Heuristic approaches to size microgrids: a methodology to compile multiple design options

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***Abstract*—With the aim of maximizing profits of specific business applications, economics, and sometimes reliability and environmental constraints, have been widely guiding developers when designing microgrids. However, mathematical indicators alone, yet relevant, may not be able to fully capture the sociopolitical and geographical circumstances under which developers operate, especially in rural areas of developing countries. In this paper, we propose a methodology for obtaining microgrid designs that not only achieves the traditional economic-efficient optimal solution but also suggests multiple design options that increase the eligibility for developers, which can select an option given their particular circumstances. Based on a consolidated heuristic method, Particle Swarm Optimization, our algorithm identifies several design options of the microgrid's components, by using an iterative approach that stores the simulations occurring in each iteration. The results from an illustrative numerical case study highlight that significantly different designs can lead to similar values of the objective function, i.e. investment and operational costs. Our proposed methodology is of particular interest for developers, who have the opportunity to choose among a set of different technological solutions, but similar in economic terms.**

***Index Terms*—Rural electrification; mini-grid; multi-objective; multiple sizing choices; post-processing**

I. Introduction

Microgrids are promising solutions to enhance the quality of power systems and foster the penetration of renewable sources in developed countries [1], [2], as well as to trigger the socio-economic progress in developing countries by enabling reliable electrification in far communities where extending the national grid would be too expensive [3]. While the microgrid sector in developed countries is significantly growing, investors in the rural electrification sector still heavily rely on grants or are reluctant to enter the market, since significant risks are not rewarded by adequate profits [4], [5]. While the revenue stream for a renewable project in a developed country is usually known, especially where auctions or feed-in-tariff take place [6], the project sustainability of a rural microgrid is questionable as the revenues usually depend on the energy consumption and the community behavior, which are typically very uncertain, given that new consumers have often never used electricity.

Economics have traditionally been used in most of the optimization algorithms [7], [8], even when reliability [9], [10], environmental [11], [12], socio-political [13] or technical [14], [15] considerations have also been included. Nevertheless, representing the challenging and particular circumstances under which microgrid developers operate is difficult and traditional techniques, such as optimizing a single indicator [7], often based on economics like the Net Present Cost (NPC) or Net Present Value (NPV) [16], fails.

Despite this, economics-based optimization algorithms have usually been proposed for designing microgrids, isolated or interconnected to the main power system [7], [10], [17]. For example, Mixed-Integer Linear Programming (MILP) has been widely used in the literature for optimizing both the sizing [18] and operation [19] of power systems. Although proved to converge towards the global solution, the computational requirements of MILPs may be considerable, depending on the complexity and time horizon [20], and simplifications are needed when problems are non-linear. On the other hand, heuristic approaches can easily handle complex non-linear problems and achieve the solution much faster than traditional programming techniques [21], like MILPs. Authors in [21] compared the solutions after using Particle Swarm Optimization (PSO) and MILP-based approach. Even though the solutions were similar, the computational requirements with PSO were more than halved than with MILP. In [22], authors compared a home-energy management system, with a formulation based on Genetic Algorithm (GA), another heuristic approach, which turned out to achieve similar solutions of the MILP formulation, but in 10% of the computational time. This evidence has led to extensively accept heuristic algorithms.

However, both heuristic and traditional linear optimization techniques focus on optimizing a specific mathematical objective function, which is basically pure economics and disregards the multiple intangible features a microgrid investment is composed of. In fact, beyond economics, social and political concerns play a relevant role [3], [5], [23], as well as technical aspects do. The reliability or the uncertainty in the lifespan of components can affect the final decision; so it happens that a sub-optimal solution A, slightly worse in terms of objective function with respect to another design B, could be preferred by the investor, due to factors difficult to be valued and included into the optimization algorithm. In this regard, private developers can benefit from methodologies providing multiple sizing outputs, as done by commercial tools, like HOMER [24], yet in a limited manner. Few methodologies have been proposed to tackle this topic, to the best of authors' knowledge.

