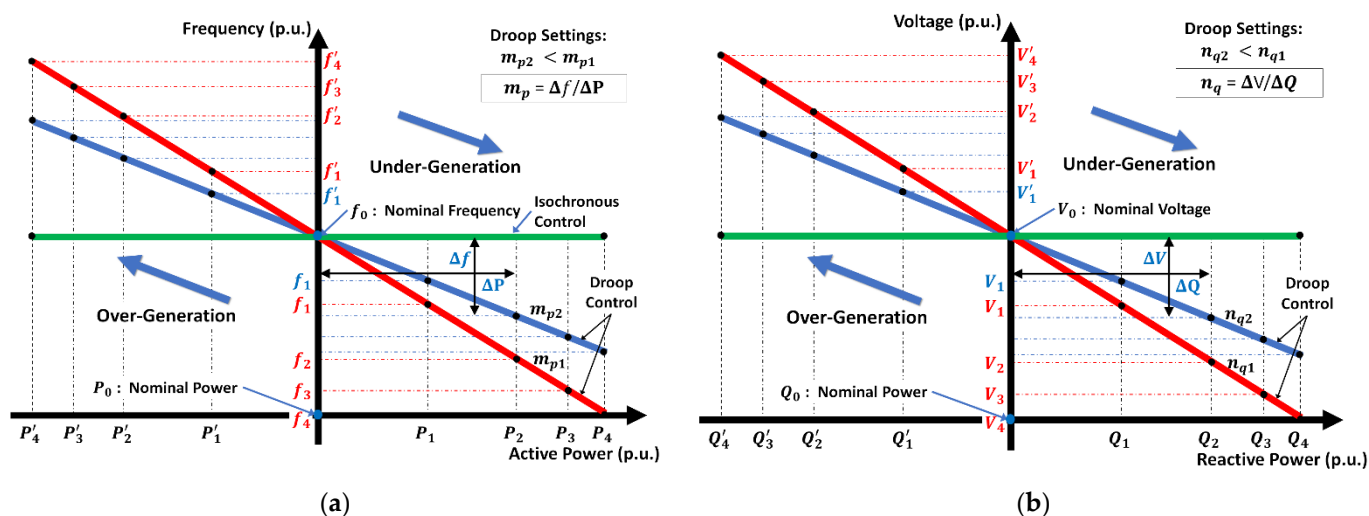

Figure 4. Typical IBDG unit droop characteristics: (**a**) *P–f* curves; (**b**) *Q–V* curves.

As shown in Figure 4a, when load exceeds generation, the active power output of the DG unit increases from P_0 to P_4 to respond to the sudden fall in system frequency until it settles to a steady-state value f_4 below the nominal frequency f_0. Similarly, if DG output exceeds load, the active power will decrease from P_0 to P'_4 and the frequency will settle at f'_4 above f_0. As for the DG reactive power output and demand variations shown in Figure 4b, in case of an under-generation situation, the reactive power output will increase from Q_0 to Q_4 to maintain the bus voltage at a value V_4 below the nominal value V_0. Similarly, in an over-generation situation, the reactive power output will decrease from Q_0 to Q'_4, and the bus voltage will settle at V'_4 above V_0. It should be noted though that the values of (P_4, Q_4) and (P'_4, Q'_4) should not exceed the maximum- and minimum-rated power value of the DG unit. Otherwise, DG units must be set to constant PQ control.

The primary control action is undertaken in matter of seconds in response to load changes without the need for complex communication structure in flexible and reliable manner. Nevertheless, this basic method still suffers from certain drawbacks mainly in reactive power sharing and voltage level impact [27,34,46–51]; frequency restoration and active power sharing [32,52–55]; poor renewable energy integration [20,56–59]; slow damping response to oscillations in the system [60–65]; vulnerability to line impedance and coupling inductance [11,66,67]; inaccurate harmonic compensation [68,69]; and protection scheme interference [11,69]. These limitations of the basic droop control method are addressed by optimal design and selection of the parameters and coefficients [54,60,70] and by proposing new adjustments and techniques to enhance the basic droop control performance [52,53,71]. However, most of these adjustments and enhancements will increase cost and reduce its reliability by needing more communication and more infrastructure development, which acts against the fundamental principle of decentralized control in flexibility, simplicity, and reliability. Hence, the need for multi-criteria optimization problems to find the optimal trade-off between efficiency and cost becomes fundamental to harvest the best possible performance of DCIMG.

2.2.2. Secondary Control

From this stage, the voltage and frequency of the system are restored to the nominal values in a closed control loop manner. This is necessary to rectify the primary control action of the system where it drives the steady-state values of voltage and frequency away from the pre-defined reference points as a result of the virtual impedance and inertias of the system. The secondary control action uses a proportional–integral (PI) controller to compare the new values of voltage and frequency with the reference values and eventually minimize the resultant error to zero. In another words, the secondary control action forces the $P–f$ and $Q–V$ droop curves to shift vertically to eliminate the deviation error in voltage and frequency without inflicting a change in the slope of the droop curves. Figure 5 demonstrates the secondary control action for a typical IBDG unit controller. After the completion of primary control action for active power in under-generation situation, the red $P–f$ curve of Figure 5a will be shifted vertically upwards to become the green $P–f$ curve by means of the PI controller action mentioned earlier, and that will drive the steady-state frequency to return from f_4 to f_o. Similarly, in an over-generation situation, the red $P–f$ curve of Figure 5a will be shifted vertically downward to become the blue $P–f$ curve, where the steady-state frequency reverts back to f_o from f'_4. Likewise, the reactive power mismatch recovery by primary control action is adjusted according to the $Q–V$ droop curves of Figure 5b. In the over-generation situation, the steady-state value for bus voltage V'_4 is adjusted to V_0 by shifting the curve vertically downwards, while the curve is shifted vertically upwards in the event of reactive power under-generation to restore nominal bus voltage.
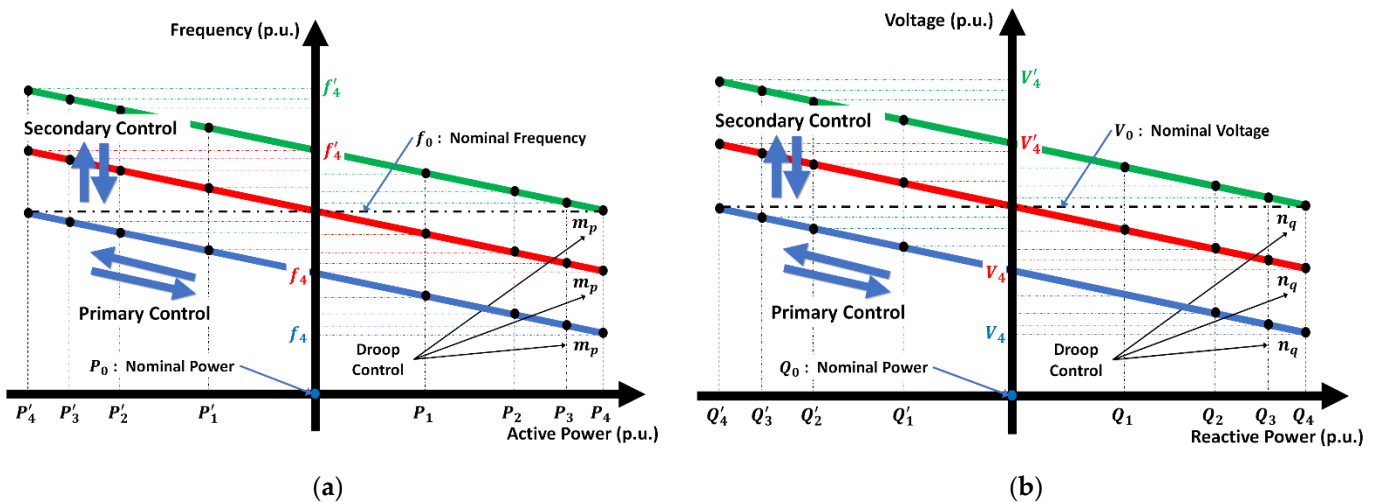
Figure 5. Secondary control action for typical IBDG unit: (**a**) P–f secondary control; (**b**) Q–V secondary control.

To address certain limitations of primary control, many research studies have focused on reinforcing primary and secondary control action to achieve accurate and dynamic reactive power sharing [61–64,72]. Accurate voltage reference adjustments have been achieved by means of classical and metaheuristic optimization techniques in [73,74], while battery energy storage systems' (BESS) charging and discharging balance has been obtained in [27,33,35] by adopting a unified cooperative secondary controller to minimize voltage regulation error on a common DC bus in droop-regulated DCIMG. Multi-agent systems (MAS) were employed in [75–81] as a secondary control mechanism in a distributed control manner to reduce participating DG units' reliance on a central controller. Furthermore, by relying on a fully distributed secondary controller, the local communication between DG units was improved to achieve optimal technical and economic power-sharing objectives.

To improve islanded microgrid stability and enhance droop response speed, studies [60,82,83] have proposed a secondary level controller design to minimize damping in AC system DCIMG, while the authors from [31,36] have addressed damping issues in DC-based DCIMG by optimally selecting the converter parameters. To minimize the virtual impedance effect on droop control, [66] suggested an optimal range for virtual impedance size, as seen by the inverter, while [67] focused on obtaining the optimal controller parameters to administer the best virtual impedance value that minimizes power-sharing error. Dynamic tuning of PI controller parameters in the secondary control loop was suggested by [49,51,83] to enhance the voltage and frequency response of the islanded MG. Furthermore, according to [50], the master–slave control strategy was employed to dynamically tune the PI controller and achieve accurate power sharing. However, the achieved results lacked reliability, while the full cost analysis of the proposed strategy in [50] was not provided.

2.2.3. Tertiary Control

At this higher level of control, a complete load flow of the MG is carried out by the microgrid central controller (MGCC) to determine the MG set points [11]. The operation of tertiary control usually involves collecting data and measurements and then using them in an optimization process to yield the optimum setting for the MG-controllable components. This complete strategy, also referred to as EMS, aims to achieve the desired objectives such as optimal droop coefficients for an environmentally friendly DG unit operation [84,85]; secondary PI controller parameter selection to preserve MG stability [60,71]; efficient charge and discharge of BESS [86–88]; contingency reserve management [89–92]; and economic dispatch of DG units [28,93].

The optimization process happens in timed intervals or cycles through the MGCC, while the frequency of optimization cycles depends on the size of the optimized processes

and data provided to the MGCC [84]. This type of operation often involves forecasted data of supply and demand for electricity and heating. Furthermore, volatility in fuel costs and emissions penalties of the dispatchable DG units are provided as well as the uncertainties in renewable generation and load behavior.

Forecasted data are fed to the MGCC by low-bandwidth and non-critical communication channels, while the optimized settings are sent to dispatchable DG units using the same channels accordingly [84]. This type of communication protocol reduces the probability of interruption since minimal contact exists between MGCC and controllable elements in the MG. Moreover, the longer the optimization cycle intervals, the less vulnerable the system is to communication delays. The usage of such a communication scheme at the tertiary control level increases the accuracy of droop control without compromising reliability, since DG units have the freedom between each optimization cycle to share the load autonomously, relying on the optimized settings received at the end of each cycle.

Dependence on tertiary-level control manifested by an MGCC is necessary to realize the complete model of reliable and accurate EMS for islanded networks. Nevertheless, MGCC requires the existence of communication infrastructure and may increase the amortization cost of an MG. Therefore, other studies dedicated to the optimization of DCIMG went on to eliminate the need for MGCC by adopting MAS communication systems as in [79], where a fully distributed consensus-based strategy was adopted, while in [80], a finite time algorithm was implemented on a strongly connected directed graph infrastructure MAS. The need for costly MGCC was alleviated via a simplified approach based on constrained hierarchal theory to prepare an MG for emergency islanding [94]; however, only maximized loadability was considered in that study without regard to supply quality during inadvertent islanding. On the other hand, an interior point method was adopted for an MG scheduling with stochastic wind and load modeling in the absence of MGCC [95].

2.3. Microgrid Optimization Problems

In accordance with the required goals for DCIMG adaptation, whether for technical, environmental, commercial, or rural communities' electrification reasons, the planning and design approach for such microgrids must take into careful consideration the different aspects of the problem. Quite often, the continuous operation of microgrids is desired in a smooth, efficient, and cost-effective manner, hence, the reliance on optimization techniques becomes a necessity to realize the successful planning and scheduling of DCIMG. Optimization problems in this aspect can be divided into two main categories: long-term and short-term optimization problems.

Long-term problems aim to identify decision variables of a design problem similar to those but not limited to: finding the location of a DG unit or BESS; the size range of a dump load (DL) or virtual impedance; the length or type of a distribution line; or the type of a controller. Long-term optimization is concerned with the class of design problems where the optimization span for the problem could be months or years, and the solution must cover that period, while short-term optimization problems evolve around daily operational DCIMG issues where the decision variable of the problem covers a short aspect of the optimization problem span in a matter of minutes or hours. Such short-term problems include but are not limited to the dispatch of generating units, charge/discharge cycles of BESS, the change in DG and ESS control parameters, and the reconfiguration of tie lines.

A brief description of common optimization problems tackled in DCIMG is explained in this section as follows.

2.3.1. Allocation Problem

An allocation problem can be defined as obtaining the optimal size, type, and location of an MG element subject to technical and economic constraints [5]. Those microgrid elements could be either active, similar to DG units or ESS, or passive, such as a capacitor, protection relay, or DL. Aside from the obvious technical and economic motivations for optimal allocation of elements in DCIMG, this type of long-term problem often involves

environmental and customer satisfaction aims. Since proper integration of renewable generation will significantly influence greenhouse gas emission level reduction, while optimal allocation of generation units will enhance customer experience with an expedited connection for their prospective DG investments.

Allocation studies of DG at the distribution level are widely investigated and reviewed in the literature [1,2,4,5,7,9,10,16,17,21–23]. However, optimal allocation of MG elements considering DCIMG operation nature is scarce. As in [96,97], the capital, running, and maintenance costs of BESS allocation in an islanded MG have been minimized, while the optimal allocation of ESS in DCIMG has been studied for stability margin enhancements [98] and emissions reduction [99]. A dump load integration in DCIMG has been investigated to help with voltage and frequency regulation during off-peak hours [100–102]. Considering solar radiation and wind speed uncertainties' impact on the total annual cost of a remote islanded DC microgrid, the optimal number of wind turbines, PV cells, and BESS was determined by the particle swarm optimization (PSO) method, while uncertainties were accounted for by means of Monte-Carlo simulation (MCS) [103].

The optimal size and location of DG units in DCIMG considering economic objectives were investigated by [104–106], while MG stability objectives were considered in [107–110]. Džamarija and Keane [111] have investigated DCIMG optimal wind turbine (WT) allocation impact on renewable energy curtailment reduction as well as the maximization of net energy export to transmission networks. On the other hand, Guo et al. [112] addressed the impact of WT and diesel DG locations on the internal rate of return to maximize isolated MG profit capacity, while Bukar et al. [39] determined the number of days for autonomous operation in the hybrid AC/DC microgrid by investigating a sizing problem related to WT and PV numbers. Lastly, the voltage stability margin has been maximized considering optimal capacitor allocation in DCIMG as presented in [113].

2.3.2. Reconfiguration Problem

One particular short-term optimization problem in DCIMG is the one related to the reconfiguration of network topology, which involves changing the state of an MG tie and sectionalizing switches as well as circuit breakers from an on to off state or vice versa [8]. The purpose of sectionalizing switches is to isolate faulted areas of an MG, while tie switches reconfigure the topological state of distribution lines [8]. Optimal reconfiguration has many advantages in distribution networks operation and protection. Such advantages include the prevention of overloaded lines, thus minimizing losses; isolation of faulted lines or areas in an MG; improving the voltage profile; deferring capital investments in distribution networks; and enabling faster connection to nearby available DG units.

Due to the many benefits a radial network topology offers compared to a meshed structure in terms of design simplicity, low implementation cost, and ease of protection, almost all reconfiguration problems in DCIMG often insist on some sort of radiality constraint where the radial topology of the network should remain intact before and after tie switches opening or closing [109,110,114–118]. Reconfiguration of DCIMG can have a notable impact on MG stability margin minimization. Hence, the authors in [115] used a social-based metaheuristic technique to achieve optimal stability by means of network reconfiguration, while [116] relied on a physics-inspired optimization method to obtain the same outcome. Furthermore, reducing the coupling of power to divide multiple microgrids into clusters was another target for DCIMG reconfiguration [99,119], as were the distribution line losses' reduction [109,110,118] as well as maximizing the number of loads served [114,117,120].

2.3.3. Scheduling and Dispatch Problem

Another form of the short-term optimization problem is the scheduling and dispatch problem. This tactical planning problem is one of the most prevailing types of problems in DCIMG due to its high technical, economic, and environmental significance. Furthermore, the focus of this problem is on handling existing generation and storage resources; hence,

this problem does not change the topology of the network or address an allocation issue. A dispatch problem is a real-time problem defined as determining the power output of dispatchable DG units and the charge and discharge rate of ESS for the next five-to-fifteen minutes of the operational horizon [21]. The most common goal of the dispatch problem is the economic operation of microgrids; hence, it is also known as economic dispatch problem (EDP). However, EDP could have an additional technical or environmental objective depending on the policy of MG operation.

While scheduling, on the other hand, is related to the act of day-ahead planning of available generation, storage, grid-connectivity, spinning reserve, demand volume, and the uncertainties associated with microgrids [4]. A scheduling problem is usually referred to as a unit commitment problem (UCP) if it involves the start-up and shut-down of DG units [21]. Day-ahead scheduling of microgrids is a challenging task considering the intermittent nature of wind and solar power generation as well as the uncontrollable load behavior. Therefore, many scheduling problems rely on the availability of generation and load forecasting data to the MGCC, which can be in a form of past monthly or yearly load patterns or estimated renewable energy data for wind speeds and solar radiation levels [57,84,121].

Numerous EDP studies have targeted various MG cost types while using different classical or AI optimization methods [30,75,76,81,86,90,93,95,122–145]. However, besides cost analysis in DCIMG, dispatch problems also accounted for emissions reductions [37,84,89,121,145–149] and grid-connection possibilities [88,150–152]. On the other hand, dispatch and scheduling problems could have technical objectives, such as voltage stability enhancement [57,72–74,153–156], thermal losses mitigation [157,158], load curtailment reduction [85,94,159–164], and power-sharing error minimization [38,41,42].

A UCP has been considered for spinning and non-spinning reserve scheduling, taking into consideration frequency excursion minimization to acceptable levels [91,92,165–168]. The optimal charge and discharge rates for distributed ESS with different types and sizes have been determined [87]; the latter dispatch study has utilized the existence of multiple charging stations for electric vehicles (EV) to handle the intermittent nature of renewable generation in DCIMG. Despite the innovative methodology of [87] in relying on smart charging/discharging of EV, there is no clear indication of how to handle the behavioral issues of such EV smart-charging techniques or the impact on total MG stability.

