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Research paper

Optimizing the penetration of standalone microgrid, incorporating demand side management as a guiding principle

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ABSTRACT

In this work, we demonstrate the importance of implementing techniques that allow us to include demand side management as a tool for the planning of energy systems, in this particular case, standalone power systems. Penetration indexes are also proposed and calculated to establish the minimum requirements for the energy supply of a predominantly residential system powered by renewable resources. The indexes were optimized using meta-heuristic optimization techniques based on a genetic algorithm and particle swarm optimization. Periods of one, five and 10 years were analyzed in order to understand the importance of the penetration of these technologies. Through the use of numerical tools, the relationship between generation and demand is optimized for different cases, with the aim of reducing the energy that is not supplied to the system at minimum cost. This document analyzes a series of penetration indexes that were obtained by optimizing an energy system. The mentioned indexes allow to visualize the behavior of the technologies susceptible of being implemented in the western region of Mexico. The purpose of the work is focused on understanding the potential of demand management as a structural element and foundation of energy networks that use renewable energy.

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1. Introduction

Historically, demand side management (DSM) has been relegated to a secondary role. Even in the United States in the 1970s, motivated by economic interests derived from energy blockades, pilot programs were proposed for the implementation of active controls and demand management. One of the crucial elements of management is an extensive knowledge of two guidelines. One of which is related to the geographical location of the site and the other is dependent on the vocation, considering the theoretical operation limits of it. The objective of the previous premises is adapted to the sector that impacts, while it could be visualized as an abrupt interruption in the electrical supply. On the other hand, it could also represent a decrease in the production capacity, both translated into economic losses (Thakur and Chakraborty, 2016).

Over the last decade, due to various socio-political factors, conditions in the electricity markets have led to the continuous rethinking of the logic and mode of its operation. The incorporation of new products, services, agents, market segmentation, and a proactive role for demand. All of these elements are becoming increasingly important, and the preferences of the participating agents are a key element in the decision-making process. The focus is on the type of energy matrix required to fulfill the various political schedule and how much customers would be willing to pay. They are gradually transiting by marked guidelines, since the beginning of the first industrial revolution, such as the design of optimal operation strategies that can maximize the benefits to all parties, thus guaranteeing energy and power at a reasonable cost.

Paradoxically, with the boom of a social phenomenon that links the actions of the subjects to what is considered correct, these movements have become increasingly complex, and the choices and the conditioning change from a mono nature to a multi nature. This is because they were previously limited to the only reason that could be of a technical or economic nature, and now they must be technical-economic and environmentally acceptable to civil society. The market results from certain optics a natural evolution, in search of the best decisions for optimal management and operation. Where and from the economic rationality, the minimum cost is the first approximation, but there are additional components which ultimately allow a better decision-making (Duttagupta and Singh, 2006; Yuan et al., 2008; Hossain et al., 2014; Kärkkäinen et al., 2008; Luna-Rubio et al., 2012).

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List Abbreviature

SysP	Total Power System
DSM	Demand Side Management
LPSP	Loss of Power Supply Probability
COE	Cost of energy
SSM	Source Side management
MG	Microgrids
DE	Diesel Engine generators
BESS	Battery Energy Storage Systems
EMS	Energy Management Systems
TNPC	Total System Net Present Cost
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
SPV	Stand-alone photovoltaic
Psys	Demand Total power system
Rp	Renewable Power of the system
SP	Sun Power
WP	Wind Power
WCR	Without Cost Restriction
BP	Battery bank Power of the system
DP	Conventional energy of the system
IpRP	Penetration index Renewable Power
IpWP	Penetration index Wind Power
IpSP	Penetration index Sun Power
IpBP	Penetration index Battery Power
IpDSM	Penetration index Demand side management Power
IpDP	Penetration index diesel Power
ENS	Energy not supplied
CT	Fixed total cost
ACS	Costs of the system of operation, maintenance and installation
BES	Energy that the generating elements do not deliver to the system
FCRP	Fixed cost of Renewable Power
FCBP	Fixed cost of Battery Power
FCDSMP	Fixed cost of Demand Side Management Power
FCDP	Fixed cost of Diesel Power
VCRP	Variable cost of Renewable Power
VCBP	Variable cost of Battery Power
VCDSMP	Variable cost of Demand Side Management Power
VCDP	Variable cost of Diesel Power

These developments have contributed to an increase in the quality of life of individuals, which in turn has resulted in economic growth. Thus, it should include technologies that allow for eco-systemic diversity and a contractual balance between profit and nature, which significantly increases the responsibility of the electrical sector industries (Morgan et al., 2004; Xenos et al., 2016; Manco et al., 2021).

Finding a balance between the generation and consumption of electricity is an essential and prevailing condition from the pre-history of the electric power systems to that of the marginal cost of goods. This implies the requirements of sufficiency and energy security on the part of the electric companies, making it useful to know the variables that condition the demand on the consumer side (Tang et al., 2005). The concept of demand response, which was seen as a need to design mechanisms to modify demand behavior, was an important starting point for the creation of management models for consumption (Boshell and Veloza, 2008). In some ways, problems based on finite availability are solved in a similar manner, limiting resources to limits that allow a hierarchical distribution based on arbitrary values that ensure conditional stability (Scognamiglio et al., 2014).

