IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 23, 2021, accepted January 2, 2022, date of publication January 13, 2022, date of current version February 11, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3142810

A Comprehensive Review of Control Strategies and Optimization Methods for Individual and Community Microgrids

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This work was supported by the Spanish Ministerio de Ciencia, Innovación y Universidades (MICINN)–Agencia Estatal de Investigación (AEI), and by the European Regional Development Funds (ERDF), a way of making Europe, under Grant PGC2018-098946-B-I00 funded by MCIN/AEI/10.13039/501100011033/.

ABSTRACT Community Microgrid offers effective energy harvesting from distributed energy resources and efficient energy consumption by employing an energy management system (EMS). Therefore, the collaborative microgrids are essentially required to apply an EMS, underlying an operative control strategy in order to provide an efficient system. An EMS is apt to optimize the operation of microgrids from several points of view. Optimal production planning, optimal demand-side management, fuel and emission constraints, the revenue of trading spinning and non-spinning reserve capacity can effectively be managed by EMS. Consequently, the importance of optimization is explicit in microgrid applications. In this paper, the most common control strategies in the microgrid community with potential pros and cons are analyzed. Moreover, a comprehensive review of single objective and multi-objective optimization methods is performed by considering the practical and technical constraints, uncertainty, and intermittency of renewable energies sources. The Pareto-optimal solution as the most popular multi-objective optimization approach is investigated for the advanced optimization algorithms. Eventually, feature selection and neural network-based clustering algorithms in order to analyze the Pareto-optimal set are introduced.

INDEX TERMS Control strategy, energy management, microgrid community, multi-objective optimization, optimization methods, Pareto solution.

NOMENCLATURE

ACO	Ant Colony Optimization.
AI	Artificial Intelligence.
ANN	Artificial Neural Network.
ARIMA	Auto-regressive Integrated Moving Average.
ARIMAX	Autoregressive Integrated Moving Average with Explanatory Variable.
BE	Bee Algorithm.
BF	Bacterial Foraging.
CARIMA	Cross Correlation ARIMA.
CMPC	Centralized Model Predictive Control.
COE	Cost of Electricity.
DE	Differential Evolution.
DER	Distributed Energy Resource.
DG	Diesel Generator.
DMPC	Decentralized Model Predictive Control.
DRM	Demand Response Management.
EMS	Energy Management System.
ESS	Energy Storage System.
FC	Fuel Cell.
FCM	Fuzzy C-means.
FEMS	Fuzzy logic based EMS.
GA	Genetic Algorithm.
GPC	Generalized Predictive Control.
IPM	Interior Point Method.
KM	K-means.
LP	Linear Programming.
LPSP	Loss of Power Supply Probability.

The associate editor coordinating the review of this manuscript and approving it for publication was Youngjin Kim.

MAS	Multi-agent System.
MCDA	Multi-Criteria Decision Analysis.
MCS	Monte-Carlo Simulation.
MF	Membership Function.
MG	Microgrid.
MGC	Microgrids Community.
MILP	Mixed Integer Linear Programming.
MINLP	Mixed Integer Non-linear Programming.
MLP	Multilayer perceptron.
MOEA/D	Multi-Objective Evolutionary Algorithm based on Decomposition.
MOPSO	Multi-Objective Particle Swarm Optimization.
MPC	Model Predictive Control.
NLP	Non-linear Programming.
NSGA	Non-dominated Sorting Genetic Algorithm.
O&M	Operation and Maintenance.
P2P	Peer-to-Peer.
PCC	Point of Common Coupling.
PE	Partial Equilibrium.
PEM	Point Estimation Method.
PESA	Pareto Envelope based Selection Algorithm.
PF	Power Factor.
PSO	Particle Swarm Optimization.
PV	Photovoltaic.
RBF	Radial Basis Function.
RE	Renewable Energy.
RES	Renewable Energy Sources.
SG	Synchronous Generators
SOC	State of Charge.
SOM	Self-organized Map.
SPEA	Strength Pareto Evolutionary Algorithm.
SVM	Support Vector Machine.
VEGA	Vector Evaluated GA.
VMG	Virtual MG.
WT	Wind Turbine.

I. INTRODUCTION

As a response to rapid energy consumption in recent years, microgrids (MGs) appear as an alternative solution in order to reduce the adverse effect of using fossil fuels in conventional power plants and their adverse consequences on the environment. The significant advances in the power electronics interfaces in MG applications led to integrating renewable energies (REs) such as PV, WT, and FC into MGs [1]–[3]. Therefore, MGs develop great changes in the paradigm of conventional power systems. The unilateral power flow between power plants and consumers has changed to the reciprocal power flow between the power system and MGs [4], [5].

Harvesting energy from renewable energy sources (RES) brings out multiple difficulties associated with the operation and reliability of MGs. Uncertainty and the intermittent nature of REs disrupt the conventional methods for planning the MGs operation. The investigation to suppress the difficulties has commenced from the first moments of MG's emergence. Utilizing an energy storage system (ESS) can effectively improve employing REs due to the controllability of energy storage units such as batteries and fuel cells (FC). The controllable energy generator units such as capacity storage and backup units like diesel generators (DGs) efficiently can maintain the balance between electricity supply and demand in MGs integrated with REs [6], [7].

MGs clustering is an advanced concept to take advantage of the cooperative operation of adjacent MGs. The possibility of mutual power-sharing among a community microgrid provides a number of interests for MGs. Increasing the penetration ratio of REs into the MGs and distribution network, achieving MGs' reliable and efficient operation, and providing backup power to prioritized critical loads are some features that can offer by the microgrid community (MGC) concept [8]–[10]. Moreover, MGC can provide certain profits from the distribution network and utility grid perspective. Providing convenient replication and scaling across any distribution network and surrounding the distribution and substation area to provide reliable service for customers are the benefits can gain by MGC [11].

In order to achieve the expected goals, which are conceivable by MG and MGC concept, applying an energy management system (EMS) is inevitable [12]. EMS has to ensure the optimal and economical operation of MGs according to the defined MGs plan and schedule. The planning process must be addressed to economic feasibility regarding the geographical conditions, allocated area, and the existence of energy resources (PV, WT, DG, and ESS) [13], [14]. On the other hand, scheduling concentrates more on the available energy resources in order to minimize operational costs [15].

The EMS has to solve the optimization problem considering the short-term and long-term attributes in planning and scheduling program. From a short-term perspective avoiding mismatch in power demand and supply is the primary purpose. In grid-connected operation mode, the active and reactive power has to be controlled in order to balance the demand and supply, and voltage and frequency are determined by the main grid. However, in stand-alone operation mode, voltage and frequency also have to be controlled as well as active and reactive power to stabilize the system. Therefore, the control strategy in stand-alone operation is more intricate [16]. From a long-term perspective, economic issues play a more prominent role [17].

The optimization problem ascertains the optimal solutions for specific decision variables in EMS considering the practical and technical constraints, uncertainties, goals, and alternatives. Moreover, solving the optimization problem will be the more involved procedure by taking network communication delays into consideration [18], [19]. A wide variety of optimization methods could be exploited for EMS. However, using an appropriate method in order to fulfill the requirements is a challenging issue.

Various researches have been carried out associated with MG and MGC application in respect of the

MGC architecture [20], control strategies [21], computational optimization [22], and communication strategies [23]. A comprehensive review of MG and virtual power plant concepts was conducted in [24], and scheduling problems associated with the formulation and objective functions, solving methods, uncertainty, reliability, reactive power, and demand response are studied. Samir *et al.* in [25] conducted a review on hybrid renewable MG optimization techniques considering the probabilistic, deterministic, iterative, and artificial intelligence (AI) methods. A survey on significant benefits and challenges related to the MGC operation and control is presented in [8]. Carlos *et al.* reviewed the computational techniques applied to MG planning in [26]. Distributed communication network characteristics, classification of distributed control strategies, and communication reliability issues are discussed in [27]. A comprehensive study on the classification of optimized controller approaches concerning the RES integration into MGs and analyzing advanced and conventional optimization algorithms in MG applications is performed by M. A. Hannan *et al.* in [28].

According to the previous academic literature, with respect to the control strategies and EMS framework, the optimization technique and computational approaches play an important role in the efficient and reliable operation of MGs and MGC. Optimization problems cover a wide variety of methods and techniques in mathematics. In recent years, advanced algorithms have been applied to MGs optimization problems to gain the exquisite feathers of these algorithms. Evolutionary and co-evolutionary optimization methods are smart, reliable, accurate, and problem-independent approaches frequently apply in MG and MGC applications [29]. However, in most academic papers brief explanation of the applicable method is provided, and in some cases, essential information is skipped. This article focuses on the most practical and advanced algorithms applied in previous studies or are prone to exploit in future researches. The main contributions of the paper can be highlighted as:

- The comparison of the most practical control strategies in MGC and the inverter operation of the control schemes,
- Surveying the possible scheduling and planning problems in MGC,
- Studying applicable optimization methods in MG and MGC considering the planning problems.
- Overview of the advanced optimization algorithms in order to optimize the MG and MGC operation.

