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a review

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Computational optimization techniques applied to microgrids planning: a review

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Abstract

Microgrids are expected to become part of the next electric power system evolution, not only in rural and remote areas but also in urban communities. Since microgrids are expected to coexist with traditional power grids (such as district heating does with traditional heating systems), their planning process must be addressed to economic feasibility, as a long-term stability guarantee. Planning a microgrid is a complex process due to existing alternatives, goals, constraints and uncertainties. Usually planning goals conflict each other and, as a consequence, different optimization problems appear along the planning process. In this context, technical literature about optimization techniques applied to microgrid planning have been reviewed and the guidelines for innovative planning methodologies focused on economic feasibility can be defined. Finally, some trending techniques and new microgrid planning approaches are pointed out.

1. Introduction

Modern societies are highly dependent on electric energy supply. Following IEA energy statistics, this dependence has been increasing during the last 40 years. Nevertheless, electric power systems have not been significantly upgraded for decades. Since new enabling technologies for energy systems are being developed (such as ICT, microCHP, energy storage and renewable energy sources, smart meters, etc.), new concepts are appearing in modern power systems. One of the most popular is the microgrid concept, being a novel power grid structure based on DER, RES, power electronics and ICTs.

One of the earliest definitions of microgrids was made by CERTS. They define microgrids as *clusters of generators, including heat recovery, storage, and loads, which are operated as single controllable entities*. In addition a comparison between microgrid concepts is done by J.I. Ping et al. in [1]

Some microgrid classifications have been presented in technical papers since this concept appeared in 1998, according to Web of Science (WOS) references. P. Lilienthal points out in [2] different criteria for microgrid classification such as: other grids connection, types of energy generation, voltage level of distribution system, peak load, generation capacity, energy production, number of customers served, load management and metering. He also makes a proposal for microgrid classification regarding size and grid connection, defining four main microgrids types such as: large grid-connected microgrids, small grid-connected microgrids, large remote microgrids and small remote microgrids.

Due to the modular nature of microgrids, they can operate both independently or in conjunction with the main electrical grid. Microgrids not only have less financial commitments and require fewer technical skills to operate, but also rely more on automation [3,4]. **These advantages make microgrids a suitable solution to gradually modernize existing power grids.** Other advantages for microgrid establishment are the integration of renewable resources from local areas and the independence of the consumer from large corporations that manage actual power grids.

Despite all these advantages, planning a cost-effective microgrid is considered as a complex process due to all alternatives to consider at any decision level. Every decision taken in a planning process will influence the capacities of the system in a competitive energy market**.** Every planning process is built around specific goals and constraints. Not only goals and constraints (such as technical, environmental, geographical, social and regulatory constraints) define by themselves the whole framework of the planning process, but also uncertainties are a key factor in every planning process. They are a powerful source of risks that system planners need to avoid, or at least to control. S. French in [5] identifies several sources of uncertainties in all the main steps of a decision making process: *uncertainties in modelling, uncertainty expressed during the exploration of the model and uncertainties in the interpretation of results.* But other authors in [6], motivated by practical needs for modelling the decision making problem, have classified every uncertainties under two main categories:

- External uncertainty: related to the lack of knowledge (about the consequences of an action, outside of the control of the decision-maker), and to the nature of the environment.

- Internal uncertainties: presented in the process of identification, structuring and analysis of the decision-maker (depending on the decision maker).

Beyond these uncertainties, constraints and planning objectives, every commercial microgrid must be addressed towards two main goals: cost efficiency and customer satisfaction. In a microgrid, consumer satisfaction means reliability and quality keeping, causing as low environmental impact as possible. Hence, some of these objectives can be opposed to the others regarding costs of the system. It is generally accepted that it is necessary to invest in renewable power sources and in energy efficiency-based technologies in order to minimize the environmental impact of a microgrid. These investments may upgrade the system, but also influences economic feasibility. For instance, economic feasibility for renewable power sources will depend on different issues such as local electricity costs, space requirements, allocation, initial investment, operational and management costs, grid-connection charges, taxes and grants. Strong investments are also needed in order to raise the reliability or the quality of supply, but every project has its own economical constraints, especially at the design stage. **That is the reason why the microgrid planning process is usually based on an optimal or trade-off solution searching process**.

A microgrid (considered as a community energy system) usually encompasses a mix of traditional an renewable power sources-based technologies. Different authors have previously reviewed planning tools for microgrid-related technologies [7,8]. For example, in [7] G. Mendes et al. introduce the most common available tools for community energy systems planning. They include a survey of these tools, qualifying them as *bottom-up, simulation, equilibrium, operation optimization and investment optimization tools*. Some of these tools are suitable for microgrid planning, such as HOMER, DER-CAM, EAM, MARKAL/TIMES, RETScreen and H2RES. Also D. Conolly et al. presents in [8] a deep comparison of 37 different analysis software tools used to evaluate renewable energy sources integration projects. This paper also includes HOMER, MARKAL/TIMES, RETScreen and H2RES.

Since a **microgrid planning process can be approached as a sequence of optimization problems,** along technical literature different optimization problems have been considered at different planning levels. In this context, different researches have decided to reviewed optimization applied to microgrid-related technologies such as renewable power sources [9–11]. R. Baños et al review in [10] optimization methods applied to wind power, solar energy, hydropower, bioenergy, geothermal energy and hybrid systems. Different approaches to optimal design of renewable energy based on hybrid systems are also reviewed in [9] by O. Erdinc *et al*. M. Iqbal *et al* present in [11] a generic list of inputs, outputs, objectives and constraints resource allocation problem of renewable energy sources. They also introduce a list of optimization tools, a conflicting objective matrix, and an optimization techniques review.

