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Demand-side energy management by cooperative combination of plans: A multi-objective method applicable to isolated communities

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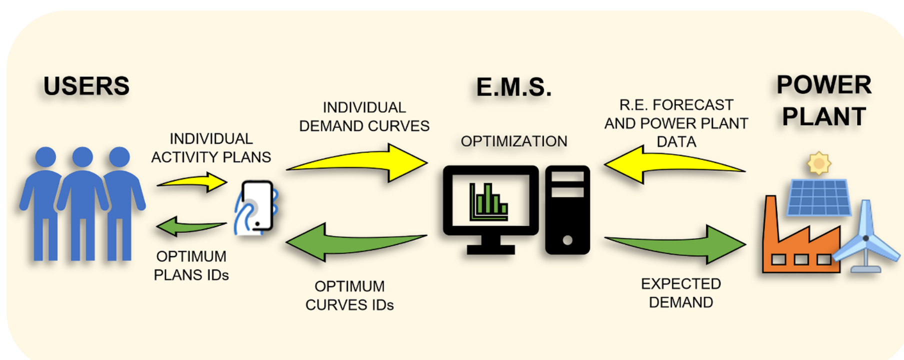
HIGHLIGHTS

- A method non-dependent of load-control devices or dynamic pricing systems.
- May allow individual consumption profiles identification without energy meters.
- Minimizes simultaneously the cost of energy production and users' discomfort.
- 8.6% of fuel savings was achieved requiring the action of only 51% of the users.
- Indirect gains in maintenance of the generators were also achieved.

GRAPHICAL ABSTRACT



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ABSTRACT

Nowadays a diversity of demand-side energy management methods have been investigated and experimented, however, the low acceptance and participation of the users and the extra costs for the monitoring and control devices installation are still listed by the literature as the main barriers to be overcome. In many cases, activities can be performed in several ways, but once planned, the replanning or cancellation can become impracticable. In Antarctic Research Stations and isolated communities, the planning of activities is even more critical due climatic time windows and facility availability. Considering these aspects, this work proposes and analyses a demand-side management method based on the cooperative combination of activity plans. The method does not depend on the installation of load-control devices neither knowledge of the user about electricity or tariffs. Based on options of plans informed by the users, the proposed multi-objective optimization algorithm search for the set of plans that both minimizes the cost of energy production and the discomfort of the whole community. Simulations performed for a wind-solar-diesel microgrid with 100 users in scenarios of lack and excess of renewable resource indicate that the proposed method can contribute to the adjustment of the aggregate demand profile of users served by isolated microgrids. In the simulations, the problem of overgeneration by the renewable sources was solved and 8.6% of fuel savings was achieved by the intervention in only 51% of the users. Improvements in the load factor of the generators and in their total operation time were also observed. As consequence, a reduction in the maintenance costs of the generators is also expected.

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1. Introduction

In energy markets, similarly to other markets, the final costs of production and distribution may have different values depending on the demand profile. In isolated communities served by microgrids the uncoordinated demand together with renewables resource intermittence can produce even more impact, in terms of energy cost [1,2], maintenance and grid reliability [3]. In general, demand curves containing uncoordinated peaks and valleys raise the final cost of energy both by the need to expand the generation and distribution infrastructure and by forcing the equipment to operate outside its optimal efficiency range.

Demand-Side Energy Management (DSM) is the term used to describe different strategies used to modify the electrical demand of consumers, aiming to reduce the mismatch between supply and demand. DSM methods that encourage the migration of loads to off-peak hours, such as real-time and day-ahead dynamic pricing, have been deep investigated [4,5] and experimented [6,7] in recent years. However, these traditional DSM methods require frequent monitoring of energy price by the users or the installation of intelligent load-control devices [8,9].

This work proposes a multi-objective day-ahead DSM method that simultaneously minimizes the cost of energy production and the discomfort of users by the cooperative combination of plans. The proposed method does not depend on the installation of load-control devices and does not require the monitoring of energy price by the user, reducing the DSM implementation costs and making human participation less stressful. The users only need to inform up to three options of how they prefer to perform their daily activities. One plan is considered the main and the others alternative plans. Each combination of plans produces an aggregate demand curve of the community. The proposed method searches for the combination that minimizes the daily energy cost with minimal selection of alternative plans.

1.1. Research contributions

This research contributes with a multi-objective cooperative method able to manage the electric demand without the need of smart meters installation, load control devices and energy price monitoring. The proposed method was initially designed for application in isolated research stations considering investigations made by the authors at the Brazilian Antarctic Station [2,10]. In this sense, the proposed method is an option for demand-side management in remote communities, Antarctic Stations and Advanced Space Stations.

The competitive differentials of the proposed method in relation to traditional DSM systems are:

- Does not depend on the installation of monitoring and load-control devices or on dynamic pricing systems;
- Ability to consider and manage the consumption of each user over all the grid area, along particular and public spaces;
- Does not require from users any knowledge of electrical equipment characteristics or about energy cost to participate; and
- May allow the identification of individual consumption profiles without measuring devices.

In addition, the research contributes with a formulation and analysis of the Variable Neighborhood Search metaheuristic, for the solution of the day-ahead DSM problem, under the cooperative approach, using parallel computation.

1.2. Paper organization

For a better understanding of the work, the main fundamental concepts related to the theme and to the proposed DSM model are organized in the Section 1.3 Literature review. The Section 1.3.1 highlights the main DSM techniques and methods investigated by the literature. Section 1.3.2 sums up the concepts related to metaheuristics and multi-objective optimization. In Section 1.3.3 are explored barriers and potentials for applying DSM in real scenarios.

After the introduction, Section 2, Proposed DSM method, details the methodology and formulation related to the proposed management method and to the optimization algorithm.

Section 3, Input data modeling, presents the definition and modeling of the electrical demand, renewable resources and the microgrid topology adopted for the simulations.

Section 4, Definition of cases to test the DSM, presents the cases defined to test the proposed DSM and the performance indicators selected for comparison in the analyses.

The Sections 5–7 respectively present the results, the discussion and the conclusions. At the end of the paper a complementary analysis of the proposed optimization versus a purely decision making by the energy system operator is presented in Appendix A, Purely decision-making vs optimization.

1.3. Literature review

In theory, the optimal management of modern energy systems composed of multiple sources such as thermoelectric, wind and solar generation, with or without energy storage systems, is fully possible with the adoption of the Smart Grid concept. In practice, the integration of monitoring and control devices, communication and data processing systems aiming the optimal management and operation of the network requires preliminary investigation, development and experimentation of techniques, methods and technologies [9,11].

The following Subsections organize relevant aspects related to the DSM systems deployment. Features like techniques of load management, type of users' interaction and time scale of the management are investigated once these are the main aspects listed by the literature to characterize the DSM systems. Concepts of multi-objective optimization are also reviewed and the use of approximate methods showed up as an alternative to deal with the complexity of cooperative users approaches. In addition, real cases of DSM implementations are investigated, and the main barriers highlighted by the literature are addressed.

1.3.1. Overview of DSM techniques and methods

Among the main demand management techniques investigated by the literature are: load shifting; peak clipping; valley filling; load building; and flexible load [4,12].

Load shifting, considered the most effective load management technique, shifts loads from peak times to off-peak time and can be done manually or automatically. Peak clipping and valley filling are techniques of direct control of load in which loads are reduced at peak time or inserted in off-peak hours. Load building and flexible loads are linked to the infrastructure provided within the Smart Grids concept. Load building increases the share of loads and energy storage systems to improve grid responsiveness, going beyond the valley fill technique. Flexible loads are loads that can and are willing to be controlled in exchange for incentives [4,12].

Besides these techniques, the DSM systems also differ according to the optimization implementation methods. The methods can be differentiated by: type of user interaction (individual or cooperative); the optimization problem approach (deterministic or stochastic); and time scale (day-ahead or real time) [12].

Type of user interaction: DSM systems can be designed to optimize the use of electrical resources by individual users or a cooperative consumer community. Optimization methods for single residential users are set to individually and locally control the loads. However, this approach may have some undesirable effects [12], since user decisions are not coordinated. In the case of DSM methods for minimizing user payments, for example, all consumers can transfer their loads to periods of day when electricity prices are low, potentially causing high peaks in demand during these low-cost periods and also interruptions of service. Cooperative models solve the problem of demand management in a coordinated way and consider the achievements of the collective action of users in the system. Cooperative models are more complex to study and solve, since they need to consider the possibilities and constraints of all users at the same time. Despite the greater complexity, cooperative modeling is the most promising to be implemented in real scenarios [4,12].

Approach of the optimization problem: Another feature is the use of deterministic or stochastic approaches to design the demand management solver. In DSM systems, parameters such as renewable energy generation and energy prices for future periods are estimated by forecasting methods. In the deterministic approach it is considered only one scenario for the simulations, while the stochastic approach evaluates multiple possible scenarios, taking into account the expected randomness of the forecast, in order to consider the uncertainty in the decision-making process [12].

Time scale: DSM systems can be deployed to manage customer assets in day-ahead or in real time. At day-ahead time scale, the operational plan for the electrical resources of the users need to be defined for the next 24-hour period. To do so, the DSM system requires forecasts and estimates of some system parameters, such as power generation from local sources and device usage preferences for the next day. On the other hand, in real-time management, the actions are made based on real-time data from the users and from the operator. As a consequence, demand side management systems in real time scale behave similarly to demand response systems [12].

Fig. 1 organizes side by side the main techniques and methods used for DSM systems characterization.

1.3.2. Concepts of metaheuristics and multi-objective optimization

The management of modern energy systems is made through optimization algorithms based on forecasted and power system information [4,12]. The forecast of renewable resources [13] and energy consumption [14], hours or days ahead, allows that possible imbalances between supply and demand to be identified in advance. With the forecasted information and the power system parameters and constraints, the optimization problem can be modeled adopting different techniques and methods.

The complexity of the optimization problem and consequently the time required to solve it can be higher or lower depending on the number of users and the methods used by the management system. In DSM systems based on cooperative users, for example, the number of possible combinations increases exponentially with the increase of users. In many cases finding the optimal solution may become impractical given the computational requirement and time limitations. In this sense, the use of approximation optimization algorithms and parallel computing [15] have been increasingly investigated and are proving to be effective in solving energy management problems [16].

The approximation methods are based on simplified procedures in order to provide a solution not necessarily optimal, but satisfactory in an acceptable time. In the last decades, several methods of approximation have been proposed with emphasis for the heuristics [16,17].

Heuristic methods can be classified into trajectory-based and population-based. Trajectory-based metaheuristics uses a main solution during the search process and gives a unique final solution. Examples of trajectory-based metaheuristics are: Greed Randomized Adaptive Search Procedures (GRASP), Hill Climbling (HC), Iterated Local Search (ILS), Simulated Annealing (SA), Tabu Search (TS) and Variable Neighborhood Search (VNS). In contrast, population-based metaheuristics uses sets of solutions (population) that evolve with each iteration for an optimized final set. Examples of population-based metaheuristics are: Artificial Bee Colony Optimization (ABCO), Ant Colony Optimization (ACO), Differential Evolution (DE), Evolutionary Algorithms (EA), Estimation of Distribution Algorithm (EDA), Genetic Algorithms (GA), Memetic Algorithms (MA), Path Relinking (PK), Particle Swarm Optimization (PSO), and Scatter Search (SS) [16].

Heuristic methods can be understood as strategies that guide a search process. One of the metaheuristics that has high degree of generalization and freedom for application in several optimization problems is the VNS [15]. The VNS metaheuristic was proposed by Mladenović & Hansen [18] and differs from other methods by the application of local searches in different neighborhoods within the solutions space [19]. Each iteration consists of three phases: shaking, local search and update of the best solution. If the local search stops presenting improvements, the algorithm explores increasingly distant neighborhoods of the current incumbent solution and jumps from this solution to a new one if and only if improvement has been made [19].

In many cases, it is desirable to simultaneously optimize multiple objectives such as cost, comfort and environmental impact. In these cases, it is necessary to choose a method capable of adequately considering the multiple objectives in each iteration. In multi-objective approaches, two methods stand out: aggregate weights functions and Pareto-dominance [16].

Aggregate weights functions combine all the objectives in the same mathematical function, where the relative importance of each objective is given by weights. Despite the simplicity of incorporating several objectives into the same function, the definition of the weights relative to each objective is complex and can compromise the results.

Pareto-based optimization methods solve this problem through the Pareto-dominance concept, which considers that a solution S_1 dominates another solution S_2 when S_1 is better than S_2 in at least objective and is not worse in the other objectives. If none of the solutions dominate one another, they are said to be indifferent. The set of non-

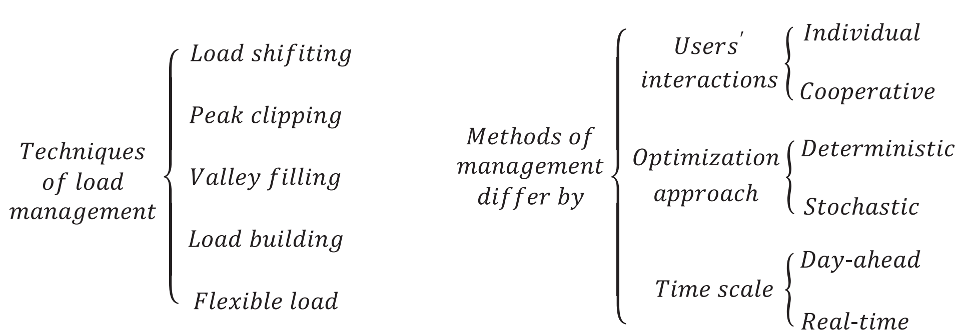


Fig. 1. Main DSM techniques and methods listed by the literature for DSM characterization.

dominated solutions constitutes the optimal set of Pareto or Pareto frontier, from where it is possible to choose the solution based on thresholds and priority criteria between the objectives.

1.3.3. DSM in real scenarios

Dynamic pricing is one of the emerging areas of research in the retail electricity sector. It is a demand side management technique that stimulates peak load reduction and valley filling by charging different prices at different times according to demand [20]. According to Dutta and Mitra [20], the peak load reduction of around 30% is registered in pilot projects of dynamic prices. The experiments registered a 4% reduction to an 8% increase in the bill values depending on the pricing scheme and the attitude of customers [20].

Another indicator used in the study of DSM systems is demand flexibility, which measures the customers' ability to modify their energy consumption [21]. Ayón et al. [21] investigated the flexibility of aggregate demands of buildings with different characteristics, such as shopping malls, offices, hotels and residences, using data from the Spanish electricity market. The flexibility in relation to aggregate demand observed was between 10% and 30% in winter and between 12% and 40% in summer, depending on the type of buildings.

Regarding the difficulties for the implementation and success of demand response systems, Good et al. [9] identifies and classifies the barriers as fundamental or secondary. The fundamental barriers are defined as economic, social or technological, while secondary barriers are related to political regulatory aspects, market design, physical issues (electric grid) or the general definition of demand response.