In this paper, the control strategies in MGC are reviewed, and the inverter control schemes are investigated in section II by considering the most well-known control strategies. Then, the planning and scheduling programs in the MGs application are discussed in order to define the proper optimization problem. Section IV introduces the classification of optimization methods and analyzes the most relevant algorithms in the MG application. Single-objective and multi-objective optimization algorithms are expressed. Section V is dedicated to investigating the artificial intelligence (AI) application on feather selection and clustering analysis. Eventually, section VI is expanded to conclude the paper.

II. CONTROL STRATEGIES

Stability and efficiency are two main requirements in the control strategies, which are basically related to the dynamic of the systems. In conventional power systems, the synchronous generators (SGs) are the most crucial part of the system from the aspect of system stability [30]. Rotor angle, voltage, and frequency stability in conventional power systems are three main stabilities to maintain the regular operation of the system facing potential disturbances [31]. Identically, the inverters in MGs are the most significant part of keeping the system stable in transients. Compared with conventional power systems with inherent large inertia of SGs, especially in high power scale, the fast response and low overcurrent capacity of inverters resulted in significant changes in operation, control, and protection of MGs [32], [33].

The control of individual MG is studied in multiple manuscripts. Among various proposed control approaches such as predictive control, intelligence control, the performance of sliding mode control, and $H\infty$ control proving more robust operation [34]. However, MGC control has received more attention recently due to increasing interest in the MGC concept. According to the researches, the MGC control strategy can be categorized as master-slave [35]–[37], peer-to-peer (P2P) [38]–[40], and hierarchical control [41]–[43].

In master-slave control, the master converter in voltage source mode is responsible for controlling the DC bus voltage, and slave converters in current source mode share the current according to the total load current [44]. Fig. 1 demonstrates the master-slave control strategy. The V/f controller in Fig. 1 is applied when the MG is in islanded operation mode, and the P/Q controller is for grid-connected mode. Droop control and V/f control are two voltage control strategies for master converter [45]. Different droop control methods with their potential advantages and disadvantages are discussed in [46]–[48]. The V/f control method, in comparison with droop control, suffers from a slow dynamic response [45]. The main disadvantage of master-slave control is the reliability dependency of the whole system to the master converter and consequently interruption of the whole system in case of master converter failure [35].

Unlike master-slave control, the P2P control strategy does not hire a hierarchy or central controller. The P2P control method is based on a computer network with a certain number of agents. Fig. 2 shows the control structure controlled by the P2P strategy. In [49], the unstructured centralized, unstructured decentralized, hybrid, and structured decentralized models of P2P architecture are discussed. Droop control is adopted in the voltage control scheme when the MGs are dominated by the P2P paradigm [45]. Several papers based on distributed control methods are performed to improve the performance and reliability of P2P control. In [50], a distributed gossip-based voltage control algorithm for P2P MGs is proposed to keep all control local and improve reliability

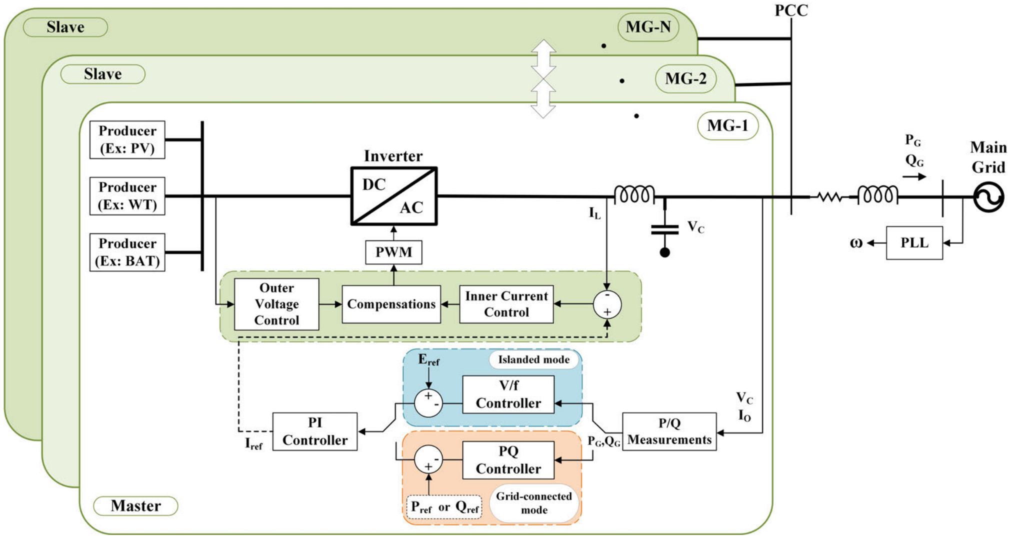

FIGURE 1. Master-slave control structure.

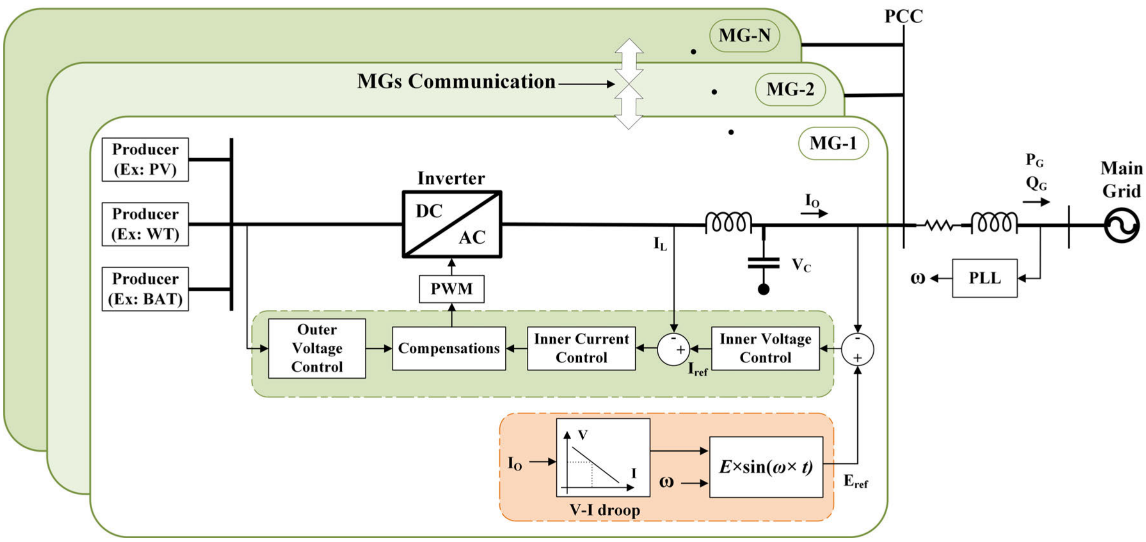

FIGURE 2. P2P control structure.

by eliminating any single point of failure. Moreover, a fully distributed P2P control scheme employing the broadcast gossip communication protocol is proposed for voltage regulation and reactive power sharing of multiple inverter-based DERs [51]. As it can be seen from Fig. 1, due to the existence of an integrator in the PI controller, the seamless transfer between grid-connected and islanding operation mode is under-effect. Therefore, the master-slave control is typically used in the islanded state, and the P2P control scheme is mainly used in the grid-connected operation mode. Multiple studies in order to improve the performance of master-slave control are done. In [44], by considering the advantages of P2P control, an improved control strategy based on I-ΔV droop is applied to master-slave control to control the smooth transition between two operation modes of MG. An improved V/f control strategy consists of feed-forward compensation, and robust feedback control is proposed in [45] to suppress the slow dynamic response of the V/f controller. In addition, a simple mixed droop-V/F control strategy for the master inverter is proposed in [52] to achieve seamless mode transfer in MG operation modes.

The hierarchical control strategy is the most adopted control structure due to providing seamless operation in transient between islanded and grid-connected modes. The hierarchical structure consists of primary, secondary, and tertiary control levels to manipulate the static and dynamic stability of MGs. Fig. 3 shows an overview of the incorporation of hierarchical control in a grid-connected individual MG.

