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Multiple design options for sizing off-grid microgrids: A novel single-objective approach to support multi-criteria decision making

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ABSTRACT

When designing a microgrid, developers usually regard economic metrics, and occasionally consider reliability and environmental aspects. However, sociopolitical, supply chain, and geographical facets, among others, are often never included in project-design because they are really difficult to model, especially, in the context of developing countries. Traditional planning methodologies offer an optimal solution, disregarding solutions with similar profitability but different size of components, even when these second-best solutions can better fit the non-considered intangible developer needs. In this paper, we define the concept of Multiple Design Options (MDO) for a single-objective optimization. We propose a novel methodology (MDO-PSO) for sizing stand-alone hybrid energy systems that, by using Particle Swarm Optimization, identifies the optimal solution and post-processes the search history to select second-best options of interest. While searching for the traditional optimum, the proposed iterative algorithm stores all tried configurations. Moreover, a Pareto-like frontier, denoted as MDO-Pareto, is proposed to highlight the tradeoff between Net Present Cost (NPC) and CAPEX. The proposed Pareto-like frontier is also compared to a standard multi-objective optimization to illustrate how MDO-PSO successfully captures multiple goals. The numerical case study for a PV-battery-diesel-tank system in Uganda confirms that MDOs differing up to 32% in capacity can achieve NPC values within 2%–5% optimality with both load following and predictive MILP rolling-horizon operating strategies, thus suggesting important implications for business decision making.

1. Introduction

1.1. Motivation

Supporting power system quality and renewable penetration [1], microgrids are increasingly being installed worldwide, not only in developed countries, but also in developing countries, where they are fostering rural electrification and socio-economic growth [2]. As there is no one-size-fits-all solution [2], the optimal design of each system shall be tailored to the specific circumstances of the project, some of which are often difficult to quantify and properly model in mathematical tools [3]. This turns out to increase the risk profile of microgrids, especially within challenging sociological, economic, political and technical contexts of rural areas in developing countries, where the uncertain load consumption and the commonly low ability-to-pay make that the expected revenues may not compensate the risks, unless stable and secured public support is available [4].

In the literature, the typical approach to design off-grid systems consists in optimizing one or more variables, that is single- or multi-objective optimization [5–8], respectively. However, in both cases, the mathematical modeling may not fully capture all external circumstances to the project [3,9]. For example, the maintenance complexity, supply chain logistics, or the bureaucratic burden, among others, are difficult to model and usually not included in the quantitative evaluations. This suggests that the traditional mathematical solution, be it a single point or a curve (single- or multi-objective optimization), may not completely capture the specific facets of the project. As a result, developers usually tend to adjust and modify the final (and optimal) obtained solution according to their expert knowledge and risk appetite; habitually, with the economic component as a major concern [10–12].

Traditional algorithms pursue the first-best economic efficient solution, typically defined in terms of cost or income (or profits). However, these algorithms tend to completely disregard second-best solutions, i.e. slightly sub-optimal design points

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within 1%–2% optimality with respect to the "optimal" solution, even though these other designs could better suit the intangible needs of a developer for a specific project. To the best of the authors' knowledge, no advanced technique, based on single-objective optimization, has been developed in the literature to satisfy the needs of developers in identifying comparable "optimal points". Acknowledging these gaps in the literature, it is worthy and timely to define, formulate and develop the concept of Multiple Design Options (MDO) that was previously qualitatively introduced in [3] and, for multi-objective optimization, in [9].

1.2. Literature analysis

Except for some impact investors [13] or the public sector [2], the majority of private developers usually aim at maximizing the economic return on their investments, thereby typical optimization tools remain focused on economic indicators [6,10,14]. However, recently, environmental [11,15] reliability [12,16], technical [17] and socio-political [18] elements have been increasingly considered, yet often with a secondary role. Nevertheless, as introduced in [3], mathematical indicators and their modeling may not exhaustively represent all the challenges of microgrid projects, especially in the context of rural electrification of developing countries. Even traditional measures like Net Present Value (NPV) or Internal Rate of Return (IRR) are subject to specific drawbacks and lead to significantly different solutions [19], which suggests that developers would be more at ease with a possible set of efficient solutions with similar economic performances but different characteristics, rather than the cheapest only. This concept could be approached in principle also with multi-objective optimization, but it is worth to remark that the main interest of developers is often a single economic indicator, which is often the main objective function to be optimized.

In terms of optimization algorithms, both metaheuristic and linear programming techniques have been used for the sizing and operation of microgrids, achieving good performances [14,16,20]. Programming techniques, such as Mixed-Integer Linear Programming (MILP), have been extensively used to optimize the design of microgrids [21] as well as their operation [20], also thanks to their capabilities to converge towards the global solution [22]. However, the intrinsic limits of the mathematical modeling emerge as the problem grows in size and the computational burden of MILP can soon be unbearable, which makes the optimization problem difficult to be solved especially for non-linear models [22]. Conversely, by using an iterative procedure, metaheuristic algorithms are able to easily solve even non-linear non-convex models and converge quicker than traditional MILP methodologies, as discussed in [14]. The comparison performed by the authors in [14] between Particle Swarm Optimization (PSO) and the standard MILP suggested that the metaheuristic problem not only can converge in half of the time, or lower, with respect to MILP but the solution obtained by the PSO was cheaper than the MILP one, when predictive operating strategies are implemented, for that particular case. Similar results are supported by the study in [23], where a Genetic Algorithm (GA) achieved an optimal solution similar to the equivalent problem formulation with MILP, but in about 10% the computational time of the latter. For these reasons, metaheuristic approaches have been widely accepted in sizing procedures both in single- [24] and multi-objective optimization [25,26]. In particular, given the good performances in terms of accuracy and computational requirements [5,14,27], in this study, Particle Swarm Optimization has been considered and improved.

Given the interests in achieving the highest profits, software tools and methodologies for the optimal sizing of microgrids have usually prioritized a single economic indicator [24]; other environmental, social and political concerns have usually a secondary role, and sometimes they are accounted for by using penalties or hard constraints [2,4,28]. For this reason, traditional sizing tools focus on achieving the optimal solution that minimizes or maximizes the given objective function(s), while all the other size configurations are disregarded, be them far or close to the optimal one(s). In this study, we aim to go beyond this traditional goal and provide developers with multiple solutions with almost the same profitability.