Le Ray et al. [7] presents the evaluation of the demand response system performed within the EcoGrid EU Experiment [6]. In the experiment, 1900 homes were equipped with smart meters and other automation devices in order to adapt consumption to electricity prices in real time every five minutes. The results showed that the houses could be considered responsible for the price in some days of testing, while in some others the results were inconclusive [7]. During the experiment, the group of customers responsible for the manual management of their demands (without automatic load actuators) showed low reaction to the variable prices. The project members involved in the field test highlighted as one of the complicating factors the high frequency of price changes. Up to half of the project, only 14% of manual response customers visited the site on a regular basis to verify the rates and by the end of the project the participation percentage did not exceed 33% [22]. On the other hand, groups of customers with automatic load-actuation showed good results. Although the installation of smart devices can demonstrate better results by not requiring customers to constantly monitor tariffs and frequently replan their activities, energy companies understood that the potential financial gain from participating in the project was small compared to the effort to upgrade the systems. In addition, the use of smart devices to control loads would introduce a potential risk of damaged goods if the local security lockout failed [22].

In extreme environments like Antarctica concepts of energy conservation and demand management have also been explored in conjunction with the inclusion of renewable energy sources [1,2]. In such environments, the dependency of a single energy source or the unregulated use of energy is even more critical. The additional cost of logistics can increase the fuel value by more than seven times [1] and its scarcity can put at risk the human survival. Antarctic stations of countries such as Australia, Belgium, New Zealand and United States are examples of buildings in extreme environments, working with renewable sources integrated to a power plant based on diesel oil [2,23].

In general, there are no individual billing of energy in Antarctica since the cost of energy is covered by the Antarctic Programs or research grants. Most of the activities in Antarctic Stations need to be planned due to researches, climatic time windows and facility reservation. In many cases, it is stressful or impracticable to replan or interrupt activities during the time of execution. In this sense, DSM systems based on dynamic pricing are not suitable for Antarctic buildings.

Among all the Stations, the Belgian Station, named Princess Elisabeth Antarctica (PEA), stands out. PEA is differentiated by its energy management algorithm that allows a 1:10 rate between production and electrical loads [24]. For this, the station has a complex Smart Grid capable of simultaneously supervising more than 2000 points of production and energy consumption. The PEA project adopted the concept that the demand of energy is subject to the conditions of generation and not that the generation must attend indiscriminately to the demand [24]. In this concept, the following levels of priority are analyzed to perform a hierarchical control of loads [23,24]: Level 1-Human security, water production and ventilation; Level 2-General Station systems such as temperature and humidity control; Level 3-Storage and maintenance of scientific records; Level 4-Kitchen, restrooms and the like; Level 5-Non-essential equipment like laptops and DVD players.

Whether in cities or extreme environments, energy management methods have been widely investigated. In common, the methods follow the concept of Smart Grid and present as main difficulties encouraging human participation and reducing the need of devices installation.

In this context, the exploration of management methods that assist users in planning their tasks without requiring advanced knowledge of energy, that do not rely on the installation of extra devices and that deal with the DSM problem in a cooperative way is justified.

2. Proposed DSM method

In this paper, a multi-objective DSM system was designed using a humanized approach. The humanized approach refers to the improvement of the DSM convenience to the user through the interaction with the users in the level of activities, one layer above the loads. Based on the activity plans informed by the users, the loads, and consequently the electrical demand curves, can be estimated and then processed by a DSM system.

Was proposed the use of up three options plans for each user. This number is realistic and is sufficient to promote a large number of combinations. One of the plans is considered as the main and the others are defined as alternative plans.

Considering the options of demand curves of each user, a multi-objective optimization algorithm searches for a combination of plans that minimizes simultaneously the cost of energy production and the discomfort index. The discomfort index is given by the number of users who need to execute one of their alternative plans.

The algorithm promotes the load shifting over time by switching between the main plans and the alternative plans. The method exploits the potential for complementarity in the electrical demand curves that a set of users may naturally present.

The problem is solved within the cooperative users approach for execution in the next day during the morning and the afternoon, from 6 a.m. to 6p.m. Night and dawn were considered as people rest time. The steps that are executed by the proposed DSM (data collection, optimization and agreement with users) and the proposed methodology to the data flow are detailed in Sections 2.1 and 2.2.

For the multi-objective optimization, a VNS metaheuristic was implemented together with parallel computing techniques and Pareto-dominance concept. Parallel VNS is a improved VNS algorithm [25] with a high degree of generality and allows the resolution of large instances of combinatorial problems [15]. The choice of VNS also aimed at evaluating the metaheuristic applied to demand side management problems. Section 2.3 details the methodology related to the optimization algorithm.

To evaluate the proposed method in cases of lack or excess of renewable energy, it was defined a scenario of 100 users attended by a wind-solar-diesel microgrid. The microgrid, the renewable resource and the demand of the users are modeled following the methodology presented in Section 3.

For the evaluation of the proposed DSM, two cases were defined. Case 1 aimed at evaluating the behavior of DSM without the presence of renewables. Case 2 was defined to evaluate the DSM in the presence of excess renewables. Section 4 describes the cases and all the performance parameters chosen to be analysed in the simulations.

2.1. The DSM workflow

The cycle of execution of the proposed DSM is daily and is divided into three parts: data collection; optimization problem resolution; and agreement of plans with users. Fig. 2 presents the workflow of the proposed DSM. The data collection phase is represented by the yellow arrows. The output of the system is represented by the green arrows. The optimization is executed at the Energy Management System (EMS) server.

Initially, to feed the optimization problem, data from the power plant, renewable resources forecast, and electric demand information are required. The data of the power plant involves the capacity of generation of the generators and renewable sources, efficiency of the systems and fuel consumption curve parameters. The data of renewable resources consists in day-ahead hourly forecasts. The electric demand is estimated based on the options of activity plans informed by the users for the following day.

The plans are informed by the users via smart phones to a demand estimator application provided by the Energy System Operator (ESO) and then only the demand curves are sent to the EMS server.

After data collection, the optimization algorithm is able to be executed. Once the solution is determined, the users are then informed about which plan each one should choose to minimize the overall cost of energy production. After the agreement with the users, the EMS sends to power plant controllers the expected demand curve.

2.2. DSM formulation

During the DSM initialization, the users are invited to present up to three possibilities of performing their next day activities (Plan 1, 2 or 3). Considering the informed plans, the possible demand curves of each user are estimated and in sequence the optimization algorithm seeks a coordinated action of the users that minimize the cost of energy production with the minimum number of users managed. In the end, each user is informed which plan need to be followed so that the whole system is improved.

For this, the activity plan of a user is defined as a vector of z hours, containing in each hour the set of activities planned by the user. Each user presents one main plan and two alternate ones, totaling three plans. Plan 1 is considered as the most convenient plan to the user. For elaboration of the alternate plans, the user is invited to migrate activities between morning and afternoon or within the same period. A fundamental premise is that the users only presents plans that are feasible.

The premise that the user presents only feasible plans allows improving the optimization performance and ensuring the feasibility of the solutions. The adoption of this premise is interesting since the verification of incompatibility of activities in time and space is performed naturally by each user considering both individual and collective constraints. This approach also ensures that the final solution found by the optimization will be realistic to the user.

The proposed method explores the understanding that the individual, and consequently its consumption, move spatially through the region served by the energy network. In this way, the plans describe the activities carried out by the users, regardless of the place of execution. So, the demand estimator system accounts the consumption all over the grid, not only inside a house or a specific building.

In the proposed approach, it is considered that every hour a person can perform a set of activities, in one or more places. Whatever the place, each activity may be linked to the use of one or more equipment (loads). So, the electrical consumption related to a specific activity like "do task × at room y", may be composed by the electrical consumption promoted by one or more loads. From this method it is possible to perform the accounting of the energy consumption caused by group of activities and so estimate the demand curve related to each one of the activity plans. This information is then stored in a matrix named Matrix of Demand Curves (MDC).

The aggregate demand curve is given by the sum of demand curves of all users. Therefore, the aggregate demand curve will have its format changed according to the plans executed by each user. Each combination of plans produces an aggregate demand curve.

The number of possible combinations is given by the number of plans raised to the number of users. Thus, considering n users with three plans each, there will be up to 3^{100} possible aggregate demand curves. Each of these aggregate demand curves is addressed by a vector of a possible combination i.e. $S_i = \{Plan\_id_1^i, Plan\_id_2^i, Plan\_id_3^i, ..., Plan\_id_n^i\}$, where $Plan\_id_n^i$ indicates the plan suggested by the solution number i for the user number n. By way of illustration, the first possible combination, the combination where all users execute their respective plans 1, main plans, is expressed by $S_1 = \{1, 1, 1, ..., 1\}$.

The renewable resources data is defined as a vector of z hours, containing the forecasted renewable energy for the day-ahead. The power plant parameters are constants and variables related to equipment capacities, efficiencies and consumption curves, limits and cost of operation, used to construct the power plant model.

Fig. 3 illustrates the DSM operating cycle, beginning and ending in the user. In the Fig. 3 it is possible to visualize the vectors of the activity plans informed by the users, the concepts of activity groups per hour and estimation of the demand curves. Based on the demand curves, renewable forecast and power plant parameters, the optimization algorithm solves the problem and returns the solution to the users. The solution is a vector containing the identifier of the plan that each user needs to follow to promote the intended objectives.

Considering the solution found by the optimization algorithm, the aggregate demand curve expected for the next day is sent to the power plant operator. With this information the operator can manage the generators in a more reliable and efficient way, as simulated inside the optimization. Some or even all the generators can be turned off during specific hours of the day, which improves the gensets load factor and reduces the generators operation hours. The planning of maintenances and the alternation of generators are also aspects that can be improved based on the knowledge of the demand curve expected for the next day.

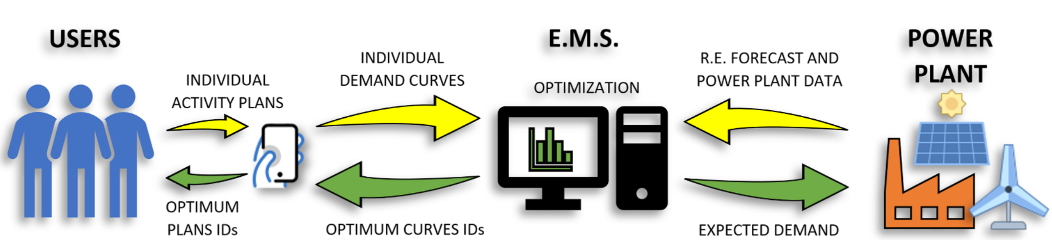


Fig. 2. Workflow of the proposed DSM.

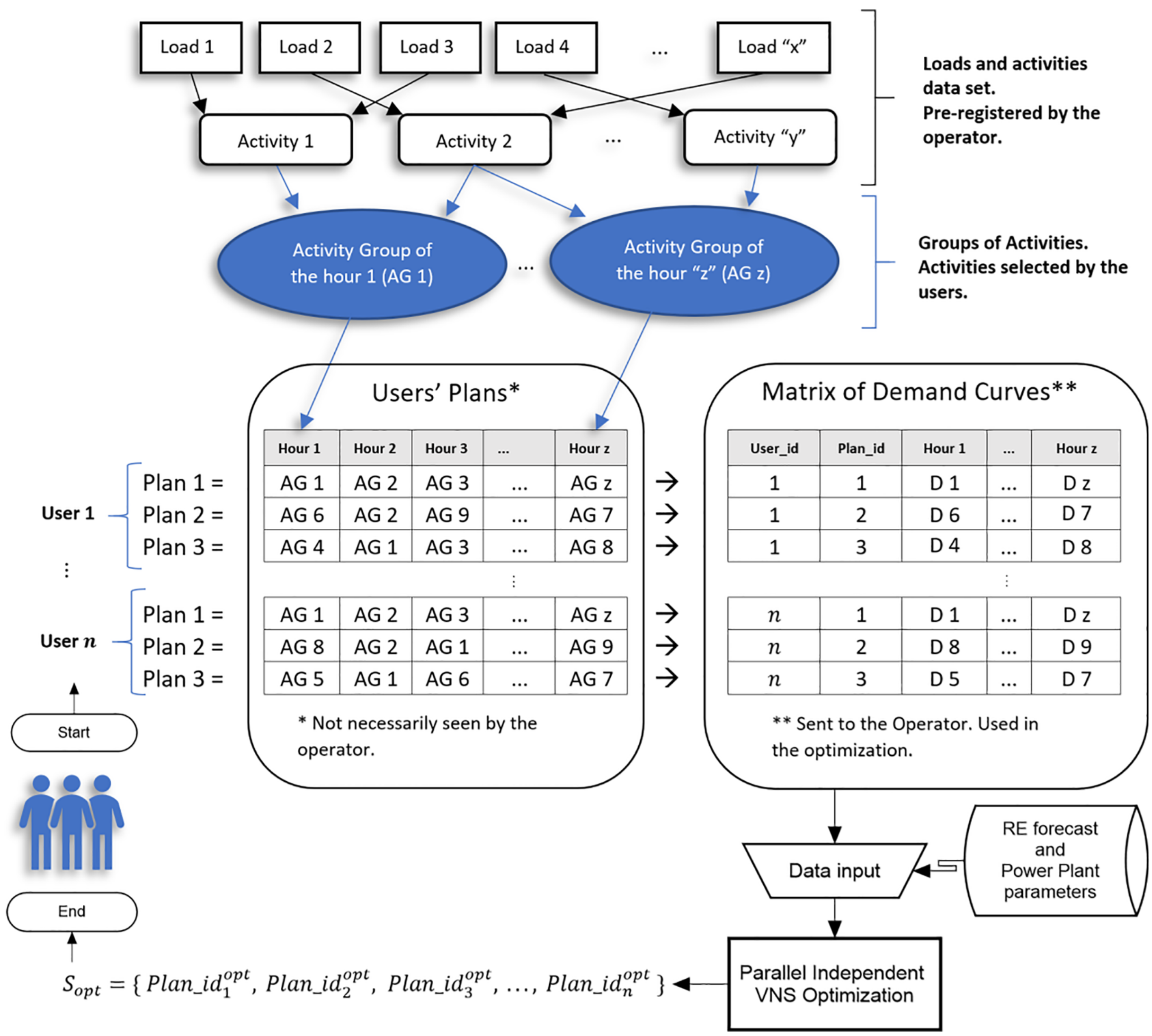


Fig. 3. Concept of the data structure and flow for the proposed DSM, beginning and ending in the user.

2.3. Optimization algorithm

As introduced in the Section 2.2, each candidate solution represents a coordinated action of the users. The objective of the optimization is to find the coordinated action that promotes the minimum cost of energy production with the minimum discomfort of the users. In this paper, the proposed DSM was applied to a wind-solar-diesel microgrid and the fuel consumption was considered as the cost to be minimized. The problem was mathematically formulated as follows.