Tafreshi et al. in Tafreshi et al. (2010), present a methodology to perform optimal unit sizing for distributed energy resources in a microgrid (MG). They implemented a method based on a genetic algorithm (GA) to calculate the optimal system configuration to achieve the loss of power supply probability (LPSP) required by the customer with a minimum cost of energy (COE). The main difference between this previous work and our study is the incorporation of a DSM control scheme that allows us to redirect energy flows and minimize the cost of implementation of the system.

Our work has a central axis, allowing the optimal sizing of MGs, managing the assets of the system in such a way that modular systems can be used to reduce the cost of installation, operation, and maintenance and the energy not supplied (ENS). The optimizer provides five data that allow us to establish the penetration rates, fixed cost, and variable cost of the technologies implemented in isolated MGs. It is important to note that an MG operates in connection with an upper grid, which determines the voltage, frequency, and angle values. The aim is to compute the percentage of penetration of each technology without the need to import energy from the upper grid.

In Wang et al. (2020) Wang et al. present a study for optimal construction of MGs. The authors design and integrate a distribution system considering the importance of reliability by using Backward–Forward load flow. In this study the distribution network is designed to be divided into several MGs in order to minimize the cost of electric generation, improving reliability and voltage profiles.

An optimization scheme for grid energy using a supervisory control and data acquisition (SCADA) system for DC MGs, including distributed energy resources and residential buildings is presented in Chauhan and Chauhan (2017). The proposed system mainly focused on distributed energy resources (DERs) for source side management (SSM) and DSM.

In Bhamidi and Sivasubramani (2019) the authors propose a joint optimization model for planning and operating residential MGs linked to the MG with the support of DSM. In their model, the residential MG includes various distributed energy resources, such as photovoltaic (PV) units, wind turbines, micro turbines, diesel engine generators (DEs), and battery energy storage systems (BESSs). They considered a bi-objective model that reduced the economic and environmental component, although they did not use heuristic methods. A later version allows us to understand the concept of optimal sizing from a particularly modern standpoint that incorporates the concept of resilience.

In an article published in Oviedo et al. (2020), Oviedo propose a solution for optimal sizing that use a heuristic approach to the gradient descent method for discrete functions. This simulation model evaluate the performance of the MG, even with an energy management system (EMS), using optimal criteria. A case study evaluation was used to prove the effectiveness of the proposed algorithm, compared to traditional heuristic techniques, such as particle swarm optimization (PSO) and a comprehensive search. They demonstrated the feasibility of the algorithm for use in independent MG planning.

In regard to the benefits of DSM strategies for an island supplied by marine renewable energy, the authors emphasized the ability of demand to control costs, and presented a scenario in which six basic demand management strategies were considered:

peak clipping, valley filling, load shifting, strategic load growth, strategic load conservation and flexible load shape (Roy et al., 2018; Battula et al., 2021).

Sufyan et al. in Sufyan et al. (2019), use a firefly algorithm (FA), and compared the efficacy of this approach with other meta-heuristic techniques in terms of two performance measurement indexes: the cost of electricity and the probability of a loss of power supply. The results showed that the proposed technique could reduce the cost of the MG and achieve the optimal size of the battery. The behavior of the system was evaluated using 24-h time windows.

In Jamshidi and Askarzadeh (2019) Jamshidi et al. use a meta-heuristic optimizer called a multi-objective crow search algorithm (MOCSA) to find a Pareto front. The impacts of different parameters (the fuel price, the cost of the fuel cell system and equipment, the emission cost, etc.) were investigated in terms of the sizing problem. Simulation results conclude that the integration of hydrogen energy technology could reduce the total cost of hybrid energy systems. Moreover, the impact of operating reserve on the Pareto front was higher than that of the uncertainties in the load and solar power.

Other studies that were similar to the one described above, but focused on rural areas, are presented in Vendoti et al. (2019) and Suresh et al. (2020). The main objective was to reduce the total system net present cost, unmet load and CO2 emissions, using a GA and HOMER Pro Software. The relevance of the above is centered on the importance of DSM in countries that are developing their production processes. In these countries, the morphology of electricity consumption is carried out through distributed generation due to the distance at which some populations are located from the main areas of residence (Rajanna and Saini, 2016).

The study in Naz et al. (2017) present the real dimensions of electric generation through the use of multiple energy sources in rural areas. The model proposed in this paper allows us to understand the importance of energy for agriculture for the purpose of ensuring an uninterrupted supply of energy and to minimize the environmental impacts and cost of electricity to consumers using multiobjective optimization.

The authors of Kyriakarakos et al. (2013) present a scheme that incorporated a demand side energy management system for autonomous polygeneration MGs. They proposed a multi-agent system for intelligent DSM for a polygeneration MG topology.

