A Generalized Framework for Optimal Sizing of Distributed Energy Resources in Micro-Grids Using an Indicator-Based Swarm Approach

Maria Luisa Di Silvestre, Giorgio Graditi, and Eleonora Riva Sanseverino

***Abstract*—In this paper, a generalized double-shell framework for the optimal design of systems managed optimally according to different criteria is developed. Optimal design is traditionally carried out by means of minimum capital and management cost formulations and does not typically consider optimized operation. In this paper, the optimized multiobjective management is explicitly considered into the design formulation. The quality of each design solution is indeed defined by the evaluation of operational costs and capital costs. Besides, the assessment of the operational costs term is deduced by means of the solution of a multiobjective optimization problem. Each design solution is evaluated using the outcomes of a multiobjective optimization run: a Pareto hyper-surface in the n-dimensional space of the operational objectives. In the literature, commonly the evaluation of each design solution is carried out based on an approximate evaluation of the operational costs, not considering the real multiobjective optimized management. In this paper, such assessment is carried out using a suitable convergence indicator typically used for multiobjective optimization algorithms. The application is devoted to the problem of optimal sizing of distributed energy resources in medium voltage or low voltage microgrids. For this problem, the identification of the multiple operational impacts comes along with the solution of the optimal unit commitment of distributed generators. After the introductory section, the problem formulation is presented and an interesting application of the considered approach to the design of distributed energy sources in a microgrid is shown.**

***Index Terms*—Glow-worm optimization, indicator based evolutionary algorithm, microgrids, NSGA-II, planning.**

I. Introduction

In the formulation of many optimal design problems, cost and efficiency must be considered with equal priority, both terms depending on how the system is operated. When management is accomplished in an optimal way, the design problem is made awkward due to the fact that the operational costs are given by the solution of an optimization problem. In this paper, the authors adopt a double-shell approach for the design of engineering systems for which it is required to carry out a multiple criteria optimized management. The investigated application field is that of the optimal sizing of distributed energy resources (DER) in microgrids where optimal management involves the minimization of active losses, operational costs and emissions. For these systems, due to the complexity of the design problem, often heuristic approaches, such as evolutionary computation, are used to solve the issue. Fig. 1 shows the flowchart with the main procedures of the algorithm for the optimal design based on a heuristic population based approach.

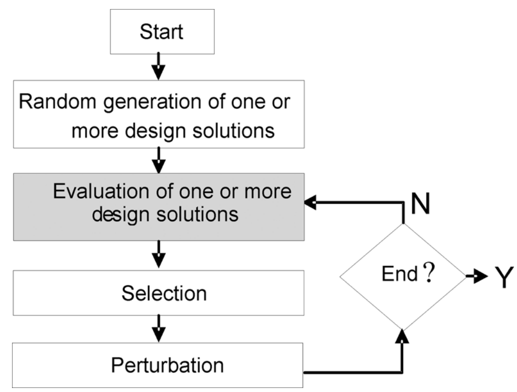

Fig. 1. Flowchart of a heuristic-based design approach.

The approach is composed of two shells. The outer shell consists of the iterative population-based heuristic algorithm. The random generation of a population of suitably coded design solutions is first carried out, then solutions are evaluated and subjected to the recombination cycle made of selection and perturbation operators. The evaluation–recombination cycle is then repeated until the termination condition is reached. The gray box represents the inner shell where the procedure for the evaluation of a design solution is carried out.

Such a procedure implies the solution of an optimal management problem in order to precisely account for management costs. Generally, the identification of the latter management costs requires the solution of a multiobjective optimization problem.

Fig. 2 describes the problem of the evaluation of a single design solution that can be operated in different modes through a double-shell approach. In the figure, the identification of the best operational solutions is carried out solving a multiobjective optimization problem.

Such a set of equally optimal operational solutions is located on a nondominated front in the n-dimensional space of the operational objectives.

It is clear that the definition of the goodness of a design solution is not easy, since each design solution can be operated in different modes.

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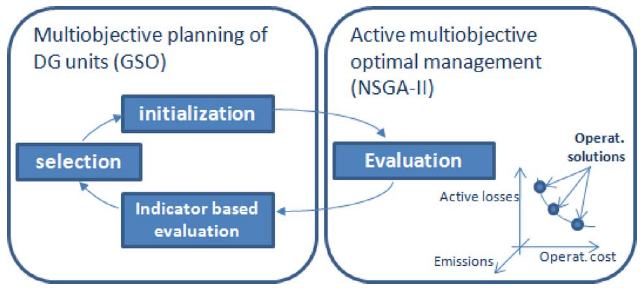

Fig. 2. Evaluation of a single design solution in the double-shell approach.

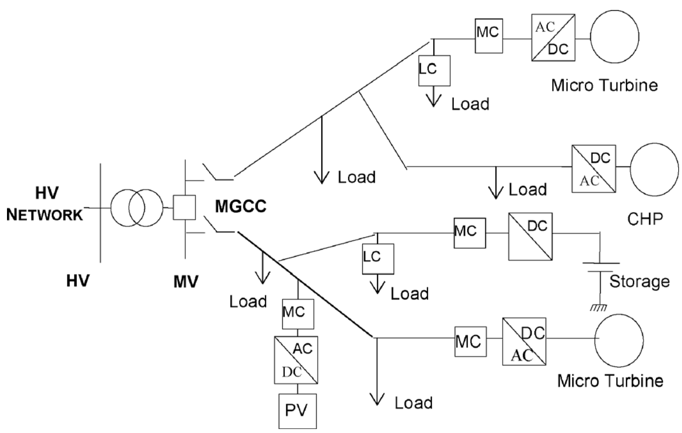

Fig. 3. Typical MV microgrid with its control devices.

Indeed, in modern distribution systems, smart grids or microgrids, differently from standard active distribution systems, the distributed energy resources are typically managed optimally and cooperatively in order to guarantee secure working conditions even in absence of the main grid.

Microgrids are indeed small medium voltage (MV) or low voltage (LV) active networks distribution systems, characterized by a high level of penetration of local electric generating units, enough to supply entirely a local load demand. Based on technologies such as internal combustion engines, small and micro gas turbines, fuel cells, photovoltaic and wind plants, the distributed generation units, (DG units), in microgrids are commonly in the range of 3 to 200 kW. DG units, located within the electric distribution system at or near the end user, are remotely controllable and can work, parallel to the electric utility or stand-alone, cooperatively to improve power quality and to reduce operational costs.

In Fig. 3, the typical layout of a MV microgrid is represented.