Each candidate solution S_i is identified by the index i and belongs to the set $I = \{S_1, S_2, \cdots, S_{k^n}\}$, $|I| = k^n$. Where k and $n \in \mathbb{Z}^+$. The constants k and n are respectively the number of plans and the number of users considered in the problem. A candidate solution S_i is a vector containing n plan identifiers, one for each user. In this way , $|S_i| = n$. Where $Plan\_id$ stores a plan identifier. The plan suggested by the solution S_i for the user number u is represented by $Plan\_id_u^i$. The set of plan identifiers is represented by $P = \{1, 2, \cdots, k\}$, $|P| = k$, $P \in \mathbb{Z}^+$. Thus, $Plan\_id_u^i \in P$.

Eqs. (1)–(6) refer to the first objective which is the fuel consumption minimization. (1) denotes the minimization of the fuel consumption function (2) inside the set I, the space of solutions. In (2), the expression $g(X_{h,S_i})$ refers to the fuel necessary for the microgrid operation under a relative demand X_{h,S_i} caused by the execution of S_i at time h.

The function g is defined considering parameters of the microgrid and vary depending on the power plant topology and its operation modes. For the microgrid investigated in this paper, the function g is a nonlinear discontinuous function. The function g and all considered parameters are detailed in the Section 3.2.

The value of the relative demand X_{h,S_i} is calculated as in (3), where Ad_{h,S_i} represents the aggregate demand of all users in the time h considering the execution of the solution number i and Re_h represents the renewable energy at the same h. The calculation of Ad_{h,S_i} is made through (4) accessing the users' demands which are stored in the Matrix of Demand Curves, presented in Section 2.2, Fig. 3. This matrix was implemented in the algorithm as a tridimensional matrix that stores the demand by user, plan and hour. The expression $MDC_{u,h,S_{i_u}}$ represents the demand that will be caused by the user u, at the hour h, if the plan proposed by S_i for the user u is executed. The expression S_{i_u} is equivalent to $Plan\_id_u^i$. The value of Re_h is calculated using Eq. (5), where W_h and S_h are respectively the average wind and solar power expected for the hour h.

The optimization of the first objective is subjected to (6), where $G_{power}^{nominal}$ is the nominal power of the generators and NG is the number of generators considered in the problem.

$$f_{obj_1} = \min_{S_i \in I} f_{fuel}(S_i) \tag{1}$$

$$f_{fuel}(S_i) = \sum_{h=1}^{z} g(X_{h,S_i}) \tag{2}$$

$$X_{h,S_i} = Ad_{h,S_i} - Re_h \tag{3}$$

$$Ad_{h,S_i} = \sum_{u=1}^{n} MDC_{u,h,S_{iu}} \tag{4}$$

$$Re_h = W_h + S_h \tag{5}$$

$$X_{h,S_i} \le NG.\ G_{power}^{nominal} \tag{6}$$

Eqs. (7)–(9) refer to the second objective, which computes the discomfort index. (7) denotes the minimization of the discomfort index function (8) inside the set I, the space of solutions. The discomfort index indicates how many users will need to follow one of their alternative plans, i.e. the summation of the individual discomfort, $d(S_{iu})$, of all the users. The individual discomfort (9) of a user is 0 if S_i maintain the main plan, plan 1, for the user u, otherwise it is 1.

$$f_{obj_2} = \min_{S_i \in I} f_{disc}(S_i) \tag{7}$$

$$f_{disc}(S_i) = \sum_{u=1}^{n} d(S_{iu}) \tag{8}$$

$$d(S_{iu}) = \begin{cases} 0, & S_{iu} = 1 \\ 1, & S_{iu} \neq 1 \end{cases} \tag{9}$$

The management of user's activity plans in a cooperative way is characterized as a multi-objective combinatorial optimization problem with a search space that grows exponentially with the number of users, $|I| = k^n$, and the time to compute each instance grows linearly.

To deal with the problem complexity, it was implemented an Independent Variable Neighborhood Search (IVNS) optimization algorithm [25], which allows the execution of multiple independent VNS structures through parallel computing. The IVNS strategy allows improving the quality of the answers without increasing the processing time, since it allows exploring a greater portion of the space of solutions in a same time interval through the parallel execution of VNS structures in multiple processors.

The VNS metaheuristic starts from an initial solution, and proceed the optimization through cycles of shaking, local searches, update of the best solution and exploration of different regions (neighborhoods) of the space of solutions [19,25]. The VNS repeats these steps until the stop criterion is reached.

In the shaking phase a solution s' is randomly selected in a given neighborhood k through a function $shake(s, k)$, where s is the best-known solution and k is the factor related to both the neighborhood and the intensity of the shaking. After the shaking procedure, the local search is carried out from the solution s'. Finally, the best solution obtained in local search, s'', is compared with the best-known solution, s. If s'' is better than s, the solution s is updated, and the algorithm continues with $k = 1$. If no improvement occurs, k is incremented and a new shaking phase is performed using the new k, thus exploring more distant neighborhoods.

In this work the IVNS algorithm was implemented with four parallel and independent VNS structures. The number of parallel structures has

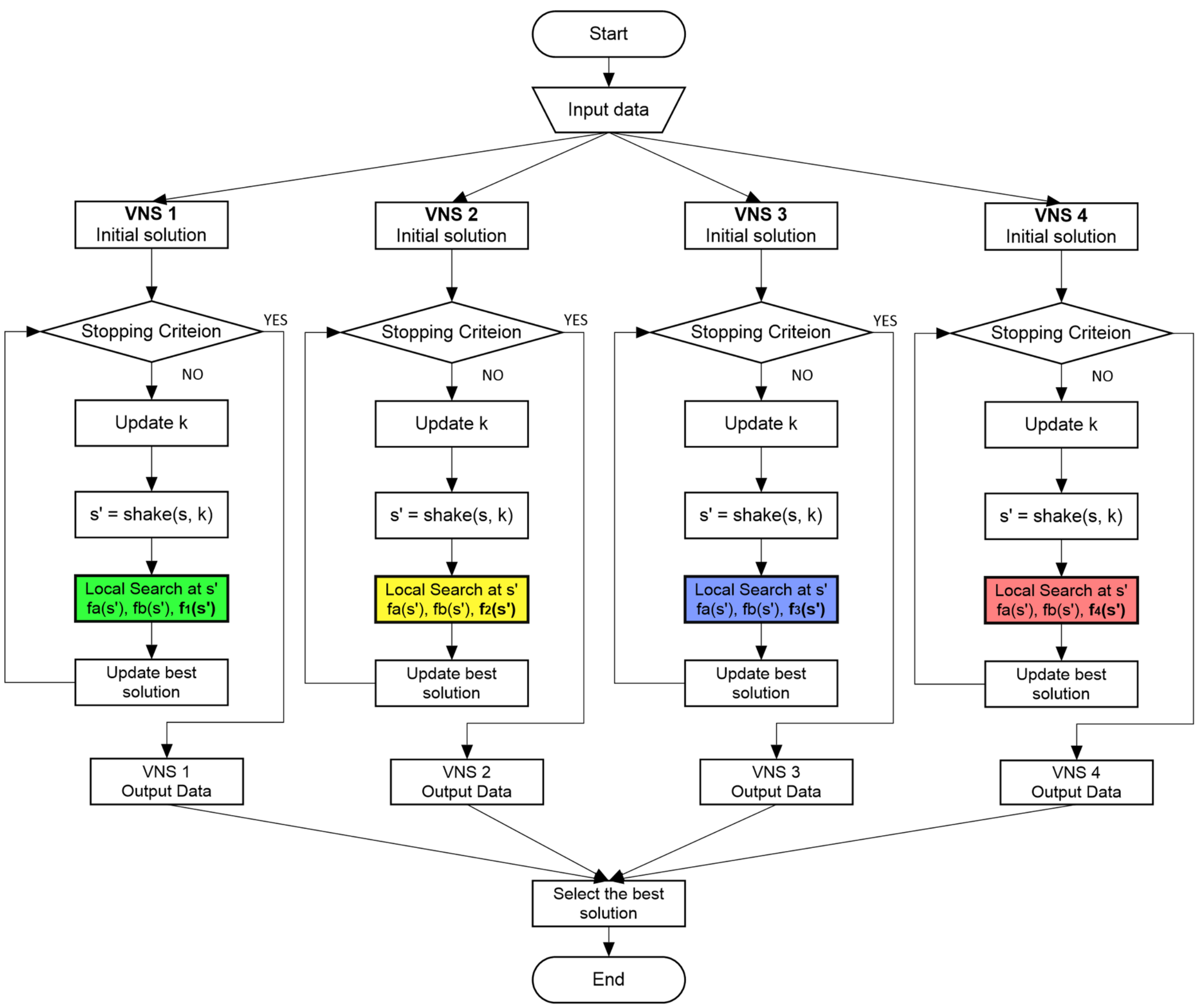


Fig. 4. IVNS algorithm flowchart implemented for the proposed DSM.

been defined for execution on a quad-core processor. Fig. 4 shows the flowchart of the implemented IVNS algorithm. Each VNS test a total of four solutions during its local search procedure. One of the tested solutions is considered as a main solution, s', and is obtained by applying a shaking to the best-known solution, s. The other three tested solutions are generated from the application of transformations in the main solution, s', to promote a local search in the neighborhood. In Fig. 4 the local search boxes are highlighted and indicate the transformation functions used in each VNS. The functions f_a and f_b are common to all VNS structures, whereas the functions, f_1, f_2, f_3 and f_4 are respectively particular to the VNS structures 1, 2, 3 and 4. Table 1 illustrates the transformation functions applied to a hypothetical s' vector of plans.

The solutions tested in every local search cycle can be created by applying transformations in at least 1% or up to 100% of s'. If it is decided to change the plan of only one user (1% of s') in each cycle, only two transformations will be feasible, f_a and f_b. Changing the plan of only one user by cycle produces a candidate solution too similar to the reference curve and also limits the number of testable solutions to only three per cycle. On the other hand, changing the plan of more users simultaneously make it possible to test demand curves a little more different and using more transformations make it possible to test more solutions every cycle.

For the comparison and update of the best solutions it was used the Pareto-dominance method considering the fuel minimization as the first objective.

Each VNS explores the solution space seeking better solutions until the stop criterion is met, which was established as the execution of 100,000 iterations for each VNS. In the tests, this number of cycles proved to be more than sufficient to ensure convergence in the four VNS, spending approximately 10 s for the simultaneous execution of the four VNS structures. The algorithm was implemented in C++ language, using the Microsoft Visual Studio Integrated Development Environment (IDE). The tests were run on a quad-core processor, operating at 3 GHz.

3. Input data modeling

The data required for simulation of the proposed DSM involve electric demand curves, power plant parameters and renewable resources information. In this work, these data were defined considering the randomness of the electric demand, the typical performance of the equipment of generation and typical intermittence of the renewable resource. The definition of the electric demand curves is detailed in Section 3.1. The definition of the microgrid and renewable resources are detailed in Sections 3.2 and 3.3.

3.1. Electricity demand curves

As described in Section 2, in the proposed method the users' demand curves are estimated from the activity plans registered by users for the morning and afternoon periods of the next day (6 a.m. to 6p.m.), i.e., activities performed during working hours of the day.

In this work, a demand emulator with the capacity to reproduce electric consumption curves of 100 users was developed using Microsoft Excel spreadsheet software. Users' consumption curves were generated by a probability distribution function following a reference aggregate demand curve. As reference, it was adopted a profile similar to the one observed at the Brazilian Antarctic Station, in the summer term, during week days [2]. Fig. 5 shows the reference aggregate demand curve side by side with the curve obtained by the emulator. The aggregate demand curve was obtained by the summation of all users' demand curves.

In practice, the demand curves vary depending on socio-demographic factors [26], user behavior, types of loads, seasons and day of the week [27,28]. To reproduce the randomness of the electrical consumption of the users every hour, a normal distribution function was used. The mean and standard deviation were settled proportional to the reference demand of each hour. The mean value used for each hour was the per capita direct consumption of the hour. The standard deviation value was settled as the half of the mean value. The per capita direct consumption of the hour is the average value consumed by the users every hour, discounting the portion of indirect consumption.

In this work, the share of indirect consumption was considered 10%. This part is intended to consider the energy consumed by equipment and other systems that have an operating regime indirectly caused by the users or even in the absence of users in the places. Examples are the consumption of standby equipment and refrigerators. This portion does not include the consumption of electricity for lighting, heating and cooling, which are treated in this work as linked to the activities. Thus, a value equivalent to 10% of total demand was considered fixed and does not change with changes in users' plans. This consideration reduces the flexibility of simulated demand but is essential to represent indirect consumption. In practice, this fixed share of demand should be estimated case-by-case.

Considering the values of mean and standard deviation of each hour and a fixed portion of 10%, the electric consumption of each one of the users was generated through the normal distribution function. This method allows reproducing, for every hour, both the randomness of the individual demand and the value of the aggregate demand, as can be seen in Figs. 6 and 7. Fig. 6 shows the hourly demands of the 100 users in a color scale. Fig. 7 presents the hourly minimum, maximum and averages values of users' demands.

The 100 demand curves created by the emulator are defined as users' Plan 1, Plans 2 and 3 and are created from Plan 1 by shifting activities. In Plan 2, sets of activities are shifted between the morning and afternoon periods. In Plan 3, the sets of activities are shifted within the same period. To illustrate the real situation that not all users will be able to change their planning and the situation in which some users have greater or less flexibility than others, exchanges are made by a random function. Figs. 8 and 9 show the quantity of hours replanned by each user in Plans 2 and 3 taking Plan 1 as a reference. Figs. 10 and 11 show the histogram of the number of hours replanned per user for Plans 2 and 3. In the histograms it is possible view that most users had their activities rescheduled 6 h or less.

3.2. Microgrid model

The design of a hybrid energy generation system involves specific studies of the loads to be fed, the available on-site renewable resource, available space, and installation, operation and maintenance costs [2,11]. However, these studies go beyond the scope of this article. In this work, the micro-grid simulated, was defined considering aspects as multiple generators, multiple renewable sources and energy storage systems for stabilization and operation even with the generators switched off. The microgrid was designed with the purpose of meeting the demand profile presented in Section 3.1 and to illustrate cases of operation with and without excess of renewables.

Thus, it was proposed an isolated hybrid microgrid composed of two diesel-powered generators of 100 kW each, a solar plant of 45 kWp and a wind plant of 45 kWp combined with an energy and stabilization storage system of 100 kWp and 100 kWh. Fig. 12 shows the topology of the microgrid set to simulate the DSM system.

Table 1
IVNS local search transformations.