2.3.4. Control and EMS Problem

Like many dynamic systems, an islanded MG requires adequate control of the system state variables that govern its optimal operation. The target of this problem is obtaining the best possible values for various parameters and coefficients for controller devices or agents embedded within active or passive elements of the MG. Furthermore, it could aim to minimize the time delay, over- or under-shoot, and steady-state error in the controlled islanded MG to ensure stability and optimality. Control problems combined with dispatch and scheduling problems form the bases for optimal EMS problems, which are responsible for implementing the hierarchal control strategy of DCIMG. Therefore, solving an EMS problem acts as a buffer to serve a variety of technical [33,35,54,59,85,91,92,117,134,148,154,163–166], economic [28–30,75–81,84,85,91,124–133,135,144,145,148–151,167,168], and environmental [84,85,91,145,148,149] objectives necessary to oversee the safe, stable, and reliable operation of microgrids.

Voltage and current PI controllers' parameters were optimized to reduce the power-sharing error in DCIMG by means of classical [65] and metaheuristic optimization techniques [58–64,71]. Likewise, the steady-state error in voltage and frequency was optimized by adjusting the PI controller setting using different techniques [48–53,70,169,170]. The over- and under-shoot errors, settling time, rise time, and integral time absolute error (ITAE) were minimized to enhance an MG voltage profile [46,47], while DC voltage regulation was enhanced by optimal PI controller setting in [27,33,34]. On the other hand, frequency

deviations were minimized based on optimal controllers setting for BESS [35], Flywheel ESS (FESS) [56], diesel engine [54,55], and a PV-fuel cell (PV-FC) hybrid system [32].

The control problem of DCIMG was extended to serve different stability and protection issues in the MG. As in [67], a virtual impedance controller has been optimized to minimize the reactive power-sharing error for IBDG. Conversely, to adjust the droop voltage reference point, the amplitude and angle of voltage harmonic component controller was simultaneously optimized in [68], while the time dial setting for a directional harmonic relay controller was carefully selected to ensure reliable and cost-effective microgrid protection [69].

2.3.5. Multi-Criteria Decision Problem

Practically, in DCIMG optimization problems there is more than one desired objective, and often these objectives are conflicting and unrelated. Additionally, the complexity of successful hierarchal control in islanded microgrids often involves a degree of trade-off between economic and technical goals. This contradiction will lead to a multi-criteria decision problem (MCDP) where the progress in one objective degrades the other and vice versa. Furthermore, MCDP, also known as multi-objective optimization (MOO), usually combines two or more optimization problem types. Therefore, there can be an allocation problem combined with a scheduling one [82,105] or an allocation with reconfiguration MCDP [99].

There are different ways to handle MOO for non-trivial problems that seek to generate an optimal solution. One common approach used is to transform the MOO into a single-objective one and assign linear set of weights to each objective, in what is known as the weighted average method. Another method based on scalarization is the epsilon-constrained method [91], where one objective is minimized while transforming the others into constraints. The former scalarized method has been widely used in DCIMG optimization problems [27,36,39,46,57,90,113,120,121,146,154] due to its ease of implementation and light computational burden. However, it requires scalarization, linearization, and approximation of the original problem. Moreover, the generated solution does not guarantee optimality as often it generates pareto-dominated solutions, and some important solutions are neglected if it lies within a non-convex solution search space.

Another popular approach in solving the MOO is to generate a trade-off set of solutions, also known as the Pareto optimal set. In this approach, a prior knowledge of the problem is not mandatory for the decision maker. Moreover, all problem objectives are treated equally and simultaneously, while the generated solutions are usually plotted on a Pareto front curve. The advantage of this method is the ability to search the non-convex solution region and generate multiple non-dominated solutions in one run. However, these methods often suffer from computation burden and may generate many similar unnecessary non-dominated solutions. Furthermore, Pareto optimal sets require another approach to select one optimal solution. Such decision-making criteria include the min–max fuzzy logic principle [47,85,99,148], fuzzy satisfying method [100–102], utopia–nadir balance [159], Nash equilibrium approach [91], and grey relation projection technique [89].

2.3.6. Optimization with Uncertainty Problem

Due to the nature of modern smart grid operation that relies on intermittent energy resources and uncoordinated demand behavior, many researchers went on to include uncertainty as random variables and dynamic constraints to their optimization problems in DCIMG [37,57,85,95,103,121,129,145,148,165]. This variant of optimization problems, known as optimization with uncertainty problem (OUP), requires careful uncertainty modeling to approximate the reality of weather and diurnal states of generation and demand as well as those unpredictable internal factors such as loss of dispatchable units [75], fault currents [60], and inadvertent islanding [94]. Moreover, uncertainties might suffer from the influence of external factors in environmental, social, and regulatorily aspects [19].

The OUP in DCIMG planning and operation problems is usually modeled by probabilistic approaches. These probabilistic approaches can be broadly classified into three main categories: Monte-Carlo simulation methods, analytical methods, and approximation methods. The MCS method is a statistical sampling method that imitates multiple random states of a system to generate samples defining the whole problem [57,92,103]. In other words, MCS performs stochastic profiling of a system by specifying inputs as probability distribution [103]. Another variant of MCS is the lattice MCS (LMCS), which has a higher degree of uniform distribution to cover a wider uncertainty spectrum compared to the ordinary MCS [166]. As for analytical methods, they use mathematical equations and calculations to reach a description of the problem's uncertainty, such as the convolution method [95], the cumulants method [137], and Taylor series expansion [37]. Lastly, the approximation methods such as the point estimate method [37,148] and scenario-based method [114] generate as many states of a given problem by relying on probability density functions of the random variables associated with the problem and then seeking to apply a scenario reduction of the generated scenarios that has low or exactly similar probability.

The uncertainty importance for DCIMG operation and planning studies was apparent as over 30 references accounted for uncertainty mainly in generation and demand. Moreover, it was deduced that the most prevailing uncertainty consideration method in DCIMG studies was scenario-based modeling [39,55,83,84,88,91,94,118,119,127,165,171] followed by the MCS method [57,92,103,136,166]. However, the computation burden of real-time problems that involves uncertainties is large. Hence, almost all of the foregoing studies relied on the weighted average method for their MCDP, which compromised the reliability and credibility of the solutions being global.

3. Optimization in Microgrids

Any mathematical optimization problem, whether it is to minimize or maximize a certain objective function, often consists of four main aspects: objective functions, equality and non-equality constraints, decision variables, and the optimization algorithm adopted. These aspects are discussed in detail in the following four sub-sections.

3.1. Objective Functions

There are different set of objectives tackled in optimization problem formulations. They can be grouped as a single objective or combination of two or more contradicting objectives. A summary of the most-pursued objectives in DCIMG planning and operation studies is presented in Table 2. Moreover, these objectives are discussed thoroughly as follows.

3.1.1. Cost Minimization and Profit Maximization

As it is the case for most real-life optimization problems, cost is a fundamental aspect to be taken into consideration. Moreover, cost-based optimization studies in DCIMG can be classified based on the nature of the cost considered. These costs are categorized into five main groups as follows: running costs, maintenance costs, security costs, penalty costs, and capital and investment costs. In practice, cost objectives often represent a collection of different types of the aforementioned categories, such as running, maintenance and penalty costs [167], or running and investment costs [172].

Out of the many running cost objectives, the fuel cost is the most prevailing type in microgrids. This is attributed to the fact that most DCIMG without direct access to the grid must have some form of dispatchable diesel or gas DG units. Fuel cost minimization could be the sole purpose of the EDP in AC microgrids [95,122,136,143,173], or this purpose could be extended to cover DC microgrids EDP as well [28–30]. Additionally, it could be combined with environmental objectives as in [84,85,89,121,146,147] or with technical objectives as in [106,148,153].

However, fuel costs are usually considered in amalgamation with other forms of costs such as curtailments costs for balanced [90,151,165] and unbalanced loads [88,131],

cost of load shedding in clustered microgrids [167], fines for imported energy from the main grid [88,145,151,167], excess emissions penalty costs [127,174], heating and boiler maintenance costs [84,85], the cost of automatic generation control (AGC) to cover for WT and PV volatility [37,75,174], and the penalty cost of energy not delivered [144].

On the other hand, ESS costs in microgrids were expanded to account for the running costs associated with charge and discharge cycles for a hydraulic ESS (HESS) [172] and BESS [89,128,129,142]. A comparison between lead–acid BESS (LABESS) and vanadium redox BESS (VRBESS) in terms of daily charge and discharge costs as part of net present value evaluation was presented in [96]. Additionally, as in [97], the accumulated annual running and maintenance costs associated with the installation of BESS on the expected capital return of the investment were minimized considering consumers payments to avoid interruptions.

Furthermore, costs associated with ESS installations in microgrids with PV and WT were optimized as part of total annual profit maximization from deferred infrastructure upgrade costs [121]. The amortization costs, referred to as the depreciation in value for intangible assets, were minimized for an island system with HESS as well as hydro, wind, and diesel generation [172]. The total annual costs (TAC) of a remote off-grid system with BESS, PV, and WT were optimized considering the capital recovery factor of interest rate and life span of the project [103]. The discount rate equality with a project present value as reflected in its profit capacity, known as the internal rate of return (IRR) [112], was enhanced to ease the conflict of interest between all participants in a DCIMG with installed BESS, WT, and diesel DG units. Alternatively, studies such as [151,163] went on to maximize MG profits during grid-connected and islanded operation in optimal business-oriented EMS.

Another form of economic objective is the security or back-up costs, where part of the total cost is reserved to guarantee adequate supply quality in the islanded MG. As previously mentioned, the solution to the UCP problem aims to determine the on/off state of dispatchable units [133,163,164]. Thus, security-based costs are often associated with the start-up/shut-down costs of thermal backup generation [126,145,150]. Subsequently, these costs are often taken into consideration to follow up expected demand changes to maintain quality of supply. Similarly, ramping costs to cover for the ramp-up/ramp-down rates are often neglected from the total cost objective [125,128]. However, ramping, defined as the rate at which a dispatchable DG unit changes its output measured in (MW/min), is necessary in load following to maintain system frequency and avoid undesirable demand curtailment. Hence, studies such as [91,167,168] have accounted for ramping costs as part of the total cost objective to sustain sudden frequency excursions.

Lastly, costs accumulated from assigning excess generation to be available upon demand to increase reliability and security are often considered in scheduling problems [145,163,171]. To that extent, reserve costs can be divided into spinning and non-spinning reserves. The former reserve is defined as the amount of residual online generation after covering system demand and losses; this reserve cost can come from ESS [172] or parallel dispatchable DG units [140,141], while non-spinning reserve costs, on the other hand, which are an offline generation that can be brought up online in a matter of minutes, are associated with fast-starting diesel generation costs or power import costs from other inter-connected grids [167].

3.1.2. Emissions Reduction

Due to policy changes across the globe that aim to reduce the carbon footprint of electricity generation, many distribution network operators (DNO) and DG owners (DGO) were eager to minimize the emissions from their conventional generation portfolio [165]. Typical emissions selected as reduction targets include carbon dioxide (CO_2) [149], nitrogen oxide (NO_x) [147], carbon monoxide (CO), and sulfur dioxide (SO_2) [89].

One way to tackle the issue of DCIMG emissions reduction targets is to include them as an independent minimization objective measured in (Kg/hour) or any other equivalent unit along with any other desired objectives [37,84,85,89,91,121,145–149]. Another way

is to convert the excess emissions into a penalty cost to be included with a total cost objective minimization [127,142,174]. Additionally, based on regulatory, geographical, or economic reasons, emissions can be considered as a boundary-constrained problem where a pre-defined level is determined to sustain an acceptable range for greenhouse gases [92,165,166].

Table 2. Overview of objectives function used in DCIMG by reference.

Objective Function	DCIMG Optimization Problem Type						
	Allocation	**Reconfiguration**	**Scheduling and Dispatch**	**Control**	**EMS**	**MCDP**	**OUP**
Costs	[39,97,99,103–106,112,121,172]	[99,114,118]	[28–30,36,37,75–81,84–86,88–91,93,95,104–106,112,121–133,135–153,159,167,168,171,173,174]	-	[28–30,75–81,84,85,91,124–133,135,144,145,148–151,167,168]	[36,37,39,84,85,90,91,99,104–106,112,114,118,121,137,145–149,153,159]	[37,39,84,85,88,91,95,99,106,114,118,121,129,136,145,148,168,171,174]
Profits	[96,111,112,121]	-	[89,112,121,151,163]	-	[151,163]	[89,112,121]	[121]
Emissions	[121]	-	[37,84,85,89,91,121,145–149]	-	[84,85,91,145,148,149]	[37,84,85,89,91,121,145–149]	[37,84,85,91,121,145,148]
Voltage Regulation	[100–102,104–106,108,110,113]	[110,115,116,118]	[38,41,57,104–106,108,110,113,137,148,153–156]	[27,33,46–53]	[33,148,154]	[27,38,41,46,47,57,100–102,104–106,108,113,115,118,137,148,153,154,156]	[57,106,118,148]
Frequency Regulation	[100–102,108,175]	[116]	[91,92,108,165,166]	[32,48–56]	[54,91,92,165,166]	[91,92,100–102,108]	[55,91,92,165,166]
Loadability	-	[114,117,120,162]	[85,86,94,117,134,159–161,163]	-	[85,117,134,163]	[85,94,114,120,159]	[85,94,114]
Losses	[109,110]	[109,110,118]	[40,41,109,110,157,158]	[27,31]	-	[27,41,118]	[41,109,118]
Power Sharing Error	[109,113]	-	[42,72–74,109,113,123,152,156]	[58,59,63–65,67,169,170]	[59]	[113,156]	[109,119]
Stability	[66,82,98,107]	[116]	[36,60,82]	[60–64]	-	[36,82]	-
Reliability	[39,99]	[99]	[75,89,90,126]	[68,69]	[75,126]	[39,89,90,99]	[39,99]

3.1.3. Voltage Regulation Objectives

Many DCIMG optimization problems of different types aim to accomplish the optimal power flow (OPF) with technical objectives. Some of the most important objectives are those dealing with voltage and frequency regulation as well as stability of islanding operation. Unstable or large voltage oscillations often lead to appliance damage, false tripping of protection equipment, and unbalanced reactive power sharing [21]. Furthermore, all islanding standards necessitate adequate voltage support and safer voltage levels across all islanded and grid-connected microgrids [25,26].

Therefore, most of the allocation and reconfiguration studies in DCIMG consider the minimization of voltage deviations from the nominal value as an objective [100–102,108], while certain control problems pursued the same objective in designing the control strategy as in [52,53].

Similarly, other optimal control problems went on to design PI controllers for the secondary level control to minimize the overshoot/undershoot, rise time, settling time [46,47], and integral time absolute error (ITAE) for IBDG output voltage regulation [48–51]. Furthermore, the common bus DC voltage regulation error was also reduced considering current sharing error reduction [27,38,41] and constant charging voltage for the PV-BESS system [33].

Moreover, voltage regulation has been addressed as a multi-objective problem to maximize the voltage stability index (VSI) and minimize total voltage variations (TVV) [104–106,153] alongside fuel reduction objectives. On the other hand, studies [113,115,155] maximized VSI to determine the weakest nodes in microgrids where voltage collapse is most probable. Additionally, the average sum of all voltage deviations from nominal values known as TVV was minimized in [118,148], while the maximum deviation of bus voltage from nominal value of 1 per unit formally known as maximum voltage error (MVE) has been optimized in [154,156].

Conversely, voltage deviation objectives could also be embedded within other stability indices targets such as the operating risk index [137], system vulnerability index [116], security margin index [57], and energy conservation index [110].

3.1.4. Frequency Regulation Objectives

Another equally important objective in islanded systems is the proper keeping of operating frequency within acceptable tolerance. Despite the high importance of frequency regulation in DCIMG, it did not obtain an equal amount of attention as the voltage regulation objectives. This is attributed to the singular variable characteristic of system frequency, unlike voltage, which is closely related to reactive power-sharing accuracy and could have many values across the network. The minimization of the frequency deviations problem in DCIMG was tackled from the perspective of BESS and FESS availability to cover for non-dispatchable renewable generation shortfalls [56,175]. Likewise, optimal frequency regulation was handled by the employment of PV-FC energy systems [32], allocation of DG units [108], and utilization of demand response (DR) programs [165].

On the other hand, optimal frequency control at the primary level was achieved by consuming excess renewable generation at off-peak hours in [100–102] and at the secondary level by optimal design for the PI controller [52,53], the proportional–integral–derivative (PID) controller [54], and the diesel generator droop regulator [55]. To avoid the large oscillations in frequency and reduce harmonics due to lack of inertia and certainty in DCIMG, studies such as [48–51] aimed to minimize frequency regulation ITAE error. Furthermore, different objectives were considered to handle frequency change indicators such as reduction of the frequency vulnerability index [116], total frequency excursions (TFE) and total rate of change of frequency (ROCOF) indexes [91,92], and the expected system frequency index [166].

3.1.5. Loadability Maximization

Another goal in optimization studies is to maximize the number of loads served across the islanded MG, satisfying certain technical and economic conditions. According to the purpose of the MG operation, loads can either be controllable, deferable, or critical [21]. Furthermore, loadability enhancement is fundamental to the electrification of rural and isolated communities in a cost-effective manner.

Many reconfiguration studies went on to maximize loadability besides other objectives such as losses [120] and minimal switching operation [114], while others have only considered load-served maximization as the sole objective [117]. Furthermore, several EDP problems aimed at achieving the OPF with maximum customer satisfaction ratings [85,86,159–163], while other dispatch problems were focused on eliminating the need for communication infrastructure (such as MGCC) to maximize the social welfare of DCIMG [94,134].

3.1.6. Losses Reduction

Losses reduction is another classical objective for many OPF problems in distribution networks. Usually, power losses are considered as the reduction in distribution lines' resistive and reactive current components, thus reducing active and reactive losses in allocation of DG units' problems [109,110] or EDP problems [157,158]. Occasionally, energy

losses are capped to a certain limit, as presented by [86], in contrast with the typical thermal limits constraint seen in most DCIMG optimization studies.

Alternatively, losses were considered as the thermally dissipated energy from power conversion in hybrid AC/DC systems by optimizing efficiency in DC–DC converters [31] and in PET equipment [40]. Similarly, losses minimization can be achieved by reducing the amount of DC/AC/DC power conversion equipment by adopting DC-only microgrids [27] or by adopting multi-connected hybrid AC/DC parallel microgrids [41].

3.1.7. Power-Sharing Error Reduction

Different optimization studies went on to treat the power-sharing error as the desired objective by treating active and reactive power deviations as decision variables. In [67], a virtual impedance controller was developed to minimize the difference between the expected reactive power and the actual reactive power. Similarly, reactive power-sharing error minimization was addressed using different approaches: modeling of 24 h forecasted loads as ZIP model [109], obtaining an optimal linear [72] and non-linear [123] droop coefficients for DG units, optimizing bus voltage error [156] and setting up reference voltage [74], and the development of a new model for IBDG for steady-state operating point calculations [73].

Conversely, power-sharing optimization studies have also included active power-sharing error in multi-microgrids. As introduced in [113,119], the best cut-off branches were determined so that power line transmission index (PLTI) [113] and potential power transfer error (PPTE) [119] between clustered microgrids were reduced. Likewise, different control problem studies in DCIMG went on to minimize both active and reactive power-sharing error in their PI controller design, where the integral absolute error (IAE) [59], integral squared error (ISE) [58], and ITAE [169,170] for power-sharing errors were minimized accordingly.

3.1.8. Stability Improvement

A class of optimization problems dealing with small-signal stability problems for islanded systems is often considered as an extension for frequency and voltage optimization problems in DCIMG. The real part of the system eigenvalues must be less than a pre-defined negative value to ensure a stable system oscillatory response [82]. Moreover, the damping ratio is improved when the eigenvalues of the islanded system are negatively large [36].