As described above, authors have presented a variety of different approaches for sizing MGs at the minimal total cost. I is observed that few of them consider DSM and the cost of ENS, as a key element to reduce the sizing of renewable energies, batteries and consequently the total cost of the system. Therefore, it is important to carry out a deeper analysis at different time horizons, including the concept of ENS with its corresponding cost.

Comparing the previous works, the contribution of this paper is summarize next:

- We propose optimal penetration indexes for each technology (PV, wind, diesel, batteries and DSM) that allow us to minimize the total cost and the ENS over different time horizons (one, five and ten years), in two cases: with and without cost assigned to the ENS.
- These penetration indexes consider both technical parameters associate with each technology, as wind speed, irradiation level, load demand, power and energy, etc., and economic parameters that are associated with the implementation, operation and maintenance costs of the technologies, including the Energy Not Supplied.
- Through a literature review process, it has been found that PSO and GA heuristic optimization techniques have the ability to solve multi objective functions, based on the system requirements. These techniques were chosen, considering three scenarios with 5 cases in each one, founding interesting results.
- Considering a cost on ENS, algorithms assign penetration indexes values for each technology, looking for balance points between total cost and ENS.

The present work is organized as follows: in Section 2, the mathematical model of the microgrid that is used for this work is described. In Section 3, the penetration indexes are introduced, which will be used to formulate the optimization problem. In Section 4, the optimization problem is developed to be solved by the optimization algorithms. In Section 5, the results obtained by the optimization algorithms are shown and discussed. In Section 6, the conclusions of the paper are presented.

2. Model description

In the model used in this work, the total power system and the DSM power are denoted by the variables Psys and DSM, respectively. RP is the power supplied to the renewable energy system, DP denotes the conventional power (e.g., diesel power), and BP is the battery bank power. The data used to characterize the solar and wind resources were obtained from the World Meteorological Organization, from a station located at the Miguel Hidalgo International Airport in Guadalajara, Jalisco, Mexico. These data were compared with those that could be extrapolated from the DesignBuilder software. The Energy Vectors are created base on the climatic stations near to city of Guadalajara. The models of the wind and the sun correspond to those put forward by Betz and Rigollier, respectively (Eraso-Checa et al., 2018; Rigollier et al., 2000).

The Betz model is given by the following equation:

$$Betz(limit) = (16/27) * (W_p) \tag{1}$$

The power of the wind is a function of the density of the air, which is symbolized by A is the Area, v is the average hourly speed and (ρ) the density of wind.

$$W_p = (1/2) * \rho * Area * v^3 \tag{2}$$

Likewise, the simplified Rigollier model is given by:

$$(\eta)_R = (I)_{ss} * (\eta_{sunmax}/1000) \tag{3}$$

where the peak solar efficiency is given by η, and is that of the sun under the following standard conditions, which involve $AM = 1.5$. Eq. (2) occurs if the following inequality is satisfied:

$$v < 4, W_p = 0;\ 4 < v < 25;\ 25 < v, W_p = 0 \tag{4}$$

The evaluated area has a residential/commercial demand profile. The morphology is a low voltage MG (127/220 V), and is composed of PV generators, wind generators, backup systems, and diesel generators (Yuan et al., 2008). Starting from the point of view of that author, a flexible MG is capable of supplying energy to an isolated system but at a high cost, as we would have to raise the days number of autonomy to ensure that the generation will cover the demand at all times (Ravibabu et al., 2008).

In this work, we use an integer linear programming approach to find the optimal reprogramming of changeable loads, and use a GA and PSO to calculate the optimal size. A considerable drawback of this approach is that DSM focuses only on reducing the razor peak while ignoring the maximization of the exploitation of renewable energy. However, we add a new element that allows

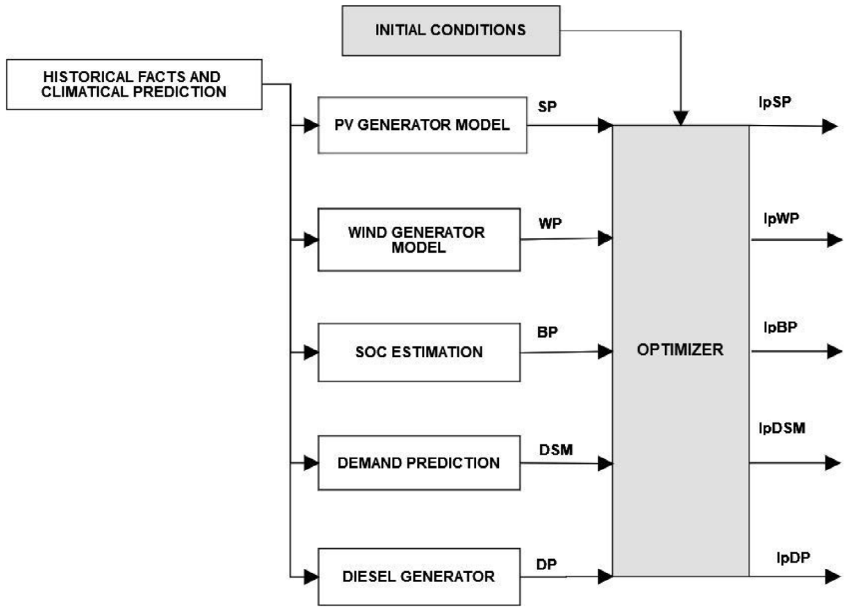

Fig. 1. Microgrid energy balance with demand side management block.