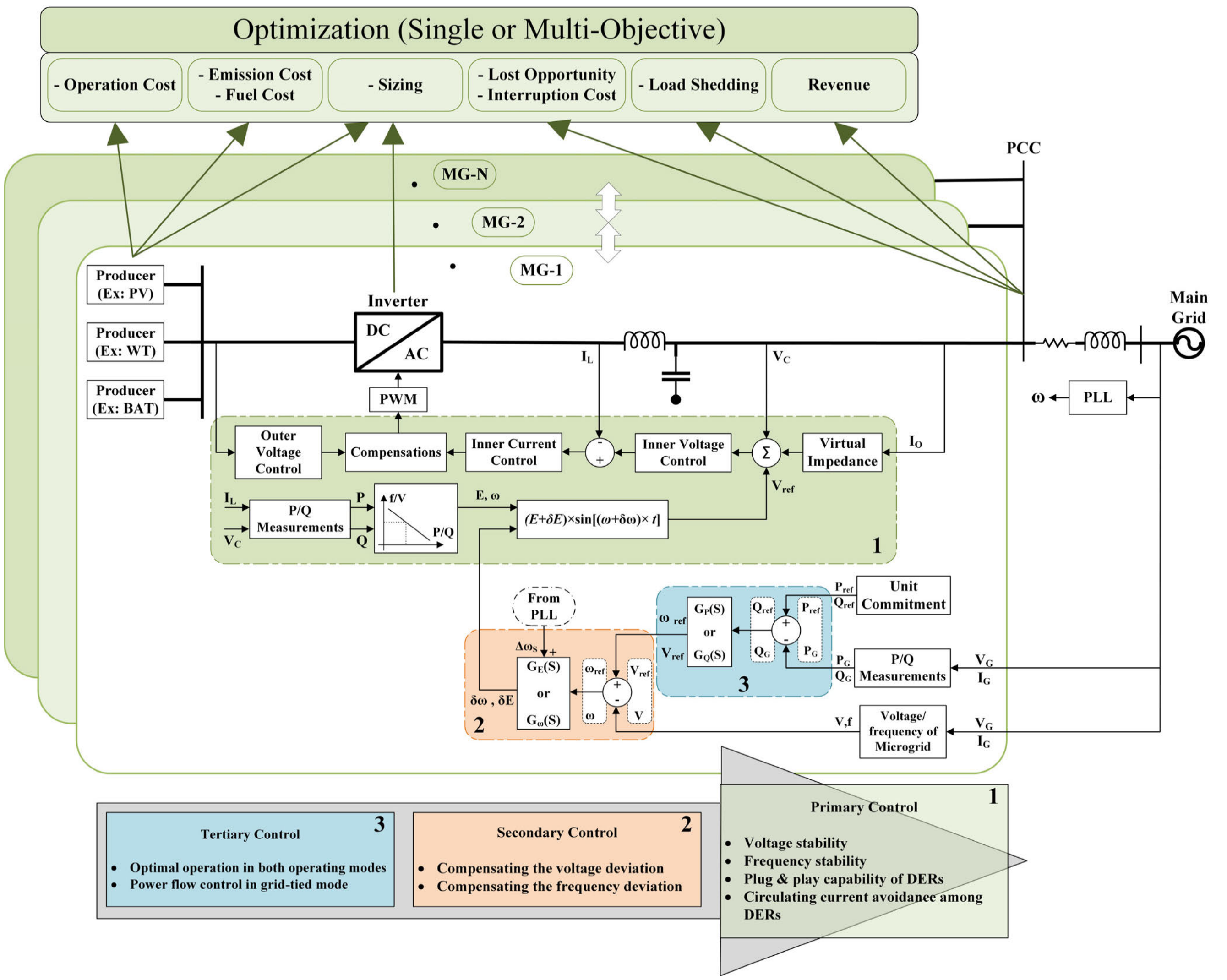

FIGURE 3. Hierarchical control structure.

The primary control is in charge of voltage and frequency stability by regulating the active and reactive power. The deviation of output voltage and frequency in primary control compensates in secondary control. Eventually, the optimum power flow between the MGs and the utility grid is under control at the tertiary control level [53], [54].

The secondary control level in hierarchical control could hire centralized, decentralized, hybrid, and distributed controller architecture based on the communication topologies [55]. In the centralized framework, the central controller has to handle large amounts of data from other MGs to analyze the optimum operation of the whole system [56]. Time-consuming data analysis, complex communication network, and low reliability of system operation by a single-point failure in communication are some important drawbacks that make the centralized approach appropriate only for small-scale MGC. On the other hand, the decentralized approach is proposed to optimize the individual MG operation with no dependency on other adjacent MGs [57]. Although in this approach, the optimization calculations reduce significantly, independent optimization of units cannot guarantee the optimum status of the whole system. In order to take advantage of the centralized and decentralized approaches, the hybrid method is introduced. Nevertheless, the drawbacks mentioned for the centralized framework is still persisted in the hybrid approach [58]. In recent years, the distributed control has drawn attention as a control scheme in MGC to tackle problems related to centralized and decentralized frameworks. In the distributed scheme, the computing burden is reduced significantly by sharing key information among MGs [59], making this control scheme appropriate for large-scale MGC.

Model predictive control (MPC) can effectively apply to the hierarchical architecture to handle the stochastic nature of REs and variable power demand based on the prediction [60]–[64]. In [60], [61], an overview of MPC in

TABLE 1. Control strategies in MGC application.

No.	Ref	Control Strategy	Explanations
1	[35]	Master-slave	Utility interface (UI) as control master for the energy gateways: 1) in grid-connected, UI performs as a grid-supporting to dispatch active and reactive power references; 2) in islanded operation: UI performs as a grid-forming voltage source to ensure power balance.
2	[36]	Master-slave	Master-slave framework containing a two-layer voltage estimator to simultaneous achievement of accurate current sharing and current economical allocation, short time consumption and faster convergence, and robustness against uncertain communication environments.
3	[37]	Master-slave	Distributed iterative event-triggered control scheme to: 1) synchronize the voltage of multiple DERs to their desired value; 2) optimal load sharing for their economic operation.
4	[44]	Improved Master-slave	Combined with the advantages of peer-to-peer control, an improved master-slave control strategy based on I-ΔV droop to control the smooth transition between grid-connected and island mode.
5	[45]	Master-slave	Improved V/f control strategy composed of two parts, feed-forward compensation and robust feedback control to enhance voltage output characteristics, dynamic characteristics and robustness in response to micro-source output power fluctuations, loads abrupt change or non-linear loads and unbalanced loads.
6	[52]	Master-slave	Simple mixed droop-v/f control strategy for the master inverter of a MG to achieve seamless mode transfer between grid connected and autonomous islanding modes by means of: 1) a modified droop control in grid connected mode; 2) v/f control in islanding mode.
7	[38]	P2P	Decentralized control system, using the ICT concept of network overlays and P2P networks to eliminate single points of failure.
8	[39]	P2P + game theory	A hierarchical system architecture model to identify and categorize the key elements and technologies involved in P2P energy trading using game theory to improve the local balance of energy generation and consumption.
9	[40]	P2P + game theory	A two settlement P2P energy market framework for joint scheduling and trading of prosumers in MGC to provide price certainty and increase localized transaction volume of DERs.
10	[49]	P2P	An overlay P2P architecture for controlling and monitoring MGs in real time with satisfactory network performance parameters proposed for MGs, such as latency and bandwidth, showing that P2P overlay networks are useful for energy grids in practice.

TABLE 1. *(Continued.)* Control strategies in MGC application.

11	[50]	P2P	A voltage control algorithm, based on P2P control and gossiping communication to operate in a distributed manner, with no central coordinator, thereby keeping all control local and eliminating any single point of failure.
12	[51]	P2P	Distributed P2P enabled through broadcast gossip communication control scheme for voltage regulation and reactive power sharing of multiple inverter-based DERs.
13	[41]	Hierarchical	A review of decentralized, distributed, and hierarchical control of grid-connected and islanded MGs.
14	[41]	Hierarchical	Enhanced hierarchical control structure with multiple current loop damping schemes consisting of the
15	[43]	Hierarchical	A review of hierarchical control strategies that provide effective and robust control for a DC MG.
16	[53]	Hierarchical	A versatile tool in managing stationary and dynamic performance of MGs while incorporating economic aspects.
17	[56]	Centralized	A mathematical model of the time-delay DC islanded MG to compensate the effect of the time-delay by three control strategies: stabilizing, robust, and robust-predictor.
18	[57]	Decentralized	Decentralized economic power sharing strategy To improve the reliability, scalability, and economy of MGs.
19	[58]	Multilevel Distributed Hybrid Control	Overcome the drawbacks of centralized and decentralized control schemes. Ability of seamlessly switching between high bandwidth communication and low bandwidth communication channels of communications.
20	[59]	Distributed control	A review of distributed control and management strategies for the next generation power system.
21	[60]	Hierarchical + MPC	Comprehensive review of MPC in individual and interconnected MGs, including both converter-level and grid-level control strategies applied to three layers of the hierarchical control architecture.
22	[61]	MPC	A study on applying a MPC approach to the problem of efficiently optimizing MG operations while satisfying a time-varying request and operation constraints by using MILP.
23	[62]	MPC	To deal with uncertainties of renewable energy, demand and price signals in real-time MG operation,
24	[63]	MPC	An MPC for load frequency control of an interconnected power system based on a simplified system model of the Nordic power system taking into account limitations on tie-line power flow, generation capacity, and generation rate of change.
25	[64]	CMPC	A coordinated control of PHEVs, PVs, and ESSs for frequency control in MG using a CMPC considering the variation of PHEV numbers to: 1) suppress the system frequency fluctuation; 2) minimize the surplus power of PV.

TABLE 1. ***(Continued.)*** **Control strategies in MGC application.**

26	[65]	DMPC	A cooperative energy management scheme based on DMPC for grid-connected MGC to minimize the operation costs and maintain power balance.
27	[66]	MAS	Sign-consensus problems of general linear multi-agent systems by a signed directed graph.
28	[68]	MAS + game theory	A structure of a MG based on MAS with a game-theory based optimization model for the capacity configuration of these agents, and economic interests between agents and their actions by the game model and the interactions between MG and power grid, and the uncertainty of wind power and solar power are taken into account.
29	[70]	Cooperative Game Theory	A review of cooperative game theory with theoretical background for the analysis of projects where participants can make collective actions to obtain mutual benefits.

individual MGs and MGC corresponding to three levels of hierarchical strategy for converter-level and grid-level control is presented. MPC ordinarily is based on the system's future behavior and can make the system more robust against uncertainties by the feedback mechanism. Centralized MPC (CMPC) requires complete information and an accurate centralized method. On the other hand, distributed MPC (DMPC) is proposed in order to reduce the data evaluation by sharing essential global information. In [65], a DMPC is applied to MGC to optimally coordinate the energy among MGs and DERs. The main contribution of this article is introducing a virtual two-level MGC, which DERs consider a virtual MG (VMG) with the possibility of power exchange with the main grid, and other MGs are virtually located in the lower level communicate with VMG. In this case, the MGs cannot directly exchange power with the utility grid; therefore, the decision variables are reduced, and computing speed increases.