As initially introduced in [3] and partially in [9], developers can be better off when provided with Multiple Design Options (MDO) that are configurations of the system with similar values of the objective function (e.g. within 1% optimality) but different size of the components. In fact, rarely the mathematical modeling capture all the specific characteristics and needs of a given project, such as logistics, maintenance complexities, availability of spare parts, country and regional risks, among others. The same concept is supported by the features of commercial tools that provide developers with tuning parameters, so that they can manually search different sizing options [29]. In the literature, except for [3,9], similar concepts have only been tackled by means of multi-objective optimization [17], but even in this case the concept of MDO still applies as multiple configurations can lead to a similar point in the Pareto frontier [9]. Furthermore, especially when the developer prioritizes a single objective function, the multi-objective optimization easily lead to excessive computational burden and/or low resolution of the Pareto frontier, which makes the tool difficult to use. In other cases [30,31], methodologies have focused on the variation of the objective functions and/or no intermediate design solutions where identified to map the feasible space, as in the proposed methodology based on MDO. In [3], the concept of MDO has only been qualitatively introduced and its rational was only highlighted by means of maps and the practical use of this first model was limited. The MDO concept has been also proposed for multi-objective optimization in [9], but when the focus is on a single indicator, this methodology can be significantly less efficient and less accurate. For these reasons, the present study properly defines MDO for single-objective optimization and also performs a detailed comparison with multi-objective optimization.

Moreover, both studies [3,9] considered only a simple Load Following strategy (LFS) to operate the system, according to which the dispatch of the resources is based on a priority-list rule: first the renewable sources, then the storage and finally the fuel-fired generators. However, predictive operating strategies are recently seen as promising solutions to reduce the system needs and the size of required components [14]. Therefore, in this study a sensitivity over the operating strategy, load-following or predictive, is also performed.

1.3. Contribution

To the authors' best knowledge, this paper details the first definition of Multiple Design Options (MDO) for single-objective optimization and develops the corresponding methodology to successfully draw MDOs. In the proposed approach, a metaheuristic optimization called MDO-PSO, based on Particle Swarm Optimization, is developed to size an off-grid microgrid and all the intermediate solutions are stored till convergence of the solver. Then, all the intermediate solutions within a given optimality tolerance with respect to the final optimal sizing are post-processed to identify a handful number of MDOs that can be manageable by the developer. Furthermore, in order to stress the possible use of MDO-PSO for identifying Pareto-like curves, typically used in multi-objective optimization, a Pareto-like curve, denoted MDO-Pareto, is derived at least in a reduced region based on the search history and compared to the standard multi-objective optimization. Finally, a sensitivity analysis with respect to the optimality tolerance is also proposed. In short, the main novelties are listed below.

1. Definition of Multiple Design Options (MDO) for single-objective optimization.
2. Development of the Multiple Design Options-Particle Swarm Optimization (MDO-PSO) method to collect MDOs in single-objective optimization for a PV-battery-diesel-tank microgrid.
3. Comparison of a novel Pareto-like frontier, denoted as MDO-Pareto frontier and focused on Net Present Cost (NPC) and the investment costs (CAPEX), with a standard multi-objective approach.
4. Sensitivity w.r.t. the operating strategy: Load Following (LFS) or predictive Rolling Horizon Strategy (RHS).

1.4. Organization

Section 2 details the topology of the system taken as a reference; Section 3 clearly states the definition of MDO for single objective optimization and Section 4 describes the MDO-PSO algorithm to calculate the optimal design of an off-grid microgrid. Section 5 and VI describe the case study and the corresponding results for a system in Soroti, Uganda, respectively. Lastly, the conclusions are drawn.

2. The microgrid system

2.1. Description

Given the multi-faceted characteristics of rural electrification, this study analyzes a traditional off-grid microgrid in developing countries, composed by a solar PV plant, a battery energy storage system, a DC/DC converter, an inverter, a diesel generator and its fuel tank, as shown in Fig. 1. The batteries and photovoltaic plant are tied at the DC busbar; the diesel generator is tied at the AC busbar, and the inverter is the component that links the AC and DC busbars.

The resources within the microgrid are dispatched by an Energy Management System (EMS) using the operating strategies detailed in the following subsection.

2.2. The system operation

The local EMS controls the devices of the microgrid with the objective of minimizing the operating charges. Traditionally, being simple and with limited hardware requirements, simple dispatching protocols based on "if-then" rules have been used for rural microgrids, by which resources are dispatched by merit-order criteria [14]: firstly the renewable energies are exploited, then the energy stored in the batteries is used and finally the fuel-fired generators are dispatched. In particular, the "Load Following Strategy" (LFS) is the most used and simple to use: the generator is turned on only to meet the residual demand when the other renewable units or storage cannot, otherwise the generator is not dispatched. With LFS, the generator is not meant to charge the batteries, contrary to other priority-list methodologies such as Cycle Charging [14].

The study in [14] also highlighted that predictive operating strategies can increase the coordination of the system and enable reducing its life-cycle costs, but the control unit is more complex and requires accurate forecasts to operate, which may be difficult to perform on rural microgrids. In such cases, the load and renewable production of the system is forecasted for a given time horizon (e.g. a day) and then an optimization algorithm

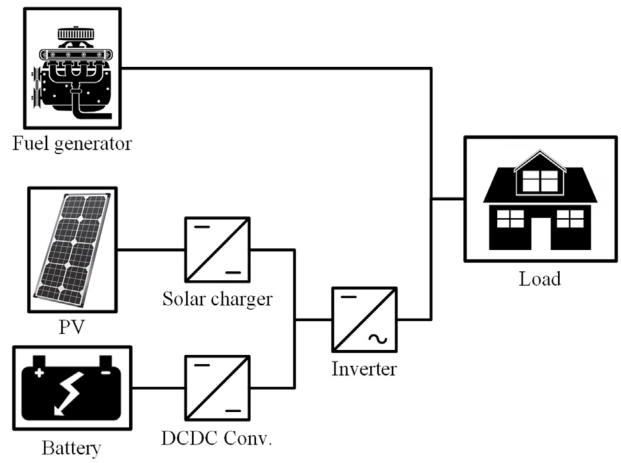


Fig. 1. The topology of the microgrid.

identifies the optimal dispatching strategy for the same time horizon. This procedure, called "Rolling Horizon Strategy" (RHS), is usually repeated every a fixed period of time (e.g. 4 h), to revise the previous scheduling once updated forecasts become available; this enables advancing the peak demand by leveraging especially on the energy storage, with corresponding benefits both on the reliability and the economics of the microgrid. In the time between two consecutive redispatching procedures, the unavoidable forecasting errors in the renewable production and the load are corrected by the EMS, typically employing simple real-time rules similarly to LFS, especially in the case of rural microgrids. When unexpected deviations of load and RES, from what forecasted, are very small, energy storage absorbs practically all of them; anyway, especially the demand forecasting must be accurate to avoid jeopardizing the benefits of predictive approaches, hence the forecasting system has to be properly calibrated.