Hence, several optimization planning techniques have been applied not only to renewable energy sources, but also to energy community systems, e.g. district heating [12–15]. Different energy community systems may require different optimization techniques due to system constraints (mainly technical, environmental and economical) and uncertainties. The appearance of new computational optimization methods and algorithms are allowing new approaches to planning problems. **The coexistence of these widely used mathematical optimization techniques with new ones makes more attractive the idea of reviewing microgrid planning problems.**

2. Computational optimization techniques: a brief introduction

The term computational optimization refers to a group of mathematical techniques focused on the selection of an optimal solution (with regard to some criteria) from a set of available alternatives. Indeed, optimization includes finding the best available values of some objective function given a defined domain or a set of constraints, including a wide range of objective functions and types of domains. The generalization of optimization theory and techniques to other formulations comprises a large area of applied mathematics. R. Baños et al. introduce in [10] different disciplines included into computational optimization such as *mathematics to formulate the model, operations research to model the system, computer science for algorithmic design and analysis, and software engineering to implement the model*.

U. Diwerak describes optimization process as an iterative procedure, which is basically composed of an optimizer and a model [16]. Modelling is defined as the *process of identifying objectives, variables and constraints for a given problem* [17]. *The optimizer invokes the model with a set of values of decision variables, while the model calculates the objective function and constraints. This information is utilized by the optimizer to calculate a new set of decisions variables. This iterative sequence continues until the optimization criteria pertaining to the optimization algorithm are satisfied* [16].

Optimization algorithms, iterative and heuristics methods are cited among computational optimization techniques. The use of different optimization algorithms depends upon the type of optimization problem. At the same time, there exist many different optimization problem classifications, depending on the type of decision variables, objective functions and constraints. J. Nocedal and S.J. Wright [17] define different categories such as: continue and discrete, constrained and unconstrained, global and local, stochastic [18] and deterministic, multimodal and multiobjective and heuristic and metaheuristic optimization [19].

Despite of the name, an optimization method will not always find the optimum solution. Sometimes an optimization problem can be unfeasible due to the characteristics of the problem. For example, when in a LP optimization problem all the unknown variables are required to be integers, the problem is called ILP or IP problem. In contrast to linear programming, which can be solved efficiently, IP problems are in many practical situations Non-deterministic Polynomial-time hard (NP-hard) [20]. Algorithms used to solve a NP-hard problem might need exponential computation time to obtain the optimum, which leads too high times for practical purposes. Thus, during the last years many authors have proposed approximate methods (including heuristic and metaheuristic approaches) to solve optimization problems.

Heuristic methods are designed to find a good solution among a large set of feasible solutions with less computational effort than optimization techniques [9]. They are useful approaches for optimization problems when classic optimization techniques are not able to find the optimal solution. Besides heuristics there exists metaheuristics. Metaheuristics are used to find an optimal solution from discrete search-space The point of metaheuristics is that they can combine more than one heuristic method: the first one can be used to find a primary solution and later another heuristic method can be used in order to find a better solution. Perhaps the most popular way of classifying metaheuristic algorithms is based on trajectory methods vs. population-based methods, but other classifications such as bio-inspired one [21] are often used:

- Trajectory meta-heuristics use a single-solution approach focused on modifying and improving a single candidate solution during the search process. The outcome is also a single optimized solution. The main meta-heuristic methods in this category includes: SA, TS, GRASP, VNS and ILS.

- Population-based meta-heuristics use a population of solutions, which evolve during a previously fixed number of iterations, returning a population of solutions when the stop condition is fulfilled. Perhaps GA and PSO are the most popular algorithms in this category.

- Bio inspired metaheuristics: are metaheuristics that mimics the nature for solving optimization problems. In [21] S. Binitha and S. Shatia classify these techniques into three main types: Evolutionary algorithms, Swarm intelligence and Ecology-based algorithms.

In addition, other kind of metaheuristics can be considered, such as *hybrid* and *parallel* metaheuristics. The *hybrid metaheuristic* combines other optimization approaches with the metaheuristic one. Meanwhile the *parallel metaheuristic* is an algorithm that runs multiple metaheuristic searches in parallel by using parallel computing techniques.

In some cases, the complexity of the problems to solve is so high that no heuristic neither metaheuristic method is able to obtain accurate solutions in reasonable runtimes. Hence, parallel computing becomes an interesting way to obtain good solutions with reduced runtimes. Parallel computing is a form of computation in which large problems can be divided into smaller ones, carrying out many calculations simultaneously. Common types of problems found in parallel computing for microgrid applications are Monte Carlo Simulation [22–24] and Dynamic Programming [25,26].

Regarding this brief introduction to computational optimization, it could be asserted that a holistic real-life microgrid planning problem can be considered constrained, stochastic, and multi-objective. But several authors have applied different approaches to microgrid planning problems. Those problems will be reviewed in the following sections, together with optimization techniques applied to solve them.

3. Optimization techniques applied to microgrid planning problems.

Community energy systems planning problems have been traditionally addressed towards cost minimization objectives [27–29]. Beyond economic goals, during the planning process other different goals can be considered, such as total environmental impact, power quality and reliability [30].

Even though each microgrid planning process has its own constraints and specific goals, **some planning problems can be considered common to every microgrid, according to the reviewed technical literature**. These planning problems are:

- ***Power generation mix selection and sizing:*** Microgrid design engineers are responsible of choosing the best available power system to satisfy demand requirements for a particular area. Power sources selection requires a deep analysis of suitable electric power supplies for microgrid applications in the influence area. Power generation and energy storage equipment must be sized according the peak-load demand and cost effectiveness criteria. Not only a high percentage of the initial investment is done at this stage, but also other critical decisions must be done. Types of fuels suitable for the power plant must also be selected, which is a critical issue regarding cost efficiency and reliability of the system. In summary, this problem must be considered among strategic issues for the system and there exist three main objectives to fulfil during this planning stage: high cost-effectiveness, low environmental impact and high reliability.