One way to express the stability of a DCIMG is to maximize the small signal stability margin in DG allocation problems relying on the eigenvalue analysis [36,82,107]. Alternatively, different indicators of system stability are investigated and optimized accordingly, that include but are not limited to enhancing the transient stability time margin in ESS allocation to preserve the energy function of the system [98], raising the system performance index to obtain optimal power decoupling [66], and reducing the operation vulnerability index [116], which is the ability for a system to maintain stability after loss of one or more active agents. Additionally, the focus of other stability studies [61–64] was on suppressing oscillations after shifting from grid-connected to islanding mode and vice versa through optimal PI controller design to improve system damping.

3.1.9. Reliability Maximization

In microgrid planning, especially remote and isolated types, reliability is a very important concern to determine the best compromise between the economic and technical factors of DCIMG operation. One classical indicator of reliability is the minimization of expected energy not supplied (EENS), which gives an estimate of the energy not delivered to consumers due to interruptions [99]. Similarly, the loss of some part of supply will increase the probability of load curtailment during islanding; this was covered by the maximization of the customer satisfaction index (CSI) in [89] and the minimization of the deficiency of power supply probability (DPSP) in [39].

Additionally, reliability indicators can take the form of protection optimization problem, where the ability to have adequate protection and safe operation for islanded microgrids is considered via minimal time response for the harmonic directional relay [69] and the minimal MG total harmonic distortion (THD) factor [68].

3.2. Constraints

As discussed earlier, almost all practical optimization studies include certain equality or inequality constraints or both. The basis for adopting most of the constraints are the technical aspect of DCIMG operation for stability, reliability, and protection, while cost considerations were behind few numbers of constraints adopted. Table 3 shows the common constraints used in those studies, which are briefly described as follows.

Table 3. Overview of constraints used in DCIMG by reference.

Constraint	DCIMG Optimization Problem Type						
	Allocation	Reconfiguration	Scheduling and Dispatch	Control	EMS	MCDP	OUP
Power flow and balance equality constraints	[66,99,106,112, 113,121]	[99,116–119,162]	[29,30,36,37,40,42,57,73, 77,84–86,88,89,91– 93,95,106,112,113,117,121, 122,124,125,127– 129,131,133,134,136,138, 140–145,147,148,151– 153,155,156,159–161,163– 167,171,174]	[31]	[29,30,77,84,85, 91,92,117,124,125, 127–129,131,133, 134,144,145,148, 151,163–167]	[36,37,57,84,85, 89,91,92,106,112, 113,121,145,147, 153,156,159,163]	[37,57,84,85,88, 91,92,95,99,106, 118,119,121,127, 129,136,145,148, 164–167,171,174]
DG power limits	[66,104–106,108– 110,112,113,121]	[109,110,114,115, 118,162]	[28,30,36,39,40,42,57,75, 80,81,84–86,88,89,91,92, 94,95,99,104–106,108– 110,112,113,119,121– 123,125– 131,133,134,137,139– 142,144–150,152– 156,158,159,163,164,166– 168,171,174]	[54]	[28– 30,54,75,80,81,84, 85,91,92,125– 131,133,134,144, 145,148–150,154, 163,164,166–168]	[36,39,57,84,85, 89,91,92,99,104– 106,108,112–115, 118,121,137,145– 149,153,154,156, 159]	[39,57,84,85,88, 91,92,95,99,106, 109,114,118,119, 121,127,129,131, 145,148,164,166, 168,171,174]
Cost limits	-	-	[92,129,150,165,166]	-	[92,129,150,165, 166]	[92]	[92,129,165,166]
Frequency limits	[82,98,101,121, 172]	[114,116,117,119]	[40,42,82,84,86,88,91,92, 95,117,121,122,126,131, 135–137,139,151,155– 157,159,160,165–168,174]	[56,58]	[84,91,92,117,126, 131,135,151,165– 168]	[82,84,91,92,101, 114,121,137,156, 159]	[84,88,91,92,95, 114,119,121,131, 136,165,166,168, 172,174]
Voltage limits	[66,82,97– 102,104–106,108– 113,121,153]	[99,109,110,114, 116,117,119]	[28,36–38,40– 42,57,72,74,82,84– 86,88,94,95,104–106,108– 110,112,113,117,121,122, 127,131,136,137,142,146, 148,151,153– 156,159,160,174]	[56]	[84,85,117,127, 131,148,151,154]	[36–38,41,57,82, 84,85,99–102,104– 106,108,112– 114,121,137,146, 153,154,156,159]	[37,57,84,85,88, 94,95,99,106,109, 114,119,121,127, 131,136,148,174]
Thermal limits	[97,99–102,104– 106,108– 111,113,121,153]	[99,109,110,114, 116,118,119]	[36,37,42,84–86,88,104– 106,108–110,113,121,127, 131,136,140,146,148,153, 157,158,163]	-	[84,85,127,131, 148,163]	[36,37,84,85,99– 102,104–106,108, 113,114,118,121, 146,148,153]	[37,84,85,88,99, 106,109,114,118, 119,121,127,131, 136,148]
ESS limits	[96,97,103,112, 121,172]	-	[84,86,88– 90,112,121,125,127– 131,133,134,137,144,145, 149,152,163,164,171]	[33,35,54, 56]	[33,35,54,84,125, 127–131,133,134, 145,149,163,164]	[84,89,90,112,121, 137,145,149]	[84,88,103,121, 127,131,145,164, 171,172]
DR limits	[97]	-	[78–81,122,124–126,128– 130,133,137,139,144,147, 152,174]	-	[78–81,124– 126,128– 130,133,144]	[137,147]	[129,174]
Radiality limits	-	[109,110,114– 118]	-	-	-	[114,115,118]	[109,115,118]

3.2.1. Power Flow and Balance Equality Constraint

Most optimization problems in DCIMG will involve a certain degree of load flow calculations, where the main balance to be sustained is related to equality between all generated power and total network demand including losses. This type of constraint is found in a significant number of economic dispatch studies dealing with the OPF problem [29–31,36,40,77, 84–86,88,89,91,93,95,122,124,125,127–129,131,136,138,140–145,147,148,151–153,171,174]. Ad-

ditionally, the next significant association of power balance constraint in DCIMG was with allocation [66,99,106,112,113,121] and then reconfiguration problems [116–119,162]. Conversely, power limits were applied as renewable power curtailment limits to ensure power flow convergence during peak [111,114] and off-peak hours of operation [100–102].

3.2.2. DG Power Limits

Another set of popular constraints are those dealing with DG units' output power. Those include power output limits, ramping limits, and spinning reserve limits. Output power of dispatchable DG units must remain within min–max limits; this is necessary to ensure a safe operating region for DG with an acceptable range (0.8–1) of lagging power factor [84]. Hence, many studies of EDP focus on the active power limits of DG units, assuming that reactive power sharing is handled at different control levels [28,30,39,40,42,54,75,80,81,88,92,126–131,133,134,140,141,144,148–150,158,163,164,171,174].

Similarly, other studies have accounted for the reserve limits for DG units, which means that the dedicated output of a DG unit and the respective scheduled reserve must be within the unit's maximum capability [89,91,92,140,145,163,166–168,171,174]. Additionally, load following and frequency regulation dispatch studies are often accompanied by ramp-up/ramp-down limits [125,128,133,144,150,152]. These ramping limits are necessary to set a boundary for the response from DG units to load changes and the point when load following is not possible. In converter- or inverter-controlled DG units, a current limit is often applied to limit the generated active power [31,38,41] or to ensure the safe operation of equipment [69].

To ensure the autonomous operation of DCIMG and prevent voltage collapse and circulating currents, many dispatch [36,57,66,84–86,94,95,99,104,105,113,119,122,123,137, 139,142,146,147,153,154,156,159] and reconfiguration [114,115,118,162] optimization studies limit the generator reactive output power to min–max limits to ensure adequate reactive power sharing without power factor degradation.

3.2.3. Cost Limits

Although cost is often tackled as an objective in DCIMG optimization problems, it might be considered as a constraint sometimes. This is important in the planning of autonomous operation of microgrids in rural or isolated environments. Cost limits in autonomous MG design could be expressed as fines for relying on the main grid support [129,150] or having to adhere to a certain cap for emissions costs [165].

Another way to bound the cost of microgrids is to set a fixed budget for all of the capital, installation, running, and maintenance costs of the MG design problem; this is also known as the total cost index (TCI) [92,166].

3.2.4. Frequency Limits

Most rural microgrids have some sort of frequency tolerance, where frequency swings are permissible but within a certain range. However, if critical loads or rotating machines exist in DCIMG, then frequency must be kept within a strict limit (typically 0.99–1.01 per unit of rated frequency) or less [82,84,86,88,91,92,95,98,119,121,122,126,131,135–137,157,159,166,172,174].

3.2.5. Voltage Limits

Since most prevailing DCIMG applications are of radial or weakly meshed topologies, voltage across the network tends to drop below acceptable levels further downstream nodes. Likewise, volatility in demand and generation could cause damaging voltage spikes or voltage collapse. Therefore, bus voltage limits (usually 0.95–1.05 per unit of rated voltage) are applied in most DCIMG optimization studies [36,37,40,66,82,88,97,100,104–106,109–113,117,127,131,146,148,151,155,174].

3.2.6. Thermal Limits

Optimization studies that focus on power and current flow through lines and feeders of the distribution network must ensure that the thermal ratings of the lines are not exceeded. Therefore, most studies in DCIMG include an inequality constraint to ensure the current is less than a maximum thermal rating of the line [36,37,84–86,88,97,100–102,104–106,109–111,118,119,121,127,140,146,153,157,163]. Conversely, other studies have considered a limit for power losses across the MG as a way to reduce total current flow [86,109,110,122] or to reduce unwanted harmonic currents [151].

3.2.7. ESS Limits

There are certain limitations for ESS use in microgrids, which include the capacity of ESS, charging and discharging currents, state of charge (SOC), and efficiency [89] since life expectancy of the most predominantly used ESS type, the BESS, is linked with SOC and charge/discharge currents. Higher charge/discharge currents could lead to damage in BESS units, while prolonged low SOC experienced by BESS will affect its ability to reach 100% charge and deteriorate its efficiency with time.

Therefore, most optimization studies with BESS specify power limits to regulate charge/discharge currents [54,127,130,133,134,144,145,152,163,164,171] or time change limits for the rate of charge and discharge [56]. Similarly, SOC of any BESS must be kept within min–max limits, as seen in control [33,35] and dispatch [90] problems. Lastly, any SOC must not exceed the maximum capacity of the BESS, where that can be pre-set to a 100% target in dispatch studies [86,88,125,128,129,131,137,149] or limited to battery selection based on rated energy capacity in planning problems [96,97,103,121,172].

3.2.8. DR Limits

Optimization studies that rely on load shedding and DR to preserve the power balance in DCIMG often include limits to the maximum number of loads to be served [78–81,139] or the margin available for the DR program for load curtailment [97,126,137] or deferment [125,128–130,133,144,152]. Likewise, it could also limit the minimum amount of heat demand that must be met within a specific scheduling horizon [122,124,174].

3.2.9. Radiality Limits

As previously mentioned in reconfiguration problems, many of them must adhere to a certain topology structure of a tree or radial nature. This is often expressed as the inexistence of a closed energized loop between nodes. In other words, according to graph theory, this represents a tree or connected graph without loops, where the sum of all switching variables $st_{(i,j)}$ (or vertices) must be equal to a pre-defined integer related to the total number of edges in the graph n [114]:

$$\sum_i st_{(i,j)} = n - 1, \ \forall \, i, j \, \in N \tag{6}$$

where N is a set of all buses of the islanded MG. The radiality constraint is found in many reconfiguration studies in DCIMG, similar to those found in [109,110,114–118].

3.3. Decision Variables

The third aspect of any optimization problem is the decision variables, also referred to as the control variables. These variables are varied by the optimization technique to obtain the desired objective function value that satisfies any imposed constraints. The most commonly used decision variables in DCIMG are discussed briefly below and also illustrated in Table 4.

Table 4. Overview of decision variables used in DCIMG by reference.

Decision Variable	DCIMG Optimization Problem Type					
	Allocation	**Reconfiguration**	**Scheduling and Dispatch**	**Control**	**EMS**	**MCDP**
DG variables	[82,99,104–113,120,121]	-	[28–30,75–82,86,89–93,104–106,108–110,112, 113,117,121,125,128–130,132–138,140–147,149–152,155,158,160,161,163–168,171]	-	[82,89–92,99,104–106,108,112,113, 121,137,145–147,149]	[91,92,99,106,109, 121,129,136,145, 164–166,168,171]
ESS variables	[96–99,103,112, 121,172,175]	[99]	[79–81,86–90,112,121,125,128–131,133,137,144–146,150,151,163,164]	[33,35]	[89,90,99,112,121, 137,145,146]	[88,99,103,121, 129,131,145,164, 172]
DR variables	[97]	-	[88,91,92,117,125,128, 129,131,144,151,164,166–168]	-	[91,92]	[88,91,92,129,131, 164,166–168]
Renewable generation variables	[39,100–103,111,112]	-	[57,86,88,112,125,131]	-	[39,57,100–102,112]	[39,57,88,103,131]
Droop and PI controller parameters	[66,82,104–107,113,121]	[114]	[36–38,40–42,57,60,72–74,82,84–86,94,95,104–106,113,121–124,126,127, 132,139,148,153,154,156–159,173,174]	[27,31,32,46–56,58–65,67, 68,70,71,83, 169,170]	[36–38,41,46,47, 57,82,84,85,104–106,113,114,121, 148,153,154,156, 159]	[37,55,57,83–85,94,95,106,114, 121,127,148,174]
Reconfiguration variables	[99,109,110]	[99,109,110,114–120,162]	[109,110,117]	-	[99,114,115,118, 120]	[99,109,114,118, 119]

3.3.1. DG Variables

A global variable found in every dispatch and scheduling problem is the power output of dispatchable DG units. Depending on the purpose of the dispatch problem, the active [28–30,75–81,86,90,93,117,128,129,132–136,138,140,141,143–146,149–152,158,161,163–165,171] and reactive [89,109,110,125,130,137,142,147,155,160] power output of dispatchable units has to be adjusted between the min–max range. Alternatively, in the DG allocation problem, the decision variable can be size [121], location [82,99,104–107,111,113], number [112], or a combination of those [108–110]. In UCP, a binary variable is usually adopted to describe the status of a generator as on or off, where zero indicates that the DG unit is out of service, while online status is indicated by one [91,92,166–168].

3.3.2. ESS Variables

Another fundamental variable that is gaining popularity in recent years is the ESS charge/discharge power rate [79–81,86–90,125,128–131,133,137,144–146,150,151,163,164], as well as the discharge rate coefficients for BESS [33,35]. Furthermore, in planning studies, the number of required ESS is another variable of interest [103], while capacity (in Ah) [96,97,99,112,121,172,175], power rating (in kW) [121,172,175], type (such as LABESS, VRBESS, FESS, HESS) [96,99], and location of ESS [96–99,112] are also core variables for storage allocation studies in DCIMG.

3.3.3. DR Variables

In stand-alone microgrids with unpredictable demand, the load might exceed available generation. Hence, many optimization studies choose to regulate the demand side by selecting the size or order of load to be shed or deferred. These decision variables might be referred to as DR input [125,144], amount or number of load curtailed [88,91,92,97,128,129, 131,151,166–168], or total required load power [117,164].

3.3.4. Renewable Generation Variables

Conversely, if the amount of variable renewable generation is greater than demand, then the output of renewable power must be curtailed or stored depending on its size. If the amount to be curtailed is quite significant, then a decision variable is determined based on power dissipated into DL [100–102]. Otherwise, if the study aims to increase renewable utilization, then the amount of curtailed renewable power can be set as a decision variable to maximize renewable energy potential directly [57,86,88,125,131] or via setting parameters for a decentralized curtailment controller (DCC) [111]. Some allocation studies, on the other hand, consider renewable energy such as WT and PV to be dispatchable; hence, the number of units selected can be modeled as another decision variable [39,103,112].

3.3.5. Droop and PI Controller Parameters

These types of decision variables are the bases for DCIMG optimal operation and power-sharing capabilities. They could be selected by MGCC to achieve optimal operation of dispatchable DG units at the primary control level for linear [57,72,73,82,84,104,106,107, 121,122,124,126,127,132,153,157,158], non-linear [123,139], and DC [31,36–38,41,42] droop coefficients. Similarly, these coefficients can be manually pre-determined in the absence of MGCC [94,95,114]. Alternatively, they could be used for PI controller parameter selection to adjust the reference for active units' output voltage magnitude [27,31,46,47,57,67,74,154,156], angle [65,68], and frequency [32,54–56] at the secondary control level. Additionally, the parameters could be selected to restore voltage and frequency to steady-state value after islanding [48–53]. Furthermore, for the sake of voltage regulation and reactive power control, other DCIMG studies went on to determine the optimal capacitor location [113] or virtual impedance size and feasible range [66].

3.3.6. Reconfiguration Variables

A unique set of binary decision variables is those only found in reconfiguration problems, making it a combinatorial type of optimization problem. Such variables include determining the number of switching operations required [99,118,120], the location of tie and sectionalizing switches to be closed or opened [99,115–118,162], and the boundaries for zones splitting multi-microgrids [119].

3.4. Optimization Algorithms

In this section, the techniques used in DCIMG optimization problems are described exhaustively. The adopted algorithms can be divided into two main categories: classical and AI techniques. The former techniques cover a wide range of deterministic mathematical optimization approaches including analytical, iterative, and basic search methods, while the latter techniques, on the other hand, are concerned with stochastic metaheuristics methods inspired by nature, social, and physical behaviors.

3.4.1. Classical Optimization Algorithms

In many optimization problems, several attempts of approximations and linearization are made for the original problem to simplify the equations and relationship between the different decision variables. This enables the problem to be solved mathematically to obtain an exact optimal solution within a reasonable amount of time for academic purposes and sometime real-time applications. Hence, these methods are commonly referred to as deterministic optimization techniques, where the global optimal solution is guaranteed to be found for certain class of tractable problems. This is beneficial in some real-life problems where the guarantee of the optimal solution globality is fundamental to the decision-making process. Furthermore, another main feature of this class of optimization techniques is that they require pre-conditions to be met by the objective and constraint functions such as linearity, continuity, and convexity. Likewise, whenever possible, a prior knowledge about the solution search space upper and lower boundaries is of great importance to achieve a solution in polynomial time.

In basic search methods, the exhaustive search (ES) method, also known as the brute force or generate and test method, is a well-known method that tries every possible solution to the objective function. Despite its ability to find an optimal solution, ES methods tend to become inefficient or impossible when the problem grows larger. The ES method was utilized to find the best BESS location [98] and optimal charge and discharge rate [87], while the operational cost for a voltage source converter (VSC) has been reduced using the ES method in [122]. Another basic search method, named the continuation power flow (CPF), was adopted in [161] to find the most vulnerable bus for voltage collapse hence maximizing loadability.