Conversely to the previous work in [3,9], which was limited to LFS, in this activity both LFS and RHS are simulated, so to highlight the benefits of the MDO method in different operating conditions. The forecasting uncertainties of RHS are simulated and corrected in real-time by using LFS-based rules [14].

3. Definition of multiple design option

Let us assume an optimization problem in the form of (1) where $\bar{x}$ is the optimal design with value $f(\bar{x})$. In this document, we define the set of Multiple Design Options (MDOs) $\hat{X}$ as a selected group of system configurations whose value of objective function(s) is nearly equivalent (tolerance $\overline{\Delta}$ on distance function $d(\cdot,\cdot)$) to the optimal solution provided by the optimization problem but highlights important features of interest by the developer, as described by functions $\gamma_i(\cdot)$ in (2). In fact, given the externalities in practical applications, objective functions within a reduced tolerance (i.e. 2%) may be practically equivalent. This is captured by the concept of nearly-equivalent solutions described by the distance function d, such as a norm-1 function ($d(f(\hat{x}), f(\bar{x})) = \|f(\hat{x}) - f(\bar{x})\|_1$).

$$\bar{x} = \min\left\{f(x)\, s.t.\, g(x) \leq 0\right\} \tag{1}$$

$$\hat{X} = \bigcup_{i \in I} \arg\min\left\{\gamma_i(\hat{x})\, s.t.\, d\big(f(\hat{x}), f(\bar{x})\big) \leq \overline{\Delta}\right\} \tag{2}$$

The above novel definition has been proposed accounting for the relevant literature on MDOs and near-optimal design [3,9,32].

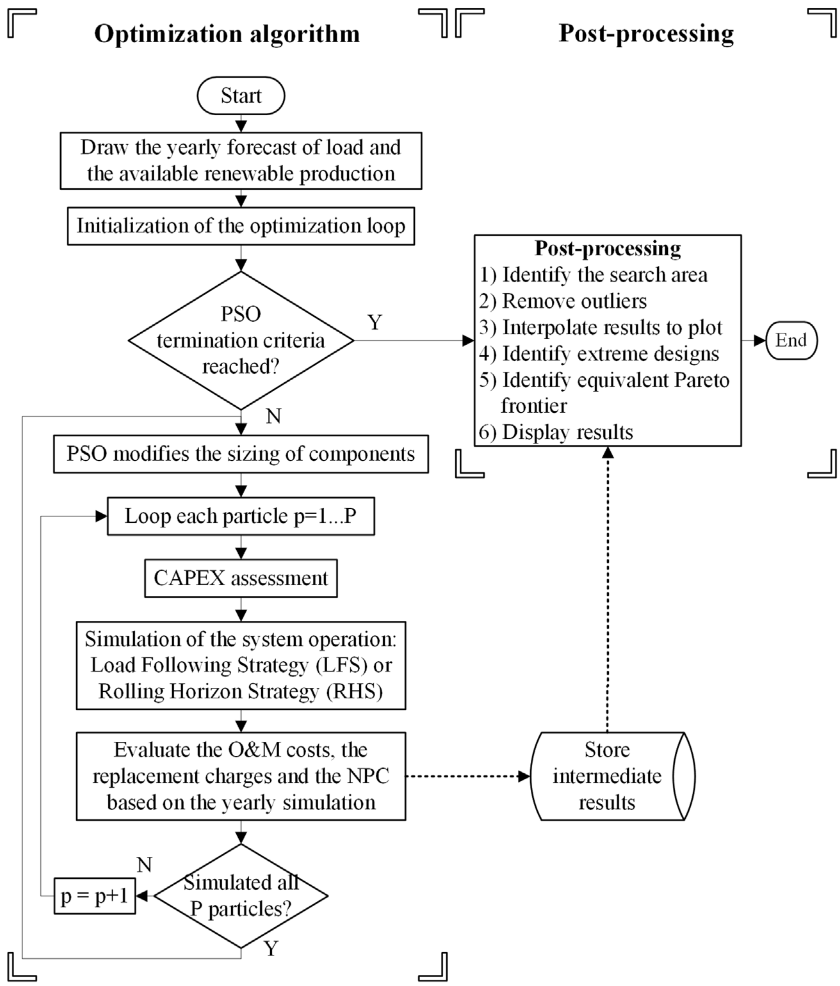


Fig. 2. The proposed sizing method based on MDO-PSO.

The following sections detail a robust methodology to automatically obtain MDOs from a standard automatic optimization procedure, including selection criteria to provide the developer with a handful number of meaningful MDOs that are easier to compare. In particular, in this paper the $\gamma_i(\cdot)$ functions are specialized to capture the specific extreme design of the system topology.

4. The multiple design option approach

This section aims at detailing the mathematical model of the optimization problem and the proposed MDO-PSO technique, shown in Fig. 2, that calculates the optimal sizing of an off-grid microgrid, selects all MDOs within a given tolerance, and reduces the within-tolerance MDO set to a handful number of suitable options that are manageable for the developer. Similarly to other approaches [3,9], in every iteration of the MDO procedure the processed relevant information is stored, but, once convergence is reached, the data are post-processed to select a handful set of suitable options for the developer and compare them to multi-objective optimization, also including sensitivity analyses w.r.t. operating strategies and optimality tolerance.

The proposed approach is an advancement of current PSO algorithms [33] on which our additions have allowed us to successfully implement the proposed post-processing, as detailed in this section. The source code of the optimization algorithm has been released in [34] as discussed in Appendix.