us to control the power demand of the system. The purpose of incorporating this element is to evaluate the behavior and response of the load before exerting active control over the demand. At all times, the objective of the system is to minimize the ENS, which would mean that the system stopped providing energy to one or more of the components of the load. The system is initially fed primarily by solar and wind energy, but if necessary, a battery bank can be discharged to guarantee the power supply to the system. In the case where the power provided by the battery bank is insufficient, the system will turn off those loads that are manageable at the time, and as a last resort, it will use a diesel generator to provide the necessary power.

In this MG, the priority of the energy sources is defined based on the order in which they are introduced during the operation of the MG when the energy demand increases. The priority of the energy sources is therefore:

1. Solar and Wind energy
2. Battery Bank energy
3. Demand Side Management
4. Diesel Generator energy

The MG described above has a maximum power of 1000 kW. It is important to mention that the energy of the battery bank and diesel generator become a priority when the system experiences a critical power failure, due to the high demand for energy in the MG. However, both sources operate with the aim of supplying the greatest quantity at the lowest possible cost. The manageable capacity of the system is 600 kW, as shown in Fig. 1.

The parameter (penetration indexes) are defined as a percentage of the priority demand, in this case 400 kW, which will be supplied by each of the technologies of the MG. The scheme proposed in this work will be optimized by means of numerical simulations, which will allow us to reduce the ENS. It will also allow us to provide a mixture of renewable energy and DSM. The primary objective of this system is to give importance to the management of the demand from the planning of the system. The optimization algorithm calculates the penetration indexes as the proportion of energy used from each source, and these proportions should be understood as a percentage of the total energy evaluated over periods of one, five and 10 years. Fig. 1 shows the structure of the MG used in this work, where the optimizer is the element that manages the connection and disconnection of the energy in the MG. The energy supplied by each source is denoted by SP, WP, BP, DSM, and DP; these play an important role in the numerical simulations, as they allow us to establish the combinatorial criteria that will give rise to the penetration rates of each technology. Each energy supply is denoted by two letters: the first represents the resource (solar, wind, battery, and diesel), and the second acts as a common suffix (P) to symbolize power. The regulation will not apply to DSM due to the importance of it for this work.

The architecture of the MG is based on the integration of the generating, regulating and consumer elements, such that the minimum load allowed before the system establishes a control action is 40%

The main aim of developing this system is to find the optimal balance between the energy generated and the energy demanded by the system (grid connection). As in a grid-connected system, autonomous systems seek to avoid energy shortages, and there should also be no excessive generation of energy, as this would cause wastage of time, money and effort on the part of the generating units, as expressed mathematically in the following equation:

$$Sys_P = \sum_{t=1}^{t=8760} ERP + EDP + \sum_{t=1}^{t=8760} EBP + \sum_{t=1}^{t=8760} EDSM \tag{5}$$

The sum of the energy generated by the conventional and non-conventional elements (ERP + EDP), plus the sum of the stored energy (EBP) and the sum of the energy gained by utility (EDSM), is equal to the sum of the power demanded by the system. The control algorithm appropriately ranks the available resources, placing renewable resources as an energy vector at all times. The flow of power to sub-systems such as batteries depends on the priority resource. If the renewable energy and the state of charge of the batteries are not sufficient, the algorithm manages the demand to reach an energy balance, leaving diesel as a last resort. The value of t, shown as a superscript to each variable, denotes that it is an analysis at a given and continuous instant of time, where the value in Eq. (5) represents a decade. The architecture of the proposed system is outlined in Fig. 2, and the elements are presented schematically.

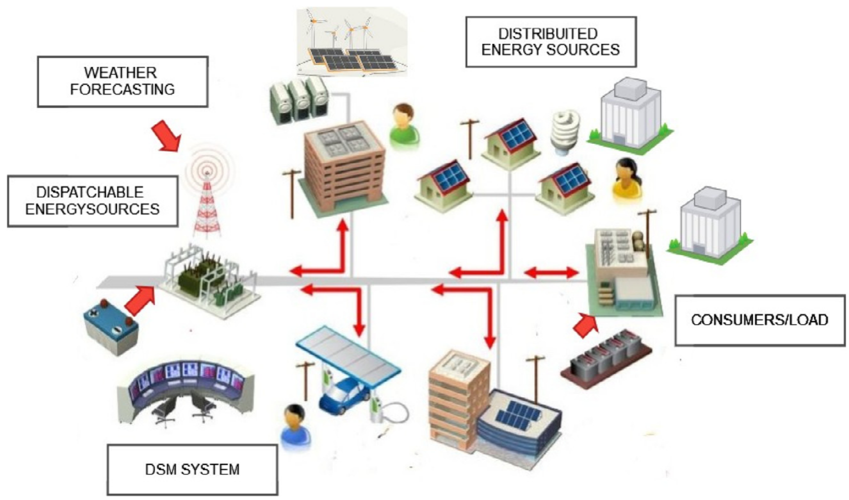

Fig. 2. Architecture of the microgrid.