As Fig. 3 shows, the microgrid is supplied from the main high voltage (HV) grid through an HV/MV transformer. The microgrid central controller (MGCC), is located downstream the transformer; the microsource controller (MC) and the load controller (LCO) are respectively installed close to the distributed energy resources (DERs), including DG units, storage units, and loads. In the same figure, PV identifies the photovoltaic units, CHP indicates the combined heat and power generating units, while ac/dc indicates the inverter. The inverter interfaces the generating units with the electric grid. It is able to change voltage module and displacement in order to adapt to the current operating requirements. The load controllers and microsource controllers are usually implemented into inverters control logic. Every generating unit produces LV electric power and is connected to the grid through an MV/LV transformer. Among other functions, the MGCC [1] plays a fundamental role for optimal power generation dispatch (generation unit commitment), arranging the active and reactive power set points for the following day in order to minimize various technical, environmental, and economical objectives. It is thus clear that the design of modern power distribution systems cannot ignore a precise evaluation of operational costs. Some papers on the issue of the optimal design of DER units in distribution systems do not even consider explicitly the solution of the operational problem into the design problem [2]–[5]. This is due to the fact either that the DER units are considered to be operated not cooperatively or that they are not controllable and thus based on renewables. To understand the reasons behind the different formulations of the design issue that can be found in the literature, it is important indeed to consider the different points of view. It can indeed be the case that the distribution utility does not own the plants or that the distribution utility owns the plants. A large review on the state of the art on the theme of designing microgrids (also named smart grids) is reported in [6]. The work gives also a large insight into the formulation of the design problem putting into evidence the different aspects to be considered.

More recently, in [7], the authors find an optimal location of customer-owned renewable-based DER in a distribution system so as to minimize energy losses. The methodology is based on generating a probabilistic generation-load model that combines all possible operating conditions of the renewable generation units, with their probabilities, hence accommodating this model in a deterministic planning problem.

In [8], the power losses are considered in the problem formulation, but they are evaluated considering an estimated working condition of the installed DG units. Also in this case, the units are owned by customers. Soroudi and Ehsan in [9] consider the design issue as a multiobjective problem for a distribution utility owning the DG plants, but the running costs are not considered in the problem formulation, while a further objective about technical constraints dissatisfaction is introduced. Therefore, capital costs are considered in the formulation, but no optimal management problem is solved. Also, [10] does not consider optimized management of utility owned DG units, although it adopts a formulation that includes reliability and islanded operation issues. Reference [11] and, more recently, [12] solve the design issue comparing the attained results with those available in existing systems but still not accounting for optimal operation of DG units. Other papers evaluate the operational costs considering that they are derived from the optimal and coordinated management of DER.

In [13] and [14], the point of view is still that of the distribution utility owning the DER plants. In this case, the multiobjective optimal design is executed taking into account single-objective formulations for the operational issue but neglecting its multiobjective nature. Indeed, the optimal operation issue is formulated considering just costs minimization and calculating the other operational objectives (yearly CO_2 emissions and energy losses) required for the multiobjective optimal design based on the minimum cost solution. In fields like electrical power distribution, where the market liberalization has created many different interests and where ICT (Information and Communications Technology) allows cheap monitoring and control of energy resources, it is requested to use suitable tools both for solving operation and design issues. In this sense, cooperative approaches such as multiobjective optimization, to model interactions between different actors, appear to be acceptable if there is a unique point of view and a unique owner of the plants; otherwise, it would be advisable to formulate the operational problem considering competing interests. In any case, appropriate design of microgrids should be grounded on the evaluation of optimal management strategies of the DER; this is one of the elements of novelty of the proposed approach based on a double-shell architecture.

The approach is a general framework for the solution of any design issue for systems that can be operated considering different objectives. The choice of dividing the problem into two different subproblems (two shells) is grounded on the following considerations. Consider a unique multiobjective optimization problem consisting both of the design problem and of the optimal operation. In this case, the optimization variables is a string that can ideally be separated in two parts. The first, say part A, contains data about size and/or type and/or location of the DER to be installed, while the second, say part B, contains their management plan in the considered time frame. Such formulation leads to two major drawbacks. First of all, the number of variables is increased. Second, there is in general a large difference in weight between the two parts of the optimization string, thus leading to a "deceptive"[1] behavior. Indeed, for each design plan (part A), there may be both very good and very bad solutions according to the operational plan (part B) considered. Hence, the optimal design solution, leading to very few good operational plans, can be easily lost during the search.[2] It is possible to overcome both drawbacks above by separating the two issues considering a nested formulation of the multiobjective operational issue into the general multiobjective optimization design problem.

In this paper, following the route traced in [17], the authors consider the nested formulation with the internal shell providing the outer shell an evaluation of multiobjective operation of each design solution. The point of view is that of the distribution utility owning the DG plants. Another methodological element of novelty in the proposed approach is the use of a multimodal optimizer with an indicator-based methodology to evaluate the quality of each single design solution. The use of an efficient multimodal optimizer as the Glow-worm optimizer allows indeed to capture more optima, namely more design solutions showing high quality.

The indicator-based evaluation implicitly expresses the possibility to operate the solution in different modes that are almost equally optimal. The indicator-based evaluation is outlined in the following section.

[1]In the GA's literature, a problem is said to be "deceptive" if the building blocks of the solution string identified actually lead the GA away from the global objective. In this case, the term is referring to the large difference, in terms of influence on the objective function's value, of contribution of the two parts of the optimization string.

[2]In this case, the average fitness of the relevant "schema" is quite low; see "Building block hypothesis" [15] (founding the GAs approach and their extension to real coded GAs [16]): *A genetic algorithm creates stepwise better solutions by recombining, crossing, and mutating short, low-order, high-fitness schemata* [15]. If the optimal design solution is A^*, the relevant fitness (calculated as the average fitness of all solutions attainable with those bits kept at a fixed value) may be lower than that of others and will not be considered for further improvements.

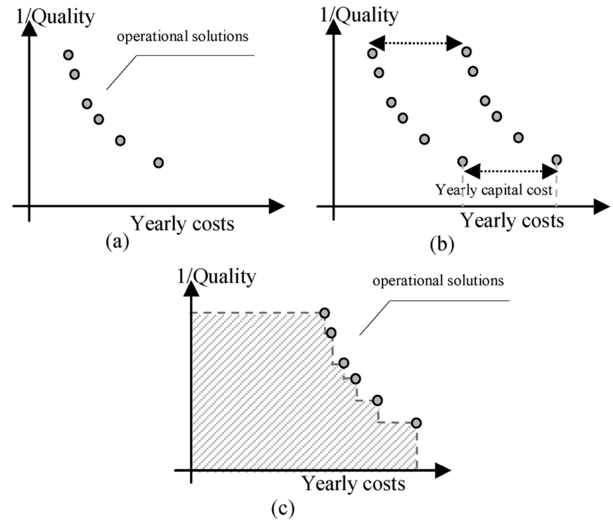

Fig. 4. (a) Set of nondominated solutions outputted by the optimal management algorithm. (b) From the optimal management to the optimal design evaluation. (c) Size of space covered in the yearly cost/quality-1 objectives space.

II. Indicator-Based Evaluation of a Design Solution

At this point, it is important to operatively clear out how the management costs for a design solution can be evaluated.