4.1. Mathematical model

The objective of the optimization algorithm is to minimize NPC that accounts, as detailed in (3), for the investment costs ($CAPEX_y$), the operating charges ($OPEX_y$), the replacement expenses (REP_y), and the residual value (RES_y) of the system at the last year of the project; d is the discount rate, N_T refers to the project lifetime and y denotes the year. The operating costs ($OPEX_y$) take into account the fuel costs, the maintenance and the economic value of the load curtailment, according to the management strategy (LFS or RHS). RES_y models the residual value of each asset, calculated as a linear proportion to the remaining lifetime of each component.

$$\min \; NPC = \sum_{y=0}^{N_T} \frac{CAPEX_y + OPEX_y + REP_y - RES_y}{(1+d)^y} \tag{3}$$

The CAPEX formulation accounts for the economies of scale and volume as detailed in (4), where C_0^a represents the cost of the asset a sized to capacity x_0^a, and parameter β^a is a specific parameter to shape the cost function. Operating charges $OPEX_y$ account for the maintenance fees $C_y^{a,M}$ of all assets, except for the fuel-fired generator, the fuel costs C_t^D, the maintenance charges C_t^{DM} of the generator, and the costs related to the Energy Not Served (ENS) C_t^{LC}, assumed to be linear to the quantity of ENS (P_t^{LC}). A piece-wise linear function is used to model the fuel consumption F_t^D and the fuel price is assumed to be a constant parameter.

$$CAPEX = \sum_{a \in A} C_0^a \left(\frac{x^a}{x_0^a}\right)^{\beta^a} \tag{4}$$

$$OPEX_y = \sum_{a \in A/\{D\}} C_y^{a,M} + \sum_{t=1}^{8760} C_t^D + C_t^{D,M} + C_t^{LC} \tag{5}$$

Eqs. (6) and (7) guarantee the AC and DC electrical balance. In the first, P_t^D represents the dispatch of the diesel generator, P_t^{I+} is the power supplied by the inverter, P_t^{I-} is the power absorbed by the inverter, P_t^L refers to the load demand and P_t^{LC} is the curtailed power. In the DC balance (7), P_t^R represents the dispatch of the renewable plant, and P_t^{B+} and P_t^{B-} represent the dispatch of the battery, with similar notation to the inverter. The efficiency of the inverter is η^I.

$$P_t^D + P_t^{I+} - P_t^{I-} = P_t^L - P_t^{LC} \tag{6}$$

$$P_t^R + P_t^{B+} - P_t^{B-} - \frac{P_t^{I+}}{\eta^I} + P_t^{I-}\eta^I = 0 \tag{7}$$

The maximum power limits of the generator (D), the battery converter (B), the inverter (I) and the renewable production unit (R) are modeled with constraints from (8) to (11). The capacity of each asset a is denoted with x^a and is optimized by the algorithm. It is worth noticing that the power P_t^D dispatched to the generator is guaranteed to be above the technical minimum ($\alpha^{D,min}$) when it is committed, otherwise the diesel production is strictly zero, as modeled in (8) where z_t^D denotes the status of the generator. Furthermore, the specific photovoltaic production, for each unit of installed capacity, is denoted with p_t^R in (11). x^D, x^C, x^I and x^R denote the installed capacity of the diesel generator, the battery converter, the inverter and the renewable assets, respectively.

$$\alpha^{D,min} x^D z_t^D \le P_t^D \le x^D z_t^D \tag{8}$$

$$P_t^{B+} + P_t^{B-} \le x^C \tag{9}$$

$$P_t^{I+} + P_t^{I-} \le x^I \tag{10}$$

$$P_t^R \le p_t^R x^R \tag{11}$$

The energy E_t^B stored in the battery is modeled using Eq. (12), as a function of the dispatch of the battery converter and the round-trip efficiency η^B of the battery and converter system. Constraint (13) guarantees that the battery is not charged nor discharged beyond specific thresholds, to guarantee an adequate lifetime of the storage system. Lastly, the modeling of the fuel V_t^T available is expressed by (14), where F_t^{Refill} denotes the quantity of fuel the tank is refilled with in each time step, occurred after that a refilling is requested. In particular, when the available fuel goes below the 20% of the nominal capacity of the tank, a new shipping is requested and the delay between the request and the arrival is modeled by using a Weibull probability density function.

$$E_t^B = E_{t-1}^B - \frac{P_t^{B+}}{\sqrt{\eta^B}} + P_t^{B-}\sqrt{\eta^B} \tag{12}$$

$$\alpha^{B,min} x^B \le E_t^B \le \alpha^{B,max} x^B \tag{13}$$

$$V_t^T = V_{t-1}^T - F_t^D + F_t^{Refill} \tag{14}$$

The specific dispatch of the resources is then managed by the EMS according to the two main strategies that best represent the current state-of-the-art in rural microgrids [14,35]: LFS and RHS. When LFS is used, the fuel-fired generator is typically kept shut down and the batteries are used as a buffer to keep the system stable and operating. When the other production units (renewable sources and batteries) cannot entirely meet the demand, then the generator is dispatched, if it is economically profitable. The generator, however, does not focus on charging the batteries. Yet, when RHS is used, the generator is usually dispatched as scheduled and the battery still balances possible power mismatches; the dispatching is modified only to avoid RES or load curtailment [14]. In RHS, the objective of the predictive dispatch is minimizing $OPEX_y$ for the given time horizon (24 h) and the model of the system is equivalent to the formulation described in this section. More details can be found in [14].

4.2. The optimization algorithm

In order to minimize NPC and select MDOs, a modified version of the Particle Swarm Optimization, denoted as MDO-PSO, is proposed in this paper and discussed, building upon previous works [3,33]. Conversely to the standard PSO that only aims to calculate the design the minimizes the objective function [14], MDO-PSO stores all the intermediate solutions during the optimization procedure, in order to use them in the post-processing phase, as depicted in the left-hand side of Fig. 2. In each iteration, MDO-PSO draws P (80) different size configurations of the microgrid, or particles, simulates the corresponding yearly system operation according to the selected operating strategy (LFS or RHS), and calculate the objective function. With no loss of generality and to keep down the resource requirements, the quantities to be stored along the iterative procedure are pre-defined, such as the size of the components, the production share and main economic parameters (NPC, OPEX, CAPEX). Also according to the standard PSO, the convergence is reached when no improvements in the objective function occur along a number (15) of consecutive iterations with a given tolerance (0.1%).