In this study, we propose a methodology that enables developers to choose among multiple design options related to an off-grid microgrid. While our approach can be generalized to any heuristic algorithm, PSO is used as an example to minimize the NPC of the system. In every iteration of the PSO, the intermediate results elaborated by the algorithm are stored, and when the PSO converges, the collected information is post-processed with the aim of compiling multiple design options. By doing so, developers can select the best suited option for their investment, without significantly affecting the optimality of the solution.

In Section II, the sizing technique is explained, including the novel post-processing methodology. Section III illustrates the numerical case study and Section IV describes the results. Finally, conclusions are discussed.

II. The Multi-Solution Sizing Technique

As depicted in Fig. 1, the proposed sizing technique is composed by an optimization based on an iterative heuristic approach coupled with a post-processing phase, which analyzes the simulated results from the optimization. The sizing technique is similar to other approaches (see [21]), with the difference that during each iteration all the processed information is stored and used, when the optimization algorithm converges, as described below.

A. *The optimization algorithm*

The optimization phase is based on a heuristic iterative algorithm that aims at minimizing the NPC of the system that includes the investment costs ($CAPEX_y$), operating expenses ($OPEX_y$) and residual value (RES_y) of the investment at the end of the project lifetime, as detailed in (1), where d represents the discount rate and N_T corresponds to the lifetime of the project in years. OPEX considers the fuel expenses, the maintenance of the components and the equivalent cost of the Energy-Not-Served (ENS). The RES of each component is calculated as the investment cost multiplied by the fraction of the remaining lifetime of such component.

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

The system is supposed to be operated using the load following strategy, selected because it represents a state-of-the-art approach for current microgrids [21], [25]. The use

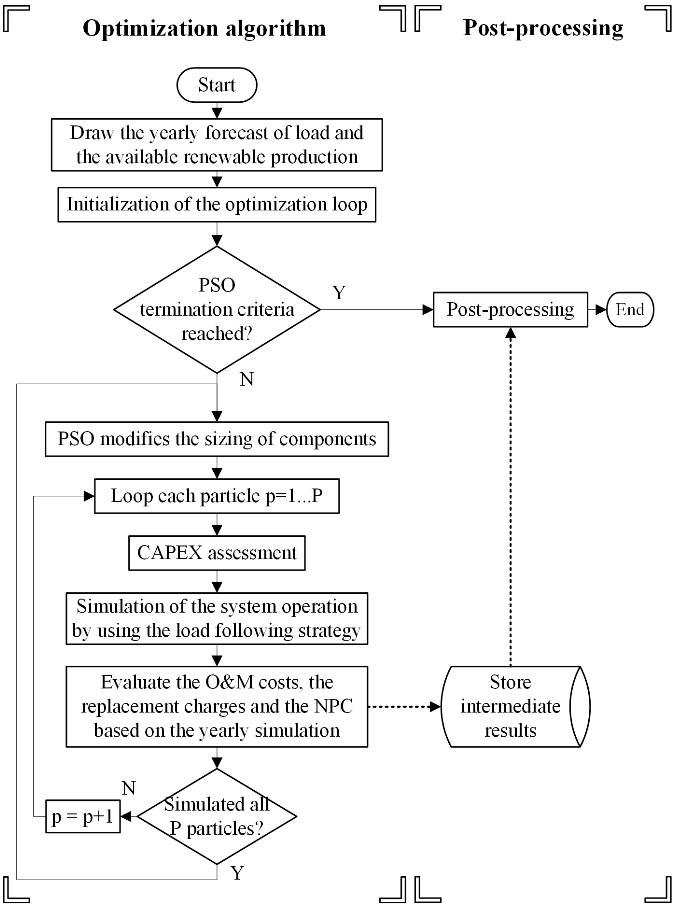


Fig. 1: The proposed sizing method.

of other alternatives, like predictive methodologies, can lead to reduce the NPC of the system at the cost of higher computational requirements; however, the optimal designs of the major components obtained with the two approaches are similar [21]. Therefore, in this activity, we decided to focus on the load-following strategy, given its simplicity and wide use in rural microgrids.