- **Siting problem** covers power sources allocation and power lines layout in order to keep quality constraints. In this process not only actual consumers, but also potential customers must be considered. As a result power lines must serve customers areas and also must be addressed to potential areas. This problem can also be considered among strategic level problems. As in sizing problem, initial investment depends directly on final design at this stage. In this planning stage not only it is necessary to provide high cost-effectiveness and high reliability as in the previous one, but also low power losses are required.

- ***Scheduling*** is the main problem of tactical planning level, because it is focused on available resources planning, such as generators and storage devices. Scheduling problem is aimed at minimizing operational costs, environmental impact and quality keeping while demand is covered. Optimal operational conditions for different microgrid configurations are searched using different **optimization techniques towards one or more than one objective optimization.**

These stages are common in every feasibility study when planning a microgrid. A survey of optimization techniques taking part in these stages is presented in this section. In addition, some related mathematical techniques such as simulation, fuzzy logic and forecasting, including uncertainty management, will also be presented.

3.1. Power generation mix selection and sizing: economic load dispatch problem basis

Economic issues are a high priority in the microgrid planning in order to address long-term establishment for the system. The successful deployment of a microgrid depends on the economic success of small clusters of mixed technology generators, grouped with storage devices and other reliability-based factors such as fuels allowed. Main problems in technical papers at strategic planning level are power sources selection [31] and sizing [9], energy storage devices selection and sizing [32] and siting. Determination of the real power outputs for the generators so that the total cost of the system is minimized is also known as **the problem of economic load dispatch**. As it will be described below, power mix selection and sizing problems are addressed towards ELD problem.

Traditional optimization techniques are used in [33] by M. Vafaei and M. Kazerani, selecting and sizing, different power generation technologies and storage devices for a microgrid, in order to minimize operational costs. The optimization model is formulated as a MIP (Mixed Integer Programming) problem in GAMS environment. Also, a classical optimization method is reviewed towards microgrid modelling purposes in [34] by Augustine *et al*. They perform the power mix selection of four different types of microgrids by using the *Reduced-Gradient Method for Economic Dispatch* algorithm and Matlab software in order to simulate the system. In this paper the final selection is based on economic dispatch costs, taking into account renewable energy sources penetration, costs and receipts associated.

Y. Han et al. in [35] solve the ELD problem using the Karush-Kuhn-Tucker (KKT) conditions. Allowing inequality constraints, the KKT approach to nonlinear programming generalizes the method of Lagrange multipliers, which allows only equality constraints. The KKT approach guarantees to find the true optimum (versus heuristic search approaches), but is also readily capable of being extended with further realistic constraints/costs, versus purely analytic approaches.

In [36] T. Logenthiran compares a classical Integer Minimization Problemn (IMP) with Evolutionary Strategy (ES) method (a generic population-based optimization metaheuristic algorithm) in order to size power equipment for an islanded microgrid. The optimization aim is to minimize the sum of the total capital, operational and maintenance cost of DERs.

Heuristics are widely used in sizing and power generation mix selection. Erdinc in [9] highlights some heuristic optimization techniques for hybrid renewable energy systems sizing such as: GA, PSO, SA and some promising techniques such as Ant Colony and AIS. In [37] S.M.M. Tafreshi et al model a microgrid using MATLAB and GA to solve the sizing problem with some restrictions. They evaluate the system considering costs and benefits such as: the cost function annualized capital, replacement, operational, maintenance, fuel costs and annual earning by selling power to grid. SA algorithm is used to solve the optimal sizing problem for renewable energy generations and combined heat and power (CHP) units in a hybrid energy microgrid in [38] . Stochastic variability of renewable energy resources and the heat and power requirements are considered in order to meet customer requirements with minimum system annual cost.

Energy efficiency and renewable power sources are nowadays the guidelines to minimize the environmental impact of a microgrid. But since renewable power sources are not always ready to produce energy at their peak power, energy storage becomes an important topic in microgrids. Thus, **sizing problem concerns not only to power sources but also to energy storage devices.** These devices must be sized and located regarding cost-effectiveness, environmental impact, reliability and quality goals. This topic is introduced by S. Bahramirad et al. in [39] in which the optimal ESS sizing problem is proposed both for initial investment and expansion problems. The problem is analysed from an economical point of view, using a MIP approach in order to minimize investment in storage devices and microgrid operational costs.

S.X. Chen et al. propose in [32] a method based on the cost-benefit analysis for optimal sizing of an energy storage system in a microgrid. *Time series* and *Feed-forward neural network* techniques are used for forecasting the wind speed and solar radiations respectively. The main problem is formulated as a MILP, which is solved in AMPL *(A Modelling Language for Mathematical Programming*). A specific Artificial Neural Network algorithm is used for production forecasting, meanwhile a classical approach is used for the optimization problem. An heuristic method is again used in [40] by Navaeefard *et al*. They introduce uncertainty in a microgrid sizing problem that includes photovoltaic PV/wind hybrid system with storage energy systems. Wind power uncertainty is proposed and reliability index are considered as a constraint. PSO algorithm is used to obtain global optimal solutions using MATLAB.

In [41] O. Menniti et al. propose a **methodology** to determine the optimum sizing and configuration of a grid-connected hybrid Photovoltaic/Wind system, including energy storage systems and ensuring that the system total cost is minimized while guaranteeing a highly reliable source of load power. They base their analysis on simulation techniques.

Some of these mathematical programming methods **are nowadays implemented by software tools,** which are widely used in microgrid planning. Most of these tools, instead of not being specifically focused on microgrids, are suitable for microgrid modelling. ETAP is introduced as one of these tools in [42]. A comparison between two different technology selection and sizing softwares such as HOMER and

WEBOPT is done by A. Litchy et al. in [43]. Since WebOpt is based in a MILP optimization, HOMER is based on alternatives simulation, creating a list of feasible configurations sorted by net present cost. DER-CAM software is the main tool for a commercial-building microgrid technology selection and operation in [44]. The output from DER-CAM is a cost-minimizing equipment combination for a building, including CHP equipment and RES. The results of DER-CAM suggest not only an optimal (potentially mixed technology) microgrid, but also an optimal operating schedule that can serve as the basis for a microgrid control strategy.