Algorithm 1 depicts the pseudocode of the proposed optimization algorithm.

Algorithm 1 Modified Particle Swarm Optimization

```
Require: Objective function, variable bounds, parameters
  Create N random particles within bounds
  Set particles speed using an uniform random distribution
  Evaluate objective function for every particle location
  while Convergence not met do
     for Every particle i do
        Update speed based on current and past best particles
        Update location of particles
        Evaluate objective function
        Store optimization results of the iteration
     end for
     Update stopping criteria: iteration count and iter. within tolerance
  end while
```

4.3. The post-processing phase

The main novelty of the proposed approach relies on the post-processing of the information stored along all iterations of the MDO-PSO optimization, as shown in Fig. 2. In order to focus the analyses only on the area of the size configurations that are closer to the optimal solution, a first screening collects only the points within a given NPC tolerance with respect to the optimal solution, which are MDOs by definition. Secondly, all outliers, such as configurations where batteries are installed without converters or vice versa, are disregarded. Thirdly, detailed pictures are drawn to qualitatively show the desired results, so to provide the developers with preliminary information on the MDOs, for instance to evaluate the variability of the results or to understand the shape of the objective function. Subsequently, in order to provide the developers with a handful number of options that can be manageable, extreme system configurations, which correspond, for instance, to higher photovoltaic or diesel production, are selected among the MDOs within-tolerance [9]. Finally, the Pareto-like frontier, denoted MDO-Pareto, is calculated to highlight the relationship between NPC and CAPEX; this curve is also compared to the traditional Pareto frontier calculated with Dynamic Multi Search (DMS) algorithm [36], which is typically used for multi-objective optimization and is also included in MATLAB [37]. More in detail, the following steps are taken:

1. Collect all size configurations among the MDO-PSO search history within a given NPC tolerance with respect to the minimum NPC obtained with MDO-PSO.
2. Remove outliers, for instance size configurations where batteries are installed without their converter or vice versa.
3. Perform a cubic interpolation method to properly draw selected quantities representing the developers' interest: size of the assets, energy shares and economic performances.
4. Select the extreme MDOs: size configurations that correspond to the maximum or minimum value of selected quantities, such as photovoltaic production, diesel share, ENS, battery capacity, or CAPEX. Note that, with respect to (2), this means that the functions $\gamma_i(\cdot)$ correspond to expressions discussed in Section 4.1, such as $\gamma_{CAPEX}(\cdot) = CAPEX_0$, in the case of CAPEX, or $\gamma_{PV}(\cdot) = -\sum_{t=1}^{8760} P_t^R$, in the case of the photovoltaic production, for example.
5. Identify the trade-off between selected indicators (NPC and CAPEX), by applying a Pareto-like approach on the entire search history.
6. Display the results.

It is worth noticing that, given the strong interest both on CAPEX and the life-cycle cost of the project (NPC), the trade-off between these two indicators is highlighted with a specific graph. As traditionally done in multi-objective optimization, the so-called "non-dominated" solutions among the search history are identified and plotted [36]: a configuration A is called "dominated" when all the indicators (CAPEX and NPC) of A are worse than at least another configuration B; when the above does not apply, then A is called "non-dominated". This procedure performed on the MDOs is referred to MDO-Pareto, as the optimization procedure is not a multi-objective optimization, hence the corresponding frontier may differ from the optimal curve. In the case study, this trade-off is then compared with a traditional multi-objective approach to highlight benefits and drawbacks.

Algorithm 2 depicts the pseudocode of the proposed method.

Algorithm 2 Postprocessing

Require: Search history stored by Algorithm 1
Select solutions in the search history within tolerance
Remove outliers
Perform interpolation to improve readability of results
Select extreme MDOs
Identify trade-offs between indicators
Display results

5. Case study

5.1. Description

The MDO-PSO methodology is tested for the optimal sizing of a typical off-grid system to be deployed in Soroti, Uganda. Being conventionally installed in a microgrid for developing countries, the assets to be sized are the photovoltaic plant, the lithium battery, the converters, the fuel-fired generator and the diesel tank, according to the topology shown in Fig. 1.

Table 1
Cost parameters of the main components.

Asset (i)	x_0^a UM	C_0^a \$/UM	β^a –	Mainten. \$/UM/y	Efficiency %	Lifetime
PV	1 kW	800	1	16	–	25 y
Battery	1 kWh	350	1	3	96[a]	3000 eq.cyc.
Bat. conv.	1 kW	1258	0.5	2	98	15 y
Inverter	1 kW	1887	0.5	2	96	15 y
Fuel gen.	1 kW	1013	0.8	0.05 \$/kW/h	≤33%	30000 h
Fuel tank	1 liter	52.2	0.45	0.15	–	25 y

[a]Roundtrip efficiency.

The community is composed of around 100 households and some commercial entities. The procedure described in [3] is used to assess the demand and its typical daily power profile, and a Gaussian noise is introduced to stress the power yearly fluctuations, reaching a peak power of about 80–86 kW. The standard deviation equals on average the 13% the hourly demand. The methods presented in [38–40] have been implemented to assess the hourly photovoltaic power production of the proposed case study. When no adequate historic dataset was available for Soroti, measures collected at the close weather station in Kitale, Kenya, were used.

5.2. Cost and technical parameters

Table 1 reports the main economic and technical parameters of the proposed case study. It is worth noticing that our model correctly takes into account that, when fuel generator operates below the rated power, the efficiency decreases. Furthermore, it is considered that the generator cannot operate below its technical minimum of 10% its rated power [3]. Finally, the fuel price is 0.9\$/l and the equivalent cost of the ENS is 1\$/kWh [9]. The Weibull function used to model the arrival time of the fuel track is characterized by its 50% and 90% percentiles that equal 4 and 7 days, respectively. The request for a new refueling is triggered when the available fuel falls below 20% the nominal tank capacity. The project lifetime is 15 years and the discounted rate equals 8%.