The iterative methods, on the other hand, where the algorithm choses an initial solution to generate a sequence of improving approximate solutions until a termination criterion is met, are implemented for both differentiable and non-differentiable problems. In differentiable optimization problems such as those presented in [28–30,40,78–81,135,143], a gradient descent method was adopted to solve the EDP for best running costs. However, changing the objective function to a technical nature converts many dispatch problems into a non-differentiable or computationally expensive type where obtaining the Jacobean or Hessian matrix is impossible or at least very difficult. Hence, the quasi Newton iterative (QNI) method was used to minimize reactive power-sharing error in [73], while the trust region method (TRM) was applied to an OPF algorithm to obtain the best droop setting for IBDG to minimize losses [158]. Additionally, the pattern search method (PSM) was utilized to maximize both loadability [160] and VSI [155] in DCIMG when the gradient of the objective function did not exist.

Optimization solvers for linear and nonlinear problems have been widely used in many optimization problems in DCIMG where the objective function is approximated or linearized. As in [88,95,159], linear programming (LP) has been adopted to minimize costs for continuous decision variable problems, while commercial solvers such as GUROBI [136] and open-source solvers such as the COIN project [172] have been used to solve constrained LP for fuel cost minimization problems. Likewise, when the decision variables of the problem are continuous and discrete, then a mixed-integer linear programming (MILP) software called CPLEX is used. This is a commonly used software for classical optimization programming techniques in the literature and is usually modeled in different platforms such as the general algebraic modeling system (GAMS) [69,92,126,133,150,152,163–168], a mathematical programming language (AMPL) [86,131], or MATLAB [109,110]. Moreover, a reconfiguration problem to maximize the loadability of multi-connected microgrids has been solved by CPLEX using the mixed-integer second-order cone programming (MISOCP) algorithm to expedite the calculation time [117].

Conversely, when unavoidable nonlinear equations are present in the objective or constraint function, then the problem is categorized as nonlinear programming (NLP), which can be modeled and solved by available solvers such as interior point optimizer (IPOPT) [88] or COIN-IPOPT [133] for fuel cost minimization. Similarly, constrained NLP can be tackled by using Fmincon functionality [154] or the convex optimization (CVX) module [151] in MATLAB. Furthermore, when the NLP problem undertaken is twice continually differentiable, then sequential quadratic programming (SQP) is used. As presented in [33,35,42], the OPF was solved by means of SQP for accurate power sharing in hybrid DCIMG. However, when the nonlinear problem has discrete variables such as the ramping and charging states of DG and ESS units, respectively, then the problem is classified as Mixed-integer nonlinear programming (MINLP) and is thus solved by CONOPT as modeled in the GAMS environment [54,144]. Lastly, if the EDP has an element of time varying communication and event-triggered control systems, then dynamic programming (DP) is utilized to break down the optimization problem into smaller problems and then solved sequentially in a timely manner [136].

3.4.2. AI Optimization Algorithms

In many real-life situations, the optimization problem computational effort tends to grow exponentially by relying on classical optimization methods or it might be impossible to reach an exact solution mathematically. This type of optimization problems is often classified in hardness levels according to the time and memory required to reach the optimal solution, most notably the non-deterministic polynomial-time hard (NP-hard) problems [4]. Hence, heuristics and metaheuristics algorithms have gained popularity in solving NP-hard problems where classical optimization problems fail or when the pre-specified conditions required by classical methods might deform the original optimization problem beyond practical recognition. A heuristic is an algorithm that ranks the alternatives for a selected direction in the solution search space based on given criteria that define this method and is usually a problem-specific or white-box algorithm. Metaheuristics, on the other hand, use heuristics to find a quick and sufficient solution to the problem and are often reliant on generating random variables to find the optimal solution to a wide range of problems in what is called a black-box algorithm. This randomness in the objective or constraint functions or both differentiates this class of optimization algorithms from deterministic techniques, where often there is no guarantee that a global optimal solution will be found but rather a probability distribution that the obtained solution is as close to global optimality as possible. Hence, this class of optimization techniques is usually referred to as stochastic optimization.

The decision criteria for the exploration and exploitation by metaheuristics are usually derived from nature or social or physical behaviors and processes, or they could be a hybrid of those sources. In the following sub-sections, there is a brief summary of the used metaheuristics in DCIMG optimization problems.

- Socially and Physically Inspired Metaheuristics

This family of metaheuristics is derived from human social behavior and physical phenomena in nature. Such human-influenced algorithms include harmony search (HS), the imperialist competitive algorithm (ICA), teaching–learning based optimization (TLBO). The origin of the HS algorithm is based on the search by musicians for harmonization in sound from their musical instruments until an aesthetic standard has been achieved [115]. The HS algorithm has been applied to the minimization of voltage deviations [106,153] and cost [104] objectives as well as its variant for the multi-objective problem for loss reduction and VSI enhancement called the adaptive multi-objective HS (AMOHS) [115]. Another human-behavior-inspired algorithm is the TLBO, which is based on the learning process in classrooms; this method has been combined with the self-adaptive probabilistic modification strategy (SAPMS) in [145] to avoid being trapped in a local optimum solution for the DG dispatch problem to minimize cost and emissions, and it is therefore called improved-TLBO (ITLBO). Similarly, the human social evolution strategy in countries' competition for power and expansion has inspired researchers to propose the ICA. This population-based algorithm is represented by imperialist and colonized countries' relationships, which may lead to growth or destruction in the empire [9]. The ICA has been applied in DG economic dispatch problems in [105,129], where in [129] a multi-period ICA was proposed to enhance the convergence and computation time of the original ICA as applied to a complete EMS problem.

On the other hand, a combination of fuzzy logic (FL), neural networks (NNs) and inference systems (IS) has been utilized in DCIMG control problems. An IS, also called inference engine, is a process of applying digital logic to a knowledge base to construct new data, while NNs are computing systems that mimic the neurons in the animal brain to identify the connection between large amounts of data [53]. An adaptive neuro-fuzzy inference system (ANFIS) has been proposed for the optimal design of general droop controller (GDC) to reduce the error in voltage and frequency at steady state [53]. In FL, a value is set between 0 and 1 to assign a degree of membership for each objective of the problem at hand; this is an important aspect of the decision-making process in uncertain and conflicting optimization environments [9]. The FL principle has been utilized in Fuzzy-

PI controller optimal parameter selection to minimize the error in power sharing [71] as well as the frequency [32] and voltage [52] recovery at the secondary control layer.

Conversely, physical theories describing events in nature such as the evolution of universe and how energy particles are randomly scattered and then drawn into order, as described in the big bang–big crunch theory (BB-BC), have influenced researchers to adopt this population-based optimization method for single- and multi-objectives for voltage error reduction in the PI controller design [46,47]. Another physics-law-inspired population algorithm that features an excellent convergence rate is the searching vector artificial physics optimization (SVAPO) [116]. The idea behind this method is based on Newton's second law of motion and how each population member adjusts its movement based on the inertia and force exerted by other members. The vulnerability index of the MG has been improved using SVAPO to determine the optimal location of reconfiguration switches [116].

- Nature-Inspired Metaheuristics

This group of metaheuristics covers swarm and evolutionary algorithms. Evolutionary algorithms (EA) are group of global population-based algorithms inspired by the biological reproduction process and Darwin's theory of evolution [9]. The biological evolution processes, such as selection, reproduction, crossover, recombination, and mutation, are the key factors in EA decision criteria. In [146], a Niching EA (NEA) was selected for a multimodal ESS dispatch problem to avoid becoming stuck in a local solution by adopting a niching scheme to diversify the population and obtain multiple local optima as well as the global solution, although it might not exist. Similarly, as proposed in [89], a θ-dominance-based EA (θ-DEA) is adopted to obtain the Pareto front for the ESS multi-objective dispatch problem, striking a good balance between convergence and diversity in the solution. Conversely, differential evolution (DE), another class of EA with high convergence and low number of parameters, has been utilized for the DG multi-dimensional dispatch problem to minimize cost and emissions in combined heat and power (CHP)-based MG [147].

Another sub-class of EA that has gained popularity in the last decade is the genetic algorithm (GA) and its variant for multi-objective optimization, the non-dominated sorting GA-II (NSGA-II). The GA has been used in numerous DCIMG studies, making it one of the most reliable metaheuristics that can be applied to a vast range of problems. Various control problem studies have considered GA to improve islanded MG stability [27,31,55,62,67,83]. Likewise, other studies have relied on GA, such as the ESS allocation problem in [97], where the total cost of storage system was minimized considering customer willingness to pay for continuation of supply. Moreover, the optimal reconfiguration of an autonomous shipboard power system to maximize loadability was achieved by using GA and graph theory to model the system [162]. Another use for GA is the one applied with real numbers to the EDP problem in power systems called matrix real-coded GA (MRCGA), where each candidate solution of the population is represented by a real number matrix of generation schedule [96,130]. As for NSGA-II, it differs from GA in its selection operator process only, where the population is subdivided into hierarchical structure and sorted based on the Pareto dominance filter. The NSGA-II was successfully implemented in DCIMG allocation [100–102,108,112], dispatch and scheduling [41,82,137], and reconfiguration [114] problems.

On the other hand, swarm intelligence algorithms represent the collective intelligent behavior of decentralized and spontaneously ordered population members. Quite often, these algorithms are derived from the foraging or flocking behavior of biological animals in nature, where the interaction of an agent (or Boids) with others and the surroundings will lead to global optimum behavior not known to individual members of the population [176]. Particle swarm optimization (PSO), one of the most relied upon swarm intelligence algorithms, which was inspired by bird flocking or fish schooling behavior, has been heavily used in various DCIMG studies. PSO was employed most predominantly in the optimal tuning of parameters for secondary-level controller design [46,47,49,50,58,60,61,63,64,68,70,169,170], the optimal dispatch of DG

units for cost reduction [36,37,84,90,103,123,127,139,147,174], and voltage stability enhancement [38,57,66,72,74]. Additionally, by using the adaptive modified PSO (AMPSO), a reconfiguration problem was optimized, taking into account wind generation uncertainties [174]. The original PSO was modified with the inclusion of mutation operator and the non-linear adjustment of parameters to prevent AMPSO from being trapped in a local minima [174]. Moreover, a multi-modal allocation problem for DG and BESS was handled by multi-objective PSO (MOPSO) to reduce cost and enhance reliability [99]. As described in [99], the original PSO was modified by introducing the Pareto dominance concept with a mutation operator and an external repository to store new non-dominated solutions.

Besides PSO, there is another well-established swarm intelligence algorithm called the ant colony optimization (ACO) algorithm, which was inspired by the ant's foraging behavior as introduced by Dorgio in 1992 [9]. However, it was utilized only once in DCIMG optimization studies to minimize the total cost in an EMS problem relying on DG, ESS, and DR as the decision variables [128]. The success and efficacy of swarm intelligence algorithms in solving highly non-convex MINLP problems has inspired many other studies to implement other foraging-and-hunting-behavior-derived methods. Such swarm intelligence-based methods include the artificial bee colony (ABC), inspired by the intelligent foraging behavior of honey bees, for optimal EMS implementation [125], optimal EDP [142], and power-sharing error minimization [59]; the grey wolf optimizer (GWO), which mimics the hunting behavior and leading hierarchy of grey wolves in nature for ESS [96,121] and capacitor [113] allocation problems; the whales optimization algorithm (WOA), which mimics the hunting behavior of humpback whales in nature for DL allocation [101,102] and PI controller optimization [51]; the grasshopper optimization algorithm (GOA), inspired by grasshopper movement and hunting behavior in nature for PV and WT units' number allocation [39] as well as frequency and voltage error minimization [48]; the ant-lion optimizer (ALO), based on the ant-lion hunting mechanism in nature for the DG optimal dispatch problem [85,148]; glow-worm swarm optimization (GSO), based on the ability of glow-worms to change their luciferin emission intensity for active power loss minimization [157]; and the modified adaptive firefly algorithm (MAFA), inspired by the fireflies flashing behavior, for optimal reconfiguration of tie and sectionalizing switches [118].

3.4.3. Hybrid Optimization Algorithms

The name for these algorithms represents methods originated from cascaded or parallel combination of different AI techniques and sometimes of classical techniques at different stages. This forging of different class of AI algorithms is usually performed to enhance the exploration and exploitation capabilities as well as to expedite the convergence of these new methods. Due to the impeccable performance of GA and PSO in various optimization disciplines, they have been adopted as bases for many hybrid optimization methods.

According to the studies from [104,106,153], the merger between GA and HS to form the HS–GA algorithm was proposed to minimize fuel costs and voltage deviations for the optimal operation of DCIMG. Since the original GA mutation and crossover operators may suffer from accuracy issues in certain multi-modal problems, three harmony memories from original HS were used to enhance the exploitation and exploration of GA mutation and crossover operators, respectively [104,106,153]. The first harmony memory is used to store the fitness function obtained by HS and then the second memory is utilized to store the solution of first memory by using GA operators; in the last memory, the solutions obtained by the first and second memories are compared and then stored in the third memory to obtain the Pareto optimal set. Similarly, as discussed in [105], the ICA was cascaded with GA to enhance the accuracy of the original ICA and provide better convergence speed than HS–GA for the same problem given in [104]. This was achieved by computing the cost for each empire first and then using GA operators to generate colonies with better costs compared to the imperialists, leading eventually to the demise of weak empires and the survival of the best one where the Pareto front is stored [105].

Contrarywise, the optimal error control for IBDG output voltage was achieved by combining PSO with BB-BC to form what is known as the hybrid BB-BC (HBB-BC) [46]. The deficiency of BB-BC in becoming stuck at a local minima for some NP hard problems, such as those proposed in [46,47], was eliminated by utilizing the BB-BC center of mass concept in the local and global particle positioning system of PSO. Furthermore, by introducing the mutation probability factor, HBB-BC avoids becoming stuck in a non-improving local position situation by generating a random mutated new position (or solution) [46]. Furthermore, the latter hybrid method was expanded in [47] to handle multi-objective optimization using the Pareto dominance concept and crowding distance operator to diversify Pareto optimal points stored in the solution archive. Additionally, the reliable performance of PSO in exploration has inspired the authors of [70] to combine it with a new metaheuristic inspired by Salp fish foraging and navigating behavior in oceans called the Salp swarm-inspired algorithm (SSIA). The latter hybrid method, SSIA–PSO, was used to optimize droop and PI controller parameters to handle sudden load and renewable changes in primary and secondary control levels of MG. Furthermore, the proposed SSIA–PSO method in [70] had better convergence and faster computation time compared to individual PSO, ABC, ALO, and GWO methods.

To enhance the accuracy of AI techniques in locating a global optimal solution for a certain class of problems, a combination of AI and classical techniques at different stages of the optimization process was introduced in [57,127,130]. As in [127], a gradient decent method was utilized to enhance the solution of PSO to obtain optimal dynamic time-dependent droop gains for conventional DG units to minimize emission costs subject to the least frequency deviation limit. Moreover, a scheduling and dispatch problem was divided into two stages: the first economic dispatch was executed considering one equality constraint for power balance and then GA was used to achieve total running and penalty costs minimization subject to a time-dependent generation schedule and ESS limits [130].

Optimization in the FL environment was extended to other AI techniques to assist in the decision-making process for conflicting MCDP. The use of FL to assist with MCDP was in conjugation with PSO [36,37], ALO [85,148], NSGA-II [100–102,108], θ-DEA [89], and HBB-BC [46,47]. Moreover, as in [57,84], the advantage of FL systems in handling optimization with uncertainty was utilized by adopting Fuzzified PSO (FPSO) to minimize the reactive power-sharing error in [57] and greenhouse gas emissions in [84]. Similarly, an improved PSO (IPSO) using a fuzzy inference system (FIS) in [64] has been utilized to dynamically adjust droop parameters to minimize the reactive power-sharing error and thus improve MG voltage stability. The introduction of FIS has improved the search speed and accuracy of PSO by dynamically adjusting the learning factors and inertia weight (coefficients associated with PSO) in each iteration based on performance indicators such as iteration number, error in particle fitness, and diversity in particles spread from the optimal position [64].

4. Discussion

In light of the forgoing thematic literature survey within the scope displayed in Figure 6, a comprehensive and detailed description of the most important aspects that govern the area of optimal operation and allocation of DCIMG was carefully analyzed and critically evaluated. Out of the many existing classifications for microgrid types, perhaps those derived from system current type are the most significant ones as they require different infrastructure and equipment setting. Moreover, it was apparent that the control of islanded microgrids is not an easy task, as often there are conflicting goals for running microgrids where a balance must be struck between centralized and decentralized control philosophies. The main highlighted advantages and disadvantages of AC/DC microgrids and centralized/decentralized control schemes are depicted in Tables 5 and 6, respectively.
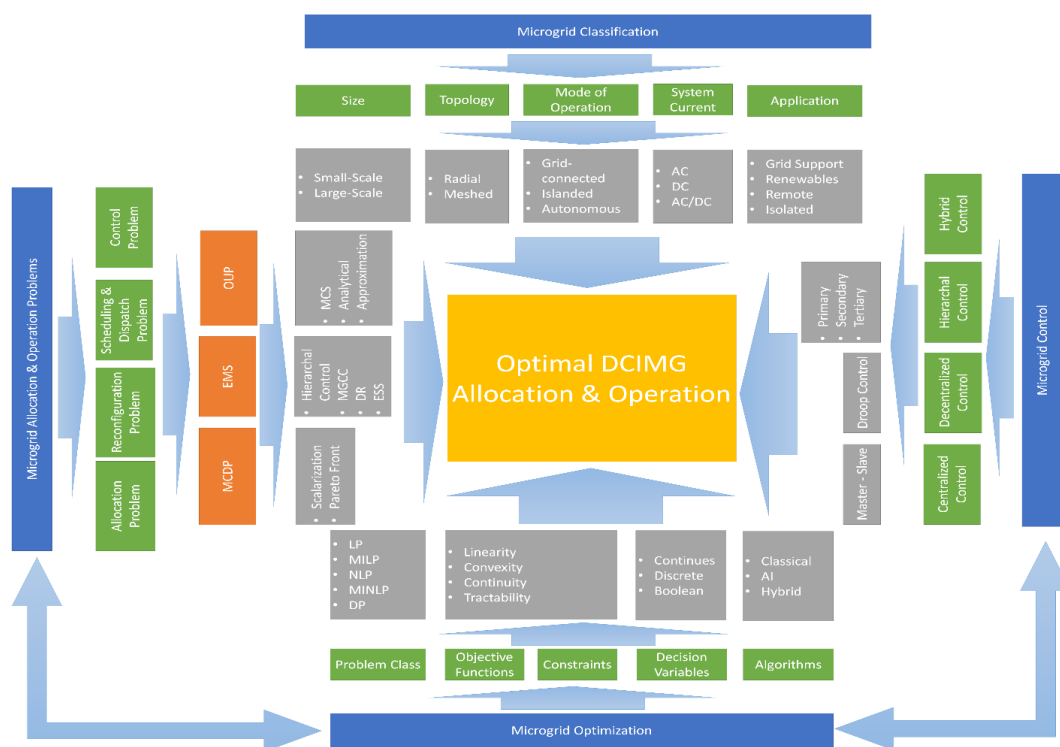
Figure 6. Overview of DCIMG optimal allocation and operation scope.

Table 5. Summary of MG type by system current.