The multi-agent system (MAS) is another control scheme that effectively can adopt the hierarchical structure in order to enhance the voltage and frequency reliability, intelligence, scalability, redundancy, and economy in MGC. The main idea of MAS-based distributed control is dividing the complex and large-scale system into several subsystems with the possibility of mutual interaction. In [32], a comprehensive overview of MAS-based distributed coordination control and optimization in MG and MGC is surveyed. In addition, the control strategies in MAS, topology model, and mathematical model are discussed, and the pros and cons of these methods are compared.

The optimal configuration and control strategy in the MAS control approach requires a proper model. In recent publications, the graph model as a topology model and the non-cooperative game model, GA, and PSO algorithm as mathematical models are overviewed in [32]. The graph model is widely adopted in MAS due to its simple model structure and high redundancy. However, the system robustness is significantly affected by the graph [66]. Non cooperative and cooperative game theory approaches can also exploit in MGC optimization. Nash equilibrium in non-cooperative game theory is used as a stable strategy solution [67]. In [68], the game model analyzes the interactions between the agents and their actions to enhance the economic interest between MG and the utility grid by considering the uncertainty of RE power generations. The comparison of the non-cooperative and cooperative game model results in decreasing the total configuration capacities by 10% in a cooperative game. Despite non-cooperative games, players or agents in cooperative games are able to coordinate with each other to increase their profit from the game by constructing alliances among themselves [69]. In [70], cooperative game theory applications such as cost and benefit allocation, transmission pricing, projects ranking, and allocation of power losses in power systems are overviewed.

In Table 1, an overview of the different control strategies in MGC applications is listed.

III. MICROGRID PLANNING

Planning and scheduling problems arise for economic purposes. Therefore, MG planning is no exception to this principle. The main goal in MG planning is to minimize the system's operation cost considering the practical and technical constraints. Practical constraints refer to some obligatory limitations with no alternatives. For example, the location and area of the construction site may not be debatable. In addition, the maximum solar irradiance and wind speed restrict the maximum harvesting energy from PV and WT. On the contrary, technical constraints are related to the incentive or punitive policies regarding the environmental impact, power quality, and reliability. Consequently, MG planning and scheduling can infer as an optimization problem subject to the corresponding constraints. In [26], the MG planning problem is examined firstly for possible configuration of different power generation types to meet the objectives such as cost-effectiveness, environmental concerns, and reliability. Secondly, the siting problem is discussed as a strategic level problem for the actual and potential customers. Eventually, scheduling as a tactical level problem is considered to minimize the operational costs according to the available energy sources. In [24], scheduling problem from various points of view is discussed. Fig. 4 depicts the correlation of explained scheduling problem in [24] and the MG planning problem defined in [26].

The optimization problem is referred to as the minimization and maximization problem. In an optimization problem, costs tend to be minimized, and profits tend to be maximized. Fig. 5 represents a general categorization of optimization in MGs and MGC. As it can be seen from Fig. 5, most of the literature researches are related to the minimization problem by introducing a cost function. In [71], [72], the cost function is defined in order to minimize fuel cost. The operation cost

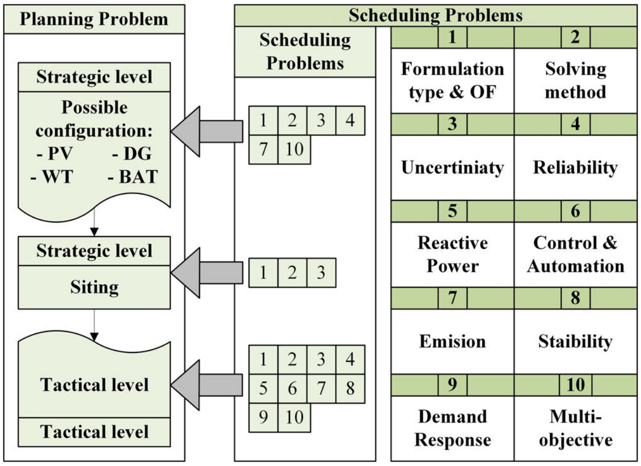

FIGURE 4. Planning and scheduling program in MGs.

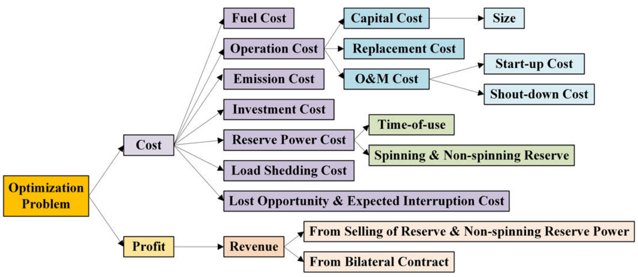

FIGURE 5. Cost and profit functions in MGs.

is the primary concern of MGs in order to reduce the capital cost [73]–[75], replacement cost [76], [77], and operation and maintenance (O&M) cost [78], [79].

Moreover, capital cost as a strategic planning program in association with the size and the efficient combination of the generation units is one of the important optimization problems related to the component size [80]. Reserve power is another important topic, especially in islanded MGs, to optimize the time-of-use of stored energy in ESS [81]. In [82], [83], the spinning and non-spinning reserves are the main objective function to be minimized. In [84], an algorithm is proposed to minimize the unmet load and consequently reduce the load shedding. Eventually, the cost of expected interruption and lost opportunity is considered a cost function in [85] to increase the system's reliability. On the other hand, the maximization problems are mostly related to maximizing the revenue from selling the spinning or non-spinning reserve power [86] or from a bilateral power exchange between MGs and the main grid [87]. Due to cost and profit functions similarity among articles, the most dominant objectives are mentioned in this section. A comprehensive study on cost and profit functions is surveyed in [88].

In addition, in recent years, several commercial software have been emerged in order to evaluate the MG's planning. HOMER, RETScreen, H2RES, DER-CAM, MDT, and MARKAL/TIMES are the most well-kwon software used in MG application. The scheduling program related to the RE accessibility, uncertainty, and technical limitation are considered and the optimal planning will be evaluated [27]. In Table 2, the capabilities and characteristics of the most well-known software in this field are compared.

IV. OPTIMIZATION TECHNIQUES FOR MICROGRIDS

According to the planning and scheduling problem, MG and MGC optimize operation is subjected to specify an objective function optimization problem. Optimization problems are widely used in computer science, economics, and engineering in order to find the minimum or maximum value among feasible solutions. Over the years, enormous optimization methods depending on the problem have been introduced. However, the most practical optimization methods regarding the MGs application are analyzed in this article. Linear programming (LP), non-linear programming (NLP), mixed-integer linear programming (MILP), mixed-integer non-linear programming (MINLP), quadratic programming, and linear least-square programming are the most popular optimization problem according to the features that can be extracted from MGs application. To obtain the optimal solution of these programming, various commercial modeling platforms such as GAMS [89], AMPL [90], and AIMMS [91] have been nominated in recent years. These modeling platforms are armed with deterministic solvers such as IPOPT, CPLEX, SCIP, BARON, CONOPT, etc. [92]. MATLAB and Python environments also provide modeling platforms for some specific optimization problems, but this software provides the possibility of implementing optimization algorithms by programming.

Principally, optimization problems can be classified as unconstraint single-objective, constraint single-objective, unconstraint multi-objective, constraint multi-objective optimization. Fig. 6 shows these classifications. The planning and scheduling program inherently imposes constraints to the problem; hence the unconstraint single-objective optimization is not a practical problem in MGs optimization.

Accordingly, except for the unconstraint single-objective optimization, the other optimization methods can be converted to each other, i.e., there is the possibility of reducing the constraints space and add to the objective space and vice versa. The usual constraint optimization approaches in MGs application are investigated in this article. Fig. 7 shows the general classification of constraints problem approaches. As shown in Fig. 7, the constraint problems considering the scheduling programming in MG applications can be discussed in two distinct procedures: the probabilistic or stochastic problems or the deterministic or robust problem [24], [25], [93].

A. PROBABILISTIC METHODS

The probabilistic procedure could be applicable in systems with uncertainties. Principally, the uncertainties in power systems and MGs can be considered uncertainties regarding future conditions and uncertainties in computational

TABLE 2. Commercial software for MG's planning.