5.3. Testing procedure

The new MDO-PSO approach discussed in Section 4 is tested for the microgrid in Soroti, including a sensitivity on the operating strategy (LFS and RHS) and on the optimality NPC tolerance (2% and 5%). In order to validate the ability of MDO-PSO technique to provide a good approximation of the traditional Pareto frontier nearby the solution that minimizes the objective function (NPC), the MDO-PSO approach is compared with the Dynamic Multi-Search (DMS) algorithm [36,37], which is typically used in multi-objective optimization. In that case, given the strong interests of developers on NPC and CAPEX, the multi-objective analysis was focused on the trade-off between these two economic indicators.

6. Results

The results of the MDO-PSO method are depicted in Figs. 3 and 4, corresponding to LFS and RHS operating strategies, respectively. The pictures depict the main economics and main technical parameters of interest for a private developer; the red dots denote all the MDOs collected by the MDO-PSO procedure, that were stored since within tolerance from the optimal solution, and then screened according to the post-processing phase; the background colors represent their cubic interpolation to ease the

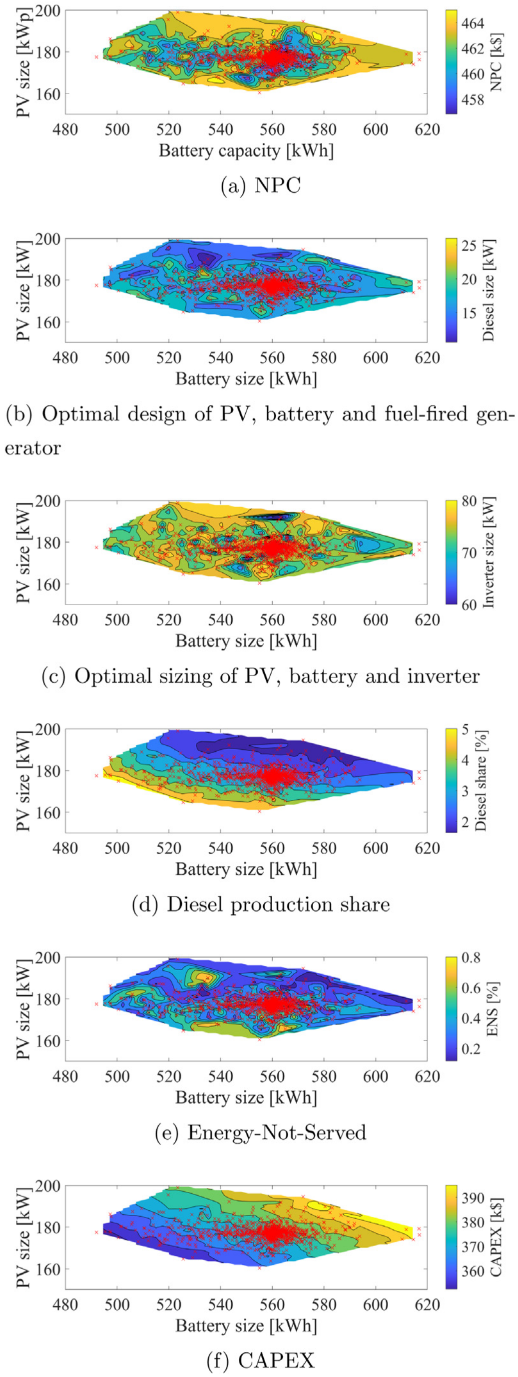


Fig. 3. Results of MDO-PSO with Load Following Strategy (LFS); the red dots denote the design configurations within 2% NPC tolerance.

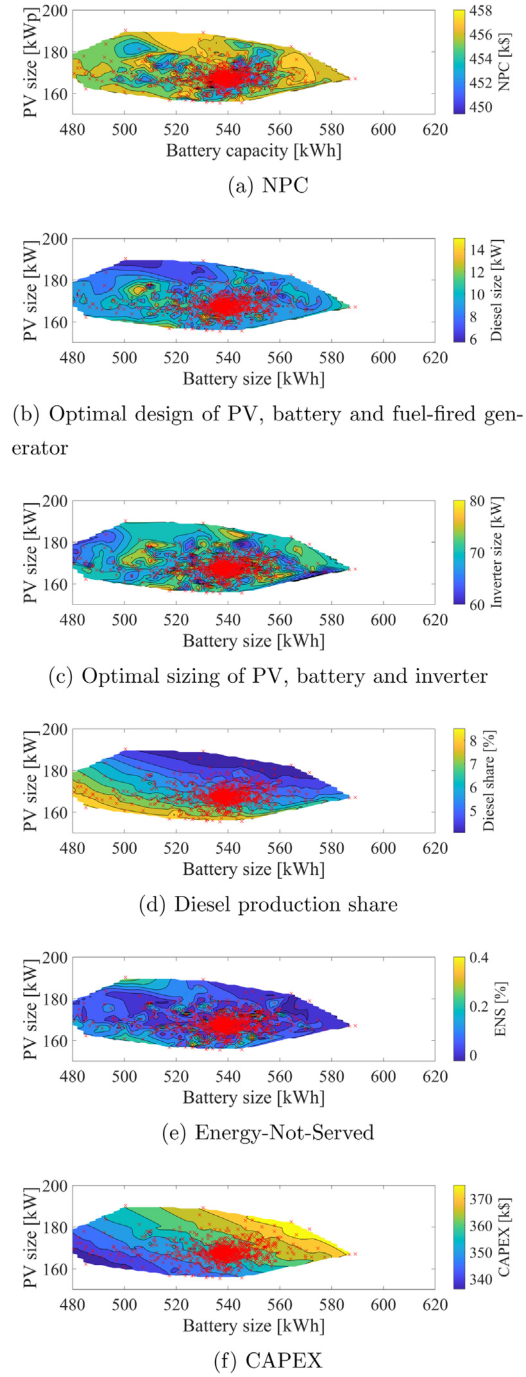


Fig. 4. Results of MDO-PSO with Rolling Horizon Strategy (RHS); the red dots denote the design configurations within 2% NPC tolerance.