HOMER software is widely used with microgrid modelling purposes. It is used by C. Nayar et al. in [45] in order to define a layout of power plants for an hybrid microgrid in remote islands in Republic of Maldives. A stand-alone microgrid is also designed in [46] for Pulau Ubin Island of Singapore. In this paper authors simulate different systems using HOMER in order to fit the needs with optimum cost and available renewable sources, including storage units sizing. A similar work is presented in [47], selecting and sizing power generators for a rural microgrid in India. Environmental objectives can also be considered using this modelling software. In [48] W. Su et al. study the planning and operation of micro-source generators to accommodate the high demand of renewable energy and the environment policy.

3.2. Siting

Nowadays there exist many papers on allocation of energy resources, not only for DERs and RES, but also for energy community systems, such as district heating [49]. However, there exist two main approaches: power lines layout and equipment siting (power and storage equipment). Both are focused on power loss minimization and quality keeping goals.

Q. Cui et al. presents in [50] **a traditional approach** to design cost-optimized microgrid architectures subject to reliability constraints. The method is based on DP and consists on determining the optimal power line layout between microsources and load points, given their locations and the rights of way for possible interconnections.

A. Khodaei presents in [51] an algorithm for microgrid planning as an alternative to the optimization of traditional electric power systems regarding generation and transmission. The optimization problem is decomposed into a planning problem and an annual reliability problem. The objective is to minimize the total system planning cost, and a software called *Versatile Energy Resource Allocation* (VERA) is used. A prediction of demand coverage based on local weather conditions is also performed. Nonlinear aspects of the problem are solved with Sequential Quadratic Programming technique (SQP).

In [52] V. Verda and C. Ciano deals with the choice of the optimal configuration of a district heating network to be built in an urban area. Users to be connected to the network are determined and an economic objective function is optimized using SA. Despite this is not a specific microgrid planning problem, a similar method could be used when a microgrid has to deal with competence in an urban area. The technique *Modified Discrete Particle Swarm Optimization* is used in [53] by M.T. Wishart et al.

to plan a distribution system upgrade over a 20 year period. The objective is to minimize the system total lifetime cost regarding: line loss, reliability costs and investment needed in DGs, capacitors, lines, and transformers. The bus voltage, feeder current and the DG output power are incorporated in the optimization procedure as constraints. M.V. Kirthiga et al. in [54] propose a methodology to transform an existing radial distribution network into an autonomous microgrid, in which sizing and siting strategies for distributed generators and structural modifications for autonomous microgrids are developed. The optimal sites and corresponding sizes of renewable resources for autonomous operation are obtained using PSO and GA. An optimization problem for system losses and costs is formulated, considering quality constraints, generators loads and balance.

Regarding microgrids siting problems, some **multi-objective optimization** algorithms are combined with sensitivity analysis. For example, in [55] K. Buayai et al. carry out using MATLAB a two stage multi-objective optimization process for MG planning in two primary distribution systems. In the first stage, loss sensitivity factor is proposed to identify the MG area in a primary distribution system. In the second stage, a Pareto-based NSGA-II is proposed to find locations and sizes of a specified number of distributed generators within microgrids. Multi-objective functions include system real power loss, load voltage deviation and annualized investment cost. A fuzzy decision making analysis is used to obtain the final trade-off optimal solution. Another multi-objective method is proposed by G. Celli et al in [56] to solve sizing and siting problems in distribution networks. The objective is to achieve the best alternative between cost of network upgrading, cost of power losses, cost of energy not supplied, power quality cost and the cost of energy required by the served customers. Using a GA, they apply the $\mathcal{E}$*-constrained* technique to obtain a compromised non-inferior solution.

As it has been described in [56], **heuristics** have also been applied to siting problems. A. Basu et al. selects in [57] bus locations by loss sensitivity analysis. PSO is implemented using MATLAB in order to maximize the value of *benefit to cost ratio* (BCR). Cost of electricity generation is minimized, not only using CHP-based DER technology but also deploying them in the microgrid system regarding their type, capacity-size and bus-location. G. Celli et al. propose in [58] a new software procedure based on a GA, capable to establish the optimal distributed generation allocation on an existing medium voltage (MV) distribution network, considering technical constraints of real size scenarios with several hundreds of nodes. In [59] G. Carpinelli presents a three step procedure, based on GA, applied to establish the best distributed generation siting and sizing on an MV distribution network.

M.R. Vallem et al in [60,61] describe a method for siting of DER within the framework of an optimal microgrid architecture regarding minimum cost interconnection, sizing, and siting of DER subject to stipulated global and local reliability criteria. The siting problem considers factors like deployment costs and savings gained by the use of CHP and it is formulated as a SA optimization problem. An optimal economic and allocation model of an industrial photovoltaic microgrid is proposed in [62] by M. Mao. The economic indexes analysed include energy cost, emission reduction benefits and payback period. The optimization problem is solved using PSO optimization technique. S.Tan considers necessary in [63] to integrate microgrid load dispatch and network reconfiguration together. This results in a non-convex non-linear problem. Four evolution computational optimization methods have been compared in this paper such as *GA, PSO, AIS and Vaccine-AIS.*

3.3. Operation scheduling: economic load dispatch problem

The control strategy of each microgrid has a great impact on the energy contribution of the different DGs. The Economic Dispatch Problem is usually solved by mathematical computing techniques and specific computer software. Final scheduling must fulfil system goals in the framework shaped by demand, operational and system constraints of the available resources and corresponding transmission capabilities. In [64] C. Colson and M. Nehrir reviewed microgrid management challenges emphasizing tasks in DER and CHP integration, power management and control as the main fields of development.