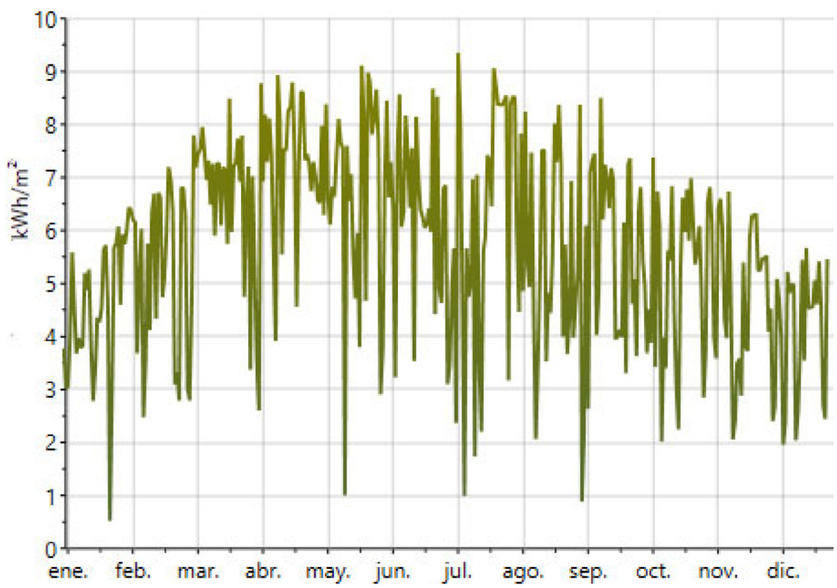

Fig. 3. Yearly solar global radiation.

It is important to consider that although the MG is powered autonomously, it allows for porting to the upper grids. The red arrows indicate the way in which the elements described above are interrelated. For our case study, we use a database that was created using .epw files from Meteonorm, and was verified based on the data that DesignBuilder uses to visualize global horizontal radiation. This can be seen in Fig. 3.

3. Indexes of penetration

One of the factors motivating this work is to compute the indexes that guarantee the best performance of a system based mainly on solar energy, at a competitive cost and with a considerable percentage of management. In the notation used for these indexes, the prefix denotes the variable penetration index and the suffix represents the technology for each case, i.e., the sun, the wind, the battery bank, DSM and diesel power, respectively. The operational logic of the aforementioned MG is based on the active control of demand. It is described using the equations below, representing a year in the time domain. The indexes are defined as I_PSP, I_PWP, I_PBP, I_PDSM, I_PDP.

The implementation, operation and maintenance costs are defined by the variable C, and they are a function of the operating time of the system, where CT is the total cost. It should be noted that the index associated with conventional generation fluctuates constantly, since in most markets in the world this affects the cost of fuel.

It should be noted that the index associated with conventional generation fluctuates constantly, since in most markets in the world this affects the cost of fuel. Eq. (1) shows a model that incorporates demand management as an active element within an energy system considering the same part of the generation process:

$$CT = \sum_{t=1}^{t=8760} I_PDSM(t) * C_{DSM} + I_PDP(t) * C_{DP}(t) + I_PB(t) * C_{BP}(t) + I_PRP(t) * C_{RP}(t) \quad (6)$$

It is important to mention that in this work, the stability of the grid is defined as the absence of ENS by the MG. In order to operate the MG in a stable way, active control of the power demand is required in order to control the load on the system.

The energy obtained from each renewable source is defined in the following section.

3.1. Renewable energy

Renewable energy in the system is defined as:

$$ERP(t) = SP(t) + WP(t). \tag{7}$$

where WP and SP are Sun and Wind Power respectively.

Eq. (8) describes the renewable power produced by the system in one year (8760 h):

$$ERP = \sum_{t=1}^{t=8760} (SP(t))(I_P SP) + (WP(t))(I_P WP(t)) \tag{8}$$

3.2. Battery energy

The battery energy in the system (EBP) is defined as

$$EBP = \sum_{t=1}^{t=8760} (BP(t))(I_P BP) \tag{9}$$

where $I_P BP$ is the battery index of penetration, and BP is the battery power over a one-year time horizon.

In Eq. (10), the minimum and maximum states of charge are represented by the variable EBP.

The process of charging and discharging the battery is typical, however these are only charged with wind and PV power.

$$EBP = EBPmin \sum_{t=1}^{t=8760} \leq \sum_{t=1}^{t=8760} \geq EBPmax \sum_{t=1}^{t=8760} \tag{10}$$

In the previous equation the minimum and maximum state of charge is represented by the variable EBP.

The process of charging and discharging the battery is typical, however these are only charged with wind and photovoltaic power.

$$EBP = \sum_{t=1}^{t=8760} +\eta charge * PCharge\Delta t - (1/\eta Discharge) * PCharge\Delta t \tag{11}$$

3.3. Manageable energy

In this study, a critical load is essential one that must not be managed, likewise the non-critical load is one that can be shedding through control since it does not affect the main activities of the system.