Software	Grid-connected & Isolation mode analysis	User define power management strategy	Time step analysis	Optimization method
HOMER	Yes	Yes	Minute – hour	Exhaustive search
RETScreen	Yes	-	Day-month-year	Search scope
H2RES	Yes	Yes (partially)	Minute – hour	LP
DER-CAM	Yes	Yes	Minute – hour	MILP
MDT	Yes	Yes (partially)	-	MILP & GA
MARKAL/TIMES	Yes	Yes (partially)	Year-multiple years	LP/MIP, PE

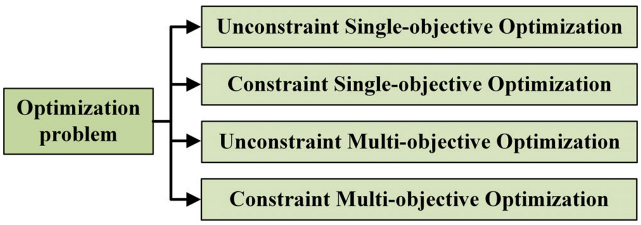

FIGURE 6. Optimization problem classification.

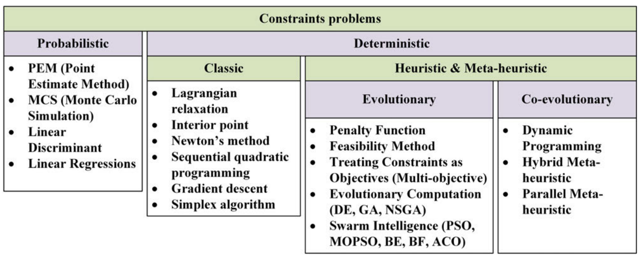

FIGURE 7. Constraint optimization classification.

modeling [94], [95]. Therefore, forecasting methods such as generalized predictive control (GPC) in model predictive control (MPC) like ARIMA, CARIMA, and ARIMAX can play an important role in diminishing the uncertainties related to wind speed, solar irradiance, load, and price forecasting. In addition, the more precise models of MG components, the more accurate estimation will be possible. Point estimated method (PEM) and Monte-Carlo simulation (MCS) are two statistical methods facing probabilistic problems, Fig 7. Nevertheless, linear discriminant and linear regressions are based on linearization and approximation methods. In [96], the PEM is applied for modeling the wind and solar power uncertainties, and a robust optimization technique is utilized to optimize an individual MG. Conventional MCS is an accurate method but time-consuming approach for uncertainty modeling. In [97], a new approach based on MCS with high precision and lower calculation time is proposed to optimize the investment and reliability of an islanded MG. The linearization and approximation methods are primarily used to discriminate or categorize the objectives to investigate linear combinations of variables that best explain the data [98], [99].

B. DETERMINISTIC METHODS

Deterministic methods are divided into classical methods and heuristic methods, Fig. 7. The classical methods are able to find the optimum solutions by means of analytical methods. Although these methods can guarantee the optimal solution, for large-scale and complex problems largely are not able to find the feasible solution (problem-dependent). Regardless of the single variable or multivariable functions in classical methods, equality and inequality constraint problems can be handled effectively considering the objective functions. For equality constraints problem the Lagrange multiplier methods, and for inequality constraints, the Kuhn-Tucker conditions can be used to identify the optimum solution [100]. Furthermore, classical methods suffer from the initial point dependency, which makes divergence in case of inappropriate initial point selection.

On the other hand, the heuristic and meta-heuristic methods are faster methods, specifically in complicated large-scale problems. The performance of these methods is to explore the search space to find the optimum solution. Therefore, these methods cannot guarantee the exact optimum solution [101]. Unlike heuristic methods, the meta-heuristic approaches are not problem-dependent [102]. Meta-heuristics methods incorporate strategies and mechanisms to guide the search process and, most importantly, avoid getting trapped in confined areas of the search space. Considering the complexity of the problem, evolutionary or co-evolutionary approaches can be applied for optimization purposes.

The main idea to use evolutionary methods is achieving the best performance with minimum information about the problem. The evolutionary approaches can be distinguished into two classes, evolutionary algorithms and swarm intelligence. The main difference of these classes refers to the exploited algorithm in order to evolve a set point among the populations of search space [103]. The GA and DE are the most famous population-based meta-heuristic algorithm that the optimization procedure is based on an evolutionary process. The PSO, ACO, BE, and BF are the most famous swarm intelligence optimization methods based on a collaborative study of individuals' behavior and interactions with one another.

There are a multiplicity of classic methods that can be studied in various papers and book chapters. Therefore, in this paper, the heuristic and meta-heuristic methods only are investigated specifically for multi-objective optimization problems. The problems are defined in minimization format, but the same procedure can be applied in maximization problems.

TABLE 3. Violation and optimization problem.

Constraint	Violation	Optimization Problem	Formulation
$g_i(x) \geq g_0$	$\nu(x) = \max(1 - \frac{g_i(x)}{g_{0,i}}, 0)$	Additive	$\hat{f}(x) = f(x) + \lambda \sum \psi(\nu_i(x))$
$g_i(x) \leq g_0$	$\nu(x) = \max(\frac{g_i(x)}{g_{0,i}} - 1, 0)$	Multiplicative	$\hat{f}(x) = f(x)(1 + \lambda \sum \psi(\nu_i(x)))$
$g_i(x) = g_0$	$\nu(x) = \left\lvert \frac{g_i(x)}{g_{0,i}} - 1 \right\rvert$	Hybrid	$\hat{f}(x) = (f(x) + \lambda \sum \psi(\nu_i(x))) \times (1 + \gamma \sum \varphi(\upsilon_j(x)))$ $\hat{f}(x) = f(x)(1 + \lambda \sum \psi(\nu_i(x))) + \gamma \sum \varphi(\upsilon_j(x))$

C. EVOLUTIONARY APPROACHES

1) PENALTY FUNCTION

In the penalty function method, the constraints of the problem aggregate to the objective function by considering a penalty factor. In fact, a constraints optimization problem converts to the unconstraint multi-objective problem in the penalty function method. In following this procedure is expressed [107]:

$$\min\ f(x)\ x \in X \tag{1}$$

$$\text{Subject to: } g_i(x) \leq g_0 \quad i = 1, 2, \ldots, N \tag{2}$$

In this method, the constraints $g_i(x)$ replace by the violation function, and the unconstrained minimization problem is defined as:

$$\min\ \hat{f}(x) = f(x) - \sum_{i=1}^{N} \lambda_i\, \nu(x) \quad x \in X \tag{3}$$

where x is the state variable, and λ_i is the co-state. The λ_i variables can be extracted from an ancillary optimization procedure to enhance the performance of the optimization. However, a constant value for λ_i mostly results in a satisfactory achievement. The violation for inequality and equality constraints is defined in Table 1. In addition, the violation can be adopted to the primal problem f(x) in the form of additive, multiplicative, and hybrid (additive-multiplicative or vice versa) [108]. These dual problems $\hat{f}(x)$ are described in Table 3.

The barrier function method, also known as the interior point method (IPM), is one of the approaches in constrained optimization problems that can effectively apply to the penalty function method [109]. In barrier methods, a very high cost impose on feasible points that lie so close to the boundary of the feasible solution region. A barrier function can hire continuous functions. However, the two most common barrier functions are logarithmic barrier function and inverse barrier function, which are described below:

$$\psi(x) = -\sum_{i=1}^{N} \log(-\nu_i(x)) \quad x \in X \tag{4}$$

$$\psi(x) = -\sum_{i=1}^{N} \frac{1}{\nu_i(x)} \quad x \in X \tag{5}$$

In (4), (5), the barrier function $\psi(x) \to \infty$, if $\nu_i(x) \to 0$ for any *i*. In [65], the logarithmic barrier function is used to solve the distributed MPC problem with constraints.

2) FEASIBILITY METHOD

In the feasibility method, the response is endeavored to retain in an acceptable restriction area. This method is more applicable for the problem with equality constraints, although inequality constraints are also practical. Mathematically the feasibility method can be express as:

Suppose $x \in X$ is existed such that:

$$g_i(x) < 0 \quad i = 1, 2, \ldots, N \tag{6}$$

$$Ax = B \tag{7}$$

Thus, the feasible solution can be found by solving:

$$\min_{x,f}\ \{f \mid g_i(x) \leq f\} \quad x \in X,\ i = 1, \ldots, N, \tag{8}$$

$$\text{subject to: } Ax = B \tag{9}$$

In this method, the best solution is discovered among the feasible solutions. However, in some problems determining the feasible area is complicated. It is worth mentioning that the barrier function also can be applied to this method. In [110], to enhance the MG system performance, a feasible range to obtain the optimal value of the virtual impedance of the droop-based control is determined.

3) MULTI-OBJECTIVE OPTIMIZATION METHODS

As mentioned previously, one of the approaches to dealing with constraints optimization problems is reducing constraints space and augmenting constraints to the objective space. Treating constraints as objectives make the cognition of multi-objective optimization methods essential. In this section, the most important multi-objective optimization methods are studied.

Instead of concentrating on a single goal, the optimization algorithms in multi-objective problems take several goals

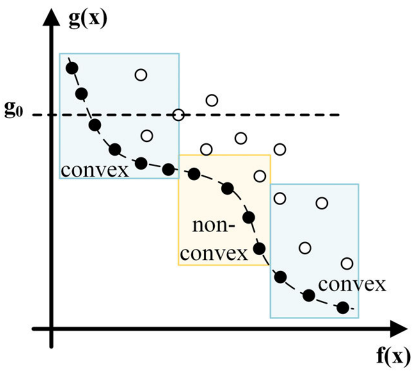

FIGURE 8. Sample pareto-front for two objective functions.