A **classical approach** for other energy community systems is presented in [65]. A Combined Cooling and Heating Power model of a rural microgrid is built and optimized by using a MINLP optimization process to improve system efficiency of energy utilization and other goals with a BONMIN solver. The whole system model is mathematically programmed into the platform of GAMS. Again MINLP is used in [66]. C.A. Hernandez-Aramburo et al. try to minimize the fuel consumption rate for a two-generation unit microgrid, while constraining it to fulfil the local energy demand (both electrical and thermal) and provide a certain minimum power reserve. P. Stluka et al. focus in [67] the problem of powering a set of buildings through a microgrid, formulating a cost-minimizing problem. Load forecasting and sitting problems are solved using a MINLP approach with the optimization software VERA.

In fact, as it can be seen in [68] and [69], classical optimization methods such as IP and LP are still a good approach depending on the problem definition, being GAMS a widely used modelling system. In both papers the optimization model for a microgrid based in a CHP generation unit operation is formulated. LP is also used in [70] by D. Quiggin et al. to model a microgrid including a mix of renewable generation technologies, energy storage and DR, based on real world data of residential energy consumption and weather variables.

DP is used to solve optimization problems in [71] by A. Sobu and in [72] by M.Y. Nguyen, et al.. A. Sobu defines a dynamic optimal schedule management method for an isolated or grid-connected microgrid system, considering forecast errors with uncertainties of solar radiation, wind speed and local user demand. Nguyen et al. try to maximize the profit that owner might achieve from energy trading in a day, either in isolated or grid-connected microgrids. C. Huang et al consider tariffs inside the ELD problem in [73]. A power-scheduling problem, solved by a MPDP approach, and considering load/generation changes and TOU tariff for a low voltage DC microgrid is developed.

F. Mohamed and H. Koivo propose in [74–77] different **multiobjective algorithms**, which are also used to determine the optimal operating strategy for a microgrid such as: SQP, GA, and MADS. MADS is a generalization of the pattern search algorithm. The aim of these papers is to minimize the cost function of the system. Multiobjective optimization based on modified game theory is applied in [76] to the environmental and economic problem of the MG.

T.S. Mahmoud introduces in [78] **fuzzy logic techniques** for storage devices scheduling. A fuzzy logic based adaptive charging price is set for charging the storage device based on the microgrids local generation price at the time of charging, and the amount of daily storage device participation in the microgrid dispatch. A multi-objective PSO method is applied to optimize the energy dispatch for the managed microgrid. H. Kanchev et al. in [79] presents a microgrid energy tactical optimization in the presence of PV-based active generators. The optimization objective function is focused on the CO_2 equivalent emissions (environmental criteria), the fuel consumption (economical criteria) or a trade off between these two. This study is developed using fuzzy logic theories and PSO. Tools as MATLAB, TRNSYS, GenOpt and TRNOPT are proposed to solve this kind of problems [46,86]

T. Niknam et al propose in [82] a probabilistic approach for economic/emission management of microgrids from a **probabilistic optimization method**, including uncertainties covering and a modified multi-objective algorithm based on the MGSA to find Pareto-optimal front of the operation management problem.

Forecasting techniques have been introduced in optimization problems due to stochastic nature of demand and renewable energy resources. R.Y. Jaganmohan et al, design in [83] a system that forecasts the short (daily), medium (seasonal) and long term (yearly) load demand and the availability of energy resources at the microgrids. They use ANN feature to forecast both load and availability of energy resources at microgrids in different scenarios like daily, seasonal, and yearly. The layered ANN architecture is developed and trained with Levenberg-Marqurardt Back Propagation Algorithm. Other authors use in [84,85] forecasting techniques based on ANN. Although forecasting technique changes from some papers to others, the most common objective of these techniques is to forecast both load and availability of energy resources, as in [86].

In [87] C. Chen et al. propose one unified model so that smart management of ESS, economic load dispatch and operation optimization of distributed generation are simplified into a single-objective optimization problem. They use an improved GA to solve the problem. Same algorithm is used by C. Chansong et al. in [93] to determine an optimal schedule of all available units over a planning horizon so as to meet all system, plant and unit constraints, as well as meet the load and ancillary service demands. An ANN power forecasting is used to predict hourly power outputs. A GA is developed to make good operation and trading decisions while meeting constraints.

S. Obara and E.G. El-Sayed in [89] develop an optimal operation algorithm of a compound microgrid using numerical weather information (NWI) which is freely available and a GA is developed to minimize system fuel consumption. L Ricalde et al. introduce in [90] some forecasting methods depending on temporal range of look-ahead times, and they address ANN as excellent approximations for nonlinear and stochastic models.

Operation of a microgrid with more than two DER units, especially in an autonomous mode, requires an Energy Management System (EMS). Fast response of the EMS is more critical for a microgrid compared with a conventional power system. The real-time management block receives the present and the forecasted values of load, generation, and market information to impose appropriate controls on power flow, output generation, consumption level of the utility grid, dispatchable sources, and controllable loads, respectively, as it is shown in figure 1. An EMS should ensure a set of control function, such as supply of electrical energy, participation in the energy market, pre-specified service level for critical loads, black start subsequent to a failure, provision for ancillary services, and so forth. The objectives are achieved through either a centralized or a decentralized supervisory control that includes three hierarchical levels:

- ✓ distribution network and market operator (PCC Level)
- ✓ local controllers (LCs) associated with each DER unit and/or load
- ✓ Customer level associated to demand-based control strategies