Given its long-proved use in power systems [21], [26], [27], PSO has been used in this study as the heuristic solver for the considered microgrid. As depicted in Fig. 1, the PSO iteratively draws P different design scenarios (100) of the components of the system, also referred to as particles, based on the solution of the previous iterations. Then, the yearly system operation corresponding to each particle is simulated using the load-following strategy, and the objective function is finally calculated. Conversely to standard approaches [21], during the iterative procedure, the intermediate results are stored to be used later in the post-processing phase. Aiming to reduce the computational burden, the stored information is reduced to the size of the components and the value of the objective function. The PSO algorithm converges when the objective function does not change beyond a given threshold (0.1%) within a preset number (20) of iterations.

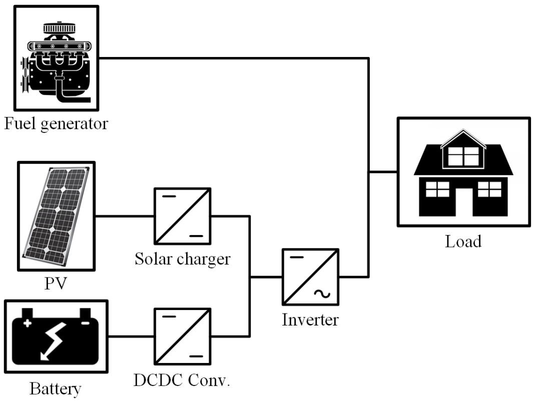


Fig. 2: The topology of the microgrid.

B. The post-processing phase

As shown in Fig. 1, the data relevant to the particles simulated during the PSO optimization are post-processed when the PSO converges. In particular, only the design scenarios within a preset optimality tolerance are selected. Subsequently, their major characteristics are shown by means of color maps that highlight to developers various design options with significantly different characteristics in terms of size of components, ENS and initial investment, while maintaining very close values of the objective function. More in detail, the following steps were taken:

1) Selection of particles within a preset NPC tolerance with respect to the minimum NPC achieved with the PSO.
2) Calculation of desired quantities of interest for the developer, i.e. ENS and CAPEX.
3) Data interpolation using the cubic method (e.g. as provided by MATLAB).
4) Display of results.

III. Case Study

The proposed case study is based on a hybrid microgrid to be installed in Soroti, Uganda, composed by one photovoltaic (PV) plant, one battery storage, one inverter, one battery converter, one diesel generator and its fuel tank. As shown in Fig. 2, the PV and battery are coupled at the DC busbar, while the diesel generator and the inverter supply power to the load at the AC busbar, as is in typical microgrid of developing countries.

The community is composed by 100 households and some commercial activities, whose typical load profile shown in Fig. 3 was estimated with the procedure described in [28], in which a Monte Carlo method draws the entire yearly profile by using a hourly Gaussian probability density function. The yearly peak power is around 80-86kW. The renewable energy production has been estimated using the methodology detailed in [29] and with the Graham model [30], [31], both tailored using the data of the close weather station in Kitale, Kenya, as information for Soroti was limited.

The cost function of the components of the microgrid reflects the economies of scale and volume (2) whose coeffi-

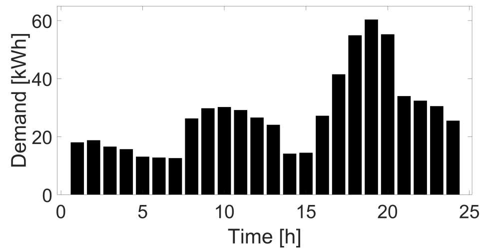


Fig. 3: The load profile.

TABLE I: Cost parameters of the main components.

Asset (i)	$S_{i,0}$; UM	$C_{i,0}$ $/UM	β_i -	Mainten. $/UM/y	Lifetime
PV	1 kW	800	1	16	25y
Battery	1 kWh	925	1	3	3000 eq.cyc.
Bat. conv.	1 kW	1258	0.5	2	15y
Inverter	1 kW	1887	0.5	2	15y
Fuel gen.	1 kW	1013	0.8	0.05$/kW/h	30000h
Fuel tank	1 liter	52.2	0.45	0.15	25y

cients are detailed in Table I. Eq. (2) is modeled by using the reference cost $C_{i,0}$ of the component i with capacity $S_{i,0}$ and the effects of the economies of scale are modeled with parameter β_i, which describes the cost reduction with respect to the capacity S_i of the each component. The table also reports the lifetime and the specific maintenance expense for each asset. The efficiency of the inverter is 96% and the roundtrip efficiency of the battery, including the converter, is 92%. The diesel generator operates between 10% and 100% of the rated power, with a maximum efficiency of 33%. The fuel price is 0.9$/l and the load curtailment cost is 1$/kWh.