Current s'	Transformation functions applied to s'					
s'= {1, 2, 3. ..}	$f_a(s')$= {2, 3, 1. ..}	$f_b(s')$= {3, 1, 2. ..}	$f_1(s')$= {*Random*. ..}	$f_2(s')$= {1, 3, 2. ..}	$f_3(s')$= {2, 3, 2. ..}	$f_4(s')$= {3, 3, 2. ..}

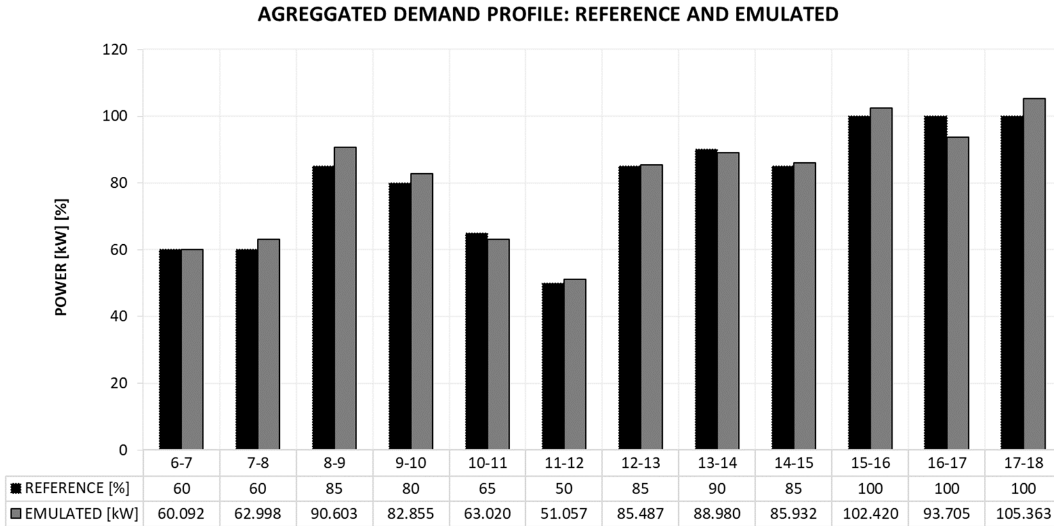


Fig. 5. Aggregated electric demand curves. Defined reference curve and summation of the emulated curves of the 100 users.

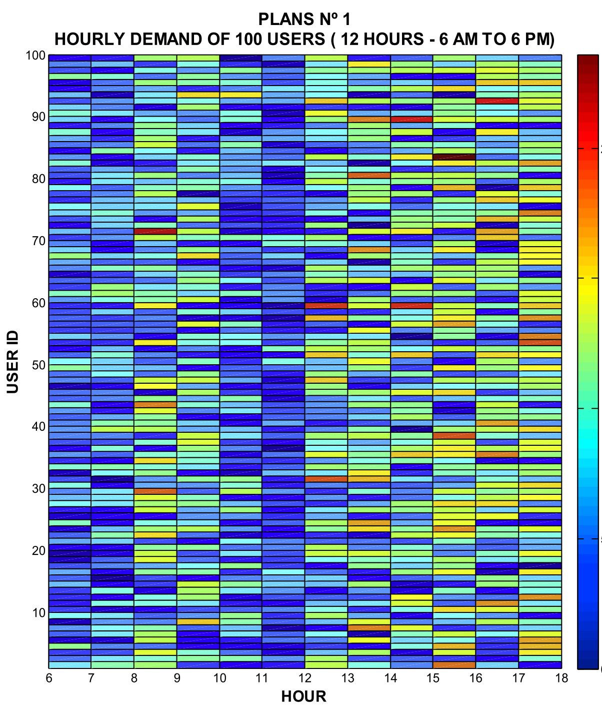


Fig. 6. Electric demand per hour of each of the 100 users.

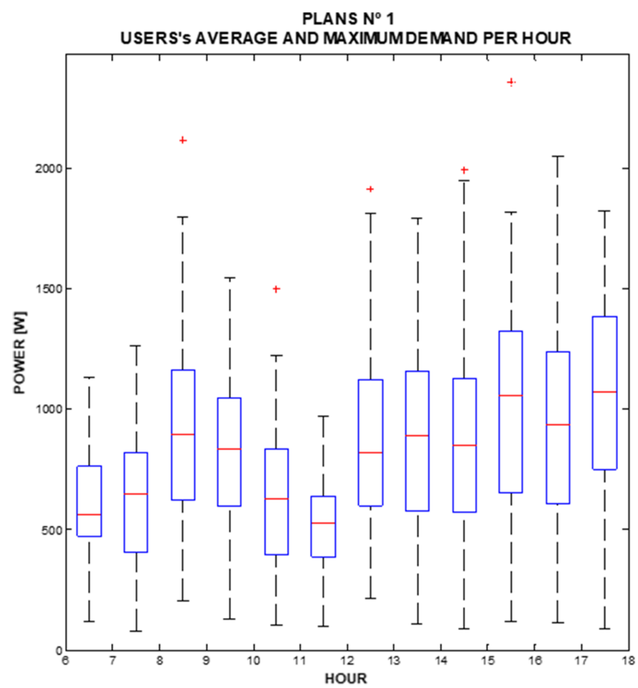


Fig. 7. Average, minimum and maximum values of users demands by hour.

In power systems powered by combustion engines, the amount of fuel needed to generate 1 kWh varies according to the generator load factor. This is due to the portion of energy consumed by the generator for the operation of its regulation and ventilation subsystems, as well as the variation of the thermal machine performance with the load factor. Fig. 13 presents the global and specific consumption curves of a 100 kW (125 kVA), turbocharged, 6-cylinder, diesel-powered generator operating at 1800 RPM in the range of 25% to 100% of its nominal power, tested in accordance with ISO-3046. The average load factor can be understood as the ratio between the average demand and the nominal power of the generator.

From the graph shown in Fig. 13, it is important to observe that lowest values of specific consumption are reached around 75% of load and that the operation below 50% of load increases considerably the specific consumption. Moreover, the technical recommendation to ensure the durability and efficiency of the generator is to avoid operating with generators below 30% load for long periods [29].

For the safe and efficient operation of the microgrid it is necessary to define start and shutdown points for generators and inverters. The generator shutdown point by low load factor was set at 30% and the power reserve of the generators was set at 20%. Thus, Generator 1 will operate alone on average hourly demand conditions from 30 kW to 80 kW. In an average hourly demand situation below 30 kW, the generator is switched off to prevent premature wear of components. Thus, with average hourly demand below 30 kW, the microgrid starts to operate only with the energy of the batteries, which will be recharged when the generators are already operating or when the renewable resource is more than sufficient to meet all the users' demand. In a situation with an average hourly demand greater than 80 kW, Generator 2 is turned on to guarantee the fulfillment of demand peaks, increase the stability of the microgrid and preserve Generator 1. Thus, above 80 kW, the two generators operate in parallel.

In case of excess of renewable generation and impossibility to store the surplus energy in batteries, the generators are disconnected and the frequency of the system is adjusted in order to limit the injection of

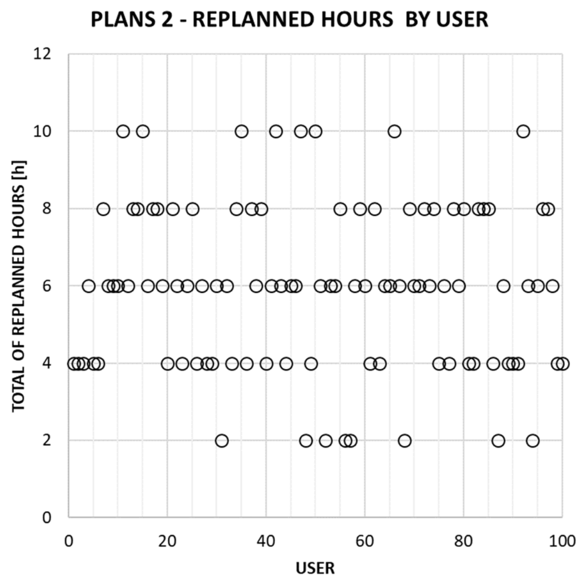


Fig. 8. Quantity of hours replanned by each user in plans 2, taking the plans 1 as reference.

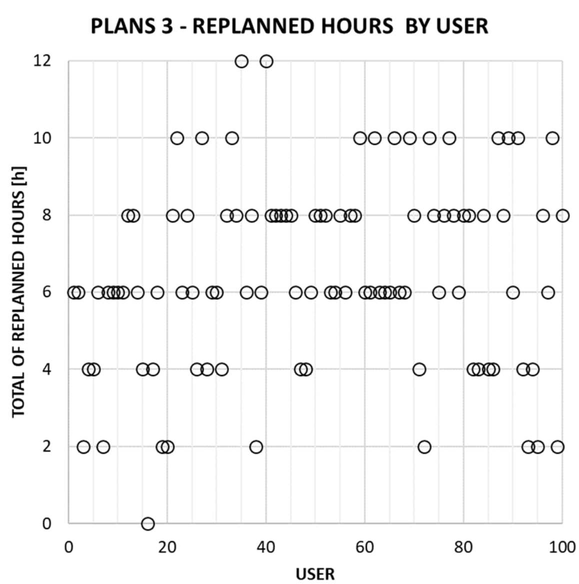


Fig. 9. Quantity of hours replanned by each user in plans 3, taking the plans 1 as reference.

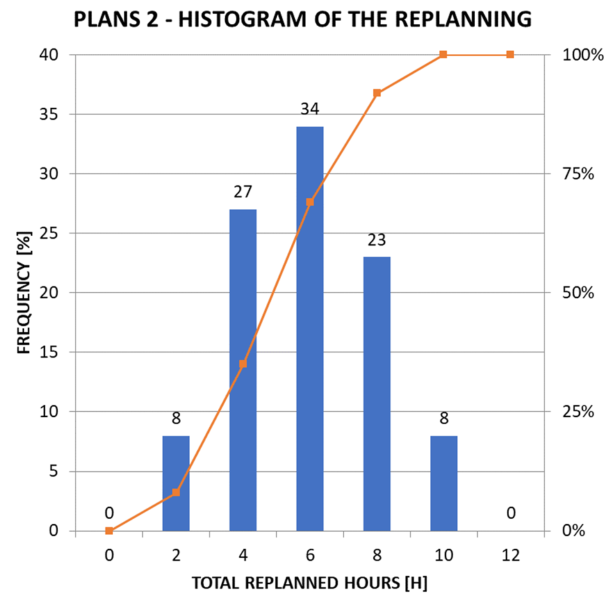


Fig. 10. Histogram of the number of hours replanned per user in plans 2, taking the plans 1 as reference.

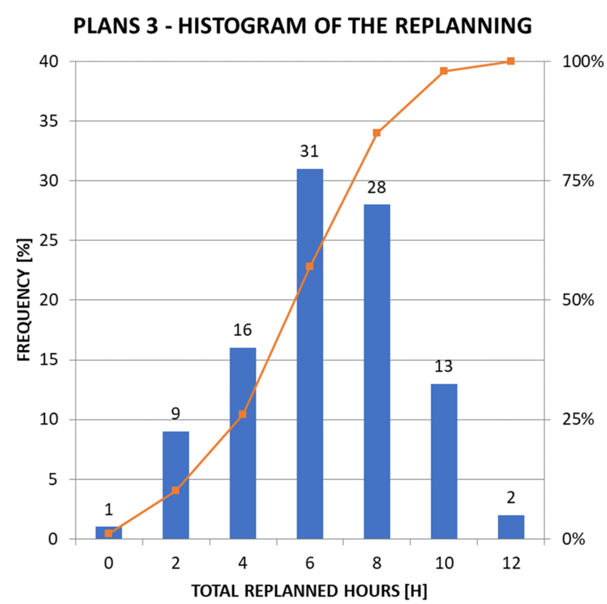


Fig. 11. Histogram of the number of hours replanned per user in plans 3, taking the plans 1 as reference.

power by renewable sources and guarantee the stability of the system [30]. In this condition the generators can be switched off for fuel economy and equipment protection. The inverters of the batteries will provide the frequency reference of the electric grid. During this operation mode, part of the renewable resource that could be generated is limited and is not used by the grid.

Considering the defined microgrid and the described mode of operation, (10) presents the function g. The expression $g(X_{h,S_i})$ returns how many liters of fuel will be consumed by the microgrid to deal with a relative average demand X_{h,S_i} for one hour. The value of X_{h,S_i} is calculated using (3) and all its subfunctions as detailed in the Section 2.3. The renewable sources over-generation is considered ing by the interval $X_{h,S_i} \le 0$. In (10) the terms m, a, b and c are the coefficients of the polynomial expressions that represent the fuel consumption curves. G_{power}^{low} represents the generator shutdown point by low load factor, $G_{power}^{nominal}$ represents the generator nominal power and G_{power}^{res} the reserved power. The values considered in the problem were: $m = 0.328$; $a = 630E-6$; $b = 0.21$; $c = 2.94$; $G_{power}^{low} = 30$; $G_{power}^{nominal} = 100$; $G_{power}^{res} = 20$ and $NG = 2$.

$$g(X_{h,S_i}) = \begin{cases} 0 & if \quad X_{h,S_i} \le 0 \\ m.\ X_{h,S_i} & if \quad 0 < X_{h,S_i} \le G_{power}^{low} \\ a.\ (X_{h,S_i})^2 + b.\ (X_{h,S_i}) + c & if \quad G_{power}^{low} < X_{h,S_i} \le G_{power}^{nominal} - G_{power}^{res} \\ 2.\left(a.\left(\frac{X_{h,S_i}}{2}\right)^2 + b.\left(\frac{X_{h,S_i}}{2}\right) + c\right) & if \quad G_{power}^{nominal} - G_{power}^{res} < X_{h,S_i} \le 2.\ G_{power}^{nominal} \end{cases} \tag{10}$$

Fig. 14 shows the microgrid global and specific consumption curves considering the two generators and the defined start and shutdown points.