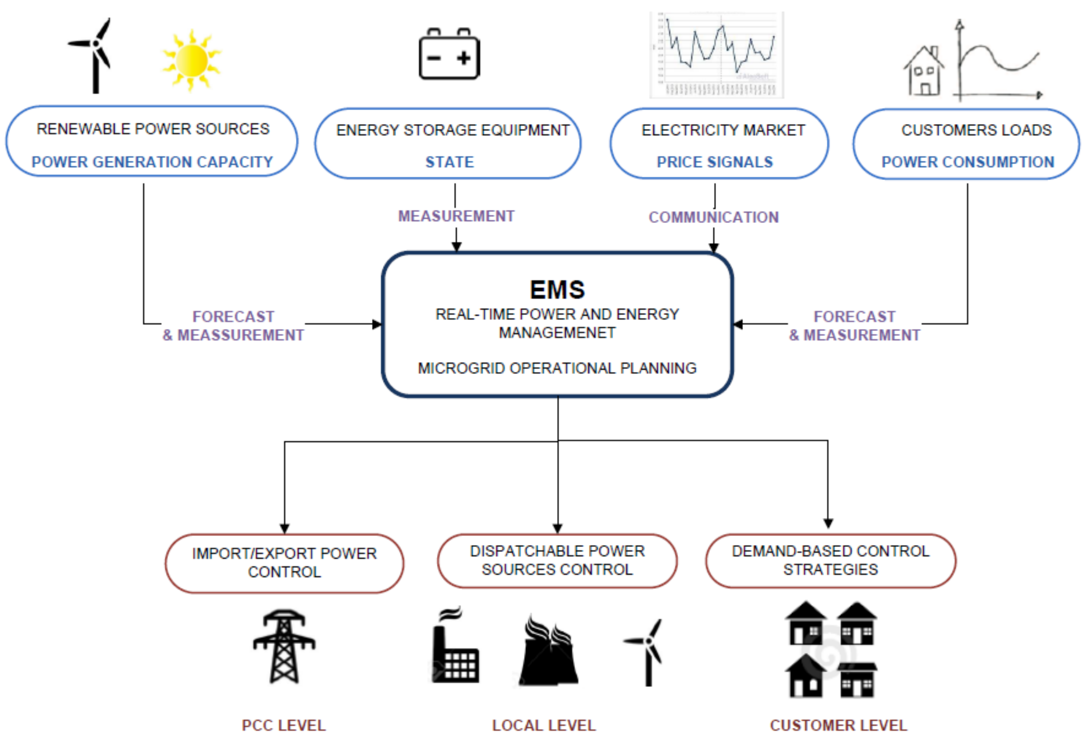

Figure 1. Energy Management System

Trends in microgrid control have been recently pointed out by D. Olivares et al. in [91]. They also present a brief review of the existing **EMS** architectures for microgrids in [92], identifying the main advantages of each approach, and have proposed a centralized EMS architecture for implementation on isolated microgrids in stand-alone mode of operation. D. Olivares D. y C.A. Cañizares search for a proper dispatch of the energy power and storage units, designing a centralized energy management system in [93]. In this paper, energy management problem is decomposed into unit commitment and optimal power flow problems in order to avoid a mixed-integer non-linear formulation.

Some authors look for new approaches for power sources scheduling in microgrids. A calculation method of microgrid surplus load is proposed by M. Chen et al. and the features and influencing factors of its ultra-short-term forecasting are discussed in [94]. A simulation model of microgrid with wind farms, micro-turbines and fuel cells is established. A similar vision of the same problem, including demand side management is introduced by R. Palma-Behnke et al. in [95]. An energy management system (EMS) minimizes the operational costs while supplying the load demands. Also, a neural network method for a two days ahead electric consumption forecasting is presented.

G. Celli et al in [96] develop a novel EMS that uses a Multi Layer Perceptron Neural Network for the optimal scheduling of generators in an industrial park. They train the Neural Network by using information about energy price, weather conditions and the forecasts on the energy and thermal load demand.

H. Kanchev in [97] proposes a deterministic EMS for a microgrid, including advanced PV generators with embedded storage units and a gas microturbine. A. Borghetti describes in [98] the functions of an energy resources scheduler implemented in a microgrid management system. The scheduler periodically updates the set points of DERs regulators in order to achieve economic, reliability and power quality objectives, starting from the load and renewable production forecasts and from the results of the system state estimation.

S. Chakraborty and M.G. Simoes in [99] and in [100], focus on renewable energy sources integration in a distributed generation system, implementing a distributed intelligent EMS to optimize operating costs. A Fuzzy ARTMAP Neural Network is used to predict hourly day-type outputs, based on which generation can be forecasted. Same authors introduce in [101] a Distributed Intelligent Energy Management System (DIEMS) to optimize operating costs of a representative PV-based microgrid.

A probabilistic EMS based on an efficient Point Estimate Method is proposed in [102] by S. Mohammadi. This method models the uncertainty in the power generation of the wind farms and the PV systems, the market prices and the load demands. Moreover, an AMFA is employed to achieve an optimal operational planning with regard to cost minimization. Niknam et al. introduce in [103,104] two different probabilistic algorithms in order to optimize a microgrid operation: a self-adaptive mutation technique of the GSA and a self-adaptive Charged System Search called SCSS, devised to upgrade the original CSS algorithm.

H. Vahedi et al study in [105], the optimal operating strategy and cost optimization scheme using Bacterial Foraging Algorithm (BFA). L. Lu et al. study in [106] propose a class of competitive online algorithms, called CHASE, which tracks the offline optimal in an online fashion. They also extend these algorithms to intelligently leverage on limited prediction of the future, such as near-term demand or wind forecast.

S. Tan et al in [107] search for an integrated solution that takes care of both microgrid load dispatch and network reconfiguration problems. The stochastic nature of wind, PV and load is taken into consideration and the bio-inspired optimization scheme Vaccine-AIS is adopted to solve the problem. A bio-inspired algorithm description is elaborated by S. Binitha and S. Sathya in [21]. In [108] a new bi-level prediction strategy is proposed for short-term load forecasting of microgrids by N. Amjady et al.. They propose a strategy composed of a feature selection technique and a forecast engine (including NN and EA) in the lower level as the forecaster and an enhanced differential evolution algorithm in the upper level for optimizing the performance of the forecaster.