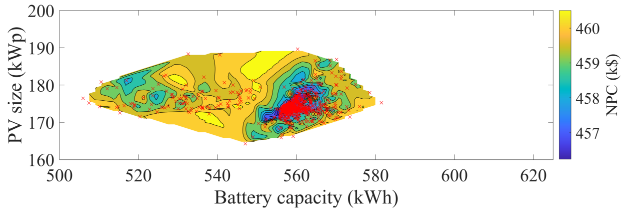
$$CAPEX_y = \sum_i C_{i,0} \left(\frac{S_i}{S_{i,0}} \right)^{\beta_i} \tag{2}$$

The logistics of the fuel generator are also considered: when the fuel stored in the tank falls below 20% of the rated capacity, a refill is requested for the missing quantity (80%). The time required for the arrival of the truck is modeled using a Weibull function whose 50% and 90% percentiles are 4 and 7 days respectively, but no refill can occur within the following 24 hours after the request. The lifetime of the project is 15 years and the discount rate is 8%.

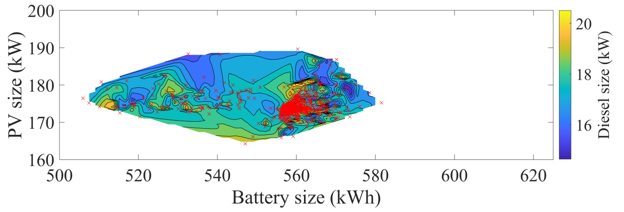
The proposed approach is applied to this case study with two possible values of the optimality tolerance on NPC: 1% and 5%.

IV. Results

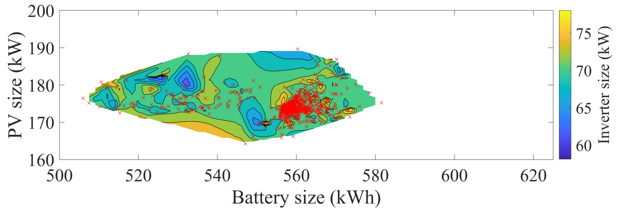
The results of the proposed procedure are shown in Fig. 4 and Fig. 5, corresponding to NPC tolerance of 1% and 5%, respectively. The figures show the values of the objective function (NPC), the size of the main components, the ENS and the initial investment, corresponding to the many size configurations sampled by the PSO procedure. In particular, the red dots in the images indicate directly the raw simulation points collected by the PSO procedure, whereas the color maps show their interpolation using a cubic fit. Table II details



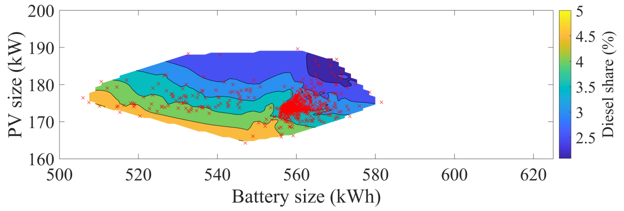
(a) NPC



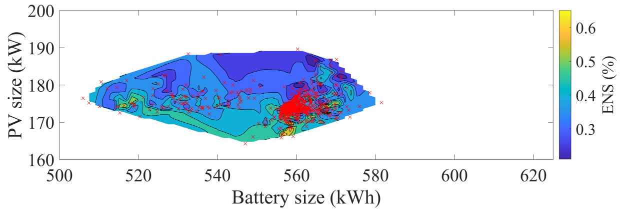
(b) Optimal design of PV, battery and fuel-fired generator