The manageable energy in the system (EDSM) is defined as:

$$EDSM = \sum_{t=1}^{t=8760} (DSM(t))(I_P DSM) \tag{12}$$

where $DSM(t)$ and $I_P DSM$, denote the DSM power potential and the DSM index of penetration, respectively.

The following matrix of Eq. (13) shows how the manageable load behaves, which is a function of how much the battery can be charged and hence a function of the renewable power.

In each case, the value is computed as the total generation minus the power demanded, taking into account that 40 percent of the system load can be turned off. Demand is controlled by the DSM system, and it was predicted through an analysis of the behavior of a characteristic curve of residential consumption.

Likewise, it was statistically treated in order to be able to evaluate said curve in a period of 10 years.

$$\begin{bmatrix} EDSM(1,1) & EDSM(1,2) & \cdots & EDSM(1,23) & EDSM(1,24) \\ EDSM(2,1) & EDSM(2,2) & \cdots & EDSM(2,23) & EDSM(2,24) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ EDSM(364,1) & EDSM(364,2) & \cdots & EDSM(364,23) & EDSM(364,24) \\ EDSM(365,1) & EDSM(365,2) & \cdots & EDSM(365,23) & EDSM(365,24) \end{bmatrix} \tag{13}$$

The first digit of each element in the matrix represents the day, and the second digit represents the hour. It should be understood that the period of this process has an annual time interval. EDSM (1, 1) represents the capacity of the system not to waste energy and schedule it over another time horizon, in order to reduce total costs. In this case, it corresponds to the first day and the first hour.

3.4. Conventional energy

The conventional energy in the system is defined as:

$$EDP = \sum_{t=1}^{t=8760} (DP(t))(I_P DP) \tag{14}$$

where $DP(t)$ and $I_P DP$ denote diesel power and the diesel index of penetration, respectively.

3.5. Energy not supplied

The energy not supplied (ENS) is defined as:

$$ENS = Psys - SP - WP - DSM - BP - DP \tag{15}$$

3.6. Fixed Total Cost

The Fixed Total Cost factor, denotes the fixed costs of the system technologies associated with the installation, where the suffixes indicate each technology, i.e., renewable, DSM, battery, and diesel power, respectively.

$$C_T = \sum_{t=1}^{t=8760} C_{RP}(t) + C_{DSM}(t) + C_{BP}(t) + C_{DP}(t) \tag{16}$$

where C_{RP}, C_{DSM}, C_{BP} and C_{DP} denotes the initial investment cost of the variables in the system throughout the year, associated with the installation of the system.

3.7. Variable Total Cost Factor

The variable Total Cost factor (VTCF) denotes the variable costs of the system technologies associated with maintenance and operation, where the suffixes indicate each technology, i.e., renewable, DSM, battery, and diesel power, respectively.

$$VTCF = \sum_{t=1}^{t=8760} VC_{RP}(t) + VC_{DSM}(t) + VC_{BP}(t) + VC_{DP}(t) \tag{17}$$

3.8. System cost

The system cost (S_C) is the sum of the fixed total cost and the variable total cost:

$$S_C = C_T + VTCF \tag{18}$$

where, S_C represents the system cost, CT, the fixed total cost, and $VTCF$ is the variable total cost factor. In this case, the ENS is the difference between the energy needed by the system to operate at