The possibility to consider as a whole the entire Pareto front outputted by the solution of the optimal management issue is given by the calculation of a general quality index, the size of space covered [18]. The latter index concerns the size of the hyper-volume in the objectives space delimited by a set of non dominated solutions. The union of all hyper-rectangles covered by the nondominated optimal solutions constitutes the space totally covered, its size is used as an indicator of the quality of the front. This concept may be extended to more than two dimensions. An advantage of this measure is that each front can be evaluated independent of the other fronts. In the field of optimal design, each solution is typically evaluated both in terms of operational costs and quality terms, such as emissions or power losses, as well as in terms of design costs.

Fig. 4(a) shows a set of nondominated solutions outputted by an optimization run devoted to optimal management in a two-dimensional space of the objectives. Of course, in order to consider the capital costs, for each solution, the yearly operational cost is summed up with the annualized capital cost of the relevant design solution [see Fig. 4(b)]. Finally, Fig. 4(c) shows the indicator size of space covered for the attained nondominated front taking into account both annualized capital and yearly management costs.

In this way, it is possible to assess a design solution giving a quality to each front, considering it as a single entity. Besides, it is also possible to compare multiobjective design solutions using a single index for each design solution catching the entire operational behavior of the design solution instead of considering a single management strategy out of the Pareto front.

Namely, the Pareto optimal operational solutions can be positioned on a multidimensional objectives space, and these are those minimizing cost and maximizing quality assessed on a yearly basis.

To evaluate the relevant design solution, it is enough to sum up, for each solution, the annualized capital cost to the yearly operational cost to get the assessment of the considered design solution according to different criteria. At this point, it is possible to evaluate the size of space covered of the attained front and to characterize it by a unique number that captures the global behavior of the design solution when it is optimally operated.

III. Microgrids Optimal Design

In recent years, the attention regarding the analysis and design of modern distribution systems is quite high. The European community indeed is supporting the research in this field with a specific platform [19]. The design of modern power distribution systems thus cannot ignore a precise evaluation of operational costs. In the following sections, the optimal management problem formulation is given (inner shell) as well as the optimal design problem formulation (outer shell).

IV. Inner Shell: Multiobjective Unit Commitment

The unit commitment problem is a research field often studied in the power systems' literature. This is an optimization problem in which the scheduling of generators (and other resources) give rise to minimum cost or maximum profit while meeting electrical energy request is searched. The unit commitment problem can be included into higher level system design where broad parameters such as generators size, electricity and/or heat storage capacity, and boiler capacity are optimized based on their optimal operational schedule. The state of the art on the topic can be divided based on the different solution techniques for this issue: methods like dynamic programming, simulated annealing, tabu search, fuzzy computing, and genetic algorithms can be implemented to bring to a successful conclusion the issue. The literature on the unit commitment can also be dealt with from the point of view of the formulation of the optimization problem as well as of the analysis of particular technical constraints, such as generator ramp limits, or environmental constraints and carbon dioxide emissions targets. The contribution in [20] shows a complete survey of the most interesting works on the topic. More recently, in [21], a multiobjective approach using a fuzzy formulation for representing the input variables allows the handling of uncertainties. In addition, the test system in [21] is small, and this allows the authors to neglect the power losses term and to consider an easier formulation of the problem. Paper [22] also does not account for power losses evaluation due to the limited size of the system. The work in [23] aiming at optimal management of modern distribution systems proposes a neural network-based approach, including a distribution management systems (DMS) policy both for intraday and on a one-day-ahead scheduling. The proposed approach could be easily integrated as an inner shell for evaluating the operating objectives but only after a suitable training phase carried out on already known optimized layouts. Reference [24] also deals with optimal management proposing a new constrained multiobjective optimization technique, which seems to outperform NSGA-II. However, it cannot still account for mixed integer variables. In the case studied in this paper, it is more suitable to adopt a strategy to derive the optimized layouts using a classical unit commitment formulation within the design problem formulation. From the analytical point of view, the problem of optimal power dispatch among DER units through unit commitment in microgrids seems to be very complex due to the nonlinear nature of the multiple objectives to be optimized. Moreover, the possible presence of real and reactive storage units affects the power dispatch and the way in which voltage regulation is carried out; thus, it is required to control their insertion status. For a given design layout (capacity, typology, and location of dispersed generation units; capacity and location of capacitor banks; capacity and location of storage units), knowing the hourly upper and lower production limits of each DG unit and the hourly loading level of each bus of the electrical distribution network, the objectives to be achieved are as follows:

1) the minimization of the yearly power losses;
2) the minimization of the yearly overall production costs;
3) the minimization of the yearly CO_2 emissions.

The independent optimization variables are the hourly power productions of the DER units. While other unknowns of the problem are as follows:

1) the hourly storage units level;
2) the hourly capacitor banks status.

Consider a n-bus microgrid system with the following:

— $N\mathrm{fix}$ load or generation nodes with fixed forecasted real and reactive power demands or injections;
— $N\mathrm{DER}$ controllable DER units;
— $N\mathrm{c}$ controllable capacitor banks.

The problem is that to identify the real-valued vector identifying the operating points of the DER units (electrical generation and storage units) in the network hour by hour of the $N\mathrm{day}$ representative days of the different periods of the year. The vector has $2 \times N_{\mathrm{DER}} \times 24 \times N\mathrm{day}$ real elements; a subset of it taken for a generic hour h of the generic day d takes the following form:

$$x_{h,d} = \left[P_1^{g,h,d}, P_2^{g,h,d}, \ldots, P_{N_{\mathrm{DER}}}^{g,h,d}, Q_1^{g,h,d}, Q_2^{g,h,d}, \ldots, Q_{N_{\mathrm{DER}}}^{g,h,d}\right] \quad (1)$$

the entire vector x can thus be written as

$$x = [x_{1,1}, x_{2,1}, \ldots, x_{24,1}, x_{1,2}, x_{2,2}, \ldots, x_{24,2}, \ldots x_{1,N\mathrm{day}}, x_{2,N\mathrm{day}}, \ldots x_{24,N\mathrm{day}}] \quad (2)$$

subject to the following constraints:

1) upper and lower limits of the values of the controlled variables, namely the DER units power outputs, taking into account the required power reserves:

$$P_{j\min}^{g} \leq P_j^{g,h,d} \leq P_{j\max}^{g} \quad (3)$$
$$Q_{j\min}^{g} \leq Q_j^{g,h,d} \leq Q_{j\max}^{g}$$
$$h = 1, \ldots 24,\ d = 1, \ldots .N_{\mathrm{day}},\ j = 1, 2, \ldots .N_{\mathrm{DER}} \quad (4)$$

where

a) $P_j^{g,h,d}$, P_{jmin}^{g}, P_{jmax}^{g}, j $= 1, 2, \ldots .N_{\mathrm{DER}}$, respectively, represent the active production at hour h of day

d, the minimum and maximum limits of real power at the j^{th} DER units;

b) $Q_j^{g,h,d}$, $Q_{\mathrm{jmin}}^{g,}$, Q_{jmax}^{g}, j $= 1, 2, \ldots N_{\mathrm{DER}}$, respectively, represent the reactive production at hour h of day d, the minimum and maximum limits of the reactive power at the j^{th} DER unit;

2) the solution must give rise at all nodes to limited voltage drops;
3) the solution must satisfy the constraint about power transfer limits in the network lines;
4) the solution must satisfy the integral constraint about the energy stored in batteries, namely the starting state of charge (SOC) level must equal the ending SOC level;
5) the solution must satisfy the generators ramping limit constraint.