Multi-objective Optimization Problem	
Decomposition	**Direct solution**
• Weighted Sum • Weighted Metric Method • Ɛ-constraint	• NSGA-II • MOPSO • SPEA-II • MOEA/D • PESA-II

FIGURE 9. Multi-objective optimization methods.

under evaluation simultaneously. Multi-objective optimization proposes a set of optimized solutions as Pareto-optimal solutions. Fig. 8 shows a sample Pareto-front with two objective functions. To produce the Pareto-optimal frontier, the non-dominated solutions are evaluated by the dominance concept [111]. In (10) dominance concept is stated:

$$x \text{ dom } y \Leftrightarrow \begin{cases} \forall i: & x_i \leq y_i \\ \exists i_0: & x_{i0} < y_{i0} \end{cases} \tag{10}$$

The relations in (10) state that x dominates y if solution x is no worse than y in all objectives, and solution x is strictly better than y in at least one objective. Fig. 8 shows a two-objective problem, the solid points represent the non-dominated solutions, and the hollow ones are the dominated solutions. The Pareto solution proposes a variety of optimum solutions. Therefore, to select a proper solution, the solutions have to be evaluated by considering the constraints. In the constraints problems, the limits of the constraints can be exploited to specify the best optimal value. For instance, as can be seen in Fig. 8, the closest solid point to the line $g(x) = g_0$ is the best acceptable solution to fulfill the constraint $g(x) < g_0$. Furthermore, the feature selection methods and clustering analysis can also be applied to determine the best solution in the Pareto-optimal solutions set.

Figure 9 demonstrates the general classification of multi-objective optimization methods. In decomposing approaches, the multi-objective problem converts to a single objective problem. Weighted sum, weighted metric sum, and ε-constraint are some decomposition approaches widely used in multi-objective optimizations and constraints problems. The main disadvantage of decomposition approaches is that the Pareto-front set will find after multiple iterations. On the other hand, direct solutions utilize a more complicated algorithm to find the Pareto-optimal solutions in only one single run considering all objective functions.

a: DECOMPOSITION APPROACHES

i) WEIGHTED SUM

This method is widely used in multi-optimization problems due to its simplicity and usability in convex objective functions. In the weighted sum method, a set of objective functions are scalarized into a single objective function considering different pre-multiplier weights for each objective function. Mathematically, the weighted sum method is expressed as [112]:

$$\min f_{WS}(x) = \sum_{i=1}^{N} W_i f_i(x) \quad x \in X,\ i \in \{1, 2, \ldots, N\} \tag{11}$$

$$\text{Subject to}: \ g_i(x) \leq g_0 \tag{12}$$

where the weights W_i determine the relative importance of the objective functions, f(x) is the objective function, and N is the number of objective functions. There are two main disadvantages to using this method. Determine a weight vector set to obtain the Pareto-optimal solution in the desired region in the objective space is complex. Also, this method is not able to detect the Pareto-optimal solution for the non-convex part of the objective space. In the case of facing non-convex cost function in the MG application, the linearization methods can be used to obtain an approximate convex cost function. According to the constraints in (12), the best solution among the Pareto-optimal set can be determined. However, as discussed for the penalty function method, by considering the violation, the constraints can also integrate with the objective function:

$$\min \left\{ f_{WS}(x) | g_i(x) \leq g_0 \right\} \Rightarrow \min f_{WS}(x) + \frac{1}{n} \sum_{i=1}^{n} \psi(\nu_i(x)) \tag{13}$$

In [99], an incentive-based demand response program is implemented to achieve the optimal economic status. The multi-objective problem in this article involves maximizing the MGs' demand response program profit, minimizing the generator cost and trading cost. To produce the Pareto-optimal solutions, the weighted sum technique is applied in this paper. In [113]–[116], also weighted sum method is used for multi-objective optimization.

ii) WEIGHTED METRIC METHOD

This method combines multiple objective functions to minimize the distance metric between all solutions and an ideal solution T_0. In (14), the formulation of this method is expressed:

$$\min \mathrm{f_{GP}(x)} = \sum_{i=1}^{N} \left(\mathrm{W_i} \left\|\mathrm{f_i(x)} - \mathrm{T_{0i}}\right\|_{\mathrm{P,W}}\right)^{\frac{1}{\mathrm{P}}}$$
$$\mathrm{x} \in \mathrm{X}, \quad \mathrm{i} \in \{1, 2, \ldots, \mathrm{N}\} \tag{14}$$
$$\text{Subject to: } \mathrm{g_i(x)} \leq \mathrm{g_0} \tag{15}$$

where W_i can effectively utilize to normalized the distance between objective functions and the target $T0$ that this distance calculation method is dependent on P. If P is equal to 1, the distance calculates by city block distance norm, and if P is equal to 2, the distance calculates by Euclidean norm [117]. In these cases ($P = 1$ or 2), the weighted metric method is known as goal programming. In addition, if P tends to infinity, the distance is considered the maximum distance between objective functions and T_0, which this method is known as goal attainment or the Tchebycheff method [118]. Compared with the weighted sum technique, the main advantage of this method is producing the whole Pareto-optimal solution, either convex or non-convex problem, by ideal solution T_0. However, knowledge about minimum or maximum objective values is required to choose a proper ideal solution T_0.

In [119], a multi-objective optimization problem in order to maximize the investor's profit and MG operational cost considering the optimal storage power rating, energy capacity, and the year of installation is solved using a goal programming approach. Also, goal programming is applied in [120] to minimize the emission, storage operating, and startup/shutdown cost of DG units and maximize their efficiency. In [121], a multi-criteria decision analysis (MCDA) uses goal attainment programming to solve the multi-objective dispatch function for scheduling the dispatch in MGs. Goal programming and goal attainment are used in many articles for the purpose of optimization [122]–[125].

iii) ε-CONSTRAINT

In this method, unlike the two previous methods, only one objective function keeps the main objective, and the rest of the objective functions are considered the constraints [126]. This method is expressed mathematically in (16):

$$\min \mathrm{f_M(x)} \ \mathrm{x} \in \mathrm{X} \tag{16}$$
$$\text{Subject to: } \mathrm{f_i(x)} \leq \varepsilon_{\mathrm{i}} \quad \mathrm{i} = 1, 2, \ldots, \mathrm{N}\ (\mathrm{N} \neq \mathrm{M}) \tag{17}$$

where $\mathrm{f_M(x)}$ is the main objective function, and the other objective functions $\mathrm{f_i(x)}$ are considered constraints restricted to ε_i. This method is also able to find all Pareto-optimal solutions for either convex or non-convex objective functions. However, the main disadvantage of this method is that the ε vector has to be chosen precisely considering the minimum and maximum values of the individual objective functions. In [127], an augmented ε-constraint method is implemented to solve the multi-objective optimization problem in order to achieve economic optimization and peak-load reduction of the combined cooling heating and power (CCHP) MGs model. In [128], an optimal energy management technique using the ε-constraint method for grid-tied and stand-alone battery-based MGs is studied. The ε-constraint method is applied in further researches [129]–[133] as an optimization technique.

b: DIRECT APPROACH

The main difference between single-objective optimization algorithms like GA, PSO, DE, and multi-objective optimization algorithms like NSGA-II, MOPSO, PESA-II, SPEA-II, and MOEA/D is referred to the population sorting algorithm.

The non-dominated sorting genetic algorithm (NSGA) [134] is one of the first multi-optimization methods which produce a set of Pareto-optimal solutions in a single run. However, the high computational complexity of non-dominated sorting, lack of elitism, and need for specifying the sharing parameter led to proposing the modified version of this method as NSGA-II [135]. In this algorithm, in the initialization phase, the main population P(t = 0) is produced. The population P(t) merges with offspring population Q(t) and mutation population R(t) in each iteration. Then, the merged population is sorted considering the rank and crowded distance of individuals to determine the non-dominated solution. NSGA-II is utilized in MG applications for different purposes. In [136], NSGA-II is used in order to establish a smart networked MG with the lowest operating cost and the most negligible pollutant emission. In [137], the membership functions (MFs) of a fuzzy logic-based energy management system (FEMS) are optimized by the NSGA-II algorithm. The proposed FEMS is responsible for reducing the average peak load and operating cost. Moreover, in [138], NSGA-II is applied to the controller of the inverters of distributed generators with inner and outer control loops to seamless transition operation between grid-connected and islanding mode. In [139]–[142] the more applications of NSGA-II are presented.

The Strength Pareto evolutionary algorithm (SPEA-II) is proposed by Zitzler and Thiele as an efficient algorithm to face multi-objective optimization. The second version of SPEA could eliminate the potential weaknesses of the first edition by improving the fitness assignment scheme, more accurate guidance of the search process by incorporating a nearest neighbor density estimation technique, and preserving boundary solutions by a new archive truncation method [143]. This algorithm presents an acceptable performance in terms of convergence and diversity by introducing the concept of strength for non-domination solutions. SPEA-II is applied in multiple studies in MG application [144]–[146]. In [147], SPEA-II is used in demand response management (DRM) to meet the peak load demand and decreasing customer expenditure. In [148], a multi-level algorithm is proposed to optimize the revenue and expense while preserving the quality of service (QoS) of the data center and power network stability. The proposed algorithm uses SPEA-II for the multi-objective constrained optimization problem. A multi-objective algorithm based on the Six Sigma approach is proposed in [149] to solve the sizing problem of the hybrid MG system consists of multiple resources and multiple constraints. Among MOPSO, PESA-II, and SPEA-II, which are applied to the optimization algorithm, the results show SPEA-II has better performance in this article.