In Fig. 14 it can be observed that the curve of specific consumption changes depending on the range of demand met by the generators. In the 0–30 kW range, the generators do not work, but the power supplied by the batteries will need to be recharged. The specific equivalent consumption in the range of 0–30 kW can be estimated considering the cycle efficiency of the battery system and the specific consumption of the generator at the time

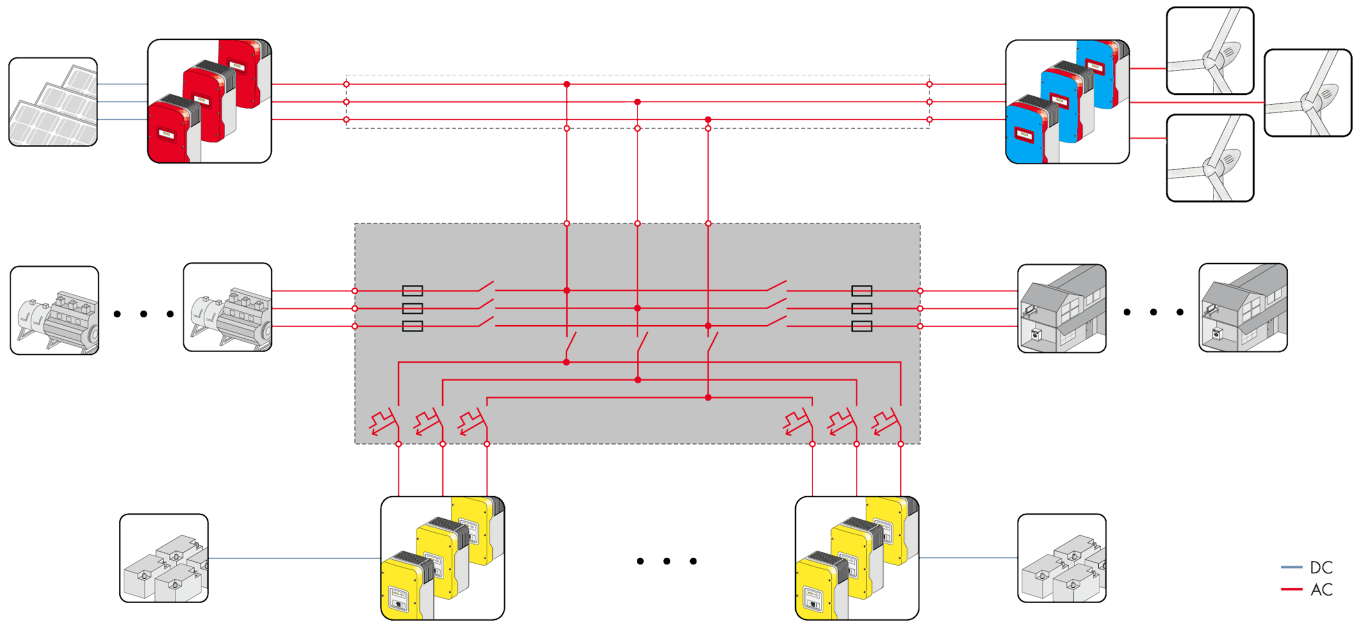


Fig. 12. Hybrid microgrid topology defined for DSM system simulation.

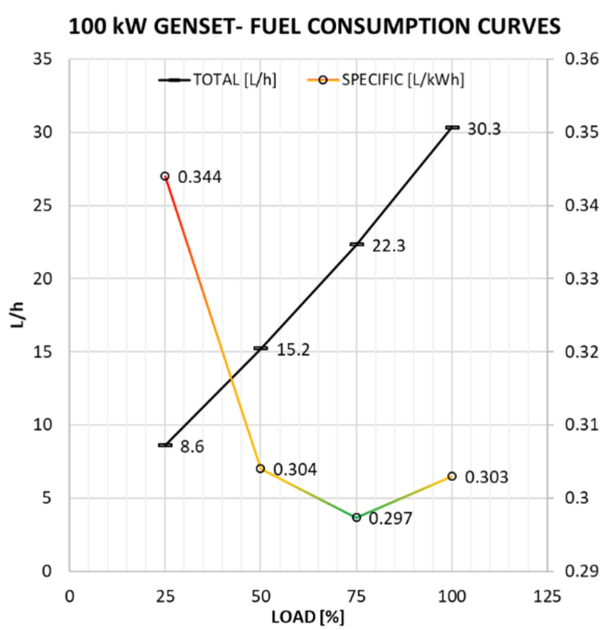


Fig. 13. Global and specific consumption curves of a 100 kW generator, powered by diesel.

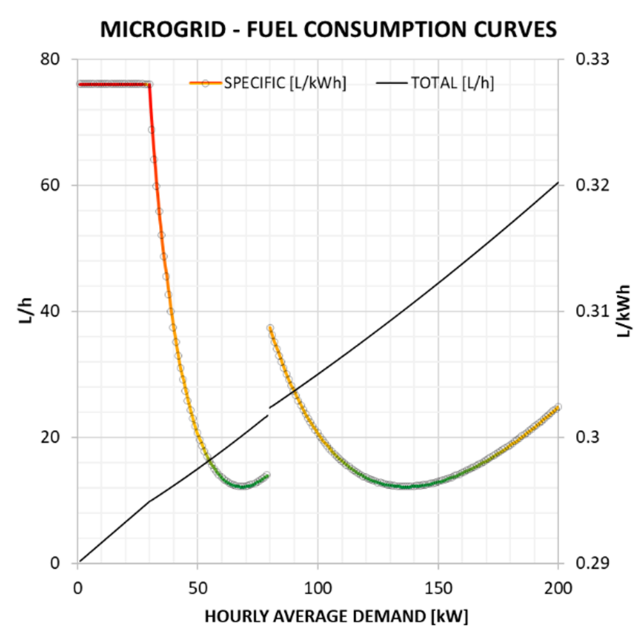


Fig. 14. Global and specific microgrid consumption curves with two 100 kW generators.

of the recharge. For the simulations, it was considered a cycle efficiency of 90% [31] and the minimum specific generator consumption (0.297 L/kWh). So, the equivalent value of 0.328 L/kWh was defined for the 0 to 30 kW range. In the range of 30 kW to 80 kW, the specific consumption curve of only one generator is considered. Above 80 kW the demand is divided between the two generators. Consequently, in the 80 kW to 200 kW range, the specific consumption value is given by the fuel consumption of the two generators divided by the total demanded power.

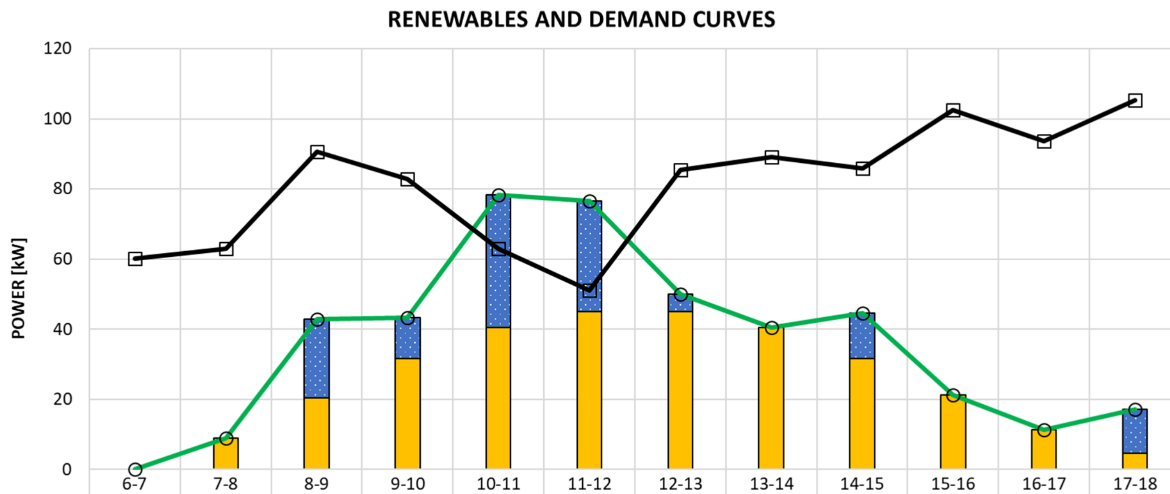
3.3. Renewable resource curves

To reproduce situations of high penetration of renewables and to evaluate the behavior of the proposed DSM in these situations, the curves of solar and wind resource were defined to promote a typical overgeneration problem around midday hours [32]. The solar resource was defined considering daily pattern of solar incidence. The wind resource was defined in a complementary way to portray a situation of excess renewables during some hours of the day and shortage during others. So, for the wind resource was reproduced a day in which the wind only had enough speed to generate energy from 8 a.m. to 13 p.m., 14 to 15 p.m. and 17 to 18 p.m.

Fig. 15 shows the renewable resources and aggregated demand curves over one another for comparison. In Fig. 15, it can be observed the problem of overgeneration from 10 a.m. to midday and the lack of renewable resource in the other hours.

4. Definition of cases to test the DSM

Fundamentally, the proposed DSM always tries to adjust the aggregated demand profile to make the generators operate as close as



	6-7	7-8	8-9	9-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
WIND	0.000	0.000	22.500	11.700	37.800	31.500	4.950	0.000	13.050	0.000	0.000	12.600
SOLAR	0.000	9.000	20.250	31.500	40.500	45.000	45.000	40.500	31.500	21.150	11.250	4.500
RE TOTAL	0.000	9.000	42.750	43.200	78.300	76.500	49.950	40.500	44.550	21.150	11.250	17.100
DEMAND	60.092	62.998	90.603	82.855	63.020	51.057	85.487	88.980	85.932	102.420	93.705	105.363

Fig. 15. Solar and wind resource curves, superimposed over the aggregate demand curve.

possible to its optimum points (minimum specific consumption point). Consequently, improvements in the load factor of the generators and reduction of hours of use of Generator 2 are also achieved.

To evaluate the ability of the proposed DSM and the improvements that can be expected in real situations, the following cases were investigated:

- Case 1 - Demand management in the absence of renewable sources; and
- Case 2 - Demand management in the presence of renewable sources.

Case 1 aims to assess the DSM load shifting capacity in the absence of renewables. This case covers the situation of no renewable sources installed or a situation when the renewable power plant needs to stay disconnected. In this case the DSM is mainly expected to improve the load factor and reduce the operating time of the generators.

Case 2 aims to evaluate the DSM load shifting capacity in scenarios of excess renewables. In this case the DSM is expected to be able to increase the participation of renewable sources by shifting loads to hours of overgeneration. In this way, the DSM should reduce the problem of overgeneration and reduce fuel consumption, once the share of renewable energy that initially was over the demand becomes usable.

To measure the improvements, each of the two cases was simulated with and without DSM operation. To evaluate the deviation that might be expected in the results using the proposed optimization technique, the simulations were repeated 100 times for each case. The dispersion of the results was evaluated, and the best solution found was detailed. The convergence, the improvements trajectory, the Pareto frontier and the final solution pattern were analyzed.

As a reference value for the evaluation of each case, it was calculated the maximum fuel reduction that could be achieved in an ideal situation of 100% of load flexibility. This would be the savings if the demand could be fully managed to make the generators operate at optimal load factor (75%). In practice, and in the simulated cases, this reference value of savings will not be reached given the flexibility constraints imposed by users.

To evaluate the performance of the proposed DSM, the following indicators were chosen:

- Fuel consumption savings. Measured in liters of diesel and in percentage, compared to operation without DSM;
- Discomfort index or managed users. Indicates the number of users that should opt for one of their alternative plans;
- Managed energy. It measures how much load was shifted from a time to another;
- Renewable penetration rate. Indicates how much of the demand was served by renewables;
- Generator load factor. Indicates the average percentage of the nominal power of the generator that serves the demand; and
- Generators hours of use. Indicates how many hours the generators have been in operation.

5. Results

Considering the definitions presented in the previous Sections, the proposed DSM method and the optimization algorithm were evaluated in the absence of renewable sources, Case 1, and in the presence of renewable sources, Case 2.

In both cases, the proposed DSM method was able to improve the aggregated demand profile. It was observed an improvement of the load factor of the generators, reduction of the number of operation hours of the Generator 2, improvement of renewable penetration and reduction of the fuel consumption.

The VNS metaheuristics implemented with the parallel computing was able to solve the problem satisfactorily in both cases. In all the simulations, the algorithm demonstrated the ability to converge to an approximate optimal solution, exploring a minimum part of the solution space.

5.1. Simulation and analysis of Case 1

The simulation of Case 1 aims to evaluate the performance of the proposed DSM method and the optimization algorithm in the absence of renewable sources. This case covers situations where renewable sources are not installed or situations where renewable sources are inoperative or disconnected.

As a reference value to compare the results achieved by the proposed DSM method, it was calculated the maximum savings if the demand could be fully managed to make the generators operate at optimal load factor (75%). In Case 1, considering 100% of load flexibility, the reference value of saving is 1.8%. This value exposes the fact that the percentage of savings possible to be achieved is highly dependent on two factors: the difference between the original demand profile seen by the generators and their optimum load factor range; and the difference between the minimum and maximum specific fuel consumption rate of the generators. In the absence of renewables, the lower these differences, the lower the potential for reducing fuel consumption will be. However, fuel savings is only one of desired improvements, and it is necessary to verify the gains in load factor and hours of use of generators to really measure the DSM advantages.

In the 100 simulations performed with DSM in Case 1, consumption was reduced by an average of 1% with an average of 40 users being managed. Fig. 16 shows the dispersion of the results obtained in the 100 consecutive simulations. The best solution achieved a 1.2% reduction in fuel consumption with the participation of 47 users (simulation 52). The worst simulation achieved 0.9% of fuel savings with the participation of 54 users (simulation 54). Considering the theoretical limit of Case 1, 1.8%, and the percentage reduction achieved with the DSM, 1.2%, the DSM was able to reach 67% of the limit value, even with the limitations of load flexibility.

To evaluate the convergence of the optimization algorithm, Fig. 17 shows the convergence of the algorithm during the simulation 52. Although the solution space was 3^{100}, it was observed that the convergence for the solution found occurred mostly before 20,000 cycles

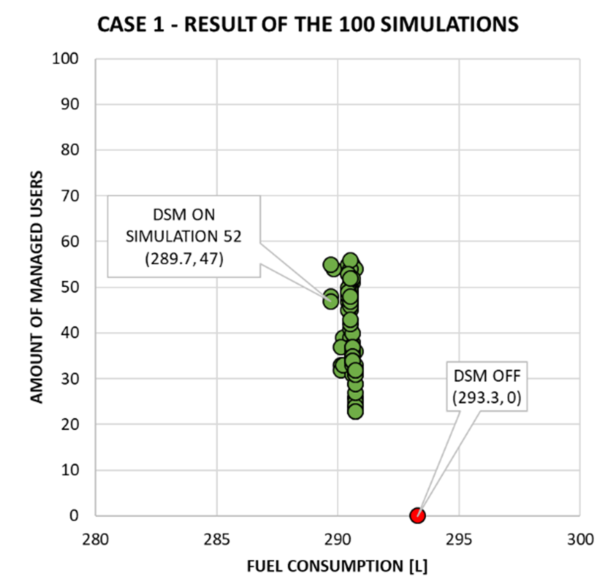


Fig. 16. Dispersion of the results obtained in 100 consecutive simulations of Case 1.

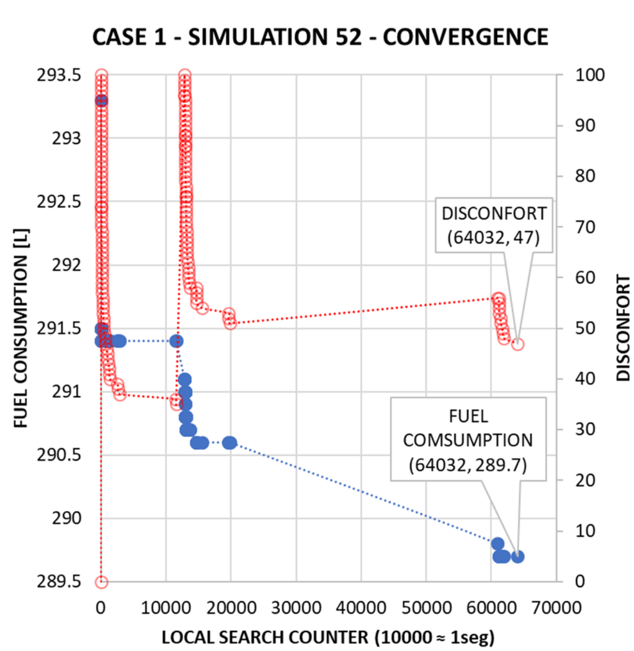


Fig. 17. Solution convergence graph obtained in simulation 52, Case 1.

and that the best solution was achieved in 64,032 cycles, equivalent to 7 s of execution of the algorithm (processor operating at 3.0 GHz).