As far as the latter constraint is concerned, it must be here underlined that for microgrids, where, in general, generators are of small size (rated power below 1 MW), the constraint can be reasonably neglected with an elementary time interval of 1 h. Anyway, if required, depending on the optimization algorithm employed such constraint can easily be considered. In particular, for evolutionary algorithms, it will be sufficient to integrate suitable limits to the variables perturbation in each time interval. The issue is that of finding the feasible vector x optimizing the following criteria:

— Yearly joule losses in the system:

$$O_1(x) = \sum_{d=1,N\mathrm{day}} \sum_{h=1,24} \sum_{i=1,n} (P_i^{g,h,d} - P_i^{c,h,d})\Delta t. \qquad (5)$$

In this expression, the energy losses in the system are assessed as the summation of the differences between the generated ($P_i^{g,h,d}$) power and the consumed ($P_i^{c,h,d}$) power at each bus multiplied by $\Delta \mathrm{t}$ which, in this case, is 1 hour. The quantities in round brackets are considered constant in the considered time interval.

— Yearly fuel consumption cost:

$$O_2(\boldsymbol{x}) = \sum_{d=1,N\mathrm{day}} \sum_{h=1,24} \sum_{i=1}^{N_{\mathrm{DER}}} C_{\mathrm{Pi}} P_i^{g,h,d} \Delta t \qquad (6)$$

where $\mathrm{C_{Pi}}$ is the unitary fuel consumption cost of the i^{th} source, $P_i^{g,h,d}$ the power output of the i^{th} source at hour h and day d, considered constant in time interval $\Delta \mathrm{t}$ (in this case, it is 1 hour).

— Yearly CO_2 emissions [25]:

$$O_3(\boldsymbol{x}) = \sum_{d=1,N\mathrm{day}} \sum_{h=1,24} \sum_{i=1}^{N_{\mathrm{DER}}} Em_i^{h,d}. \qquad (7)$$

where $Em_i^{h,d}$ is the amount of $\mathrm{CO_2}$ emissions from the i^{th} DER unit at hour h during day d. Therefore, the formulated problem is that to determine the operating points of the DER units (generation and storage units) giving rise to a technical–economical optimum as a compromise between minimum cost operation and high-quality service. Minimum cost operation is ensured if the overall fuel consumption is minimum.

The problem is dealt with using a multiobjective evolutionary approach: the nondominated Sorting Genetic Algorithm II [26]. Constraints are taken into account by means of the constraint domination concept [28]. In the following section, a few concepts about non domination and multiobjective optimization are recalled.

A. NSGA-II for Multiobjective Optimization

A multiobjective optimization problem has a number of objectives that have to be maximized or minimized [27]. There are different ways to deal with a multiobjective optimization problem, e.g., objectives can be aggregated into a single one, but a lot of work in the area of multiobjective optimization has concentrated on the approximation of the Pareto set by stochastic population-based methods. Evolutionary and metaheuristic techniques are suitable for this task, since many of these methods proceed through the modification of sets of solutions (population-based algorithms). Accordingly, the outcome of a population-based multiobjective optimization algorithm is considered to be a set of mutually nondominated solutions, or Pareto set approximation. The concept of nondominance is one of the basic concepts in multiobjective optimization. Further details can be found in [27]. It is important to underline that the concept of optimality in multiobjective optimization is related to a set of solutions, rather than to a single one. Sets of solutions can be equivalent if we aim at optimizing more than one objective. From the above discussion, it is possible to point out that there are primarily two goals that a multicriterion optimization algorithm must achieve:

1) guide the search towards the global Pareto-optimal region;
2) maintain population diversity in the Pareto-optimal front (prevent crowding of solutions).

In the following section, the well-known Nondominated Sorting Genetic Algorithm II proposed by Deb *et al.* [26] is briefly recalled. In this algorithm, the concept of non dominance is used for solutions prizing. The algorithm described in the following applies to constrained multiobjective problems, using the constraint domination concept for solutions selection. The Non-dominated Sorting Genetic Algorithm II is an evolutionary optimization method, where sets of solutions are evolved by means of recombination operators such as mutation and crossover. As Non-dominated Sorting Genetic Algorithm [27], NSGAII divides the population in fronts of nondominated solutions so that the search can be addressed towards interesting areas of the search space, where the global Pareto optimal region is presumably located. In NSGA and NSGA-II, solutions are prized on the basis of their non-domination level, which is called solutions ranking. However, basically, NSGA-II varies from the NSGA in three main things. It is more efficient computationally, since the ranking of solutions based on nondomination is performed with an $O(mNP2)$ algorithm, instead of $O(mNP3)$, where m is the number of objectives, and NP is the population size; it significantly prevents the loss of good solutions once they have been found (elitism); it does not need any parameter specification. A binary tournament selection operator is used to select the offspring population, whereas crossover and mutation operators remain as usual. Before selection is performed, the population is ranked on the basis of an individual's nondomination level and, to allow the diversification, a crowding factor is calculated for each solution. In [26], further details about the main operators of the algorithm are given.

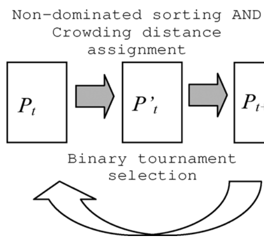

Fig. 5. NSGA-II algorithm.

B. Crossover and Mutation Operators

Crossover and mutation operators have an implementation depending on the problem at hand. In this paper, these operators are implemented so as not to disrupt feasible solutions (energy balance in storage systems at every hour); please check [17]. In Fig. 5, one cycle of the NSGA-II procedure is represented. P_t and P_{t+1} are the populations of solutions at iteration t and $t+1$, while P_t' is a partially ordered ($\geq_n$) set of solutions.

In the following section, the outer shell, devoted to the optimal design of microgrids, is described.