Microgrid Type	Advantages	Disadvantages
AC Microgrids	• Efficient power transfer for longer distance. • Low implementation cost. • Good voltage conversion support. • Easier integration with main power grids. • Fairly easier protection. • Suitable for small and large-scale microgrids. • Supports radial and meshed network topologies. • Simple design requirements.	• Challenging frequency synchronization. • Inaccurate reactive power sharing. • More AC/DC conversion systems are required. • Challenging harmonics control.
DC Microgrids	• No frequency synchronization issues. • More efficient in prevailing DC loads microgrids. • More efficient for energy storage systems integration. • Fewer AC/DC conversion systems are required.	• Small scale microgrids. • High implementation costs. • Inadequate infrastructure for integration with main grids. • High losses in long-distance power transfer. • More AC/DC conversion systems are required for better renewables integration. • Not a suitable candidate for expansion to large-scale. • Common DC bus regulation issues.
AC/DC Microgrids	• Combines advantage of AC and DC systems. • Efficient power transfer for longer distance. • Better frequency synchronization. • Better harmonics control. • Excellent voltage conversion support. • Excellent energy storage support.	• Might not be practical for electrification of rural and isolated communities. • Complex design. • Stability and protection challenge. • Much higher implementation costs.

Table 6. Summary of MG control methods.

Control Methods	Advantages	Disadvantages
Centralized Control	- Accurate power sharing. - Adequate voltage and frequency regulation. - Easier control at one point of common coupling. - Immune to load variations. - Adopts master–slave philosophy. - Majority of units are of the grid-following inverter type.	- High implementation costs. - Low reliability. - High bandwidth communication infrastructure requirements. - Impractical for rural and less-developed communities. - Large capacity requirement for at least one DG unit.
Decentralized Control	- Low implementation cost. - No communication channels required. - High reliability. - Good solution for isolated and rural communities. - Easier agent-based control implementation. - No special capacity requirements for DG units. - Adopts droop control philosophy. - Majority of units are of the grid-forming inverter type.	- More difficult to control. - Requires secondary control action to restore nominal voltage and frequency. - Inaccurate power sharing. - Basic voltage and frequency regulation. - Influenced by load variations and line impedance.
Hybrid Control	- Advanced power sharing. - Advanced voltage and frequency regulation. - High reliability. - Immune to load variations. - Adopts master–slave and droop control philosophies. - Hierarchal control structure. - Both grid-forming and grid-following inverters.	- Much higher implementation cost. - Low/high bandwidth communication infrastructure requirements. - Impractical for rural and less developed communities.

Conversely, this review has identified two distinct areas for optimization problems faced by DCIMG planning and operation based on the optimization cycle they cover: short-term and long-term problems. However, to ensure adequate provisions for these microgrids, these two types of problems are often combined. Figure 7 illustrates the sprawl of DCIMG optimization problems during the last decade, where the highest share went to dispatch and scheduling problems followed by control and EMS problems. Additionally, the distribution of optimization problems in DCIMG by objectives number count in each sole problem was not balanced, as shown in Figure 8. The number of single objective problems compared to MCDP was almost three times as much, while the use of the weighted average method (and sometimes epsilon constrained method) vs. the non-dominated Pareto front approach for the MOO problem solution was similar.

It is worth mentioning here that most real-time short-term optimization problems in DCIMG preferred the single objective approach to the problem, making them less accurate and less reliable. Moreover, short-term optimization problems that considered MOO for potential real-time application have relied on the weighted average sum approach to save on computation time, neglecting the advantage of higher chance of accuracy for the Pareto-front optimization techniques.

Similarly, the distribution of objective functions among optimization problems by article number was not symmetrical to reflect the three main objective function themes: economic, environmental, and technical. As seen from Figure 9, it was clear that the largest emphasis in most DCIMG optimization problems was on the economic objectives, out of which cost minimization was the most desired objective function.
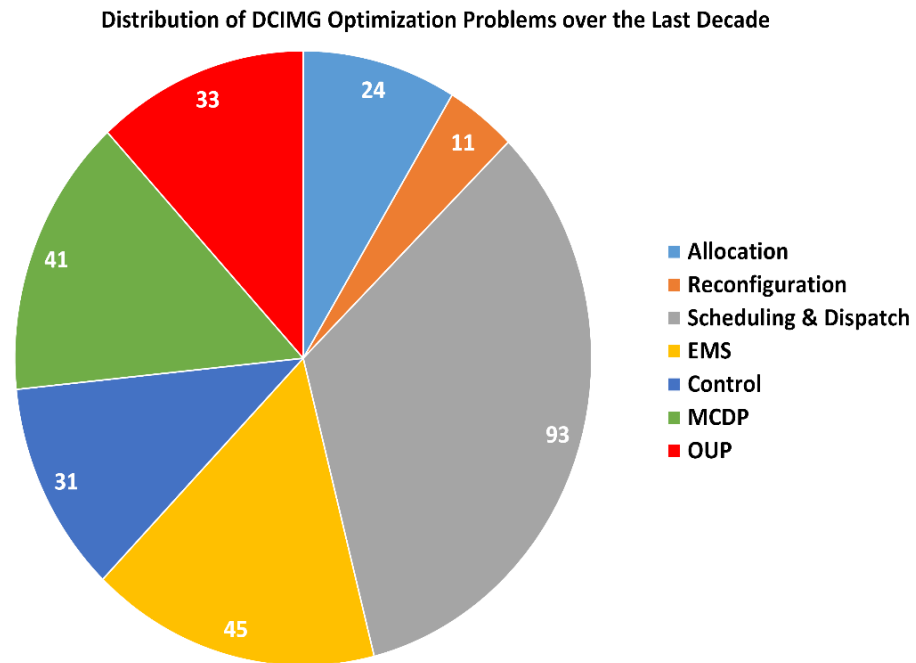
Distribution of DCIMG Optimization Problems over the Last Decade

Figure 7. Distribution of DCIMG optimization problems over the last decade.

DCIMG Optimization Problems Solution Approach
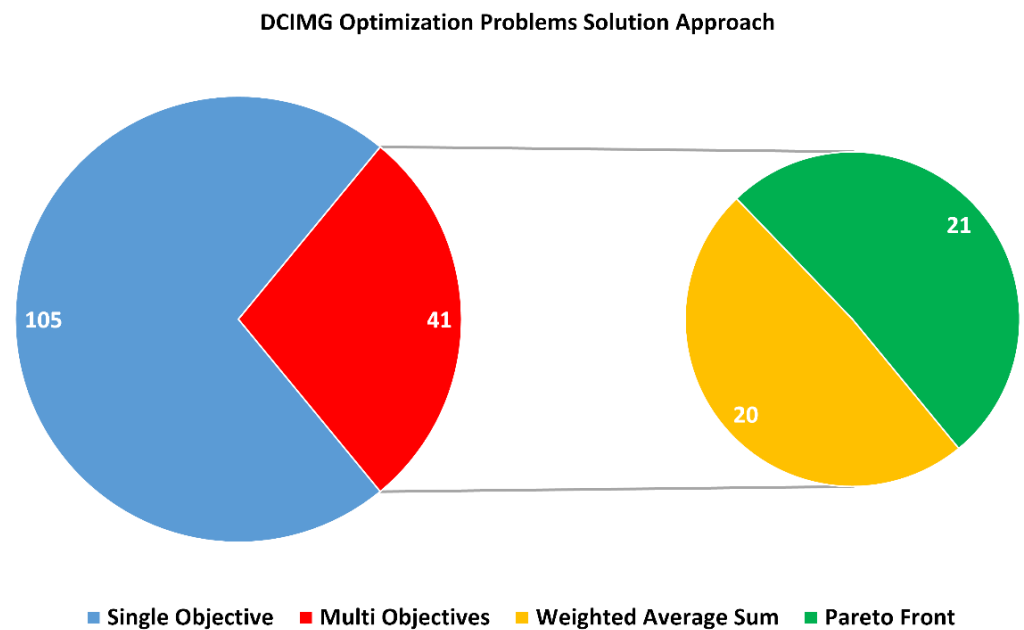

Figure 8. Optimization problems solution approach by objectives number count in each problem.

Likewise, as depicted in the cost objectives breakdown of Figure 10, the highest share went to fuel cost minimization, followed by DG maintenance and load shedding costs, respectively. This high focus on cost objectives can be understood as means of running and securing adequate supply for islanded microgrids within certain boundaries. Furthermore, this trend was evident from the highest percentage of running cost objectives (57%) among the total number of costs considered as objective function by DCIMG optimization studies, followed by (14%) and (13%) for security and penalty cost objectives, respectively, as shown in Figure 11. Besides the economic objectives, the technical aspect was manifested by the high share of papers that addressed voltage and frequency regulation objectives, as seen in Figure 9. This new trend can be attributed to the higher importance of adequate voltage

and frequency regulation for reliable and safe operation of isolated microgrids if compared to the influence of economic and environmental objectives on MG operation.
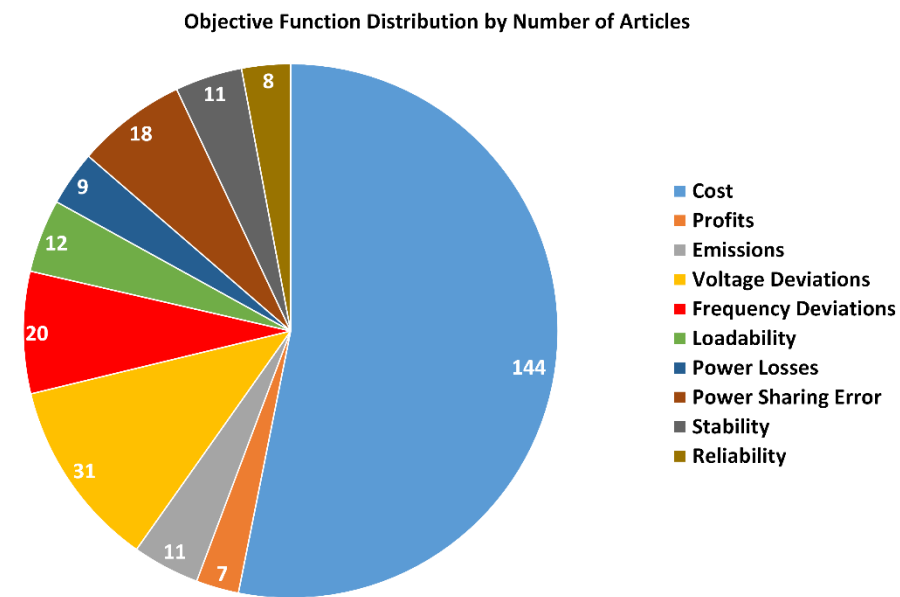
Objective Function Distribution by Number of Articles

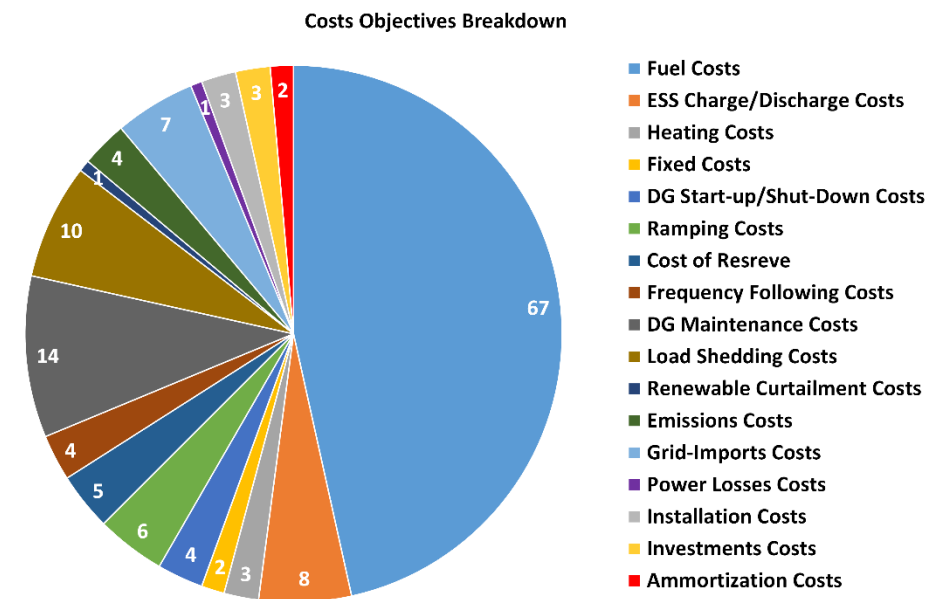**Figure 9.** Distribution of DCIMG objectives' function by number of articles.

Costs Objectives Breakdown

Figure 10. DCIMG cost objectives' breakdown by number of articles.

As for optimization constraints, on the other hand, the highest share went to DG power limits, followed by power balance and load flow equality constraints, as illustrated in Figure 12. This can be easily realized by the significance of accurate and convergent load flow solution in any power system to ensure the stability of operation, while the efficient dispatch of DG units lies at the backbone of islanded microgrids operation. Similarly, voltage, frequency, and thermal limits have gained considerable interest from many optimization studies that addressed the optimal allocation and dispatch problems for autonomous microgrids with a higher portion of renewable DG and ESS units. This can be interpreted as an increased need for vulnerability indices for safe and reliable islanding operation at the event of any unit failure.
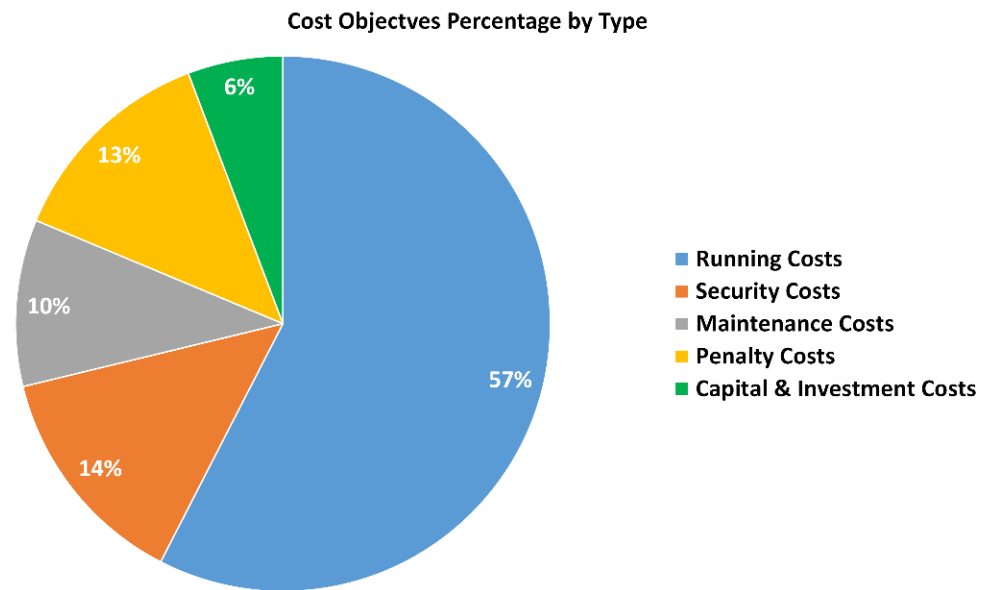
Cost Objectves Percentage by Type

Figure 11. Costs distribution by type of cost group in DCIMG total cost objectives considered.

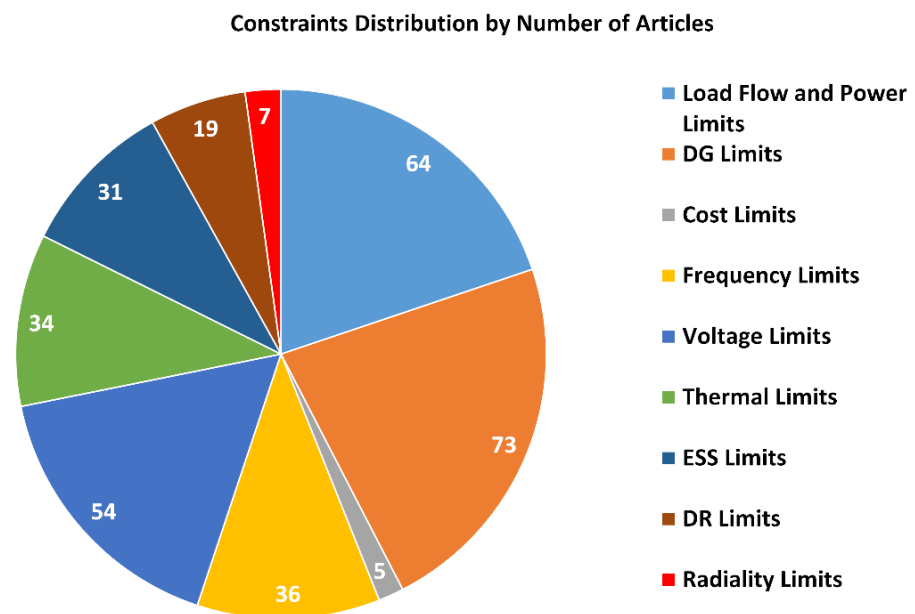**Constraints Distribution by Number of Articles**

Figure 12. Distribution of DCIMG constraints by number of articles.

Additionally, decision variables spread in DCIMG optimization problems came at a more evenly distributed scale between renewables, DR, and reconfiguration variables, as shown in Figure 13, while the highest share of coverage by papers went to droop and PI controller variables, followed by DG and then ESS variables, respectively. This significant number of control variables is closely related to allocation, scheduling, dispatch, and control optimization studies.

Lastly, the balance in optimization algorithm use between classical and AI techniques has been shifting toward the latter technique. This can be seen by looking into Figure 14, where out of the 174 investigated DCIMG problems, AI techniques accounted for 104 problems, leaving 70 for classical algorithms. Perhaps the rise in real-life MINLP optimization problems faced by DCIMG has warranted the use of more stochastic optimization techniques to find an acceptable optimal solution with high global optimality chance. This was necessary since deterministic classical optimization techniques need very long

and complex computation or sometimes fail to converge to a solution at all for challenging highly non-linear and non-convex MINLP and MCDP problems.
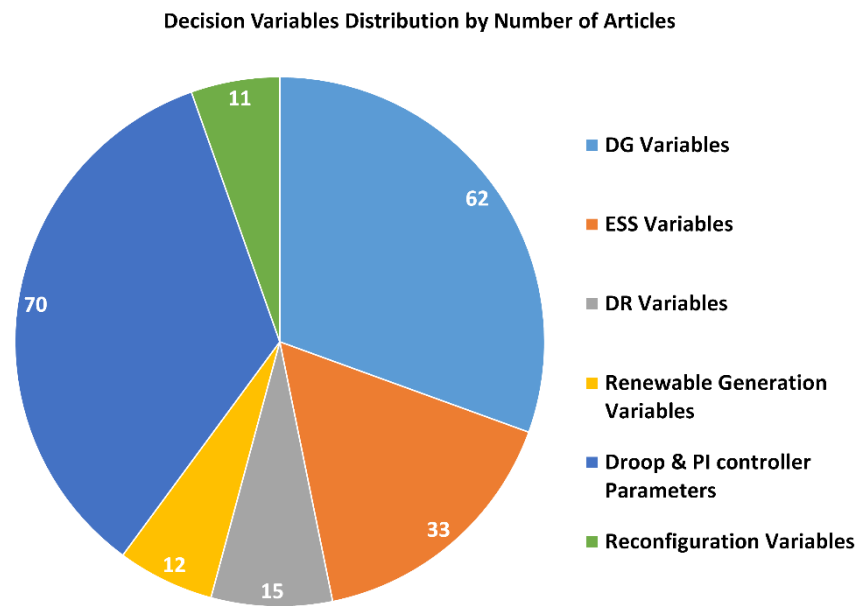
Decision Variables Distribution by Number of Articles

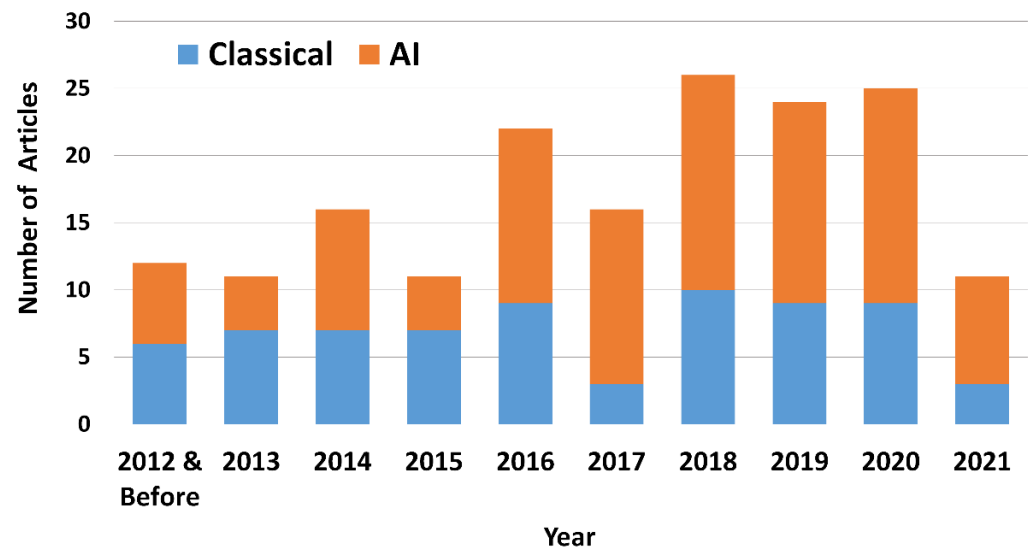**Figure 13.** Distribution of DCIMG decision variables by article numbers.