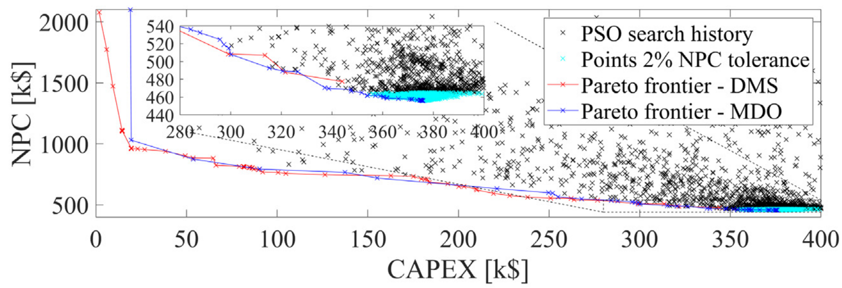
visualization. The effects of the NPC tolerance and of the operating strategy on the size of the components are shown in Table 6. The optimal size of the components and the corresponding main economic quantities obtained with MDO-PSO are reported in Table 2, for both LFS and RHS. Fig. 5 shows the MDO-Pareto frontier obtained with the proposed MDO approach and compared with the traditional frontier calculated with a solid multi-objective methodology (DMS). Finally, the computational requirements of all methodologies are shown in Table 5.

Figs. 3(a) and 4(a) depict the NPC of all size configurations within 2%-optimality, respectively for LFS and RHS operating strategies, in relationship to the size of the battery system and

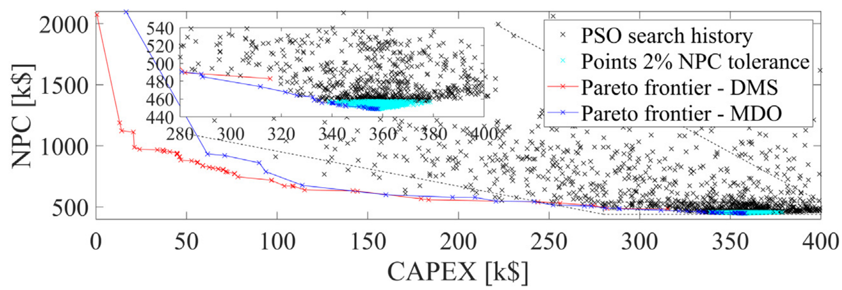
Table 2
Economics and design characteristics of the optimal solution calculated by MDO-PSO.

Strategy	NPC k$	CAPEX k$	OPEX k$/y	PV kW	Batt kWh	DCDC kW	Inv kW	Diesel kW	Tank l
LFS	456	376	8.5	177	559	89	69	17	283
RHS	449	358	9.7	168	540	87	68	10	635

of the PV plant. Be the operating strategy LFS or RHS, it turns out that the color map is quite uniform, as a large number of points lead to similar values of the objective function, which means that



(a) Load Following Strategy (LFS)



(b) Rolling Horizon Strategy (RHS)

Fig. 5. Pareto frontiers calculated with MDO (in blue) and the traditional DMS approach (in red); black dots represent the PSO search history and the light blue ones represent the in-tolerance MDOs within 2% NPC optimality. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the objective function is quite flat nearby the optimum. Although all the points shown in the pictures are only within 2% tolerance with respect to the lowest NPC (456k$ and 449k$ for LFS and RHS), the corresponding sizing of the PV and battery span over a wide range, up to ±10%–26%. Using RHS, the variability, though still considerable, is lower than with LFS. These results confirm that almost the same economic performances can be obtained with many different designs for both LFS and RHS; therefore, the proposed approach can provide private developers with many different, but similarly profitable, design options.

When looking at the effect on the diesel generator (Figs. 3(b) and 4(b)) and on the inverter (Figs. 3(c) and 4(c)), it is worth noticing that the variability is generally lower, with both LFS and RHS, than for the battery or the PV system: the color map is typically the same in a large area. The nominal size of the diesel generator may tend to slightly increase as the sizes of the PV plant and of the battery decrease, but the difference is very limited, also according the proposed realistic cost parameters. As a remark, the design of the two assets (generator and inverter) is significantly correlated, as together they shall meet the load and in particular its peak power, as described in (6). Thus, the total installed capacity at the AC busbar is generally around the value of the peak demand. Moreover, when the renewable penetration is significant, as in this case, the generator produces for a minimal fraction of the time and the inverter meets the entire energy demand most of the time. Therefore, the inverter capacity tends to be correlated to the peak demand and this partially supports why Figs. 3(c) and 4(c) are relatively flat. Similar considerations can be drawn for the tank.

Unlike the size of the diesel generator, its fuel consumption is greatly affected by the size of the renewable and storage assets, as highlighted in Figs. 3(d) and 4(d). Similarly, ENS is affected as well (Figs. 3(e) and 4(e)). When the capacity of the PV plant and batteries is reduced, the diesel generator intervenes more often to supply the load, but sometimes its production is not enough, thus the risk of generation shortage increases, and ENS as well. However, for this case study, ENS of MDOs within tolerance is always below 1% for LFS and even below 0.2–0.5% for RHS. Nonetheless, the energy produced by the diesel generator can reach 5% of the total demand in LFS and 8%–9% in RHS.

The larger the PV plant and the lithium batteries, the lower the operating costs related to ENS and the diesel generator, however CAPEX significantly increases (Figs. 3(f) and 4(f)). The optimal solution obtained by MDO-PSO lays in the equilibrium point between this tradeoff. However, depending on the local circumstances of the specific project, a developer may be interested to select a different solution, slightly less profitable than the optimal one, according to the MDO rational.

As private developers usually look for a reasonable number of options, the procedure described in Section 4.3 narrows down the desired solutions (Figs. 3 and 4) to a reduced number of designs that maximize or minimize predefined indicators. These results are shown in Tables 3 and 4, reporting each selected configuration, combined with the corresponding selection criterion and operating strategy (LFS or RHS). All the solutions are within 2% with respect to the NPC of the optimal solution shown in Table 2; however, significant differences among the optimal design and economic structure are highlighted. The solutions minimizing NPC generally require about 20–24k$ more investment than the ones with the lowest CAPEX, at the cost of increasing OPEX by about 30%, which in terms of NPC is roughly 2%–3%, both for LFS and RHS. The solutions minimizing ENS enable significantly reducing the curtailed energy with respect to the ones that minimize NPC: with LFS the reduction is 75%, while with RHS it is beyond 90%. Furthermore, the solution minimizing the diesel production share, or maximizing the renewable source, enables to identify solutions that are 28%–40% less reliant on fuel than the traditional solution at minimum NPC. These results can support the decision making of developers, which can better match the circumstances of their project with the proposed multiple design options.