V. Outer Shell: Optimal Design Using Glow-Worm Swarm Optimization

The optimal sizing of distributed energy resources, whether storage systems, renewables-generation based (wind or PV units) or not (CHP and gas micro-turbines), is carried out solving an optimal design problem. The optimal location problem is not studied here since often there are spatial and environmental (mostly PV and wind) constraints over it. The objective function is the size of space covered calculated as described in Section I. The space of the objectives in which the SSC index is calculated includes the yearly Joule losses, the yearly costs (capital and management), and the yearly CO_2 emissions. The function to be minimized is thus

$$\begin{aligned}\text{Min } f(y) &\\ = \text{Min} \sum_{k=1}^{N\text{nd}} &\big[O_1(x_k) * \big(O_2(x_k) + \text{YearlyCapitalCost }(y)\big)\\ &*O_3(x_k)\big] \end{aligned} \tag{8}$$

where

$$y = [A_{n1}, A_{n2}, \ \ldots \ , A_{n_{\text{NDG}}}],$$

namely y is the design solution giving rise to many possible operational solutions, and x is described in (2). Such solutions are optimized and a subset of $N\text{nd}$ nondominated solutions x_k is identified using the inner shell algorithm (NSGA-II). Such subset is used to evaluate the function $f(y)$ in (8). A_{nj} is the rated size of the jth DER unit to be optimized. This value can range between 0 and the maximum possible commercial size.

The solution method is the Glow-worm Swarm Optimization (GSO) algorithm [29]. The latter takes inspiration from competitive learning, and, for this reason, it has the property of capturing many optima and thus many design solutions for the same problem showing the same SSC index. In GSO, a swarm of agents are initially randomly distributed in the search space. Agents (glow-worms) are characterized by a real quantity (luciferin, l) whose intensity is proportional to the associated capacity to interact with other agents within a variable neighborhood. In particular, the neighborhood is defined as a local-decision domain that has a variable neighborhood range r_{id} bounded by a radial sensor range r_s ($0 < r_{\text{id}} \leq r_s$). An agent i considers another agent j as its neighbor if j is within the neighborhood range of i and the luciferin level of j is higher than that of i. The decision domain enables selective neighbor interactions and aids information of disjoint subswarms. Each agent is attracted by those agents in the neighborhood with a higher level of luciferin. Agents in GSO depend only on information available in their neighborhood to make decisions. Each agent selects, using a probabilistic mechanism, a neighbor that has a luciferin value higher than its own and moves towards it. These movements, which are based only on local information and selective neighbor interactions, enable the swarm of agents to partition into disjoint subgroups that steer toward, and meet at, multiple optima of a given multimodal function.

The GSO algorithm starts by placing a population of n_g agents randomly in the search space so that they are well dispersed. Initially, all the agents contain an equal quantity of luciferin l_0. Each iteration consists of a luciferin-update phase followed by a movement phase (update-position) based on a transition rule.

A. Luciferin-Update Phase

The luciferin update depends on the function value at the agent's position.

$$l_i(\mathrm{t}+1) = (1-\rho)\cdot \mathrm{l}_i(\mathrm{t}) + \gamma \cdot f(y_i(\mathrm{t}+1)) \tag{9}$$

where $l_i(t+1)$ represents the luciferin level associated with glow-worm i at time t, ρ is the luciferin decay constant ($0 < \rho < 1$), γ is the luciferin enhancement constant, and $f(y_i(t))$ represents the value of the objective function at agent i's location ($y_i(\mathrm{t})$) at time t evaluated according to (8).

B. Update-Position Phase

During the update position phase, each agent decides, using a probabilistic mechanism, to move toward a neighbor that has a luciferin value higher than its own:

$$y_i(t+1) = y_i(t) + s\left(\frac{y_j(t) - y_i(t)}{\|y_j(t) - y_i(t)\|}\right) \tag{10}$$

where $yi(\mathrm{t}) \in R^{N\text{DER}}$ is the location of glowworm i, at time t n the N_{DER}-dimensional real space $R^{N\text{DER}}$ and s (> 0) is the step size. Further details about the algorithm can be found in [29].

Below, Fig. 6 shows the flowchart of the glow-worm-based outer shell for optimal design of microgrids.

VI. Application and Results

Simulations have been carried out on a low voltage 15-buses network taken from the literature [17], [30].

The planning methodology has been entirely implemented using an object-oriented programming language (Delphi Pascal). The algorithm for the load flow is the classical Newton Raphson. In the network, it is decided to install two photovoltaic generation systems. In the system, also three storage units are installed as well as three reactive compensation units. A micro-turbine is also installed at one of the buses. The system is connected to the main grid. The system is depicted in Fig. 7.

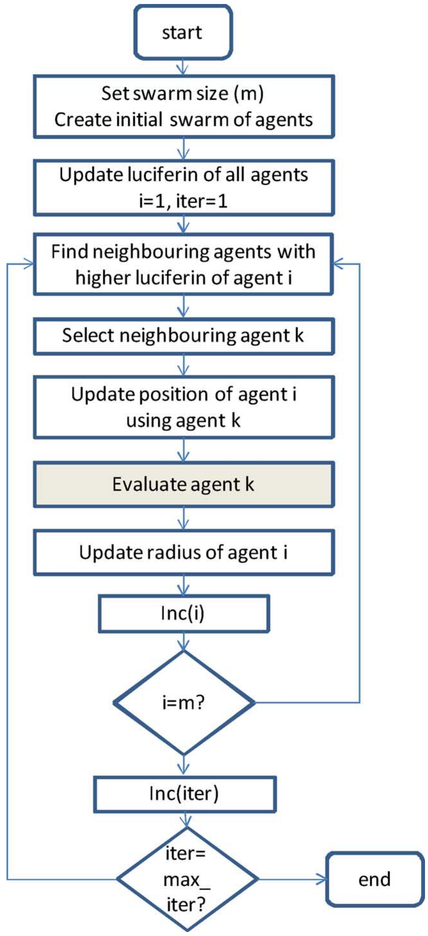

Fig. 6. Flowchart of the double-shell approach (outer shell).

TABLE I
COST OF THE DIFFERENT UNITS

unit	Cost [u.m.]
Battery	450 u.m./kWh
PV plant	10 u.m./kW
Microturbine	2 u.m./kW

TABLE II
ELECTRICAL FEATURES OF THE LINES

branches	R[Ω]	X [Ω]
2-3	0.0088	0.00462
2-14	0.004	0.00168
2-15	0.0104	0.00546
4-5	0.132	0.0028
4-10	0.1875	0.027375
6-10	0.01625	0.00455
7-10	0.013	0.00546
8-9	0.03	0.0126
8-10	0.004	0.00168
9-11	0.024	0.01008
11-12	0.004	0.00168
11-14	0.02	0.0084
12-13	0.016	0.00672

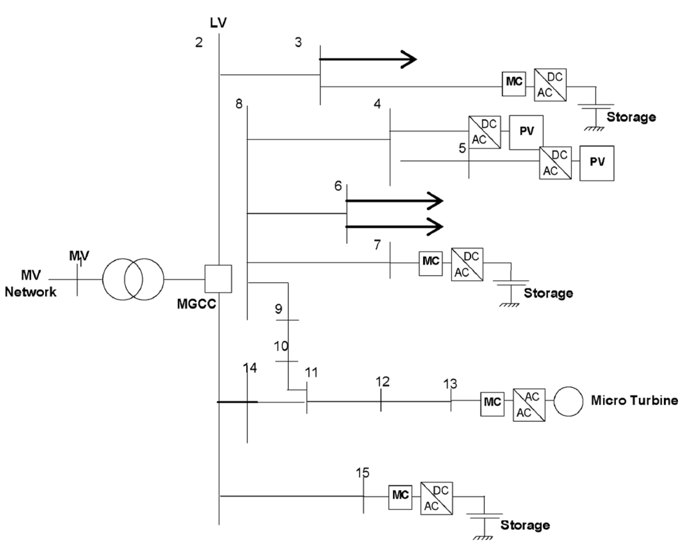

Fig. 7. Test system.