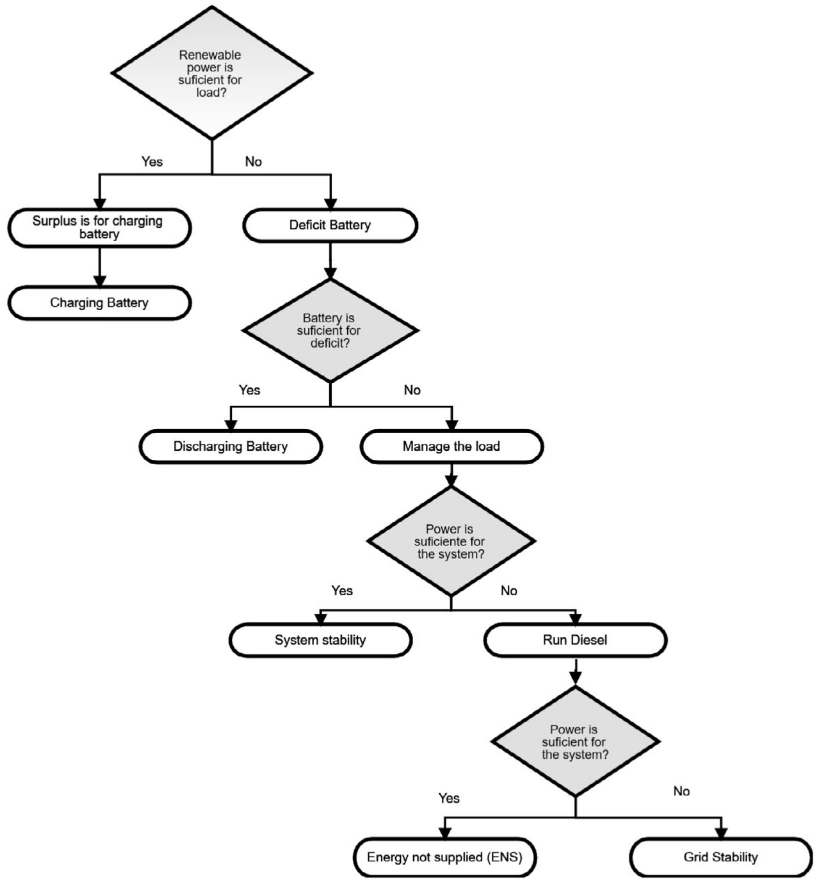

Fig. 4. Schematic representation of the control scheme for the microgrid.

full load and the energy delivered to the system by the generation elements.

Fig. 4, shows how the element generators function to keep the load stable. The operational logic of the proposed scheme can be described as follows. Initially, renewable energy is used, but if this energy is insufficient then battery energy is used. If insufficient energy is still being supplied, load management comes into operation, and as the last alternative, the backup diesel generator is activated. This operating mechanism is designed so that priority for energy use is given to renewable resources, in order to reduce the impact of fossil energy.

The ENS is a fundamental element in a primordial post-oil urban-energy model, which must have an accessible and consolidated grid. The MGs must locate nodes and points of connection in specific places of this new urban nucleus, and the policies of transport and land use must be integrated. From this new perspective on global energy use, distributed generation based on renewable sources is becoming very relevant. A new model of an electrical MG is required based on four pillars that have equal relevance and importance: demand management, distributed generation, autonomy of control, and the use of information technologies to transmit and manage all the data (see Fig. 4).

Fig. 5 illustrates the elements that make up the system. On the left, we can see the input variables, in the center the optimizer and in the lower part the penetration rates obtained as a result of the iterations. A more detailed description of how the process works is given in Sections 4.1 to 4.6.

An MG with the previously described characteristics is presented in which the objective of minimizing the ENS is achieved with minimal use of conventional energy (Majid et al., 2006; Palensky et al., 2008).

Once the MG scheme used in this work has been established, the next step is to define an optimization strategy to find the best configuration associated with a specific objective. It is important to clarify that this work provides a link between consumption in a responsible way (via DSM techniques) and the incorporation of elements of both conventional and unconventional generation. The importance of developing resilient grids has been discussed by the authors of Wilke et al. (2021) and Richter et al. (2021). The foregoing answers the question about the ability to generate a considerable power of energy through micro wind systems and about the feasibility of creating low-carbon cities, since these points can be understood through the operation of a system that includes DSM.

4. Formulation of the optimization problem with genetic algorithms and particle swarm optimization

The sizing of an MG such as the one proposed in this work requires us to calculate the degree of participation of each energy source needed to maintain stability in the electrical network. The MG sizing problem can then be formulated as an optimization problem based on simulating the MG over a given time interval. There are several analytical methods for solving optimization problems, but in cases where the objective function is not explicitly defined or varies over time, obtaining an analytical solution is