The Pareto envelope-based selection algorithm (PESA-II) uses the GA mechanism by applying hyper-grids to make the selections and create the next generation. The individuals-based selection in the first edition of PESA is replaced by the region-based selection in PESA-II for objective space [150]. This technique shows more sensitivity to ensure a good spread of development along the Pareto-front. In [151], the techno-economic objectives are optimized by the iterative-PESA-II algorithm to optimally sizing a stand-alone MG with PV and battery storage resources.

Multiple objective particle swarm optimization (MOPSO) is also one of the practical algorithms among swarm intelligence methods. MOPSO applied the same technique used in PESA-II by replacing GA with the PSO algorithm. In MOPSO, the particles dynamically change their position according to the velocity vector by considering the individuals' best and global best. In [152], the MOPSO algorithm is proposed by using an external repository of non-dominated vectors to guide the other particles in each iteration meanwhile maintaining the diversity. Multiple studies were carried out by applying MOPSO in order to optimize the multi-criteria objectives in MGs. In [153], MOPSO is used to find the best configuration and sizing the components of a hybrid PV, WT, DG, and battery storage system, considering a tradeoff between cost and reliability of the system. In [154], the energy management unit employed the MOPSO algorithm to ensure the maximum utilization of resources by maintaining the state of charge (SOC) in batteries to manage power exchange between MGs. In [155], MOPSO makes able the proposed EMS to minimize the operation cost of the MG concerning the renewable penetration, the fluctuation in the generated power, uncertainty in the power demand, and utility market price. More uses of MOPSO are investigated in MG application in various researches [156]–[159].

The multi-objective evolutionary algorithm based on decomposition (MOEA/D) is one of the algorithms in multi-objective optimization problems. The main difference between MOEA/D and the other algorithms discussed for direct approach solutions is not using the concept of dominance to produce the Pareto-frontier. In this algorithm, a multi-objective optimization problem decomposed into several scalar optimization sub-problems and optimized them simultaneously. Weighted sum, Tchebycheff, and boundary intersection (BI) are three approaches discussed in [160] to decompose a multi-objective optimization. Despite the weighted sum and weighed metric method discussed in the previous section, in the MOEA/D algorithm, the Pareto-front produces in only a single run. Multi-objective optimization using MOEA/D also draws attention to be used in MG applications. In [161], the optimal design of a hybrid MG system consists of PV, WT, DG, and storage devices considering load uncertainty is analyzed. MOED/D and transforming to

TABLE 4. Optimization in MGC application.

Algorithm	Time execution	Complexity	Accuracy & performance
NSGA-II	High	High	High
SPEA-II	Relatively high	Moderate	Moderate
PESA-II	Relatively high	Moderate	Moderate
MOPSO	Relatively low	low	Relatively high
MOEA/D	High	High	Moderate

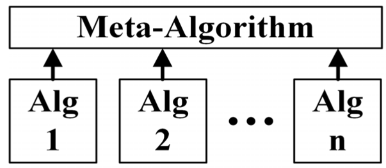

FIGURE 10. Co-evolutionary algorithm.

a single objective function are two optimization methods applied in this article to optimize the loss of power supply probability (LPSP) and cost of electricity (COE). In [162], a three-level hierarchical control architecture is proposed in order to mitigate the unbalance currents through the MG's point of common coupling (PCC) and degradation of power factor (PF). The MOEA/D in the second level is employed to maximize the active power injection and minimize the currents unbalance into the main grid. MOEA/D is widely used for optimization purposes in distribution networks and MGs [163]–[166].

Table 4 compares the performance of the direct approach algorithms discussed in this section.

D. CO-EVOLUTIONARY APPROACHES

In the case of facing an extremely complex problem, the evolutionary approaches may not be able to attain the solution with adequate accuracy. Therefore, co-evolutionary approaches proposed a computational procedure by converting a large problem to smaller ones and do parallel calculations by applying several optimization algorithms simultaneously. Fig. 10 illustrates the general performance of a co-evolutionary approach. As it can be observed from Fig. 10, a meta-algorithm is in charge of coordinating other algorithms in order to obtain the optimum solution amongst the optimum feasible solutions by the sub-algorithms.

Dynamic programming as the most popular co-evolutionary approach is a promising optimization method specifically in large-scale MGs and MGC to tackle dimensionality. In [104], [105], a dynamic programming method is developed to achieve the maximum profit from energy trading in a day. Furthermore, in the hybrid meta-heuristic approach, a heuristic algorithm combines with other optimization methods in order to exploit the complementary identity of different optimization methods. Vector evaluated genetic algorithm (VEGA) provides a robust search technique for a complicated multi-objective optimization problem. VEGA divides the population into multiple sub-population, and by considering Pareto dominance, only in the process of optimization, the

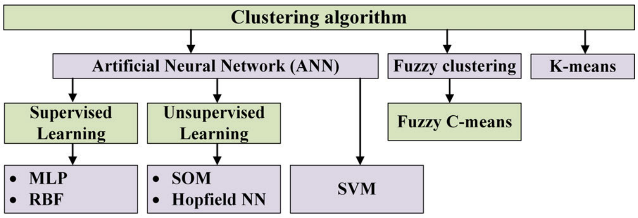

FIGURE 11. Clustering methods.

individuals evolve toward the single objective. In consequence, the optimal non-dominated solution evaluates by a non-Pareto optimization algorithm [106]. The same policy is applied in parallel meta-heuristic approaches by taking advantage of multiple meta-heuristic algorithms.

In Table 5, an overview of the different optimization methods in MGC applications is presented.

V. FEATURE SELECTION AND CLUSTERING ALGORITHMS

In multi-objective optimization problems, a wide variety of optimum solutions are proposed by the algorithm. Therefore, a supplementary evaluation is typically essential to select the proper Pareto-front solution. Various methods can be applied to these problems in order to evaluate the Pareto-front solutions. The first and preliminary approach that could be utilized in these problems is exploiting the experience of the designer. For instance, in [167], a certain amount of Pareto-front solutions are tabulated for three different cases, and the results can be evaluated for each solution to select the final proper solution according to the best operation of the system. Moreover, the knee point for convex Pareto front is typically an appropriate solution as a trade-off between two or several objective extremes. In [78], [129], the knee point is used as a compromise solution.

A sort of intelligent approach has been introduced in recent years that can be effectively applied in selecting a proper solution amongst a set of optimal solutions presented in Pareto-front. Feature selection and clustering algorithms are two important approaches in data miming science that can apply in data analysis related to the Pareto-optimal set.

Artificial intelligence (AI) is a practical tool using in feature selection and clustering data analysis. Feature selection is a process of selecting a small subset of essential features from the data. On the other hand, in clustering analysis, the data points are assigned to belong to the clusters such that items in the same cluster are as similar as possible from the aspects of similarity measurement like distance, connectivity, and intensity. Supervised learning artificial neural networks (ANN) such as multilayer perceptron (MLP), radial basis function (RBF), and unsupervised learning ANN like self-organized map (SOM) and Hopfield neural network are able to apply to the algorithms in feature selection or clustering applications. Support vector machines (SVM) are also a kind of neural network that, unlike MLP and RBF, minimizes the operational

TABLE 5. Optimization in MGC application.

No.	Ref	Optimization Method	No. of OFs	Objective Functions
1	[65]	logarithmic-barrier method	4	Minimizing the cost function of 4 MGs
2	[110]	Feasibility method + PSO	1	comprehensive assessment indices such as node voltage, power decoupling, system damping, and reactive power sharing
3	[99]	Weighted sum method	3	Maximizing MG's demand response program profit, minimizing generators cost and trading cost
4	[113] [114]	Weighted sum + Fuzzy techniques	2	Carbon emission and operation cost
5	[115]	Weighted sum + Fuzzy techniques	3-4	Loss minimization, minimizing apparent power transmitting, voltage deviation index (VDI), and system load balancing index (SLBI)
6	[116]	Weighted sum	3	Generation cost, pollutant gas emission and expected energy not supplied (EENS)
7	[119]	Goal programming	3	Storage power rating, energy capacity, and the year of installation
8	[120]	Goal programming	4	Minimize the emission cost, the storage operating cost, startup/shutdown cost of the generation units, and maximizing their efficiency
9	[121]	MCDA + goal attainment	3	Cost of operation, peak load reduction, and emissions
10	[122]	Goal programming	3	Minimize the operational costs, the emissions produced, and the loss of life of assets exposed to excess temperatures
11	[123]	Goal programming	4	Minimize the deep discharge of battery, overcharging of battery, the curtailment amount of REs and Loads
12	[124]	Goal attainment	3	Minimize the energy cost, the active electrical losses, the natural gas losses
13	[125]	Weighted metric method	2	Minimizing fuel consumption and battery degradation costs
14	[127]	Augmented ε-constrain	2	Minimizing total cost and peak load
15	[128]	ε-constrain	2	Minimizing the MG total generation cost and the active power losses in the LCL filter of each inverter
16	[129]	ε-constrain	2	Minimization of total investment cost and loss of load expectation
17	[130]	Augmented ε-constrain	2	Minimizing the ship operating cost and gas emissions
18	[131]	ε-constrain	2	minimizing the cost of installing power/heat generation sources and the expected energy not served (EENS)
19	[132]	Augmented ε-constrain +	2	Economical (active and reactive power transfers from the external network,