Figure 14. Trend in DCIMG articles with optimization methods adopted by year.

Despite the advantages of AI optimization techniques against classical ones in speed and convergence ability, they still suffer from practical implementation, exploitation, and exploration issues, and the inherent computational burdens. Hence, the search is still ongoing for more compact stochastic optimization techniques with higher capabilities to achieve a global optimal solution in an accurate and fast fashion. A comparison table between the major benefits and drawbacks for each optimization category is illustrated in Table 7.

Table 7. Summary of DCIMG optimization methods.

Optimization Methods	Advantages	Disadvantages
Classical Methods	- Deterministic optimization in nature. - Incudes basic and exhaustive search techniques. - Mathematical and iterative numerical-based methods. - Provides a guarantee that the obtained solution is global. - Minimal coding is required for the optimization algorithm. - Offers a high degree of accuracy. - Widely available in the literature and commercial solvers. - Minimal or non-existing number of parameters is required.	- Limited flexibility, can only be applied to limited number of problems. - Requires pre-existing conditions for constraints and objective functions such as linearity, convexity, and continuity. - Limited practicality, can only handle single objectives problems. - Mainly white box coding, requires different coding with each different problem. - Slow calculation time and convergence rate. - May not converge to a solution at all
AI Methods	- Stochastic optimization in nature. - Socially and physically derived techniques. - Swarm and evolutionary intelligence. - High flexibility, does not require pre-knowledge about the optimization problem. - High practicality, tackles single and multi-objective problems. - High efficiency, can handle uncertainty in decision variables and constraints. - Offers black box coding ability. - Faster calculation time and high rate of convergence. - More peer-reviewed literature is available compared to hybrid methods.	- No guarantee of global optimality to the solution, only probability of global optimality. - Can become stuck in local optimal solutions. - Harder to code the optimization algorithm. - Might suffer from premature convergence. - Needs proper parameter settings and adequate tuning. - Unpredictable results and uncertain calculation time for some problems.
Hybrid Methods	- Stochastic optimization in nature. - Higher precision compared to AI methods, can transform into deterministic approach with higher probability of global optimality. - High flexibility, does not require pre-knowledge about the optimization problem. - High practicality, tackles single and many objective problems. - High efficiency, can handle uncertainty in decision variables and constraints. - Offers black box coding ability. - Much faster calculation time and much higher rate of convergence.	- Much harder to code the optimization algorithms. - Might still become stuck in local optimal solution for complex problems. - Higher number of parameters and more difficult to tune adequately. - Few studies available, and some with ambiguous and improper description of new methods.

5. Future Trends

According to the topics and direction of research in the articles investigated so far, it is believed that future research trends should tackle the lacunas identified in this review. That is, if DCIMG were to be considered in a large and more practical-scale implementation, this would include but not be limited to:

1. Generation mix allocation: The importance of having a balanced generation portfolio is fundamental to increase the competitiveness of DCIMG. Hence, determining the optimal DG type, fuel mix, and renewable technology based on economic, environmental, and technical objectives in an aggregated manner is another important direction in future research for the optimal allocation and operation of DCIMG.

2. ESS efficiency and environmental impact: Quite often, ESS studies neglect the efficiency and environmental aspect of ESS allocation and operation. It is important to have a thorough investigation to analyze the cost associated with ESS decommissioning and the environmental consequences in storage unit recycling, if any. Similarly, the need is still there for adopting more energy-efficient and fast-charging/discharging ESS technologies at lower costs to make this investment a viable option for isolated and remote DCIMG.

3. DR and EV charging coordination issues: DR and EV charging programs are necessary to drive down the generation costs and emissions. However, studies often neglect the behavioral and coordination impact of utilizing these programs for practical voltage and frequency support in DCIMG. Thus, including DR and EV charging programs as uncertain stochastic variables is necessary in future planning and dispatch studies.

4. Protection consideration: A comprehensive protection scheme is necessary to ensure safe and reliable disconnection and restoration of supply in the events of faults. Optimization studies must consider protection strategy costs, short circuit calculation, fault levels, and X/R ratio impact on DCIMG operation. This should be of high interest, especially with future DG and ESS allocation studies.

5. Uncertainty in microgrids operation: The uncertainty considered in most optimization studies is based on pattern observation or historical recorded data for generation and demand and is often studied in planning studies only. However, in reality, dispatch operations may suffer from unaccounted for uncertainties occurring in a very short period, much smaller than normal load cycles, which could lead the MG to rely on conventional generation or grid-imported power to compensate for any mismatch. This has a negative impact on the carbon footprint of these microgrids and the design philosophy for autonomous operation of DCIMG. Therefore, future scheduling and dispatch studies must include a safety margin in the EMS execution time to account for unseen risks and be equipped with fast analysis techniques to handle short-term uncertainty forecast data.

6. Off-peak hours of operation: According to most reviewed articles with intermittent renewable energy utilization, the probability of high generation-to-load mismatch is higher at off-peak hours of operation. Therefore, future studies should focus on useful DL applications to manage excess generation taking cost, emissions, and uncertainty as deciding factors. Additionally, there is a growing need for a comprehensive EMS that is capable of managing power sharing accurately in DCIMG during peak and off-peak hours of operation.

7. Applicability of control systems: Many of the control and EMS solutions discussed in this review were applied to small-scale microgrids with few numbers of buses. Furthermore, many of the associated costs for the communication infrastructure and additional equipment were not accounted for. Hence, future research must take into consideration the applicability of these power control solutions on large-scale DCIMG and conduct a cost-based analysis to recommend these systems for practice, especially in low-budget, remote, and isolated microgrids.

8. Optimization methods practicality: Despite the significant number of metaheuristics used in DCIMG optimization, many of them lack the accuracy classical methods offer. This is necessary to decrease the computation time without compromising on accuracy to enable real-time application of these AI optimization methods. Furthermore, embedding more adaptable decision-making criteria with these algorithms is vital to avoid guiding the pareto selection process into an area of unbalanced weights for the objectives.

6. Conclusions

In this review paper, an investigation of the most related state-of-the-art literature in DCIMG operation and allocation was presented. A detailed and comprehensive background for the main aspects of DCIMG composition was provided. Several outcomes were documented by this review, mainly the classification of DCIMG optimization problems into four distinct areas: allocation, scheduling and dispatch, reconfiguration, control, and EMS. Furthermore, an additional two categories that often combine the forgoing problems were identified as MCDP and OUP. Similarly, this review has presented ten equally important objective functions often subjected to a combination of up to nine optimization constraint types with six possible groups for decision variables. The motives behind the consideration for each of the previously mentioned objectives, constraints, and variables by the investigated studies in this review were presented in a detailed and comprehensive manner. Moreover, the most notable optimization techniques utilized for DCIMG problems have been reviewed and sorted into two main groups, classical and AI, with the latter often combined as hybrid algorithms. It was concluded that AI has been gaining significant interest in the last decade, mainly for the promising advancement in AI algorithms and the rise in complexity for non-convex MINLP problems faced by microgrids planning and operation studies.

This review's key findings, the identification of research gaps, and recommendations for future trends should provide an insight to guide the direction of research in DCIMG. By serving as a helpful tool, this review can assist with future microgrids planning and operation for both researchers and developers of autonomous and isolated microgrids. The documented lacunas of this review paper have shed more light on some overlooked aspects necessary for proper DCIMG operation, mainly cost, technical, environmental considerations for a diverse generation mix and efficient storage facilities' allocation; coordinating practical DR programs and reliable EV smart-charging techniques; protection issues; adequate uncertainties' modeling; safer off-peak hours of operation; cost effective control schemes; and faster and accurate optimization algorithms.

Out of the equally important recommendations, the authors believe that costs, reliability, and stability issues stand out as the main obstacles to DCIMG expansion. This is of particular importance for the electrification of rural and isolated communities, especially because an estimated 12% of electricity consumers worldwide are still lacking access to affordable, reliable, and sustainable power supply. Secondly, the importance of DCIMG expansion lies at the core of further renewable energy deployment to minimize reliance on fossil fuel generation where possible. Lastly, despite the continued research into control and EMS for autonomous DCIMG, they are still vulnerable if considered for large-scale application, where uncertainties in demand and generation as well as off-peak hours of operation pose the largest threat to DCIMG reliability and stability.

Appendix A

Table A1. Acronyms and abbreviations.

Acronyms	Definition	Acronyms	Definition
ABC	Artificial Bee Colony	LP	Linear Programming
AC	Alternating Current	LV	Low Voltage
AI	Artificial Intelligence	MAS	Multi Agent System
ALO	Ant-Lion Optimizer	MCDP	Multi criteria Decision Problem
BB-BC	Big Bang-Big Crunch	MCS	Monte-Carlo Simulation
BESS	Battery Energy Storage System	MG	Microgrid
DC	Direct Current	MGCC	Microgrid Central Controller
DCIMG	Droop-Controlled Islanded Microgrid	MILP	Mixed Integer Linear Programming
DG	Distributed Generation	MINLP	Mixed-Integer Non-Linear Programming
DL	Dump Load	MOO	Multi-Objective Optimization
DR	Demand Response	MV	Medium Voltage
DP	Dynamic Programing	NLP	Non-Linear Programming
EA	Evolutionary Algorithms	NSGA	Non-dominated Sorting Genetic Algorithm
EDP	Economic Dispatch Problem	OPF	Optimal Power Flow
EMS	Energy Management System	OUP	Optimization with Uncertainty Problem
ES	Exhaustive Search	PET	Power Electronic Transformer
ESS	Energy Storage System	PI	Proportional-Integral
EV	Electric Vehicle	PSO	Particle Swarm Optimization
FESS	Flywheel Energy Storage System	PV	Photovoltaic
FL	Fuzzy Logic	SOC	State of Charge
FIS	Fuzzy Inference System	SQP	Sequential Quadratic Programming
GA	Genetic Algorithm	SSIA	Salp-swarm Inspired Algorithm
GWO	Grey Wolf Optimizer	SVAPO	Searching Vector Artificial Physics Optimization
HESS	Hydraulic Energy Storage System	TLBO	Teaching Learning Based Optimization
HS	Harmony Search	TVV	Total Voltage Variations
IBDG	Inverter-Based Distributed Generation	UCP	Unit Commitment Problem
ICA	Imperialist Competition Algorithm	VRBESS	Vanadium Redox Battery Energy Storage System
ITAE	Integral Time Absolute Error	VSI	Voltage Stability Index
LABESS	Lead-Acid Battery Energy Storage System	WT	Wind Turbine

References

1. Pohekar, S.; Ramachandran, M. Application of multi-criteria decision making to sustainable energy planning—A review. *Renew. Sustain. Energy Rev.* **2004**, *8*, 365–381. [CrossRef]
2. Georgilakis, P.; Hatziargyriou, N.D. Optimal Distributed Generation Placement in Power Distribution Networks: Models, Methods, and Future Research. *IEEE Trans. Power Syst.* **2013**, *28*, 3420–3428. [CrossRef]
3. Parhizi, S.; Lotfi, H.; Khodaei, A.; Bahramirad, S. State of the Art in Research on Microgrids: A Review. *IEEE Access* **2015**, *3*, 890–925. [CrossRef]
4. Gamarra, C.; Guerrero, J. Computational optimization techniques applied to microgrids planning: A review. *Renew. Sustain. Energy Rev.* **2015**, *48*, 413–424. [CrossRef]
5. Jordehi, A.R. Allocation of distributed generation units in electric power systems: A review. *Renew. Sustain. Energy Rev.* **2016**, *56*, 893–905. [CrossRef]
6. Khan, A.A.; Naeem, M.; Iqbal, M.; Qaisar, S.; Anpalagan, A. A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1664–1683. [CrossRef]
7. Evangelopoulos, V.A.; Georgilakis, P.S.; Hatziargyriou, N.D. Optimal operation of smart distribution networks: A review of models, methods and future research. *Electr. Power Syst. Res.* **2016**, *140*, 95–106. [CrossRef]
8. Badran, O.; Mekhilef, S.; Mokhlis, H.; Dahalan, W. Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies. *Renew. Sustain. Energy Rev.* **2017**, *73*, 854–867. [CrossRef]
9. Mahmoud Pesaran, H.A.; Huy, P.D.; Ramachandaramurthy, V.K. A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms. *Renew. Sustain. Energy Rev.* **2017**, *75*, 293–312. [CrossRef]
10. Singh, B.; Sharma, J. A review on distributed generation planning. *Renew. Sustain. Energy Rev.* **2017**, *76*, 529–544. [CrossRef]
11. Andishgar, M.H.; Gholipour, E.; Hooshmand, R.-A. An overview of control approaches of inverter-based microgrids in islanding mode of operation. *Renew. Sustain. Energy Rev.* **2017**, *80*, 1043–1060. [CrossRef]
12. Kakran, S.; Chanana, S. Smart operations of smart grids integrated with distributed generation: A review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 524–535. [CrossRef]

13. Dawoud, S.M.; Lin, X.; Okba, M.I. Hybrid renewable microgrid optimization techniques: A review. *Renew. Sustain. Energy Rev.* **2018**, *82*, 2039–2052. [CrossRef]
14. Liu, Y.; Yu, S.; Zhu, Y.; Wang, D.; Liu, J. Modeling, planning, application and management of energy systems for isolated areas: A review. *Renew. Sustain. Energy Rev.* **2018**, *82*, 460–470. [CrossRef]
15. Zia, M.F.; Elbouchikhi, E.; Benbouzid, M. Microgrids energy management systems: A critical review on methods, solutions, and prospects. *Appl. Energy* **2018**, *222*, 1033–1055. [CrossRef]
16. Wong, L.A.; Ramachandaramurthy, V.K.; Taylor, P.; Ekanayake, J.; Walker, S.L.; Padmanaban, S. Review on the optimal placement, sizing and control of an energy storage system in the distribution network. *J. Energy Storage* **2019**, *21*, 489–504. [CrossRef]
17. Pourbehzadi, M.; Niknam, T.; Aghaei, J.; Mokryani, G.; Shafie-Khah, M.; Catalão, J.P.S. Optimal operation of hybrid AC/DC microgrids under uncertainty of renewable energy resources: A comprehensive review. *Int. J. Electr. Power Energy Syst.* **2019**, *109*, 139–159. [CrossRef]
18. Fontenot, H.; Dong, B. Modeling and control of building-integrated microgrids for optimal energy management—A review. *Appl. Energy* **2019**, *254*, 113689. [CrossRef]
19. Cagnano, A.; De Tuglie, E.; Mancarella, P. Microgrids: Overview and guidelines for practical implementations and operation. *Appl. Energy* **2020**, *258*, 114039. [CrossRef]
20. Hannan, M.; Tan, S.Y.; Al-Shetwi, A.Q.; Jern, K.P.; Begum, R. Optimized controller for renewable energy sources integration into microgrid: Functions, constraints and suggestions. *J. Clean. Prod.* **2020**, *256*, 120419. [CrossRef]
21. Anderson, A.A.; Suryanarayanan, S. Review of energy management and planning of islanded microgrids. *CSEE J. Power Energy Syst.* **2020**, *6*, 329–343. [CrossRef]
22. Saad, O.; Abdeljebbar, C. Historical Literature Review of Optimal Placement of Electrical Devices in Power Systems: Critical Analysis of Renewable Distributed Generation Efforts. *IEEE Syst. J.* **2020**, 1–12. [CrossRef]
23. Hannan, M.; Faisal, M.; Ker, P.J.; Begum, R.; Dong, Z.; Zhang, C. Review of optimal methods and algorithms for sizing energy storage systems to achieve decarbonization in microgrid applications. *Renew. Sustain. Energy Rev.* **2020**, *131*, 110022. [CrossRef]
24. Jirdehi, M.A.; Tabar, V.S.; Ghassemzadeh, S.; Tohidi, S. Different aspects of microgrid management: A comprehensive review. *J. Energy Storage* **2020**, *30*, 101457. [CrossRef]
25. IEEE. *Guide for Design, Operation, and Integration of Distributed Resource Island Systems with Electric Power Systems*; IEEE Std. 15474–2011; IEEE: New York, NY, USA, 2011; pp. 1–54. [CrossRef]
26. IEEE. *Guide for Conducting Distribution Impact Studies for Distributed Resource Interconnection*; IEEE Std. 15477–2013; IEEE: New York, NY, USA, 2014; pp. 1–137. [CrossRef]
27. Basati, A.; Menhaj, M.B.; Fakharian, A. GA-based optimal droop control approach to improve voltage regulation and equal power sharing for islanded DC microgrids. In Proceedings of the PQ2016 the 10th International Conference: 2016 Electric Power Quality and Supply Reliability (PQ), Tallinn, Estonia, 29–31 August 2016. [CrossRef]
28. Angjelichinoski, M.; Scaglione, A.; Popovski, P.; Stefanovic, C. Decentralized DC Microgrid Monitoring and Optimization via Primary Control Perturbations. *IEEE Trans. Signal Process.* **2018**, *66*, 3280–3295. [CrossRef]
29. Zhao, J.; Dörfler, F. Distributed control and optimization in DC microgrids. *Automatica* **2015**, *61*, 18–26. [CrossRef]
30. Hamad, A.A.; El-Saadany, E.F. Multi-agent supervisory control for optimal economic dispatch in DC microgrids. *Sustain. Cities Soc.* **2016**, *27*, 129–136. [CrossRef]
31. Meng, L.; Dragicevic, T.; Vasquez, J.C.; Guerrero, J.M. Tertiary and Secondary Control Levels for Efficiency Optimization and System Damping in Droop Controlled DC–DC Converters. *IEEE Trans. Smart Grid* **2015**, *6*, 2615–2626. [CrossRef]
32. Nempu, P.B.; Jayalakshmi, N.; Shaji, K.; Singh, M. Fuzzy-PI Controllers for Voltage and Frequency Regulation of a PV-FC Based Autonomous Microgrid. In Proceedings of the 2019 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), Karnataka, India, 11–12 August 2019; Institute of Electrical and Electronics Engineers (IEEE): New York, NY, USA, 2019; pp. 1–6. [CrossRef]
33. Sahoo, S.; Mishra, S.; Jha, S.; Singh, B. A Cooperative Adaptive Droop Based Energy Management and Optimal Voltage Regulation Scheme for DC Microgrids. *IEEE Trans. Ind. Electron.* **2020**, *67*, 2894–2904. [CrossRef]
34. Dragicevic, T.; Guerrero, J.; Vasquez, J.C. A Distributed Control Strategy for Coordination of an Autonomous LVDC Microgrid Based on Power-Line Signaling. *IEEE Trans. Ind. Electron.* **2013**, *61*, 3313–3326. [CrossRef]
35. Hajebrahimi, H.; Kaviri, S.M.; Eren, S.; Bakhshai, A. A New Energy Management Control Method for Energy Storage Systems in Microgrids. *IEEE Trans. Power Electron.* **2020**, *35*, 11612–11624. [CrossRef]
36. Maulik, A.; Das, D. Stability Constrained Economic Operation of Islanded Droop-Controlled DC Microgrids. *IEEE Trans. Sustain. Energy* **2019**, *10*, 569–578. [CrossRef]
37. Maulik, A.; Das, D. Optimal operation of a droop-controlled DCMG with generation and load uncertainties. *IET Gener. Transm. Distrib.* **2018**, *12*, 2905–2917. [CrossRef]
38. Cingoz, F.; Elrayyah, A.; Sozer, Y. Optimized Settings of Droop Parameters Using Stochastic Load Modeling for Effective DC Microgrids Operation. *IEEE Trans. Ind. Appl.* **2017**, *53*, 1358–1371. [CrossRef]
39. Bukar, A.L.; Tan, C.W.; Lau, K.Y. Optimal sizing of an autonomous photovoltaic/wind/battery/diesel generator microgrid using grasshopper optimization algorithm. *Sol. Energy* **2019**, *188*, 685–696. [CrossRef]
40. Dong, L.; Zhang, T.; Pu, T.; Chen, N.; Sun, Y. A Decentralized Optimal Operation of AC/DC Hybrid Microgrids Equipped with Power Electronic Transformer. *IEEE Access* **2019**, *7*, 157946–157959. [CrossRef]