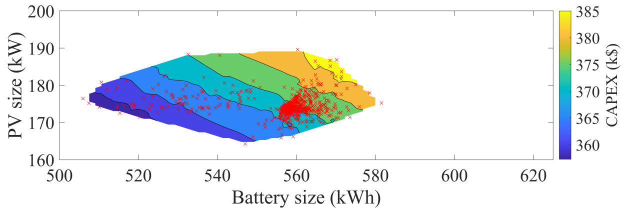
(c) Optimal sizing of PV, battery and inverter



(d) Diesel production share

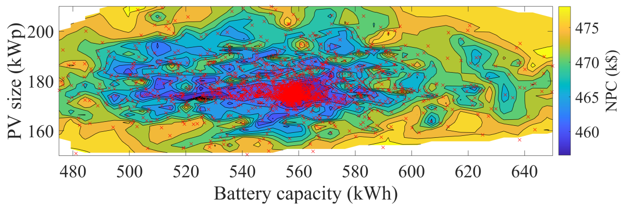


(e) Energy-Not-Served

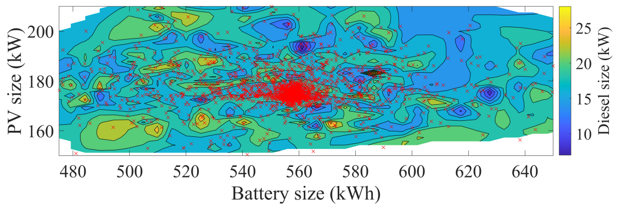


(f) CAPEX

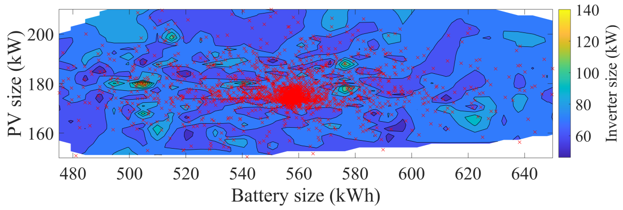
Fig. 4: Results of the proposed procedure with optimality tolerance of 1%; the red dots in the figures indicate the size configurations within tolerance.



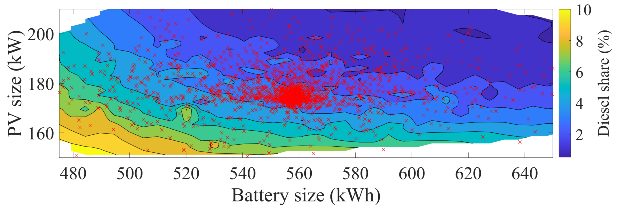
(a) NPC



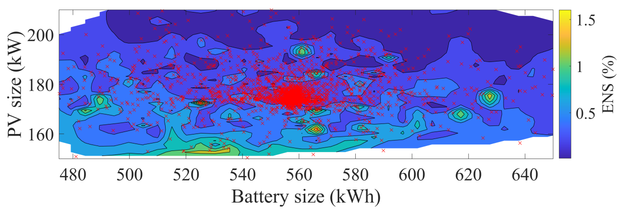
(b) Optimal design of PV, battery and fuel-fired generator



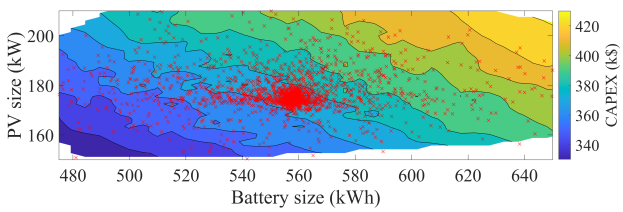
(c) Optimal sizing of PV, battery and inverter



(d) Diesel production share



(e) Energy-Not-Served



(f) CAPEX

Fig. 5: Results of the proposed procedure with optimality tolerance of 5%; the red dots in the figures indicate the size configurations within tolerance.

TABLE II: Optimal solution calculated by the PSO.

NPC k$	PV kW	Batt kWh	Inv kW	DCDC Conv kW	Diesel kW	Tank l
456	174	557	92	70	18	455

the objective function and the optimal size of components calculated by the PSO optimization.