In order to manage all the aspects that influence a microgrid deployment, the design of multi-agent and energy management systems is proposed by some authors towards an optimal microgrid control. Multi-agent systems in microgrid applications are review by A. Kulasekera y K. Hemapala in [109]. N. Hatziargyriou develops in [110] a centralized control for optimizing microgrids operation regarding information exchange, market policies, demand-side bidding and security, and quantifies economical, environmental and operational benefits for centralized controlled-microgrids in [111]. But the same authors have also published some papers about agent-based control for virtual power plants [112] and microgrids [113–116]. They present in a MAS-based control architecture for an islanded microgrid, and compares it with a centralized approach. Along these papers, these authors developed an agent control structure focused in allowing the agents to learn and adapt to the environment based on a reinforcement learning algorithm. Agents should be capable to learn to cooperate between each other and to solve a problem that requires planning for the future in a stochastic environment without the existence of a central controller.

T. Funabashi et al in [117] propose a microgrid control system using multi-agent technologies. In this control system, operation planning is realized based on generation and load forecasting by using ANN and fuzzy systems.

4. Conclusions and future trends

This paper provides an overview of the latest research developments concerning the use of optimization algorithms to aid microgrid planning. Since a general approach to microgrid planning has been developed, economic feasibility has been taken into account along the paper as a key factor. This survey of mathematical methods applied to microgrid planning can be useful for microgrid planners, or even to introduce power system engineers and young researchers in this field. After this review, some conclusions will be presented.

First of all, reviewed papers are classified in table 1 regarding the planning problem they try to solve and the optimization approach (classical vs multi-objective optimizacion). As it has been described in this table, linear optimization can be considered a good approach depending on the objective and constraints. Linear and non-linear problems are faced in technical papers in order to minimize operational costs or initial investment in generators and energy storage devices. Many optimization methods are based on traditional approaches, such as mixed-integer and interval linear-programming, while a growing number of research papers trend to use heuristic optimization. Heuristics, as it is shown in table 2, have become very popular in energy planning and designing problems such as GA, PSO and SA. As a consequence some new bio-inspired heuristics have been recently applied to microgrid planning such as AMFA, BFA, AIS and Vaccine-AIS. **GA and PSO are widely used algorithms for planning purposes in microgrids.** Operation scheduling is the most popular problem regarding economic feasibility issues for microgrids, as it has been summarized in table 3, in which a detailed list of references is presented. Regarding modern mathematical techniques, it can be highlighted that parallel processing has not been deeply explored for microgrid planning purposes.

The second conclusion of this review paper is about planning methodology. When reviewing technical literature about community systems planning, some defined problems may appear, as it is shown in figure 2. In this paper four common problems have been identified for an economic feasibility approach to microgrids: *power mix selection, sizing, siting and scheduling.* Most researchers propose techniques to solve these individual problems, but real-world planning problems require wider and deeper approaches. Since microgrid planning problems must be considered in an aggregated way. Planning and feasibility guidelines have been proposed for some specific islanded microgrid scenarios with defined constrains and uncertainties, such as for instance in military campus [118]. But suitable conditions for the long-term success of a commercial microgrid have not been still addressed. The more the real-market restrictions, uncertainties and optimization problems they can address, the better the conditions for a microgrid establishment will be defined. In conclusion, more complete optimization and multi-criteria approaches towards market-oriented solutions are expected to appear, focused not only on newer and better approaches to solve single planning problems, but also to solve global ones.

Finally, some trends in microgrid planning are described. Some of these new approaches to planning process may include GIS based techniques [50,55,119,120] and new algorithms associated to optimization, forecast and other microgrid related aspects. Other energy community systems, such as virtual power plants or district heating have many points in common with microgrids. Design and establishment processes of DH systems have been studied for a long time, such as control techniques for VPP. As a consequence, microgrid planning can be faced out using similar techniques. Technical literature previously applied to district heating systems have been considered in this paper. Regarding microgrid distributed control and operation, MAS are a hot topic in microgrids scheduling [64,121–124]. MAS-based systems are having a strong development, linking GIS, forecasting, optimization, risk analysis and decision making methods. They have been addressed to different objectives such as cost effectiveness, reliability, environmental, quality, protection and interaction with other microgrids.

Additional objectives can be considered in microgrids referring to economic feasibility. Microgrids can also be designed for supplying ancillary services. Indeed voltage support, reactive power support, peak load reduction, spinning reserve provision and thermal energy supplying are considered in some papers as [27,30,125]. As aforementioned in section 2 a real microgrid planning process can be described as a multi-objective, constrained, and stochastic optimization problem. That is the reason why sensitivity analysis has been revealed as a critical step in the microgrid planning in order to develop a robust architecture towards economic feasibility. A proposal for a microgrid planning process is presented in figure 2.

As it can be seen in this figure, an additional stage in microgrid planning called *pricing* has been also identified in this review. Pricing stage is the final stage of a commercial microgrid planning process. During this stage, microgrid managers define the final price of energy and ancillary services regarding different operational scenarios, costs and particular pricing policies. This last is out of scope of this review because: it is only applied to commercial microgrids, it is not usually based on optimization techniques, and it is a topic far from technical approach to microgrid planning. Microgrid pricing strategies may be considered in future work.

In authors' opinion, microgrids are destined to become the next electric power system evolution. At the same time, smartcities strategies are designed to integrate, or at least to coordinate different urban systems or urban services. Following this approach, electric power lines can also be used as communication buses and microgrids could be a good test bench not only for smartgrid applications, but also for smartcities system integration. This perspective will also affect the microgrid planning process in a near future.