Fig. 18 shows the trajectory of improvements and the Pareto frontier obtained in the simulation n° 52. The lower consumption is reached by the coordinated action of users and not only by the increasing of the number of managed users. In simulation 52, the best solution was found by VNS 3, modifying up to 100% of s' during the local searches.

Fig. 19 shows the optimal plans, or the coordinated action proposed by the DSM system. In it, 53 users had Plan 1 selected, 28 the Plan 2 and 19 the Plan 3.

Fig. 20 shows the demand curve without and with DSM obtained in simulation 52. The difference between the two demand curves can be visualized by the bar chart. The largest difference was approximately 25 kW, at 17–18 h, equivalent to 31% of the average demand (81 kW, from 6 a.m. to 6p.m.). The blue area indicates the flexibility range of the aggregate demand verified during the simulation. The maximum flexibility observed was 37 kW, at 11–12 h, equivalent to 46% of the average demand.

The reduction of the peak in the morning, at 8–9 h and 9–10 h allowed Generator 2 to be switched off since the average hourly demand was reduced to less than 80 kW (operating limit of Generator 1, defined

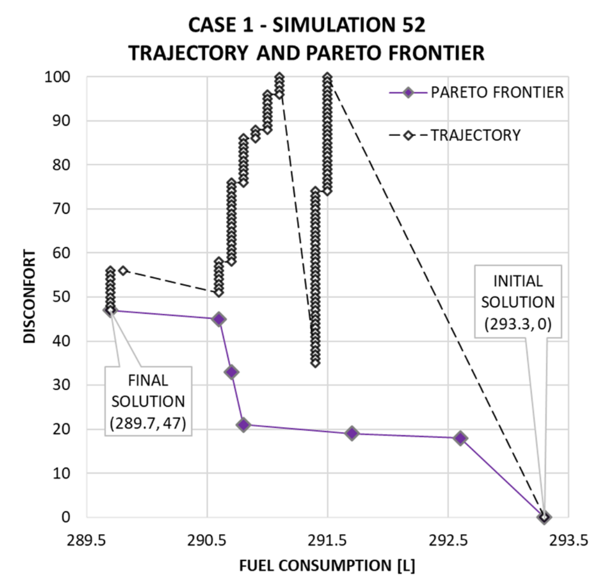
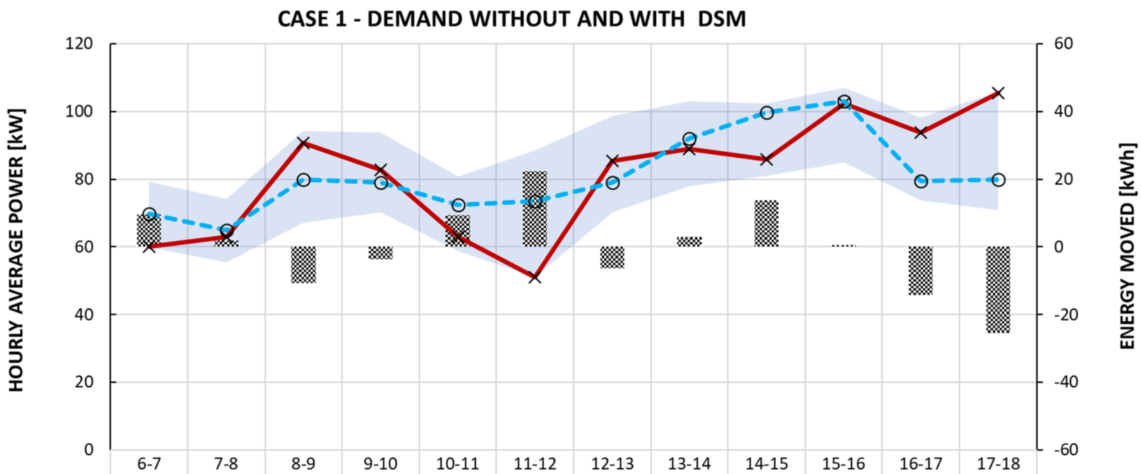


Fig. 18. Trajectory of improvements and the Pareto frontier obtained in the simulation 52, Case 1.

Fig. 19. Coordinated action proposed by the DSM, simulation 52, Case 1.



	6-7	7-8	8-9	9-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
FLEXIBILITY	19.335	18.691	27.183	23.498	22.002	37.381	28.356	25.111	21.250	21.924	24.419	34.939
FLEX. LOW LIMIT	59.814	55.411	67.087	70.296	58.802	51.057	70.265	77.928	81.092	85.042	73.665	70.977
MOVED	9.593	1.830	-10.610	-3.751	9.404	22.353	-6.386	2.936	13.695	0.544	-14.177	-25.436
DSM OFF	60.092	62.998	90.603	82.855	63.020	51.057	85.487	88.980	85.932	102.420	93.705	105.363
DSM ON	69.685	64.828	79.993	79.104	72.424	73.410	79.101	91.916	99.627	102.964	79.528	79.927

Fig. 20. Demand curve without and with DSM obtained in simulation 52, Case 1.

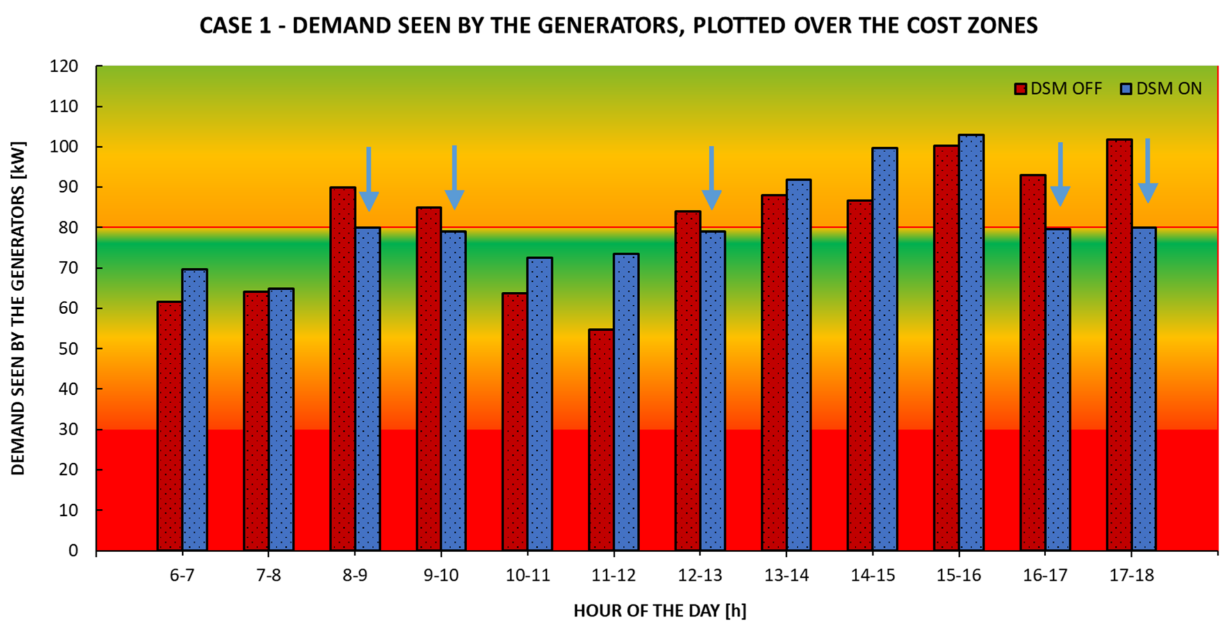


Fig. 21. Demands in Case 1, simulation 52, plotted over a color gradient that represents the specific consumption of the microgrid. Blue arrows indicate the times at which Generator 2 can be turned off.

in Section 3.2). The filling of the valley, at 11–12 h, improved the load factor of Generator 1 in the hour, going from 51% to 73%.

In the afternoon, the demand reduction achieved between 12 and 13 h allowed Generator 2 to be switched off and improved the load factor of Generator 1 from 43% to 79%. Between 14 and 15 h, the increase of about 13 kW in the demand allowed increasing the load factor from 43% to about 50% in both generators. Finally, between 16 and 18 h, the DSM also allowed the shutdown of Generator 2 and the rise of the Generator 1 load factor.

Fig. 21 presents the demands of Case 1, before and after de DSM, plotted over a color gradient that represents the specific consumption of the microgrid considering both generators. The color gradient follows the cost zones and the specific consumption curves presented in Section 3.2. The green color is related to lower values of specific consumption, and red represents higher values.

In Fig. 21 it is possible to observe that the DSM led the microgrid to operate with lower specific consumption at all times. The five blue arrows

Table 2
DSM performance indicators in Case 1, simulation 52.

CASE 1 - DSM performance			
Parameter	Without DSM	With DSM	Difference
Fuel consumption [L]	293.3	289.7	−3.6
	100.0%	98.8%	−1.2%
Managed users [Users]	0	47	47
Managed energy [kWh]	0	60.36 kWh	60.36
	0.0%	6.2%	6.2%
Renewable energy penetration [kWh]	–	–	–
Generator 1 load factor [%]	50.4%	68.8%	**18.4%**
Generator 2 load factor [%]	45.9%	49.1%	3.2%
Generator 1 hours of use [h]	12	12	0
	100.0%	100.0%	0.0%
Generator 2 hours of use [h]	8	3	−5
	66.7%	25.0%	**−41.7%**

indicate the times that DSM allowed Generator 2 to be turned off.

Table 2 presents the DSM performance indicators in Case 1. In Case 1, two indicators deserved to be highlighted: load factor of Generator 1; and number of hours that it was possible to disconnect Generator 2.

In case 1, although the reduction of fuel consumption was restricted to 1.8%, the indirect gains achieved were significant. The improvement of the operating point of the generators was of 18.4% and the reduction of the operation time of the Generator 2 was of 5 h. This indicates that the DSM indirect gains may justify its application regardless of fuel savings.

5.2. Simulation and analysis of Case 2

The simulation of Case 2 aims to evaluate the performance of the proposed DSM method and the optimization algorithm in the presence of renewable sources. This case covers the problem of renewables overgeneration and intermittence.

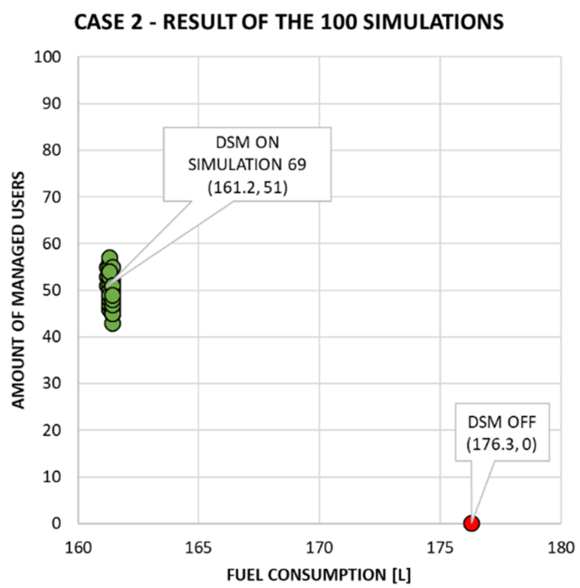


Fig. 22. Dispersion of the results obtained in 100 consecutive simulations of Case 2.

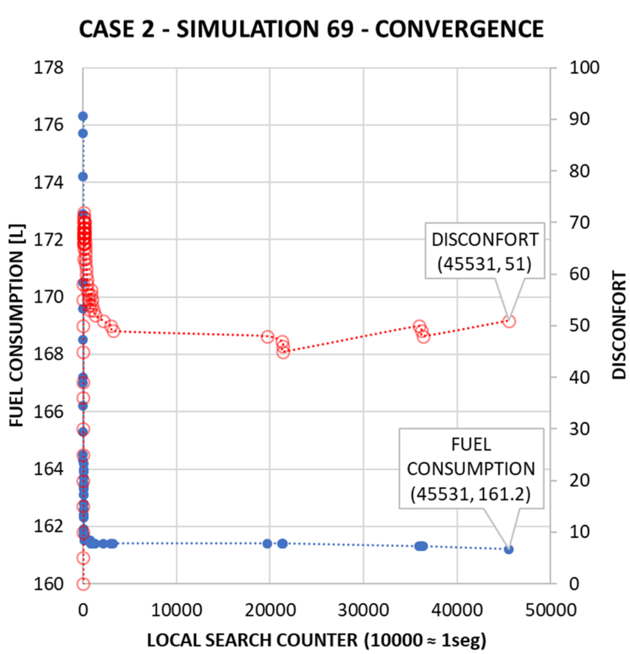


Fig. 23. Solution convergence graph obtained in simulation 69, Case 2.

Similarly to Case 1, in order to establish a reference value that allows evaluating the results achieved by the optimization algorithm and the proposed DSM method, the theoretical maximum reduction in the condition of total load flexibility was calculated. In Case 2, considering 100% flexibility, the theoretical limit of economy is 9.6%. This value is mostly promoted by the share of renewable overgeneration that becomes absorbable when the demand is managed.

Fig. 22 shows the dispersion of the results obtained in 100 consecutive simulations. On average, consumption was reduced by 8.47% with an average of 49 users managed. The best solution achieved 8.56% of fuel savings with the participation of 51 users (simulation 69). The worst simulation achieved 8.45% of fuel savings with the participation of 55 users (simulation 87). From the theoretical fuel savings limit of Case 2, 9.6%, and the reduction percentage reached, 8.6%, it is estimated that the DSM was able to reach 89% of the limit value.

To evaluate the convergence of the optimization algorithm, Fig. 23 presents the convergence graph of the solutions obtained in the

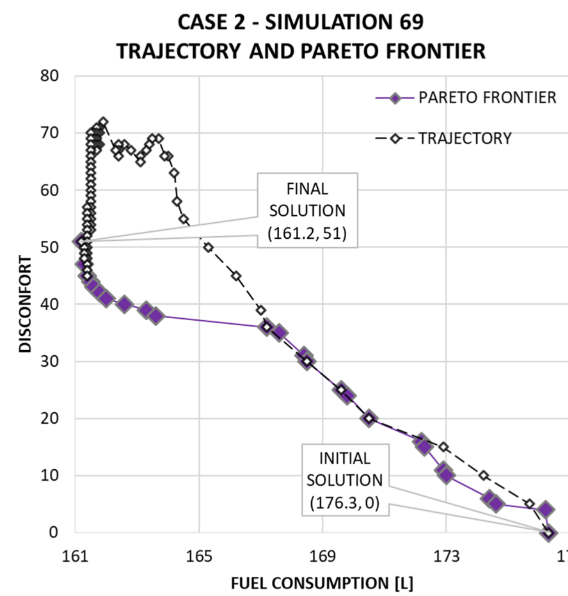


Fig. 24. Trajectory of improvements and the Pareto frontier obtained in the simulation 69, Case 2.