41. Dissanayake, A.M.; Ekneligoda, N.C. Multiobjective Optimization of Droop-Controlled Distributed Generators in DC Microgrids. *IEEE Trans. Ind. Inform.* **2020**, *16*, 2423–2435. [CrossRef]

42. Eajal, A.A.; Yazdavar, A.H.; El-Saadany, E.F.; Salama, M.M.A. Optimizing the Droop Characteristics of AC/DC Hybrid Microgrids for Precise Power Sharing. *IEEE Syst. J.* **2021**, *15*, 560–569. [CrossRef]

43. Lasseter, R.H.; Chen, Z.; Pattabiraman, D. Grid-Forming Inverters: A Critical Asset for the Power Grid. *IEEE J. Emerg. Sel. Top. Power Electron.* **2020**, *8*, 925–935. [CrossRef]

44. Zuo, Y.; Yuan, Z.; Sossan, F.; Zecchino, A.; Cherkaoui, R.; Paolone, M. Performance assessment of grid-forming and grid-following converter-interfaced battery energy storage systems on frequency regulation in low-inertia power grids. *Sustain. Energy Grids Netw.* **2021**, *27*, 100496. [CrossRef]

45. Unruh, P.; Nuschke, M.; Strauß, P.; Welck, F. Overview on Grid-Forming Inverter Control Methods. *Energies* **2020**, *13*, 2589. [CrossRef]

46. Sedighizadeh, M.; Esmaili, M.; Eisapour-Moarref, A. Voltage and frequency regulation in autonomous microgrids using Hybrid Big Bang-Big Crunch algorithm. *Appl. Soft Comput.* **2017**, *52*, 176–189. [CrossRef]

47. Eisapour-Moarref, A.; Sedighizadeh, M.; Esmaili, M. Multi-objective voltage and frequency regulation in autonomous microgrids using Pareto-based Big Bang-Big Crunch algorithm. *Control. Eng. Pract.* **2016**, *55*, 56–68. [CrossRef]

48. Jumani, T.A.; Mustafa, M.W.; Rasid, M.M.; Mirjat, N.H.; Leghari, Z.H.; Saeed, M.S. Optimal Voltage and Frequency Control of an Islanded Microgrid using Grasshopper Optimization Algorithm. *Energies* **2018**, *11*, 3191. [CrossRef]

49. Al-Saedi, W.; Lachowicz, S.W.; Habibi, D.; Bass, O. Voltage and frequency regulation based DG unit in an autonomous microgrid operation using Particle Swarm Optimization. *Int. J. Electr. Power Energy Syst.* **2013**, *53*, 742–751. [CrossRef]

50. Al-Saedi, W.; Lachowicz, S.W.; Habibi, D.; Bass, O. Power quality enhancement in autonomous microgrid operation using Particle Swarm Optimization. *Int. J. Electr. Power Energy Syst.* **2012**, *42*, 139–149. [CrossRef]

51. Qazi, S.H.; Mustafa, M.W.; Sultana, U.; Mirjat, N.H.; Soomro, S.A.; Rasheed, N. Regulation of Voltage and Frequency in Solid Oxide Fuel Cell-Based Autonomous Microgrids Using the Whales Optimisation Algorithm. *Energies* **2018**, *11*, 1318. [CrossRef]

52. Ahmadi, S.; Shokoohi, S.; Bevrani, H. A fuzzy logic-based droop control for simultaneous voltage and frequency regulation in an AC microgrid. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 148–155. [CrossRef]

53. Bevrani, H.; Shokoohi, S. An Intelligent Droop Control for Simultaneous Voltage and Frequency Regulation in Islanded Microgrids. *IEEE Trans. Smart Grid* **2013**, *4*, 1505–1513. [CrossRef]

54. Alghamdi, B.; Canizares, C.A. Frequency Regulation in Isolated Microgrids Through Optimal Droop Gain and Voltage Control. *IEEE Trans. Smart Grid* **2021**, *12*, 988–998. [CrossRef]

55. Wies, R.W.; Chukkapalli, E.; Stoffels, M.M. Improved frequency regulation in mini-grids with high wind contribution using online genetic algorithm for PID tuning. In Proceedings of the 2014 IEEE PES General Meeting, Conference & Exposition, National Harbor, MD, USA, 27–31 July 2014; pp. 1–5. [CrossRef]

56. Arani, A.A.K.; Gharehpetian, G.B.; Abedi, M. A Novel Control Method Based on Droop for Cooperation of Flywheel and Battery Energy Storage Systems in Islanded Microgrids. *IEEE Syst. J.* **2019**, *14*, 1080–1087. [CrossRef]

57. Khorramdel, B.; Raoofat, M. Optimal stochastic reactive power scheduling in a microgrid considering voltage droop scheme of DGs and uncertainty of wind farms. *Energy* **2012**, *45*, 994–1006. [CrossRef]

58. Vinayagam, A.; Abu Alqumsan, A.; Swarna, K.; Khoo, S.Y.; Stojcevski, A. Intelligent control strategy in the islanded network of a solar PV microgrid. *Electr. Power Syst. Res.* **2018**, *155*, 93–103. [CrossRef]

59. Bai, W.; Abedi, M.R.; Lee, K.Y. Distributed generation system control strategies with PV and fuel cell in microgrid operation. *Control. Eng. Pract.* **2016**, *53*, 184–193. [CrossRef]

60. Hassan, M.; Abido, M. Optimal Design of Microgrids in Autonomous and Grid-Connected Modes Using Particle Swarm Optimization. *IEEE Trans. Power Electron.* **2011**, *26*, 755–769. [CrossRef]

61. Hassan, M.; Abido, M. Real time implementation and optimal design of autonomous microgrids. *Electr. Power Syst. Res.* **2014**, *109*, 118–127. [CrossRef]

62. Yu, K.; Ai, Q.; Wang, S.; Ni, J.; Lv, T. Analysis and Optimization of Droop Controller for Microgrid System Based on Small-Signal Dynamic Model. *IEEE Trans. Smart Grid* **2015**, *7*, 1–11. [CrossRef]

63. Vemula, N.K.; Parida, S.K. Enhancement of small signal stability in inverter-dominated microgrid with optimal internal model controller. *Int. Trans. Electr. Energy Syst.* **2020**, *30*. [CrossRef]

64. Zhang, L.; Zheng, H.; Hu, Q.; Su, B.; Lyu, L. An Adaptive Droop Control Strategy for Islanded Microgrid Based on Improved Particle Swarm Optimization. *IEEE Access* **2020**, *8*, 3579–3593. [CrossRef]

65. Moussa, H.; Shahin, A.; Martin, J.-P.; Pierfederici, S.; Moubayed, N. Optimal Angle Droop for Power Sharing Enhancement with Stability Improvement in Islanded Microgrids. *IEEE Trans. Smart Grid* **2018**, *9*, 5014–5026. [CrossRef]

66. Wu, X.; Shen, C.; Iravani, R. Feasible Range and Optimal Value of the Virtual Impedance for Droop-Based Control of Microgrids. *IEEE Trans. Smart Grid* **2017**, *8*, 1242–1251. [CrossRef]

67. Zhu, Y.; Fan, Q.; Liu, B.; Wang, T. An Enhanced Virtual Impedance Optimization Method for Reactive Power Sharing in Microgrids. *IEEE Trans. Power Electron.* **2018**, *33*, 10390–10402. [CrossRef]

68. Keypour, R.; Adineh, B.; Khooban, M.H.; Blaabjerg, F. A New Population-Based Optimization Method for Online Minimization of Voltage Harmonics in Islanded Microgrids. *IEEE Trans. Circuits Syst. II Express Briefs* **2019**, *67*, 1084–1088. [CrossRef]

69. El-Sayed, W.T.; Azzouz, M.A.; Zeineldin, H.H.; El-Saadany, E.F. A Harmonic Time-Current-Voltage Directional Relay for Optimal Protection Coordination of Inverter-Based Islanded Microgrids. *IEEE Trans. Smart Grid* **2021**, *12*, 1904–1917. [CrossRef]

70. Ebrahim, M.A.; Fattah, R.M.A.; Saied, E.M.M.; Maksoud, S.M.A.; El Khashab, H. Real-Time Implementation of Self-Adaptive Salp Swarm Optimization-Based Microgrid Droop Control. *IEEE Access* **2020**, *8*, 185738–185751. [CrossRef]

71. Vigneysh, T.; Kumarappan, N. Autonomous operation and control of photovoltaic/solid oxide fuel cell/battery energy storage based microgrid using fuzzy logic controller. *Int. J. Hydrog. Energy* **2016**, *41*, 1877–1891. [CrossRef]

72. Elrayyah, A.; Sozer, Y.; Elbuluk, M. A novel load flow analysis for particle-swarm optimized microgrid power sharing. In Proceedings of the 2013 Twenty-Eighth Annual IEEE Applied Power Electronics Conference and Exposition (APEC), Long Beach, CA, USA, 17–21 March 2013; pp. 297–302. [CrossRef]

73. Mueller, J.A.; Kimball, J.W. An Efficient Method of Determining Operating Points of Droop-Controlled Microgrids. *IEEE Trans. Energy Convers.* **2017**, *32*, 1432–1446. [CrossRef]

74. Elrayyah, A.; Sozer, Y.; Elbuluk, M.E. A Novel Load-Flow Analysis for Stable and Optimized Microgrid Operation. *IEEE Trans. Power Deliv.* **2014**, *29*, 1709–1717. [CrossRef]

75. Li, Z.; Zang, C.; Zeng, P.; Yu, H.; Li, S. Agent-based distributed and economic automatic generation control for droop-controlled AC microgrids. *IET Gener. Transm. Distrib.* **2016**, *10*, 3622–3630. [CrossRef]

76. Liu, Y.; Li, Y.; Xin, H.; Gooi, H.B.; Pan, J. Distributed Optimal Tie-Line Power Flow Control for Multiple Interconnected AC Microgrids. *IEEE Trans. Power Syst.* **2019**, *34*, 1869–1880. [CrossRef]

77. Zhang, W.; Xu, Y. Distributed Optimal Control for Multiple Microgrids in a Distribution Network. *IEEE Trans. Smart Grid* **2019**, *10*, 3765–3779. [CrossRef]

78. Du, W.; Yao, L.; Wu, D.; Li, X.; Liu, G.; Yang, T. Accelerated Distributed Energy Management for Microgrids. In Proceedings of the 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, USA, 5–9 August 2018; pp. 1–5. [CrossRef]

79. Zhao, T.; Ding, Z. Distributed Agent Consensus-Based Optimal Resource Management for Microgrids. *IEEE Trans. Sustain. Energy* **2017**, *9*, 443–452. [CrossRef]

80. Zhao, T.; Ding, Z. Distributed Finite-Time Optimal Resource Management for Microgrids Based on Multi-Agent Framework. *IEEE Trans. Ind. Electron.* **2018**, *65*, 6571–6580. [CrossRef]

81. He, Y.; Wang, W.; Wu, X. Multi-Agent Based Fully Distributed Economic Dispatch in Microgrid Using Exact Diffusion Strategy. *IEEE Access* **2020**, *8*, 7020–7031. [CrossRef]

82. Dheer, D.K.; Doolla, S.; Bandyopadhyay, S.; Guerrero, J. Effect of placement of droop based generators in distribution network on small signal stability margin and network loss. *Int. J. Electr. Power Energy Syst.* **2017**, *88*, 108–118. [CrossRef]

83. Nandar, C.S.A. Robust PI control of smart controllable load for frequency stabilization of microgrid power system. *Renew. Energy* **2013**, *56*, 16–23. [CrossRef]

84. Maulik, A.; Das, D. Optimal Operation of Droop-Controlled Islanded Microgrids. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1337–1348. [CrossRef]

85. Jithendranath, J.; Das, D. Scenario-based multi-objective optimisation with loadability in islanded microgrids considering load and renewable generation uncertainties. *IET Renew. Power Gener.* **2019**, *13*, 785–800. [CrossRef]

86. Vergara, P.P.; Lopez, J.C.; Rider, M.J.; Da Silva, L.C.P. Optimal Operation of Unbalanced Three-Phase Islanded Droop-Based Microgrids. *IEEE Trans. Smart Grid* **2019**, *10*, 928–940. [CrossRef]

87. Singh, S.; Singh, M.; Kaushik, S.C. Optimal power scheduling of renewable energy systems in microgrids using distributed energy storage system. *IET Renew. Power Gener.* **2016**, *10*, 1328–1339. [CrossRef]

88. Vergara, P.P.; Rey, J.M.; Lopez, J.C.; Rider, M.J.; Da Silva, L.C.P.; Shaker, H.R.; Jorgensen, B.N. A Generalized Model for the Optimal Operation of Microgrids in Grid-Connected and Islanded Droop-Based Mode. *IEEE Trans. Smart Grid* **2019**, *10*, 5032–5045. [CrossRef]

89. Li, Y.; Yang, Z.; Zhao, D.; Lei, H.; Cui, B.; Li, S. Incorporating energy storage and user experience in isolated microgrid dispatch using a multi-objective model. *IET Renew. Power Gener.* **2019**, *13*, 973–981. [CrossRef]

90. Harasis, S.; Sozer, Y.; Elbuluk, M. Reliable Islanded Microgrid Operation Using Dynamic Optimal Power Management. *IEEE Trans. Ind. Appl.* **2021**, *57*, 1755–1766. [CrossRef]

91. Rezaei, N.; Kalantar, M. Hierarchical energy and frequency security pricing in a smart microgrid: An equilibrium-inspired epsilon constraint based multi-objective decision making approach. *Energy Convers. Manag.* **2015**, *98*, 533–543. [CrossRef]

92. Rezaei, N.; Kalantar, M. Smart microgrid hierarchical frequency control ancillary service provision based on virtual inertia concept: An integrated demand response and droop controlled distributed generation framework. *Energy Convers. Manag.* **2015**, *92*, 287–301. [CrossRef]

93. Zhou, Q.; Shahidehpour, M.; AlAbdulwahab, A.; Abusorrah, A.M. Privacy-Preserving Distributed Control Strategy for Optimal Economic Operation in Islanded Reconfigurable Microgrids. *IEEE Trans. Power Syst.* **2020**, *35*, 3847–3856. [CrossRef]

94. Abdelaziz, M.; Farag, H.E.; El-Saadany, E.F. Optimum Droop Parameter Settings of Islanded Microgrids with Renewable Energy Resources. *IEEE Trans. Sustain. Energy* **2014**, *5*, 434–445. [CrossRef]

95. Abdelaziz, M.M.; El-Saadany, E. Economic droop parameter selection for autonomous microgrids including wind turbines. *Renew. Energy* **2015**, *82*, 108–113. [CrossRef]

96. Chen, C.; Duan, S.; Cai, T.; Liu, B.; Hu, G. Optimal Allocation and Economic Analysis of Energy Storage System in Microgrids. *IEEE Trans. Power Electron.* **2011**, *26*, 2762–2773. [CrossRef]

97. Awad, A.S.A.; El-Fouly, T.; Salama, M.M.A. Optimal ESS Allocation and Load Shedding for Improving Distribution System Reliability. *IEEE Trans. Smart Grid* **2014**, *5*, 2339–2349. [CrossRef]

98. Sun, Q.; Huang, B.; Li, D.; Ma, D.; Zhang, Y. Optimal Placement of Energy Storage Devices in Microgrids via Structure Preserving Energy Function. *IEEE Trans. Ind. Inform.* **2016**, *12*, 1166–1179. [CrossRef]

99. Gazijahani, F.S.; Salehi, J. Stochastic multi-objective framework for optimal dynamic planning of interconnected microgrids. *IET Renew. Power Gener.* **2017**, *11*, 1749–1759. [CrossRef]

100. Uniyal, A.; Sarangi, S. Optimal allocation of ELC in microgrid using droop controlled load flow. *IET Gener. Transm. Distrib.* **2019**, *13*, 4566–4578. [CrossRef]

101. Uniyal, A.; Sarangi, S.; Kala, H. Optimal dump load allocation to regulate voltage and frequency in microgrid. In Proceedings of the 2019 8th International Conference on Power Systems (ICPS), Jaipur, India, 20–22 December 2019; pp. 1–6. [CrossRef]

102. Uniyal, A.; Sarangi, S.; Rawat, M.S. Optimal Dump Load Allocations in High RBDG Penetrated Microgrid for Voltage and Frequency Regulation. *Arab. J. Sci. Eng.* **2021**, *46*, 1511–1528. [CrossRef]

103. Maleki, A.; Khajeh, M.G.; Ameri, M. Optimal sizing of a grid independent hybrid renewable energy system incorporating resource uncertainty, and load uncertainty. *Int. J. Electr. Power Energy Syst.* **2016**, *83*, 514–524. [CrossRef]