Table 1 MG planning problems, methods and references regarding single or multiple objective optimization

APPROACH	METHOD-ALGORITHM	MAIN PROBLEM	REFERENCES
SINGLE-OBJECTIVE OPTIMIZATION	MILP	Power generation mix selection and sizing	32, 43, 44
	Lagrange multipliers-KKT conditions	Power generation mix selection and sizing	35
	Reduced Gradient Method	Storage devices mix selection and sizing	34
	MIP	Power generation mix selection and sizing	33, 36
		Storage devices mix selection and sizing	39
	SQP	Siting	51
		Operation scheduling	77
	DP	Siting	50
		Operation scheduling	71, 72
	MINLP	Operation scheduling	65, 66, 67
	IP	Operation scheduling	68
	LP	Operation scheduling	69,70
	MPDP	Operation scheduling	73
MULTI-OBJETIVE OPTIMIZATION	NSGA-II	Siting	55
	Simulation-accounting	Power generation mix selection and sizing	41, 42, 45, 46, 47, 48
		Storage devices mix selection and sizing	41
		Operation scheduling	42, 96, 97, 98, 99, 100, 101, 102
	Game theory	Operation scheduling	76

Table 2 MG planning problems, methods and references using heuristic optimization

HEURISTIC AND METAHEURISTIC OPTIMIZATION	EA	Power generation mix selection and sizing	36
	GA	Power generation mix selection and sizing	37
		Siting	54, 56, 58, 59, 63
		Operation scheduling	75, 88, 89, 90
	SA	Power generation mix selection and sizing	38
		Siting	52, 60, 61
	PSO	Storage devices sizing	40
		Siting	54, 57, 62,63
		Operation scheduling	77, 79
	AIS	Siting	63
	VACCINE-AIS	Siting	63
		Operation scheduling	107
	MDPSO	Siting	53
	MADS	Operation scheduling	74, 78
	MGSA	Operation scheduling	82
	AMFA	Operation scheduling	102
	GSA	Operation scheduling	103
	SCSS	Operation scheduling	103
	BFA	Operation scheduling	105
	CHASE	Operation scheduling	106

Table 3 References per planning problem and optimization approach

APPROACH	MAIN PROBLEM	PAPERS
Single objective optimization	Power generation mix selection and sizing	32, 33, 35, 36, 43, 44
	Storage generation mix selection and sizing	34, 39
	Siting	50,51
	Operation scheduling	65, 66, 67, 68, 69, 70, 71, 72, 73, 77
MO optimization	Power generation mix selection and sizing	41, 42, 45, 46, 47, 48
	Storage generation mix selection and sizing	41
	Siting	55
	Operation scheduling	42, 76, 96, 97, 98, 99, 100, 101, 102
Heuristic optimization	Power generation mix selection and sizing	36, 37, 38
	Storage generation mix selection and sizing	40
	Siting	52, 53, 54, 56, 57, 58, 59, 60, 61, 62, 63
	Operation scheduling	74, 77, 78, 79, 82, 102, 103, 105, 106, 107

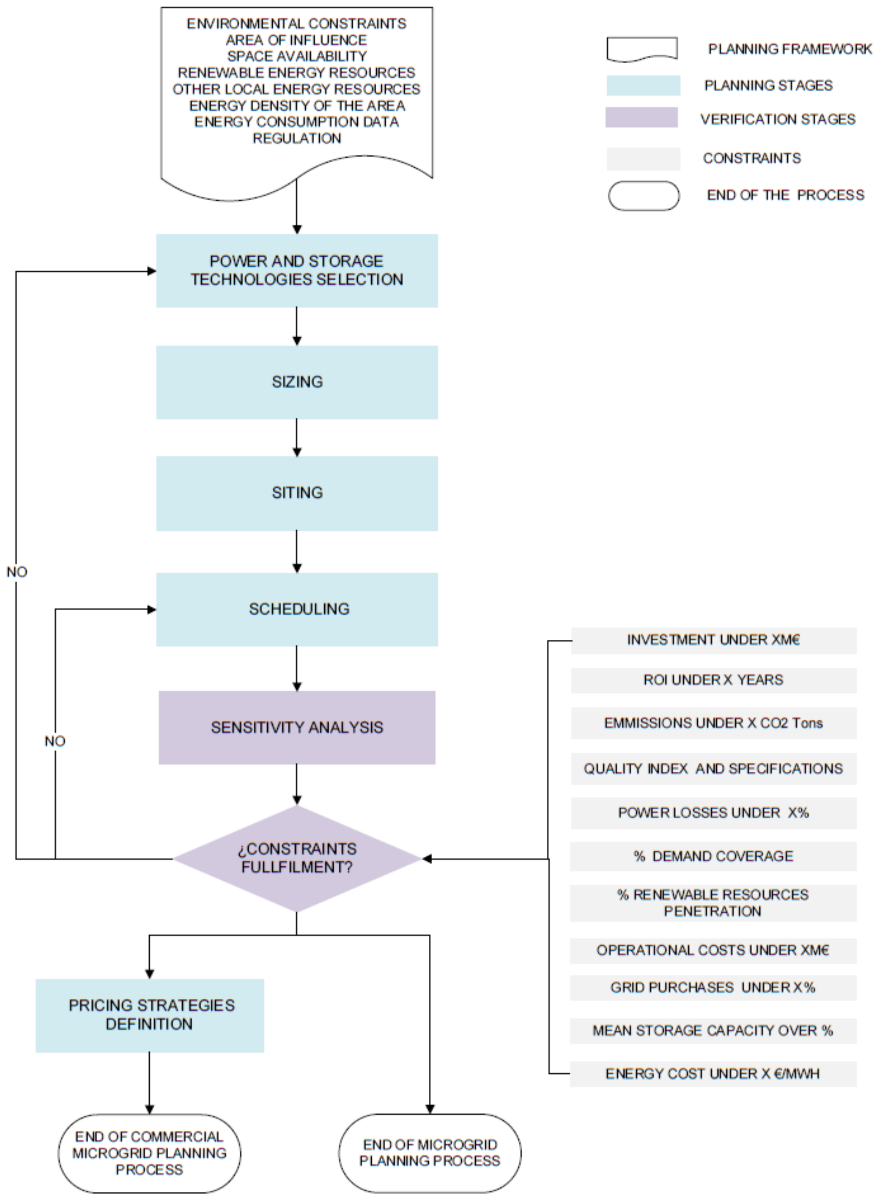

Figure 2. Microgrid planning process scheme

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