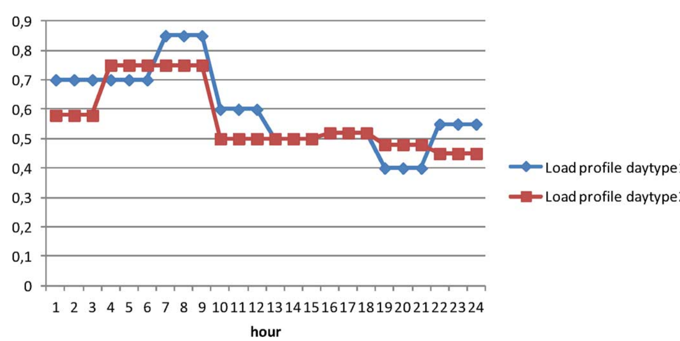

Fig. 8. Load at node 6 in the two typical days considered.

The amortization rate of all the components to be sized is 20%, the installation cost is reported in Table I.

The electrical system is described in Table II.

The load nodes have a behavior depicted in Fig. 8. Two typical days (winter day is type 1 and summer day is type 2) along the year have been considered for the optimization. The PV plant at node 5 behaves as described in Fig. 9.

In the following paragraphs, the output of the proposed design approach is presented using different graphs. The applications aim at the following:

1) showing how the GSO finds multiple optima;
2) evaluating the computational efficiency of the whole algorithm and finding the parameters on which it depends.

The internal shell NSGA-II is run with a population size of $N_P = 30$ elements and 50 iterations, mutation probability 0.1, and the crossover probability is 0.7. The outer shell, namely the glow-worm optimizer, uses $= m = 100$ glow-worms and

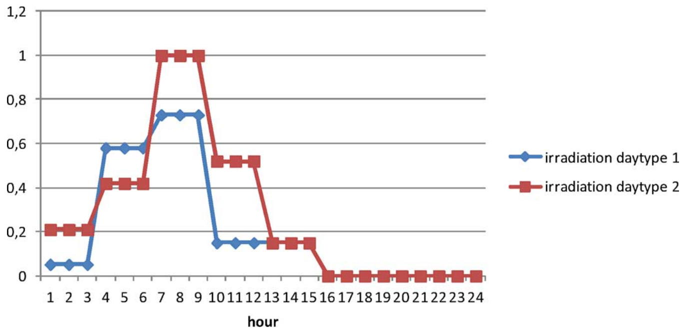

Fig. 9. PV plant irradiation at node 5 in the two typical days considered.

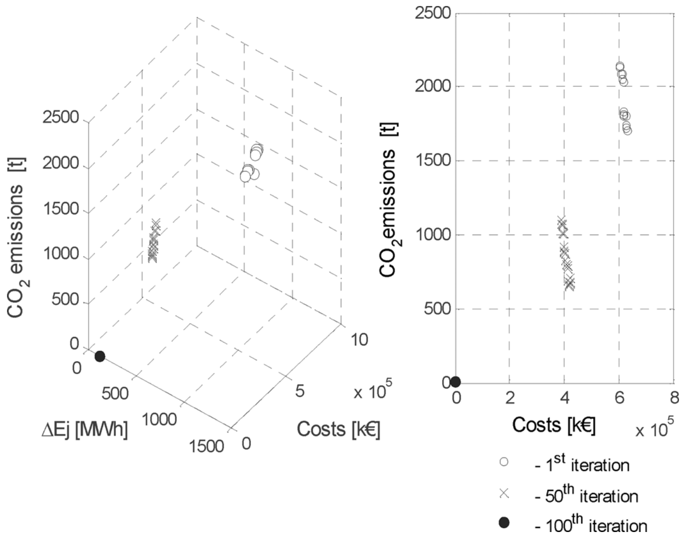

Fig. 10. Trajectory followed by a glow-worm in the three-dimensional space from the first (○) to the intermediate (X) and to (a) the final iteration (●) and (b) one of its projections.

$\max\_iter = 100$ iterations; the other parameters have the following values:

— radial sensor range r_s: 1.2;
— starting luciferin value l_0: 9;
— luciferin enhancement constant γ: 0.6;
— luciferin decay constant ρ: 0.4;
— number of neighbors: 3;
— step size s: 0.03.

Starting from the values suggested in the literature, the parameters have been fine-tuned according to the desired objectives to be reached and namely diversified design solutions showing low costs and good technical quality with affordable computational effort. Each glow-worm represents a design solution whose evaluation is carried out using the set of solutions outputted by the NSGA-II for the optimal management. The latter set is then shifted along the costs axis adding for all solutions the capital costs required to create the relevant design solution. Therefore, in the graphical representation, each glow-worm corresponds to a set of points in the three-dimensional space of the objectives.

Fig. 10(a) and (b) shows the trajectory followed by a glow-worm from the first to the final iteration (iteration 1, iteration 50, and iteration 100) in the objectives space. Fig. 10(a) shows the trajectory in the three-dimensional space, while Fig. 10(b) shows one of its projections. In Figs. 11–15, the term "quality" refers to the inverse of the size of space covered deduced as shown in Section I.

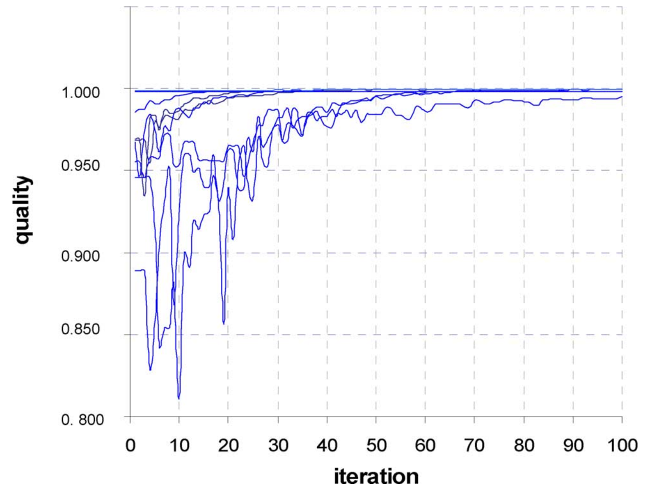

Fig. 11. Quality of a set of glow-worms along the iterations ($m = 100$ glow-worms $\max\_iter = 100$; $N_P = 30$ individuals and 50 iterations in NSGA-II).