Fig. 4a and Fig. 5a show the value of NPC corresponding to the different size scenarios sampled by the PSO procedure (red points), respectively within 1% and 5% NPC tolerance, combined with the corresponding battery capacity and rated power of the PV plant. Obviously, with 1% tolerance the post-processing procedure selects a lower number of points, yet close to the optimal solution corresponding to 456 k$ of NPC. Despite this, it is clear that the objective function is very flat. In fact, the designs leading to similar values of the objective function spread over a wide range, up to $\pm$10-25%, depending on the case. This suggests that developers can benefit from having different design options with various characteristics, as calculated with our proposed method.

In contrast to the PV panel and the battery, shown in Fig. 4a and Fig. 5a, the variability of the inverter, whose design is depicted in Fig. 4c and Fig. 5c, is much more limited: the images are very flat and the size is always close to the peak demand. In fact, when the generator is not committed, the demand has to be supplied by the PV system or the battery through the inverter. If the capacity of the inverter is limited with respect to the actual demand, the diesel generator has to step in or ENS is generated. On the other hand, the peak demand occurs only few hours in a year, thus sizing the inverter for the peak power or beyond may lead to increase the NPC, since the savings related to a lower fuel consumption or load curtailment may not cover the investment costs of the additional capacity of the inverter. Moreover, the costs related to the inverter are limited in terms of NPC, thus suggesting that the optimal design of the inverter does not affect significantly the objective function. The sizing of the tank, though not reported in the figures, is similar to the inverter one. However, it is more jagged on the image, since the impact of the tank on the NPC is low. That is, a larger tank sizes does not affect consistently the objective function.

The size of the diesel generator, reported in Fig. 4b and Fig. 5b respectively for the case of 1% and 5% NPC tolerance, tends to increase as the sizes of the PV plant and of the battery decrease. Similarly, also the fuel consumption increases as shown in Fig. 4d and Fig. 5d. In fact, the lower capacity of the PV plant or of the battery, the lower amount of renewable energy produced or stored; therefore, the diesel generators step in more often to limit the load curtailment (Fig. 4e and Fig. 4e). Given the cost parameters of the case study, the ENS is always negligible, often below 1%, while the diesel generation can increase even up to about 10% when the renewable energy production is low.

However, when the sizes of the battery and of the PV plant increase, the CAPEX of the system significantly increases (Fig. 4f and Fig. 5f), whereas the ENS and the fuel consumption decrease. On the other hand, increasing the size of the components above the optimal solution does not reduce adequately the fuel costs or ENS (Fig. 4a and Fig. 5a), in fact NPC increases for large capacities of battery and PV plant. Thanks to the proposed image-aided approach, developers can better understand the shape of the objective functions, so they can select designs suited for their specific project.

V. Conclusions

This paper proposes a methodology to augment the design options for microgrid projects by using a heuristic iterative approach combined with a post-processing analysis. During the iterations of the heuristic optimizer, the tested size configurations are stored. When the optimization algorithm converges, all configurations with an objective function within a preset tolerance from the optimal solution are selected and their characteristics are illustrated by means of color maps. The methodology has been applied to a case study of a rural microgrid in Uganda. Within the goal of minimizing the NPC, a sensitivity analysis on the optimality tolerance of the post-processing method was also considered.

The results show that several design options can lead to similar values of the NPC, thus confirming that the objective function is very flat nearby the optimal solution. Although the considered post-processing tolerances are very low in terms of NPC (no greater than 5%), the variability of the sizes of the battery and the PV plant is consistent, up to $\pm 20 - 30\%$. Even if the impact in terms of NPC is low, the different size scenarios affect other characteristics of the investment, such as the use of fuel-fired generators and the amount of the initial investment, which are easily revealed thanks to the proposed post-processing analysis.

As the circumstances where developers participate are variegated and diverse, traditional mathematical objective functions may fail to capture all details. Our proposed approach can support the decision-making in these contexts and provide reliable and complete information to develop profitable microgrid investments. Future developments of this research activity will consider the automatic clustering of the different design options, to also highlight the most repeated and, hence, promising options.

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