TABLE 5. ***(Continued.)*** **Optimization in MGC application.**

		fuzzy decision making		dispatchable distributed generations operations cost, degradation cost of plug-in electric vehicles battery), technical (Voltage deviation index)
20	[133]	ε-constrain	2	Minimizing operating cost, maximizing power quality
21	[136]	NSGA-II	2	Minimizing operating cost and the pollutants emission
22	[138]	NSGA-II	2	Optimally calculate the parameters of the system and the controllers by minimizing the maximum real part of the eigenvalues
23	[139]	Game theory + NSGA-II	N	Cost function of N microgrids (in this paper N=10)
24	[140]	NSGA-II	2	Minimizing total cost of electricity and the peak demand
25	[141]	NSGA-II	3	Minimization of operational cost, total emissions and power losses
26	[142]	NSGA-II	2	Minimize power generation cost and maximize the useful life of lead–acid batteries
27	[144]	Modified SPEA-II	2	Maximizes social welfare and minimizes losses
28	[146]	Improved SPEA-II	3	Minimizing economical cost, maximizing the average utilization rate of chargers and user's charging convenience
29	[147]	SPEA-II	2	Minimizing peak load demands and the expenditure to the costumers
30	[148]	SPEA-II	2	Maximizing revenue and minimizing expenses
31	[149]	MOPSO, PESA-II, SPEA-II	3	Minimizing the Net Present Cost, the penalty cost of emission and the quantity of the CO_2 released into the atmosphere
32	[151]	PESA-II	3	Minimizing the loss of load probability, life cycle cost, and levelized cost of energy
33	[153]	MOPSO	2	Minimizing the Cost of Electricity (COE) and Loss of Power Supply Probability (LPSP)
34	[154]	MOPSO	2	Maximize the consistency of the generation system and maximum utilization of resources
35	[155]	MOPSO	2	Minimize the operation cost of the microgrid and maximize the generated power by each source
36	[156]	MOPSO	2	Minimizing the total cost of the system optimal design with hybrid RESs in a smart microgrid to increase the availability
37	[157]	MOPSO	3	Minimizing annualized cost of the system, loss of load expected and loss of energy expected

TABLE 5. ***(Continued.)*** **Optimization in MGC application.**

38	[158]	MOPSO + fuzzy decision making	2	Optimal operation time (OT) and optimization constraints
39	[159]	MOPSO, NSGA-II	2	Minimizing the operation cost and pollution rate
40	[161]	MOEA/D	2	Minimizing the Loss of Power Supply Probability (LPSP) and Cost of Electricity (COE)
41	[162]	Cone-based multi-objective evolutionary algorithm based on decomposition	2	Maximize the active power injection by single-phase units, and minimize the currents unbalance into the main grid
42	[163]	Adaptive MOEA/D, MOEA/D	3	Minimizing the transmission losses, operating costs, and carbon emissions of multiple microgrid systems
43	[164]	Improved MOEA/D	4	Minimization of total operating cost, active network loss, voltage deviation and the total output reduction rate of renewable energy
44	[166]	MOEA/D	2	Maximizing the active power generation, minimizing the reactive power circulation and current unbalance
45	[104]	Dynamic programming	5	Maximizing Profit (Profit = Revenue – Cost) Cost = Generation cost + Start-up and Shut-down cost + Electric buying cost + Battery wear cost
46	[105]	Dynamic programming	2	Minimize the cash flow of the system and maximizing the net power import from the main grid

risk of classification or modeling instead of minimizing the error between system and model.

The k-means (KM) problem is also one of the famous clustering problems that can be solved by the Lloyd algorithm. In the k-means problem, the data partition to K cluster in which each data belongs to the nearest mean of the partitions [168]. Fuzzy clustering algorithms are another clustering method such that data points can belong in more than one cluster. Easier creating the fuzzy boundaries is the main advantage of this method from the computation point of view. In [127], a fuzzy clustering method is applied to the multi-optimization problem to deal with the large scale of the solution set. It is shown that the selection of the Pareto optimal set depends on the preference of the decision-maker. Fuzzy C-means (FCM) clustering is one of the most popular fuzzy clustering algorithms. FCM is very similar to the KM algorithm; however, FCM is extremely slower than KM due to iterative fuzzy calculation [169]. In [170],

TABLE 6. Feature selection and clustering methods in multi-objective optimization.

No.	Ref	Clustering Method	Explanations
1	[171]	k-means	To significantly reduce the computation time by determining a representative load profile.
2	[172]	k-means	To generate typical daily load scenarios and used the upper and lower ranges to describe the load and uncertainty to build a robust optimization model.
3	[173]	Wasserstein distance + k-means	To generate optimal scene and reflecting the random feature of distributed generation accurately.
4	[174]	Monte Carlo + k-means	To predict the load on the source-side and load-side.
5	[175]	Latin hypercube sampling (LHS) algorithm + k-means	To generate all uncertainties
6	[127]	Fuzzy clustering method	To select the final scheme according to the preference of decision maker.
7	[176]	Fuzzy satisfying technique	To determine the best solution among the obtained solutions.
8	[177]	Fuzzy clustering approach	To control the size of repository up to a limit range.
9	[178]	Fuzzy C-means clustering + grey relation projection	To identify the best compromise solutions from the entire solutions.
10	[179]	Fuzzy decision making method	To enhance the decision makers obtain a solution from Pareto front.
11	[159]	Fuzzy decision-making	To choose a better solution from optimal solutions to manage the MG.
12	[148]	Two extremes and the middle of a Pareto front	To analyze the optimum solution
13	[162]	VIKOR multi-criteria decision-making methods	To select the solution that best suits the preferences of the Decision-Maker.
14	[164]	Fuzzy decision method	To select the best solution to be used in the scheduling scheme.
15	[129]	Knee point	Minimization of total investment cost and loss of load expectation
16	[78]	Knee point	To find the best compromise solution as a trade-off between two quality goals i.e. shifting and shrinking in convex curve.
17	[157]	Trade-off solution by fuzzy set	The best compromise solution is chosen based on the distance of non-dominated solutions and the nearest solution to the fuzzified origin.
18	[180]	R-NSGA-II	A combination of the classic NSGA-II with a multi-criteria decision-making approach to find a single optimal solution.
19	[137]	Fuzzy set	To determine the best compromise solution from the set of Pareto optimal solutions.
20	[113]	max-min fuzzy technique	To select the best solution which compromises both objective functions
21	[132],[99],[116],[181]	Fuzzy decision-making	To select the trade-off solution amid the obtained solutions

TABLE 6. (Continued.) Feature selection and clustering methods in multi-objective optimization.

FCM clustering is utilized to reduce the total output scenarios generated by Latin hypercube sampling (LHS) to analyze the uncertainty of RE output. Fig 11 represents the different clustering methods. In Table 6, different methods to find the best compromise solution in multi-objective optimization for microgrids applications are reviewed.

VI. CONCLUSION

According to the literature researches, master-slave, peer-to-peer, and hierarchical architecture are considered as the most prominent control strategies in grid-connected or isolated MGs. Each control strategy proposes specific features to MG and MGC operation from the efficiency and reliability perspective. The analysis verifies that the hierarchical structure could provide more reliable operation by employing different control strategies such as centralized, decentralized, hybrid, and distributed control. Furthermore, planning and scheduling programs for MGs are investigated in order to determine the practical and technical specifications of the operating system. Therefore, an energy management system is essentially required not only to guarantee the optimal operation and economic feasibility but also to follow specific practical and technical considerations determined by planning and scheduling. Consequently, the optimum operation assessment of MGs is the main purpose of energy management system in MGs. The optimum operation of MGs from the mathematics point of view is considered an optimization problem. Obviously, a more appropriate utilized optimizer results in a more reliable MG operation. To this end, this paper concentrates on various optimization methods to fulfill the performance of MGs associated with practical and technical constraints, calculation burden, information communication delay, etc. A classification of optimization methods in order to solve the single objective and multi-objective problems is presented. Several multi-objective approaches are discussed, and it was observed that by applying the concept of dominance, the advanced single-objective algorithms like GA, PSO, etc., turn to multi-objective algorithms like NSGA, MOPSO, etc. The multi-objective algorithms produced the Pareto-front set. Unlike single-objective optimization, in multi-objective optimization, a set of optimum solutions is offered by the algorithm. Therefore, the optimum solutions are required to be evaluated in order to select the proper solutions. Ultimately, various methods such as feature selection and clustering methods are proposed to analyze the Pareto-optimal solutions. The performance of the optimization algorithms can enhance by incorporating deep learning approaches. In this case, the optimal solutions can be produced properly employing deep learning algorithms. Therefore, the performance will be improved by reducing the calculation burden and obtaining more accurate solutions. This incorporation can be surveyed in future works.

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