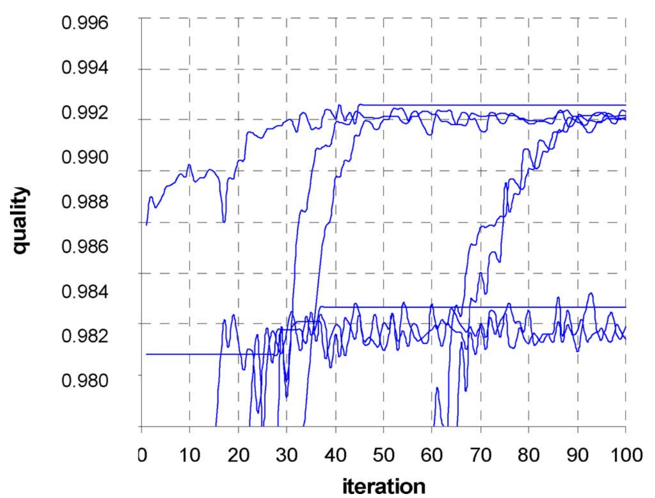

Fig. 12. Quality of a set of glow-worms along the iterations ($m = 100$ glow-worms $\max\_iter = 100$; $N_P = 30$ individuals and 50 iterations in NSGA-II). Zoom of the highest values of quality.

Fig. 11 shows the quality of the glow-worms from the first to the final iteration. Fig. 12 shows a zoom restricted to the highest values of quality. As it can be observed, there are two saturation points: an absolute maximum and a relative maximum that both attract glow-worms.

In the following Fig. 13, it is quite interesting to observe the two maximum points (absolute and relative) evidenced in Fig. 12.

In Fig. 13, the trajectories of some of the glow-worms representing design solutions are considered. Such design solutions are represented along the iterations (the arrows indicate this) in the variables space until the points where they gather around the different solutions the multimodal optimizer GSO efficiently finds.

Such an approach, using a multimodal optimizer for capturing the behavior of an entire set of solutions, is innovative and cannot be found in the literature on the topic. These trajectories are traced in a projection of the variables hyperspace.

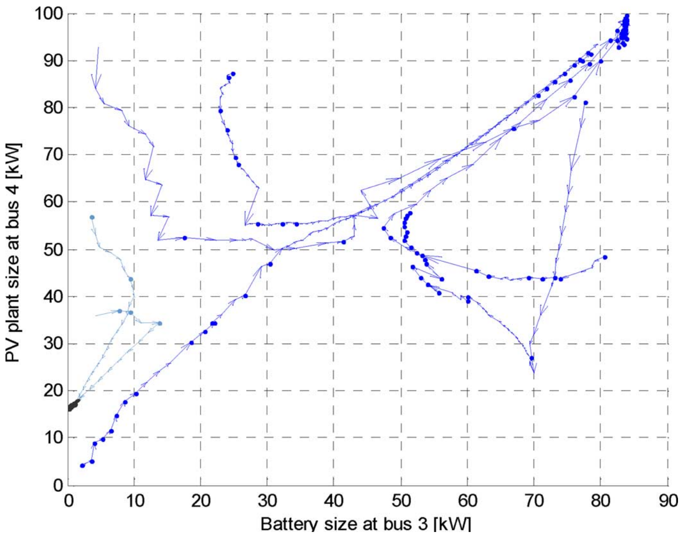

Fig. 13. Projection of the trajectory of a set of glow-worms along iterations.

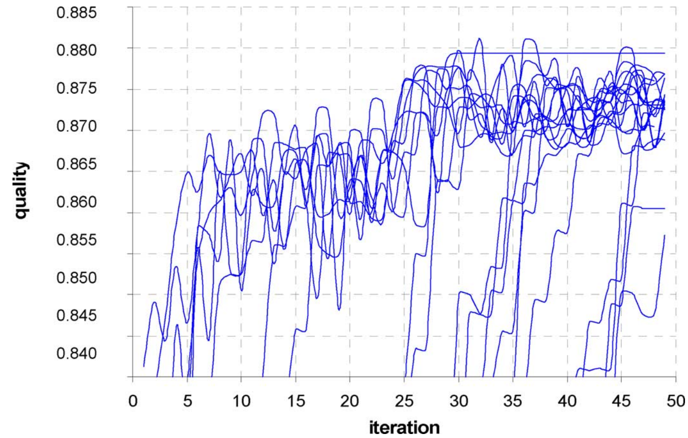

Fig. 14. Quality of a set of glow-worms along the iterations (m = 100 glow-worms $\max\_iter = 100$; $N_P = 20$ individuals and 30 iterations in NSGA-II). Zoom of the highest values of quality.

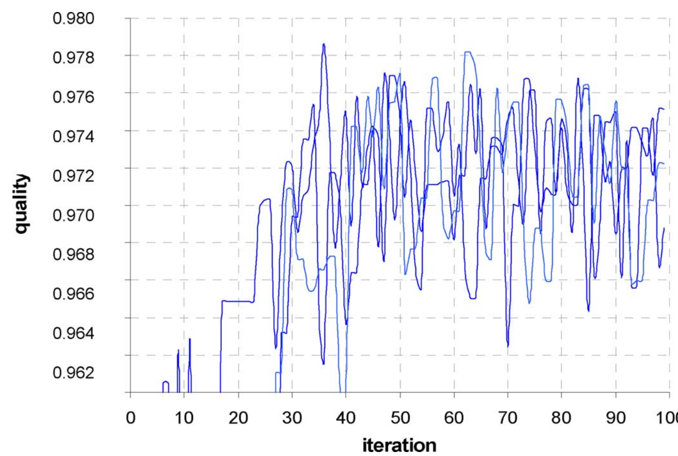

Fig. 15. Quality of a set of glow-worms along the iterations (m = 15 glow-worms $\max\_iter = 100$; $N_P = 30$ individuals and 50 iterations in NSGA-II). Zoom of the highest values of quality.

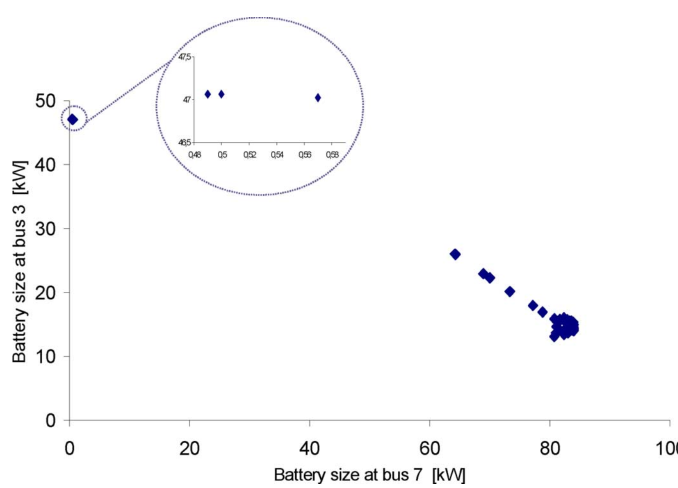

Fig. 16. Correlation of two variables at the last iteration.