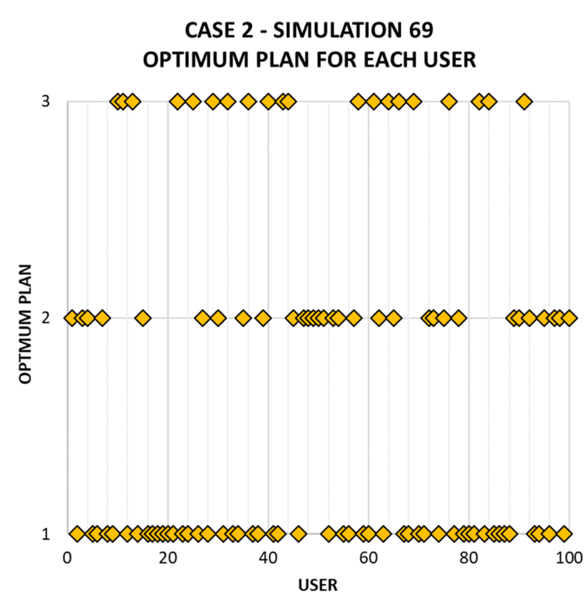


Fig. 25. Coordinated action proposed by the DSM, simulation 69, Case 2.

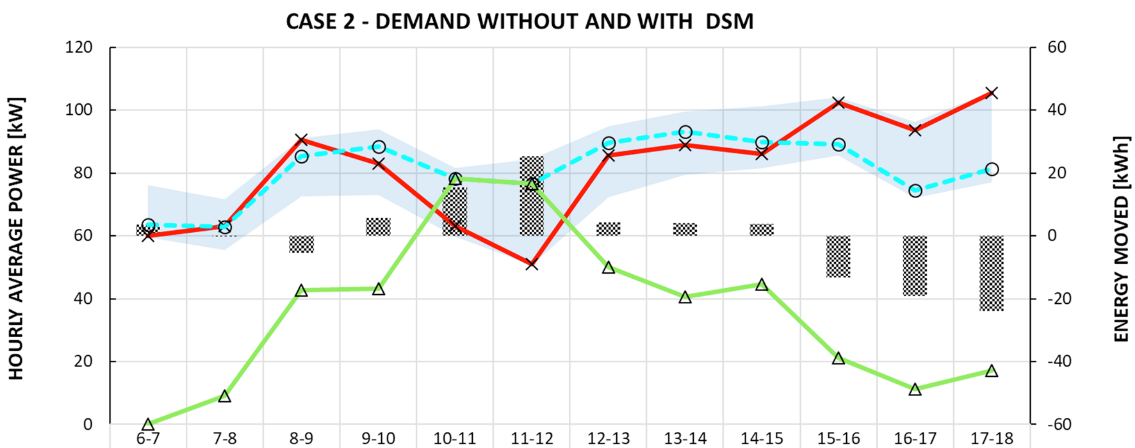
simulation 69. It was observed that the convergence occurred mostly before 5,000 cycles and that the best solution was achieved with 45,531 cycles, equivalent to 5 s of execution of the algorithm (processor operating at 3.0 GHz).

Fig. 24 shows the trajectory of improvements and the Pareto frontier obtained in the simulation 69. In Case 2, it is also possible to observe that the lowest consumption is reached by the coordinated action of users and not only by a greater amount of managed users. In simulation 69, the best solution was found by VNS 1, modifying up to 5% of s' during the local searches.

Fig. 25 shows the coordinated action proposed by the DSM system. In it, 49 users had Plan 1 selected, 31 the Plan 2 and 20 the Plan 3.

Fig. 26 shows the demand curve without and with DSM obtained in the simulation 69. The difference between the two demand curves can be visualized by the bar chart. The DSM was able to increase the penetration of renewable sources by moving 41 kWh of the consumption to hours where was the renewables overgeneration. The blue area indicates the flexibility range of the aggregate demand verified during the simulation 69. The maximum flexibility observed was 33.4 kW, equivalent to 40% of the average demand.

Fig. 27 presents the demand curves seen by the generators before and after the DSM, in Case 2. The curves are plotted over a color gradient that represents the specific consumption of the microgrid considering both generators. The color gradient follows the cost zones and the specific consumption curves presented in Section 3.2. The green color is related to lower values of specific consumption, and red represents higher values. The five blue arrows indicate the times that DSM allowed the Generator 2 to be turned off. Between 10 h and 12 h



	6-7	7-8	8-9	9-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18
FLEXIBILITY	16.654	16.207	18.445	20.858	21.647	33.479	22.485	20.096	19.523	18.536	24.084	28.804
FLEX. LOW LIMIT.	59.508	55.482	72.491	72.937	59.880	50.871	72.302	79.368	81.588	85.604	72.024	77.142
MOVED	3.548	-0.143	-5.332	5.598	15.277	25.445	4.182	4.069	3.863	-13.328	-19.210	-23.974
DSM OFF	60.092	62.998	90.603	82.855	63.020	51.057	85.487	88.980	85.932	102.420	93.705	105.363
DSM ON	63.640	62.855	85.271	88.453	78.297	76.502	89.669	93.049	89.795	89.092	74.495	81.389
RENEWABLES	0.000	9.000	42.750	43.200	78.300	76.500	49.950	40.500	44.550	21.150	11.250	17.100

Fig. 26. Demand curve without and with DSM obtained in simulation 69, Case 2.

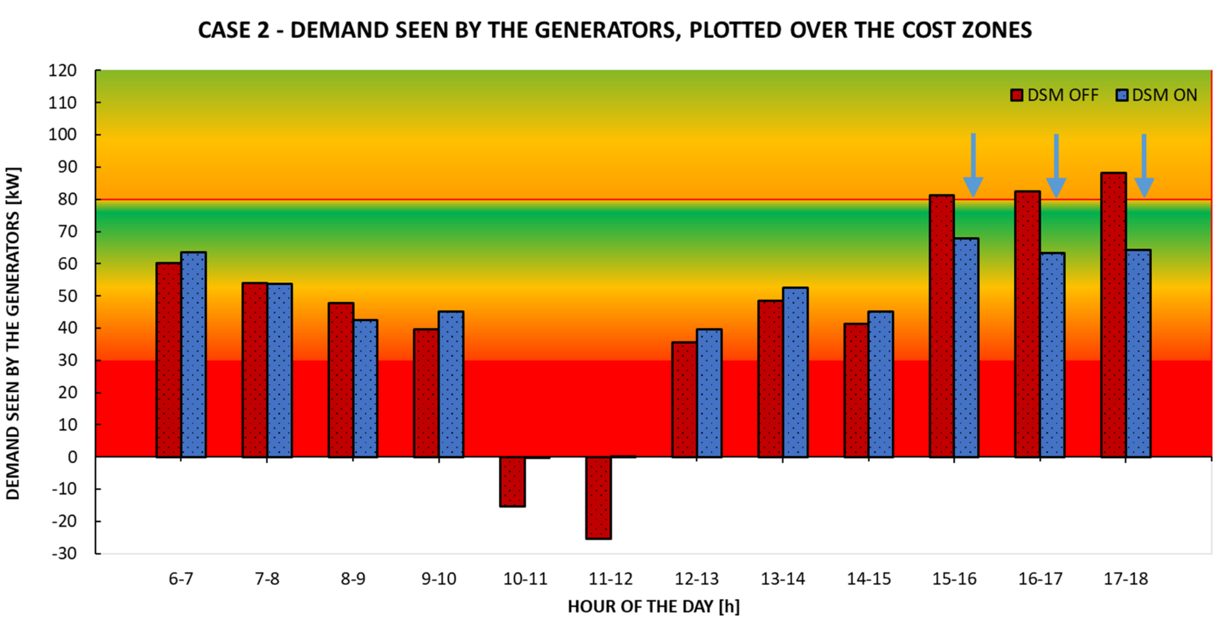


Fig. 27. Demands in Case 2, simulation 69, plotted over a color gradient that represents the specific consumption of the microgrid. Blue arrows indicate the times at which Generator 2 can be turned off.

Table 3
DSM performance indicators in Case 2, simulation 69.

CASE 2 - DSM performance			
Parameter	Without DSM	With DSM	Difference
Fuel consumption [L]	176.3	161.2	**−15.1**
	100.0%	91.4%	**−8.6%**
Managed users [Users]	0	51	51
Managed energy [kWh]	0	61.99 kWh	61.99
	0.0%	6.4%	6.4%
Renewable energy penetration [kWh]	279.45	434.25	**154.8**
	28.7%	44.7%	**15.9%**
Generator 1 load factor [%]	46.7%	55.4%	8.6%
Generator 2 load factor [%]	42.0%	Turned off	–
Generator 1 hours of use [h]	10	10	0
	83.3%	83.3%	0.0%
Generator 2 hours of use [h]	3	0	−3
	25.0%	0.0%	−25.0%

both generators did not operate either with the DSM off or with the DSM on.

The DSM led the microgrid to operate closer to regions of lower specific consumption in most of the hours and improved the average load factor of Generator 1 from 46.7% to 55.4%. In addition, the problem of renewables overgeneration was totally solved. During the afternoon, from 15 h to 18 h, the reduction in demand allowed the shutdown of Generator 2 for three consecutive hours.

In Case 2, the fuel economy was significant with the application of DSM. 15.1 L of diesel were saved with the coordinated action of 51 users. This saving was achieved due to the improvement of the penetration factor of renewable energies, which increased from 28.7% to 44.7%. This fact suggests that the adoption of the proposed DSM method can contribute to the adjustment of the demand curve in cases of hybrid microgrids subject to critical scenarios such as renewables overgeneration at certain times of the day. Scenarios that become even more frequent due to the increasing of solar energy sources in the grids [32].

Table 3 presents the DSM performance indicators in Case 2. In Case 2, two indicators deserved to be highlighted: fuel consumption; and penetration of renewable energies.

5.3. Sensitivity analysis

In a real-world application of the proposed DSM it is possible that some of the users chooses not to follow the recommended plans. To discover how much divergence can be expected if one or more users choose to change its plan unexpectedly, it was performed a sensitivity analysis of the fuel consumption and total hours of use of the generators in relation to the percentage of undecided users. For the analysis, users were randomly selected and had its recommended plans randomly changed for another plan. The analysis was made in ranges stepped by 10%. Each range was simulated 1,825 times, to make an equivalence with five years of observations. In the analysis, a range of 50%, for example, represents the situation in which up to 50% of the users can unexpectedly change their plan.

Fig. 28 presents the deviation expected in the fuel savings for the increase of the percentage of undecided users in Cases 1 and 2. For the fuel saving analysis, in booth cases, the higher the percentual of undecided users, the higher was the variation observed around the average value. It happens because depending on the user its impact in the aggregated demand is different, since the consumption profile of each user is different from one another. In Case 1, the case without renewables, a percentage of 30% of undecided users is sufficient to carry to zero the average fuel savings. In Case 2, the case with renewables, even with up to 100% of undecided users an average of 5% of fuel savings can be expected.

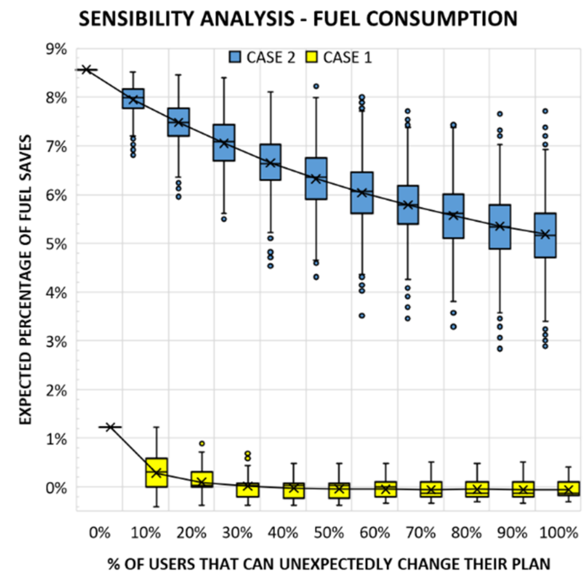


Fig. 28. Deviation expected in the fuel savings for the increase of the percentage of undecided users in Cases 1 and 2.

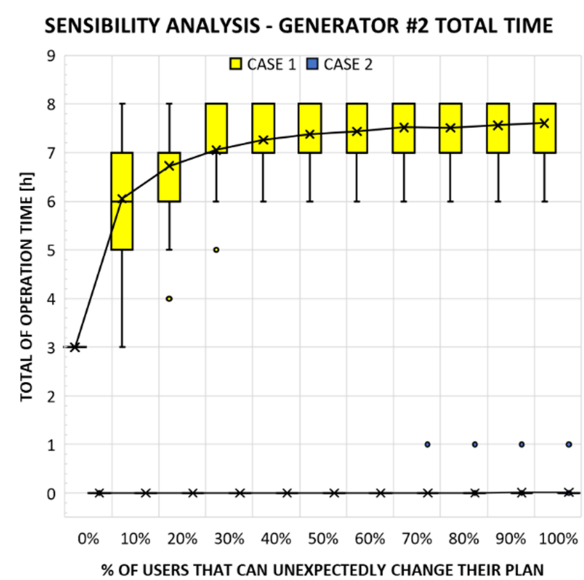


Fig. 29. Deviation expected in the time of use of Generator 2 in Cases 1 and 2.

Fig. 29 presents the deviation expected in the time of use of Generator 2 for the increase of the percentage of undecided users in Cases 1 and 2. In Case 1, with 10% of undecided users the hours of use of Generator 2 was significantly affected, passing from 3 to 6 h of operation on average. It reveals a correlation of Generator 2 total operation time with the results of fuel consumption analysis of Case 1. On the other hand, in Case 2, the operation time of the Generator 2 are only affected after 70% of undecided users and it reveals that in Case 2 the variation in the fuel savings are high related to the renewables overgeneration exploitation.

6. Discussion

The implementation of the proposed DSM does not depend on the installation of monitoring and control devices and does not require from the user knowledge about electrical equipment or about cost of energy to define and register the activity plans. In real scenarios a greater acceptance and participation of users is expected with the proposed approach compared to methods that require price monitoring or installation of control devices. However, the proposed DSM can also be applied together with load control devices. If combined these two methods may allow even greater demand flexibility and convenience to the user.