104. Moradi, M.H.; Abedini, M.; Hosseinian, S.M. Optimal operation of autonomous microgrid using HS–GA. *Int. J. Electr. Power Energy Syst.* **2016**, *77*, 210–220. [CrossRef]

105. Goodarzi, H.M.; Kazemi, M.H. A Novel Optimal Control Method for Islanded Microgrids Based on Droop Control Using the ICA-GA Algorithm. *Energies* **2017**, *10*, 485. [CrossRef]

106. Foroutan, V.B.; Moradi, M.H.; Abedini, M. Optimal operation of autonomous microgrid including wind turbines. *Renew. Energy* **2016**, *99*, 315–324. [CrossRef]

107. Dheer, D.K.; Soni, N.; Doolla, S. Improvement of small signal stability margin and transient response in inverter-dominated microgrids. *Sustain. Energy Grids Netw.* **2016**, *5*, 135–147. [CrossRef]

108. Uniyal, A.; Sarangi, S.; Kala, H. Droop based DG allocation in weakly meshed autonomous microgrid. In Proceedings of the 2019 8th International Conference on Power Systems (ICPS), Jaipur, India, 20–22 December 2019; pp. 1–6. [CrossRef]

109. Gupta, Y.; Doolla, S.; Chatterjee, K.; Pal, B.C. Optimal DG Allocation and Volt–Var Dispatch for a Droop-Based Microgrid. *IEEE Trans. Smart Grid* **2021**, *12*, 169–181. [CrossRef]

110. Gupta, Y.; Nellikkath, R.; Chatterjee, K.; Doolla, S. Volt–Var Optimization and Reconfiguration: Reducing Power Demand and Losses in a Droop-Based Microgrid. *IEEE Trans. Ind. Appl.* **2021**, *57*, 2769–2781. [CrossRef]

111. Dzamarija, M.; Keane, A. Autonomous Curtailment Control in Distributed Generation Planning. *IEEE Trans. Smart Grid* **2015**, *7*, 1337–1345. [CrossRef]

112. Guo, L.; Wang, N.; Lu, H.; Li, X.; Wang, C. Multi-objective optimal planning of the stand-alone microgrid system based on different benefit subjects. *Energy* **2016**, *116*, 353–363. [CrossRef]

113. Goodarzi, H.M.; Kazemi, M.H. An optimal autonomous microgrid cluster based on distributed generation droop parameter optimization and renewable energy sources using an improved grey wolf optimizer. *Eng. Optim.* **2017**, *50*, 819–839. [CrossRef]

114. Abdelaziz, M.; Farag, H.E.; El-Saadany, E.F. Optimum Reconfiguration of Droop-Controlled Islanded Microgrids. *IEEE Trans. Power Syst.* **2015**, *31*, 2144–2153. [CrossRef]

115. Hemmatpour, M.H.; Mohammadian, M.; Gharaveisi, A.A. Optimum islanded microgrid reconfiguration based on maximization of system loadability and minimization of power losses. *Int. J. Electr. Power Energy Syst.* **2016**, *78*, 343–355. [CrossRef]

116. Zhan, X.; Xiang, T.; Chen, H.; Zhou, B.; Yang, Z. Vulnerability assessment and reconfiguration of microgrid through search vector artificial physics optimization algorithm. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 679–688. [CrossRef]

117. Gholami, A.; Sun, X.A. Towards Resilient Operation of Multimicrogrids: An MISOCP-Based Frequency-Constrained Approach. *IEEE Trans. Control. Netw. Syst.* **2018**, *6*, 925–936. [CrossRef]

118. Niknam, T.; Kavousifard, A.; Aghaei, J. Scenario-based multiobjective distribution feeder reconfiguration considering wind power using adaptive modified particle swarm optimisation. *IET Renew. Power Gener.* **2012**, *6*, 236–247. [CrossRef]

119. Mohamed, M.Z.; Saxena, S.; Farag, H.E. Optimal Design of Islanded Microgrids Considering Distributed Dynamic State Estimation. *IEEE Trans. Ind. Inform.* **2020**, *17*, 1. [CrossRef]

120. Dheer, D.K.; Kulkarni, O.V.; Doolla, S.; Rathore, A.K. Effect of Reconfiguration and Meshed Networks on the Small-Signal Stability Margin of Droop-Based Islanded Microgrids. *IEEE Trans. Ind. Appl.* **2018**, *54*, 2821–2833. [CrossRef]

121. Mukhopadhyay, B.; Das, D. Optimal multi-objective expansion planning of a droop-regulated islanded microgrid. *Energy* **2021**, *218*, 119415. [CrossRef]

122. Divshali, P.H.; Hosseinian, S.H.; Abedi, M. A novel multi-stage fuel cost minimization in a VSC-based microgrid considering stability, frequency, and voltage constraints. *IEEE Trans. Power Syst.* **2012**, *28*, 931–939. [CrossRef]

123. Elrayyah, A.; Cingoz, F.; Sozer, Y. Construction of Nonlinear Droop Relations to Optimize Islanded Microgrid Operation. *IEEE Trans. Ind. Appl.* **2015**, *51*, 3404–3413. [CrossRef]

124. Barklund, E.; Pogaku, N.; Prodanovic, M.; Hernandez-Aramburo, C.; Green, T. Energy Management in Autonomous Microgrid Using Stability-Constrained Droop Control of Inverters. *IEEE Trans. Power Electron.* **2008**, *23*, 2346–2352. [CrossRef]

125. Marzband, M.; Azarinejadian, F.; Savaghebi, M.; Guerrero, J. An Optimal Energy Management System for Islanded Microgrids Based on Multiperiod Artificial Bee Colony Combined with Markov Chain. *IEEE Syst. J.* **2017**, *11*, 1712–1722. [CrossRef]

126. Rezaei, N.; Mazidi, M.; Gholami, M.; Mohiti, M. A new stochastic gain adaptive energy management system for smart microgrids considering frequency responsive loads. *Energy Rep.* **2020**, *6*, 914–932. [CrossRef]
127. Khaledian, A.; Ahmadian, A.; Golkar, M.A. Optimal droop gains assignment for real-time energy management in an islanding microgrid: A two-layer techno-economic approach. *IET Gener. Transm. Distrib.* **2017**, *11*, 2292–2304. [CrossRef]
128. Marzband, M.; Yousefnejad, E.; Sumper, A.; Domínguez-García, J.L. Real time experimental implementation of optimum energy management system in standalone Microgrid by using multi-layer ant colony optimization. *Int. J. Electr. Power Energy Syst.* **2016**, *75*, 265–274. [CrossRef]
129. Marzband, M.; Parhizi, N.; Savaghebi, M.; Guerrero, J. Distributed Smart Decision-Making for a Multimicrogrid System Based on a Hierarchical Interactive Architecture. *IEEE Trans. Energy Convers.* **2015**, *31*, 637–648. [CrossRef]
130. Chen, C.; Duan, S. Optimal allocation of distributed generation and energy storage system in microgrids. *IET Renew. Power Gener.* **2014**, *8*, 581–589. [CrossRef]
131. Vergara, P.P.; López, J.C.; Rider, M.J.; Shaker, H.R.; da Silva, L.C.; Jørgensen, B.N. A stochastic programming model for the optimal operation of unbalanced three-phase islanded microgrids. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105446. [CrossRef]
132. Gao, Y.; Ai, Q. A distributed coordinated economic droop control scheme for islanded AC microgrid considering communication system. *Electr. Power Syst. Res.* **2018**, *160*, 109–118. [CrossRef]
133. Olivares, D.E.; Canizares, C.A.; Kazerani, M. A Centralized Energy Management System for Isolated Microgrids. *IEEE Trans. Smart Grid* **2014**, *5*, 1864–1875. [CrossRef]
134. Xu, Y.; Li, Z. Distributed Optimal Resource Management Based on the Consensus Algorithm in a Microgrid. *IEEE Trans. Ind. Electron.* **2014**, *62*, 2584–2592. [CrossRef]
135. de Azevedo, R.; Cintuglu, M.H.; Ma, T.; Mohammed, O.A. Multiagent-Based Optimal Microgrid Control Using Fully Distributed Diffusion Strategy. *IEEE Trans. Smart Grid* **2017**, *8*, 1997–2008. [CrossRef]
136. Liu, D.; Zhang, C.; Dong, Z. Stochastic Optimal Power Flow for Islanded Microgrids Considering Droop Control. In Proceedings of the 2019 IEEE Innovative Smart Grid Technologies—Asia (ISGT Asia), Chengdu, China, 21–24 May 2019; pp. 3156–3161. [CrossRef]
137. Liu, Z.; Yang, J.; Zhang, Y.; Ji, T.; Zhou, J.; Cai, Z. Multi-Objective Coordinated Planning of Active-Reactive Power Resources for Decentralized Droop-Controlled Islanded Microgrids Based on Probabilistic Load Flow. *IEEE Access* **2018**, *6*, 40267–40280. [CrossRef]
138. Chen, G.; Li, Z.; Zhao, Z. Event-Triggered Optimal Active Power Control in Islanded Microgrid with Variable Demand and Time-Varying Communication Topology. *IEEE Trans. Smart Grid* **2019**, *10*, 4015–4025. [CrossRef]
139. Cingoz, F.; Elrayyah, A.; Sozer, Y. Plug-and-Play Nonlinear Droop Construction Scheme to Optimize Islanded Microgrid Operations. *IEEE Trans. Power Electron.* **2017**, *32*, 2743–2756. [CrossRef]
140. Ahn, S.-J.; Nam, S.-R.; Choi, J.-H.; Moon, S.-I. Power Scheduling of Distributed Generators for Economic and Stable Operation of a Microgrid. *IEEE Trans. Smart Grid* **2013**, *4*, 398–405. [CrossRef]
141. Chen, F.; Chen, M.; Li, Q.; Meng, K.; Zheng, Y.; Guerrero, J.; Abbott, D. Cost-Based Droop Schemes for Economic Dispatch in Islanded Microgrids. *IEEE Trans. Smart Grid* **2016**, *8*, 63–74. [CrossRef]
142. Manna, D.; Goswami, S.K.; Chattopadhyay, P.K. Jadavpur University Droop control for micro-grid operations including generation cost and demand side management. *CSEE J. Power Energy Syst.* **2017**, *3*, 232–242. [CrossRef]
143. Wang, Z.; Wu, W.; Zhang, B. A Fully Distributed Power Dispatch Method for Fast Frequency Recovery and Minimal Generation Cost in Autonomous Microgrids. *IEEE Trans. Smart Grid* **2016**, *7*, 19–31. [CrossRef]
144. Marzband, M.; Sumper, A.; Domínguez-García, J.L.; Gumara-Ferret, R. Experimental validation of a real time energy management system for microgrids in islanded mode using a local day-ahead electricity market and MINLP. *Energy Convers. Manag.* **2013**, *76*, 314–322. [CrossRef]
145. Niknam, T.; Azizipanah-Abarghooee, R.; Narimani, M.R. An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation. *Appl. Energy* **2012**, *99*, 455–470. [CrossRef]
146. Conti, S.; Nicolosi, R.; Rizzo, S.A.; Zeineldin, H.H. Optimal Dispatching of Distributed Generators and Storage Systems for MV Islanded Microgrids. *IEEE Trans. Power Deliv.* **2012**, *27*, 1243–1251. [CrossRef]
147. Basu, A.K.; Bhattacharya, A.; Chowdhury, S. Planned Scheduling for Economic Power Sharing in a CHP-Based Micro-Grid. *IEEE Trans. Power Syst.* **2011**, *27*, 30–38. [CrossRef]
148. Jithendranath, J.; Das, D.; Guerrero, J.M. Probabilistic optimal power flow in islanded microgrids with load, wind and solar uncertainties including intermittent generation spatial correlation. *Energy* **2021**, *222*, 119847. [CrossRef]
149. Deckmyn, C.; VanDoorn, T.L.; Van De Vyver, J.; Desmet, J.; Vandevelde, L. A Microgrid Multilayer Control Concept for Optimal Power Scheduling and Voltage Control. *IEEE Trans. Smart Grid* **2017**, *9*, 4458–4467. [CrossRef]
150. Jiang, Q.; Xue, M.; Geng, G. Energy Management of Microgrid in Grid-Connected and Stand-Alone Modes. *IEEE Trans. Power Syst.* **2013**, *28*, 3380–3389. [CrossRef]
151. Youssef, K.H. Power Quality Constrained Optimal Management of Unbalanced Smart Microgrids During Scheduled Multiple Transitions Between Grid-Connected and Islanded Modes. *IEEE Trans. Smart Grid* **2016**, *8*, 457–464. [CrossRef]
152. Khodaei, A. Microgrid Optimal Scheduling with Multi-Period Islanding Constraints. *IEEE Trans. Power Syst.* **2013**, *29*, 1383–1392. [CrossRef]

153. Abedini, M.; Abedini, M. Optimizing energy management and control of distributed generation resources in islanded microgrids. *Util. Policy* **2017**, *48*, 32–40. [CrossRef]
154. Agundis-Tinajero, G.; Aldana, N.L.D.; Luna, A.C.; Segundo-Ramirez, J.; Visairo-Cruz, N.; Guerrero, J.M.; Vazquez, J.C. Extended-Optimal-Power-Flow-Based Hierarchical Control for Islanded AC Microgrids. *IEEE Trans. Power Electron.* **2018**, *34*, 840–848. [CrossRef]
155. Abdelaziz, M.M.A.; El-Saadany, E.F. Determination of worst case loading margin of droop-controlled islanded microgrids. In Proceedings of the 2013 3rd International Conference on Electric Power and Energy Conversion Systems, Istanbul, Turkey, 2–4 October 2013; pp. 1–6. [CrossRef]
156. Yang, X.; Du, Y.; Su, J.; Chang, L.; Shi, Y.; Lai, J. An Optimal Secondary Voltage Control Strategy for an Islanded Multibus Microgrid. *IEEE J. Emerg. Sel. Top. Power Electron.* **2016**, *4*, 1236–1246. [CrossRef]
157. ESanseverino, E.R.; Nguyen, N.Q.; Di Silvestre, M.L.; Zizzo, G.; De Bosio, F.; Tran, Q.T.T. Frequency constrained optimal power flow based on glow-worm swarm optimization in islanded microgrids. In Proceedings of the 2015 AEIT International Annual Conference (AEIT), Naples, Italy, 14–16 October 2015; pp. 1–6. [CrossRef]
158. Sanseverino, E.R.; Quang, N.N.; Di Silvestre, M.L.; Guerrero, J.; Li, C. Optimal power flow in three-phase islanded microgrids with inverter interfaced units. *Electr. Power Syst. Res.* **2015**, *123*, 48–56. [CrossRef]
159. Abdelaziz, M.; El-Saadany, E.F. Maximum loadability consideration in droop-controlled islanded microgrids optimal power flow. *Electr. Power Syst. Res.* **2014**, *106*, 168–179. [CrossRef]
160. Abdelaziz, M.; El-Saadany, E.F.; Seethapathy, R. Assessment of droop-controlled islanded microgrid maximum loadability. In Proceedings of the 2013 IEEE Power & Energy Society General Meeting, Vancouver, Canada, 21–25 July 2013; pp. 1–5. [CrossRef]
161. Díaz, G. Maximum loadability of droop regulated microgrids—Formulation and analysis. *IET Gener. Transm. Distrib.* **2013**, *7*, 175–182. [CrossRef]
162. Shariatzadeh, F.; Vellaithurai, C.B.; Biswas, S.S.; Zamora, R.; Srivastava, A.K. Real-Time Implementation of Intelligent Reconfiguration Algorithm for Microgrid. *IEEE Trans. Sustain. Energy* **2014**, *5*, 598–607. [CrossRef]
163. Li, J.; Liu, Y.; Wu, L. Optimal Operation for Community Based Multi-Party Microgrid in Grid-Connected and Islanded Modes. *IEEE Trans. Smart Grid* **2016**, *9*, 1. [CrossRef]
164. Khodaei, A. Resiliency-Oriented Microgrid Optimal Scheduling. *IEEE Trans. Smart Grid* **2014**, *5*, 1584–1591. [CrossRef]
165. Rezaei, N.; Kalantar, M. Stochastic frequency-security constrained energy and reserve management of an inverter interfaced islanded microgrid considering demand response programs. *Int. J. Electr. Power Energy Syst.* **2015**, *69*, 273–286. [CrossRef]
166. Rezaei, N.; Kalantar, M. Economic–environmental hierarchical frequency management of a droop-controlled islanded microgrid. *Energy Convers. Manag.* **2014**, *88*, 498–515. [CrossRef]
167. Mazidi, M.; Rezaei, N.; Ardakani, F.J.; Mohiti, M.; Guerrero, J. A hierarchical energy management system for islanded multi-microgrid clusters considering frequency security constraints. *Int. J. Electr. Power Energy Syst.* **2020**, *121*, 106134. [CrossRef]
168. Rezaei, N.; Ahmadi, A.; Khazali, A.H.; Guerrero, J.M. Energy and Frequency Hierarchical Management System Using Information Gap Decision Theory for Islanded Microgrids. *IEEE Trans. Ind. Electron.* **2018**, *65*, 7921–7932. [CrossRef]
169. Chung, I.-Y.; Liu, W.; Cartes, D.A.; Collins, E.G.; Moon, S.-I. Control Methods of Inverter-Interfaced Distributed Generators in a Microgrid System. *IEEE Trans. Ind. Appl.* **2010**, *46*, 1078–1088. [CrossRef]
170. Chung, I.-Y.; Liu, W.; Cartes, D.A.; Schoder, K. Control parameter optimization for a microgrid system using particle swarm optimization. In Proceedings of the 2008 IEEE International Conference on Sustainable Energy Technologies, Singapore, Singapore, 12–15 October 2008; pp. 837–842. [CrossRef]
171. Mohammadi, S.; Soleymani, S.; Mozafari, B. Scenario-based stochastic operation management of MicroGrid including Wind, Photovoltaic, Micro-Turbine, Fuel Cell and Energy Storage Devices. *Int. J. Electr. Power Energy Syst.* **2014**, *54*, 525–535. [CrossRef]
172. Brown, P.D.; Lopes, J.A.P.; Matos, M. Optimization of Pumped Storage Capacity in an Isolated Power System with Large Renewable Penetration. *IEEE Trans. Power Syst.* **2008**, *23*, 523–531. [CrossRef]
173. Nutkani, I.U.; Loh, P.C.; Wang, P.; Blaabjerg, F. Linear Decentralized Power Sharing Schemes for Economic Operation of AC Microgrids. *IEEE Trans. Ind. Electron.* **2016**, *63*, 225–234. [CrossRef]
174. Yan, B.; Wang, B.; Tang, F.; Liu, D.; Ma, Z.; Shao, Y. Development of Economic and Stable Power-Sharing Scheme in an Autonomous Microgrid with Volatile Wind Power Generation. *Electr. Power Components Syst.* **2014**, *42*, 1313–1323. [CrossRef]
175. El-Bidairi, K.S.; Nguyen, H.D.; Mahmoud, T.S.; Jayasinghe, S.; Guerrero, J.M. Optimal sizing of Battery Energy Storage Systems for dynamic frequency control in an islanded microgrid: A case study of Flinders Island, Australia. *Energy* **2020**, *195*, 117059. [CrossRef]
176. Kennedy, J.; Eberhart, R.C.; Shi, Y. *Swarm Intelligence*; Morgan Kaufmann: San Mateo, CA, USA, 2001.