The search history of the MDO-PSO algorithm is used in the post-processing phase to plot the MDO-Pareto frontier among two indicators, NPC and CAPEX in this activity, as shown in

Table 3
Economics and energy share of extreme MDOs.

Criterion	Strategy	NPC k$	CAPEX k$	OPEX k$/y	PV %	Diesel %	ENS %
min NPC	LFS	456	376	8.5	96.7	2.9	0.33
min CAPEX	LFS	465	352	11.5	93.9	5.5	0.66
max PV/min Diesel	LFS	464	397	7.2	98.2	1.7	0.13
min ENS	LFS	465	387	8.3	97.1	2.8	0.08
min Batt	LFS	464	398	8.0	97.4	2.3	0.27
min NPC	RHS	449	358	9.7	94.3	5.7	0.03
min CAPEX	RHS	456	336	12.2	91.2	8.7	0.08
max PV/min Diesel	RHS	457	379	8.5	95.9	4.1	0.00
min ENS	RHS	454	374	8.6	95.7	4.3	0.00
min Batt	RHS	455	375	9.6	94.5	5.5	0.01

Table 4
Optimal sizing of extreme MDOs.

Criterion	Strategy	PV kW	Batt kWh	Inv kW	DCDC kW	Diesel kW	Tank l
min NPC	LFS	177	559	89	69	17	283
min CAPEX	LFS	177	492	77	75	15	1082
max PV/min Diesel	LFS	190	580	108	78	21	544
min ENS	LFS	179	571	95	73	29	619
min Batt	LFS	176	617	107	77	18	1323
min NPC	RHS	168	540	87	68	10	635
min CAPEX	RHS	162	485	102	71	10	932
max PV/min Diesel	RHS	183	564	91	72	10	501
min ENS	RHS	183	547	86	77	10	618
min Batt	RHS	167	589	92	67	10	700

Fig. 5: the blue dots represent the frontier obtained by post-processing the MDO-PSO search history, while the red front is the one calculated with the standard multi-objective DMS method; the black dots denote the MDO-PSO search history and the light blue ones correspond to the designs within 2% optimality. For both LFS and RHS, especially in proximity to the single-objective solutions, the methodology based on post-processing the MDO-PSO search history identifies an area that is very close to the traditional Pareto frontier. This can be useful because multi-objective approaches can be computationally expensive, as shown in right side of Table 5, especially when predictive approaches are used: the computational times (14.2 h) with the latter are about three times the single-objective formulation (4.8 h). Thus, at least in the nearby of the single-objective optimal solution, MDO can provide developers with multiple design options accounting for several factors, as done in multi-objective methodologies but without their computational complexity. In other terms, when the developer's interest is focused on a specific indicator, MDO can be very precise in identifying the optimal solutions and highlighting MDOs in the nearby. Instead, when the developer, being equally interested in several indicators, desires a solution far from the single-objective optimal solution, traditional multi-objective approaches like DMS are more suitable.

Finally, Table 6 highlights the effects of the NPC tolerance on the range of the size configurations selected by the MDO approach. Clearly, the higher the tolerance, the larger the set of in-tolerance MDOs for both LFS and RHS, as shown in [3]; the above considerations hold.

7. Conclusions

This paper proposes the concept of Multiple Design Options (MDO) for single-objective optimization and the MDO-PSO optimization technique to enrich the design options of microgrid projects. The main novelties stand in a post-processing activity on the search history of the MDO-PSO algorithm that analyzes all the partial solutions tested by the algorithm within a given NPC tolerance from the final optimal solution, and selects size

Table 5
Computational requirements of the PSO and DMS methodologies.

PSO		DMS	
LFS	RHS	LFS	RHS
1.8 min	4.8 h	0.8 min	14.2 h

Table 6
Size configuration ranges, by NPC tolerance.

Tol.	Strategy	PV kW	Batt kWh	DCDC kW	Inv kW	Diesel kW	Tank kl
2%	LFS	160–200	492–617	70–164	57–80	9–29	0.1–3.7
2%	RHS	155–190	475–589	66–185	57–80	5–16	0.2–2.9
5%	LFS	149–225	461–697	59–225	55–80	0–38	0–6
5%	RHS	143–205	432–647	60–225	50–80	4–20	0.1–6

configurations that have nearly the same economic profitability. Trade-offs between multiple economic criteria (NPC and CAPEX) are also discussed and compared to a standard multi-objective methodology. A numerical case study relevant to a rural microgrid in Uganda is discussed, including a sensitivity analysis on the operating strategy and the NPC tolerance.

This study confirms that the objective function of microgrid sizing problems is flat nearby the optimal solution, since a large number of size scenarios of the assets of the microgrid achieve similar values of NPC, even spanning $\pm 20 - 34\%$ the value of the traditional optimal size of the system, despite a tolerance no greater than 5%. This suggests that the proposed approach can provide developers with microgrid size scenarios that can better meet the specific requirements and circumstances of the project, which cannot be included in traditional mathematical modeling.

The proposed technique also successfully captures the trade-off between CAPEX and NPC in the nearby of the optimal design, since the MDO-Pareto frontier estimated by MDO was similar to the one obtained with a traditional multi-objective approach. This suggests that operators mainly interested in a single objective function could be provided with additional design configurations, without repeating any optimization process.

The methodology presented in this study is able to support developers in meeting the variegated and diverse circumstances of the business environment, whereas traditional single-objective problems cannot successfully capture the multi-faceted characteristics of microgrid projects. Even if this study was focused on microgrids, MDO-PSO can be easily applied to different energy problems and power systems, thus supporting the decision-making process in a variety of different applications.

CRediT authorship contribution statement

Davide Fioriti: Conceptualization, Methodology, Software, Formal analysis, Validation, Visualization, Writing – original draft. **Davide Poli:** Methodology, Validation, Writing – review & editing, Supervision, Project administration. **Pablo Duenas-Martinez:** Methodology, Validation, Writing – review & editing. **Andrea Micangeli:** Validation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Source code

The MDO-PSO optimization algorithm is freely accessible at [34].

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