The cooperative management of activity plans proved to be a promising method for the working hours of the day. The method can be extended to the 24 h of the day, however, during the night and dawn, the potential for activity management tend to be low, once people are in general resting. On the other hand, planning morning and afternoon activities is a daily task naturally performed by people.

The proposed DSM method was able to improve the demand profile both in the absence and in the presence of renewables, even acting in less than half of the users. This indicates that the demand profile can be improved with the coordinated action of sets of users, not requiring all users to replan their activities. This is an advantage of the cooperative versus individualized approach.

The gains in the absence of renewables happen mainly by the reduction of the hours of use of the generators and by the improvement of the load factor. These two factors can significantly reduce annual and long-term maintenance costs. In remote regions, depending on logistical constraints the reduction of maintenance costs becomes even more important.

The savings can be divided among all users, only among users who had to opt for alternative plans or even for one of the users. In this way, it is understood that different policies to encourage user participation can be implemented through concession of discounts or prizes.

The storage of information about the users' consumption is possible but is not necessary for the DSM operation. Based on the consumption information it is possible to identify profiles by types of user, by time, day or month, by neighborhoods and by many other sets. The information may be used for research purposes, enhancement of DSM and network resources, user orientation, and other similar actions. The security of the information and the authorization of data collection or use are issues that need to be discussed both by the system administrator and the community.

The major advantage of the proposed optimization compared to a purely decision-making approach, in which the controller should decide and choose one alternative among all possible alternatives, is the guarantee of a high-quality solution whatever the demand profiles or renewable resource availability. A purely decision-making algorithm will test only three, four or a few possible solutions of the problem versus 1,600,000 ($4 \times 4 \times 100,000 = 1,600,000$) of the proposed IVNS. A deep discussion and graphs comparing the two strategies are presented in the Appendix A.

7. Conclusions

Several techniques and methods for demand side energy management have been investigated and tested in parallel with conservation actions and rational use campaigns [4,12]. Among the main DSM techniques investigated by the literature are: load shifting; peak clipping; valley filling; load building; and flexible load [4]. Among these, load shifting is considered one of the most effective.

Beyond the techniques, DSM systems also differ according to the methods adopted. The methods can be differed by: type of interaction with the users (individual or cooperative); approach to the optimization problem (deterministic or stochastic); and time scale (day-ahead or real time) [12].

The complexity of the optimization problem and consequently the time required for optimization depend on the number of users, techniques and methods of the DSM system. To deal with these issues, the use of metaheuristics and parallel computing [15] have been shown effective [16].

Related to DSM implementation in real scenarios, the mains difficulties highlighted by the literature are to encourage human participation and to reduce the need of devices installation [9,22].

In this context, this work proposed a day-ahead cooperative DSM method considering the comfort of the users, based on the management of activity plans. The shifting of sets of loads through the shifting of groups of activities proved to be feasible and promising. In the simulations, the proposed DSM was able to improve the demand profile both in the absence and in the presence of renewable sources, acting on average in 40% of the users in the absence of renewables and 47% in the presence of renewables and overgeneration.

Together with the parallel computing, the VNS metaheuristic proved to be adequate for solving cooperative DSM problems. In all the simulations, the algorithm demonstrated the ability to converge to near-optimal solutions by visiting a minimal part of the solution space.

The most significant improvements achieved by the DSM in the absence of renewables were the reduction of hours of use of the generators (minus 5 h) and the improvement of the load factor (18.4%). Thus, in addition to fuel savings, the DSM can help to reduce maintenance costs.

The DSM system was also able to increase the penetration of renewables, moving part of the consumption for the hours of renewables overgeneration. In the simulations, 8.6% of fuel savings was achieved selecting alternative plans for 51 users.

Thus, it is understood that the proposed DSM method can contribute to the adjustment of the profile of the aggregate demand of users served by the same energy company or by isolated generation systems, with a minimum degree of discomfort.

Moreover, the proposed DSM is not dependent on load-control devices and does not require from the users frequent monitoring of energy prices, improving the convenience to the user and reducing implementation costs.

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Appendix A. Purely decision-making vs optimization

Fig. A1 shows possible solutions of a purely decision-making strategy and of the IVNS algorithm considering Case 1. The Fig. A2 presents a similar plot for Case 2. The purely decision-making strategy considered was to select one of the three plans or a random solution if one of these had lower fuel consumption when compared to main plans, the plans 1. For comparison with the optimized solution, it was also plotted in Figs. A1 and A2 the Pareto frontier. Analysing the graphs it is possible to observe that moving all users to plans 2 or 3 can sometimes reduce the fuel consumption but the discomfort caused to the users are maximum. High level of discomfort is undesirable. The selection of a random solution can produce less discomfort to the users, but it could also give a worse result in terms of fuel consumption, since some aggregated demand profiles caused by random selection can be worse than the main plans execution. On other the hand, the IVNS optimization grantees assertive decision-making finding solutions with low consumption and low discomfort.

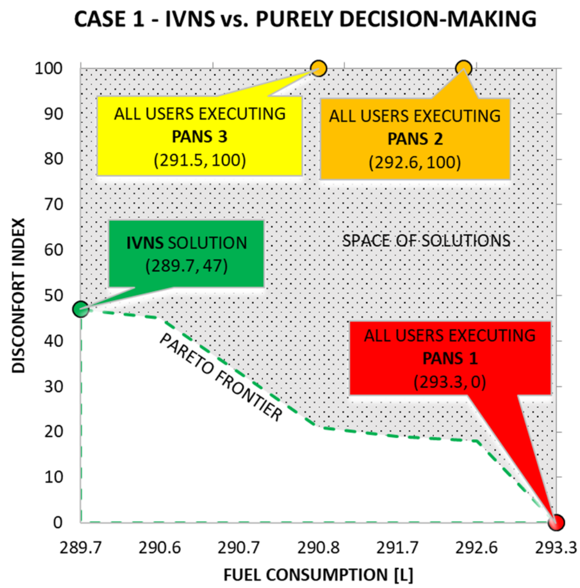

Fig. A1. Comparison of IVNS solution vs. purely decision-making possible solutions on Case 1.

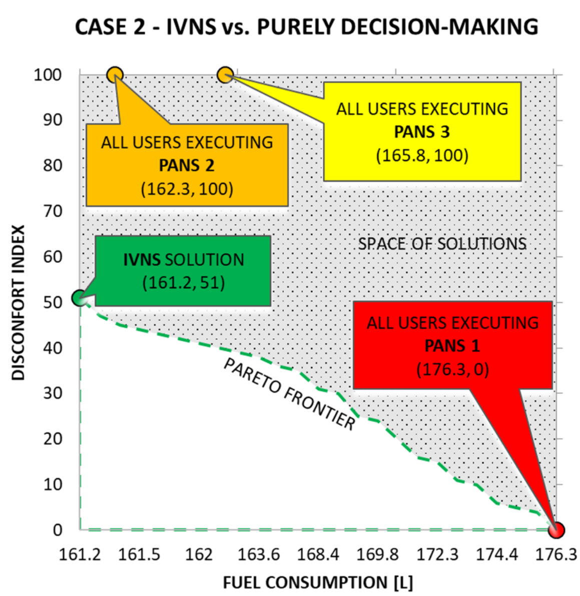

Fig. A2. Comparison of IVNS solution vs. purely decision-making possible solutions on Case 2.

To deal with time restrictions, the IVNS can have its stop criterion settled as a time limit. In this case the IVNS gives the best solution found in the settled time. In terms of speed of execution, the time spent by the IVNS to run a one cycle analysis (16 solutions tested) is similar to the time spent to execute the purely decision-making strategy (4 solutions tested). It is possible thanks to the use of parallel computation. As reference, the time spent by the implemented IVNS for the execution of 100,000 cycles is about 10 s, an average of 0.1 ms/cycle, using a 3 GHz, quad-core processor.

References

[1] Tin T, Sovacool BK, Blake D, Magill P, El Naggar S, Lidstrom S, et al. Energy efficiency and renewable energy under extreme conditions: Case studies from Antarctica. Renew Energy 2010;35:1715–23. https://doi.org/10.1016/j.renene.2009.10.020.
[2] Christo TM, Fardin JF, Simonetti DSL, Encarnação LF, de Alvarez CE. Design and analysis of hybrid energy systems: The Brazilian Antarctic Station case. Renew Energy 2016;88:236–46. https://doi.org/10.1016/j.renene.2015.11.014.
[3] Vasconcelos H, Moreira C, Madureira A, Lopes JP, Miranda V. Advanced control solutions for operating isolated power systems: examining the Portuguese islands. IEEE Electrif Mag 2015;3:25–35. https://doi.org/10.1109/MELE.2014.2380131.
[4] Esther BP, Kumar KS. A survey on residential demand side management architecture, approaches, optimization models and methods. Renew Sustain Energy Rev 2016;59:342–51. https://doi.org/10.1016/j.rser.2015.12.282.
[5] Hu Z, Kim JH, Wang J, Byrne J. Review of dynamic pricing programs in the U.S. And Europe: Status quo and policy recommendations. Renew Sustain Energy Rev 2015;42:743–51. https://doi.org/10.1016/j.rser.2014.10.078.
[6] Ding Y, Pineda S, Nyeng P, Ostergaard J, Larsen EM. Real-time market concept architecture for EcoGrid EU—A prototype for European smart grids. IEEE Trans Smart Grid 2013;4:2006–16. https://doi.org/10.1109/TSG.2013.2258048.
[7] Le Ray G, Larsen EM, Pinson P. Evaluating price-based demand response in practice - with application to the EcoGrid EU Experiment. 1 1 IEEE Trans Smart Grid 2016;3053. https://doi.org/10.1109/TSG.2016.2610518.
[8] Zehir MA, Batman A, Bagriyanik M. Review and comparison of demand response options for more effective use of renewable energy at consumer level. Renew Sustain Energy Rev 2016;56:631–42. https://doi.org/10.1016/j.rser.2015.11.082.
[9] Good N, Ellis KA, Mancarella P. Review and classification of barriers and enablers of demand response in the smart grid. Renew Sustain Energy Rev 2017;72:57–72.

https://doi.org/10.1016/j.rser.2017.01.043.
[10] De Christo TM, Fardin JF, Simonetti DSL, De Alvarez CE. Energy generation and managemnet concept for the new buildings of the Comandante Ferraz Antarctic Station. INCT-APA Annu Act Rep 2016:97–100. https://doi.org/10.4322/apa.2016.017.
[11] Momoh J. Smart grid, John Wiley & Sons, Inc., Hoboken, NJ, USA; 2012. doi:10.1002/9781118156117.
[12] Barbato A, Capone A. Optimization models and methods for demand-side management of residential users: A survey. Energies 2014;7:5787–824. https://doi.org/10.3390/en7095787.
[13] Ren Y, Suganthan PN, Srikanth N. Ensemble methods for wind and solar power forecasting - A state-of-the-art review. Renew Sustain Energy Rev 2015;50:82–91. https://doi.org/10.1016/j.rser.2015.04.081.
[14] Zhao H, Magoulès F. A review on the prediction of building energy consumption. Renew Sustain Energy Rev 2012;16:3586–92. https://doi.org/10.1016/J.RSER.2012.02.049.
[15] Alba E. Parallel metaheuristics, John Wiley & Sons, Inc., Hoboken, NJ, USA; 2005. doi:10.1002/0471739383.
[16] Baños R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gómez J. Optimization methods applied to renewable and sustainable energy: A review. Renew Sustain Energy Rev 2011;15:1753–66. https://doi.org/10.1016/j.rser.2010.12.008.
[17] Ahmad Khan A, Naeem M, Iqbal M, Qaisar S, Anpalagan A. A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids. Renew Sustain Energy Rev 2016;58:1664–83. https://doi.org/10.1016/j.rser.2015.12.259.
[18] Mladenović N, Hansen P. Variable neighborhood search. Comput Oper Res 1997;24:1097–100. https://doi.org/10.1016/S0305-0548(97)00031-2.
[19] Hansen P, Mladenović N. Variable neighborhood search: Principles and applications. Eur J Oper Res 2001;130:449–67. https://doi.org/10.1016/S0377-2217(00)00100-4.
[20] Dutta G, Mitra K. A literature review on dynamic pricing of electricity. J Oper Res Soc 2017;68:1131–45. https://doi.org/10.1057/s41274-016-0149-4.
[21] Ayón X, Gruber JK, Hayes BP, Usaola J, Prodanović M. An optimal day-ahead load scheduling approach based on the flexibility of aggregate demands. Appl Energy 2017;198:1–11. https://doi.org/10.1016/j.apenergy.2017.04.038.
[22] Lund P, Nyeng P, Duban Grandal R, Holm Sørensen S, Felicia Bendtsen M, le Ray G, et al., EcoGrid EU - A prototype for European smart grids. Deliverable D6.7 Overall evaluation and conclusion, Bornholm, Denmark; 2016. http://www.eu-ecogrid.net.
[23] Van Rattinghe K. Princess Elisabeth research station at Antarctica: renewable energy systems design, simulation and optimization. Delft University of Technology; 2008.
[24] International polar foundation, Princess Elisabeth Antarctica: The First Zero Emission Polar Research Station, 2013. http://www.antarcticstation.org/assets/uploads/documents_files/brochure_pea_19_04_2013_web.pdf.
[25] Davidović T, Crainic TG. MPI parallelization of variable neighborhood search. Electron Notes Discret Math 2012;39:241–8. https://doi.org/10.1016/j.endm.2012.10.032.
[26] Hayn M, Bertsch V, Fichtner W. Electricity load profiles in Europe: The importance of household segmentation. Energy Res Soc Sci 2014;3:30–45. https://doi.org/10.1016/j.erss.2014.07.002.
[27] Harish VSKV, Kumar A. A review on modeling and simulation of building energy systems. Renew Sustain Energy Rev 2016. https://doi.org/10.1016/j.rser.2015.12.040.
[28] Gruber JK, Prodanovic M. Residential energy load profile generation using a probabilistic approach, 2012 Sixth UKSim/AMSS. Eur Symp Comput Model Simul 2012:317–22. https://doi.org/10.1109/EMS.2012.30.
[29] Brian J. White paper: The impact of generator set underloading, CATERPILLAR; 2014. https://www.cat.com/en_IN/articles/The-impact-of-generator-set-underloading.html [accessed January 10, 2018].
[30] Allert C, Lisitschew, Rietze, Rothert M. White paper: sunny island generator, SMA Sol. Technol. AG; 2014. http://files.sma.de/dl/7910/SIGEN-13FE0914.pdf [accessed January 10, 2018].
[31] Luo X, Wang J, Dooner M, Clarke J. Overview of current development in electrical energy storage technologies and the application potential in power system operation. Appl Energy 2015;137:511–36. https://doi.org/10.1016/j.apenergy.2014.09.081.
[32] Denholm P, O'Connell M, Brinkman G, Jorgenson J. Overgeneration from solar energy in California. A field guide to the duck chart, Golden, CO (United States); 2015. doi:10.2172/1226167.