One is reached by solutions whose trajectories are indicated by a darker line, and the other by solutions whose trajectories are indicated by a lighter line. Design solutions with a high quality and thus small volume in the objectives space attract more solutions. The absolute maximum attracts more solutions than the relative maximum.

Tests concerning computational efficiency of the proposed approach relate either to the number of agents and iterations employed in the outer shell (GSO algorithm) and in the population size and iterations number of the inner shell (NSGA-II).

Actually, the complexity of the approach is mostly connected to the NSGA-II in which the nondomination ordering has a quadratic complexity in the population size, N_P ($O(mN_P^2)$, where m is the number of objective involved in the optimization) and the load flow calculation based on the Newton–Raphson method, which has a quadratic complexity in the number of nodes, Nn, of the considered electric system ($O(Nn^2)$).

It is interesting to observe that insufficient settings for the NSGA-II produce unstable solutions as shown in Fig. 14, where the internal loop was run with 20 individuals and 30 iterations.

In this case, the NSGA-II does not output stable solutions, and the agents of GSO are evaluated with a fitness showing a large random component.

Other runs have been carried out with good settings for the inner shell (30 individuals and 50 iterations for NSGA-II) and with smaller number of glow-worms in the outer shell. The results prove that smaller swarms do not address properly the search and do not stabilize over the optima. This is shown in Fig. 15, where the results of a run carried out over 100 iterations and 15 glow-worms and 30 individuals and 50 iterations in NSGA-II is reported. In this case, the mechanism of cooperative learning does not work, because the swarm is too small.

Finally, Fig. 16 shows the correlation between two of the variables at the last iteration. As it can be noted, the points where solutions collide are the two identified maxima (absolute and relative).

The sizes of the plants related to the two solutions are reported in Table III. In order to give two unique values the average values of each variable have been considered and to calculate the latter only the solutions that are sufficiently close to each other have been considered. The two columns of Table III refer to two suboptimal solutions, one of which is better than the other, but both have been identified using the proposed framework. They have been selected because both have aggregated a

TABLE III
OPTIMAL DESIGN SOLUTIONS (AVERAGE VALUES OF THE CONSIDERED SUBSETS) FOR THE ABSOLUTE AND RELATIVE MAXIMA

Node	Size [kW] Absolute maximum related solution	Size [kW] Relative maximum related solution
3 (Battery-2 hours)	82.47	0.52
4 (PV Plant)	96.59	16.50
5 (PV Plant)	62.65	35.66
7 (Battery-1 hour)	15.07	47.05
13 (Micro Turbine)	3.4	17.11
15 (Battery – 30 minutes)	8.88	14.89
Installation cost [um]	2453	1421
Management cost [um]	304,5	443

TABLE IV
COMPARISON OF THE ACTUAL SIZE OF THE ENERGY SOURCES OF THE PLANT AND THE OPTIMAL SIZE DESIGN DEDUCED BY THE PROPOSED APPROACH

Node	Size [kW] Absolute optimal solution	Size [kW] Current design solution
3 (Battery-2 hours)	82.47	45
4 (PV Plant)	96.59	14
5 (PV Plant)	62.65	10
7 (Battery-1 hour)	15.07	100
13 (Micro Turbine)	3.4	100
15 (Battery – 30 minutes)	8.88	64

good number of solutions around creating clusters. Therefore, the final choice is left to the designer, both solutions being feasible and showing, compared to many other, also good quality, namely limited operating and installation cost, limited emissions, limited power losses, and thus heating of components during operation. The last row indicates the management and installation costs.

As it can be noted, the proposed framework allows to attain solutions whose optimized operation would cost differently. It is interesting to observe that the two terms have a different order of magnitude and thus what observed in Section I is confirmed. There is indeed a large difference in weight between the two parts of the optimization string, thus leading to a "deceptive" behavior.

A strategy that would consider management and design costs together would produce only solutions whose installation cost is limited but that cannot be operated efficiently. Moreover, on average, the absolute optimum is characterized by lower emissions and lower power losses as compared with the other design solution.

It is interesting to observe that the photovoltaic plants are quite large and that one of the storage units is indeed also quite large in order to compensate for the loads during night time using the stored energy.

All the proposed results, especially those related to the optimal design solutions attained as well as the relevant values of quality, have been found with a limited dispersion observed over a sample of 50 runs of the two shells approach.

Table IV shows a comparison of the actual size of the energy sources of the plant and the size of the energy sources deduced by the application of the proposed algorithm.

The difference between the values reported in Table IV and the actual sizes of the plants that can be found in [30] raises a big question concerning the way in which sizing is currently carried out in microgrids. On the other hand, it must be said that in this paper the authors have considered only the aspects concerning tertiary regulation, therefore the sizing of the energy sources is carried out not considering the request for energy due to the primary regulation. A large battery at node 3, which is connected to the main supply point with a low-resistance connection, provides the energy required to supply the loads and provides an accumulator for the large amount of energy generated by the large PV plants. The latter have been sized quite large as compared to the current project due to the attention to emissions and due to the fact that they (and the battery at node 3) take the role of the micro-turbine, which is connected to the loads through higher resistance paths. The other sources only cover a limited part of the load diagram.

VII. CONCLUSION

In this work, the issue of efficient design of optimally managed systems is devised with a new approach. Generally, the problem of optimal design requires the evaluation of management costs. These are typically considered only in an approximated way neglecting automated and optimized management, which appears to be the standard practice in smart microgrids management.

In this paper, a new approach for the design of systems that are managed considering different issues simultaneously is proposed.

The approach explicitly accounts for multiobjective optimal operation and is composed of two shells: an internal procedure takes care of the optimal management using Nondominated Sorting Genetic Algorithm II and the external procedure chooses the design features such as ratings and/or types. The latter is implemented through a glow-worm swarm optimization to attain different design solutions whose quality is evaluated using the hypervolume indicator. Glow-worm swarm optimization is indeed quite efficient for multimodal problems such as it is a multiobjective optimization problem dealt with using non dominance ordering.

The authors have applied the new design methodology to the problem of optimal electrical microgrids design, with successful results. Further work will be addressed towards the use of specific problem formulations or optimization algorithms allowing to consider uncertainty in power production from renewable, time-varying scenarios and different time steps. Also, further developments of this work will be aimed at taking into account the issues related to primary regulation for the dispatch of the energy sources.