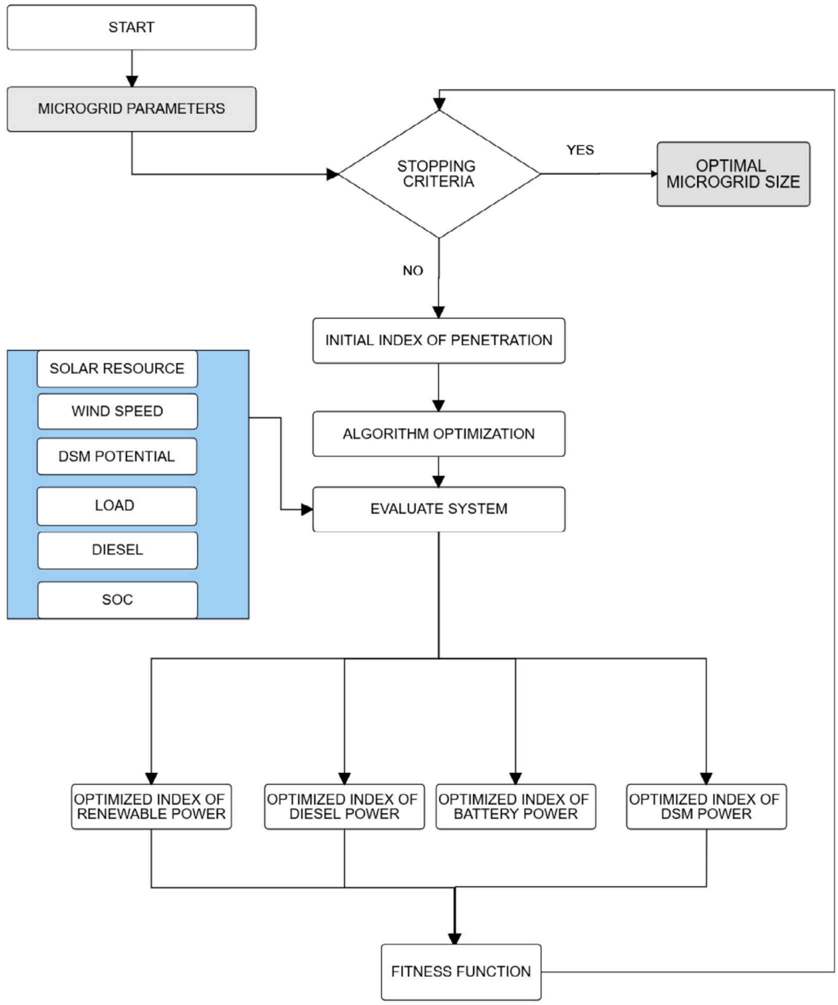

Fig. 5. Model of the microgrid.

very complicated. An alternative is to use bio-inspired optimization algorithms, which typically solve the optimization problem iteratively through a heuristic approach.

GAs are used to solve optimization problems based on a direct analogy with behavior seen in nature, given that in the natural environment, individuals compete with each other to find the necessary resources for survival. The basic principles of this technique were proposed by Holland in 1975. A fairly complete definition of a GA was proposed by Koza et al. (1999). The important thing is to visualize how the generations stop at the beginning of the algorithm. Although GAs are simple to implement, their behavior is difficult to understand.

In particular, it is difficult to understand why these algorithms are often successful in generating solutions of high aptitude when applied to practical problems. These solutions allow to establish an individual whose implicit nature is that of the best combination. To correctly model, the agents present in this simulation, acquired data, were treated in a reliable manner. For the cases derived from that acquisition, two main axes were obtained: the first is the economic axis, which reflects the cost of the system of operation, maintenance and installation (AC_S), while the second axis (BE_S) measures the amount of energy that the generating elements do not deliver to the system. For the economy axis, AC_S, it follows that:

$$AC_S = \sum_{t=1}^{t=8760} (C_T) + (VTCF) \tag{19}$$

For the ENS BE_S, it approaches by:

$$BE_S = \sum_{t=1}^{t=8760} ENS(t) \tag{20}$$

The objective of the optimization process at all times is to minimize the value of the fitness function J, which is computed as the product of the cost and the ENS, as shown in Eq. (21).

$$J = (AC_S)(BE_S) \tag{21}$$

In this work, two heuristic optimization algorithms are used to achieve DSM control. These optimization algorithms are GA and PSO, and are described in detail below. In both cases, a hierarchical control has been implemented. First, renewable energy enter to the system, then batteries, after that DSM, and at last, diesel generator. However, the penetration index of each technology, depends on the fixed and variable costs, where time horizons have a significant impact

4.1. Basic principles of GA

A GA is able to create solutions for real-world problems, and the basis for this approach was developed by Holland in 1975 (Koza et al., 1999).

The steps in a typical GA are defined as follows:

1. Define the objective function, variables, and parameters of the system.

2. Generate an initial population. Assume the evaluation function of each individual.
3. Produce a new generation.
4. Selected individuals of the previous generation.
5. cross/mutate/compute.
6. Evaluate individual.

4.2. GA objective

The objective of GA management is to minimize the total cost over the evaluated time period. The fixed costs of the manageable power, renewable power, batteries and diesel are incorporated as elements when determining the total cost. In this way, the minimum cost is found based on the percentage of power that is used. To optimize this process, we use Eq. (1). The cost of each element is influenced by its availability at the time and the power that needs to be provided. The GA scans the percentages for each power and returns the minimum cost.

4.3. GA design constraints

The algorithm seeks to create the best individual based on the penetration rates of each of the technologies used to supply system power, and considering the limitations of the generating elements.

Percentage start values are determined by the percentage of priority power. A higher initial percentage is given to the priority power. Percentage maximum GA input values are determined by the maximum available power of each element. GA criteria GAOPTIMSET was used to create a structure of options to select two plotting functions. The first function of the graph is GAPLOTBESTF, which plots the best and average scores of the population in each generation. The second plotting function is GAPLOTSTOPPING, which plots the percentage of the stop criteria that are satisfied. The default population size used by the GA is 20. This may not be sufficient for problems with a large number of variables, and a smaller population size may be sufficient for minor problems. Since we only have nine variables, we specified a population size of 20. The initial population was generated using a uniform random number generator

The initial population was generated using a uniform random number generator in a predetermined range of [0, 1]. This created an initial population where all the points were in the range 0 to 1. However, the generation by wind and sun was taken as the priority power start where these parameters were defined between [maximum percentage Max −0.3, maximum percentage], where maximum percentage is the maximum percentage that can be required from this energy, and those for gasoline [0, 0.3] for the search start. The value of each variable is between [0, maximum percentage], and in the case of gasoline, it is [0, 1]. The GA stops when the maximum number of generations is reached; by default, this number is 100. The algorithm also detects if there is no change in the best fitness value over a given time in seconds (loss time limit), or over a certain number of generations (loss generation limit). Another criterion is the maximum time limit in seconds. In this case, we modified the stop criteria to increase the maximum number of generations to 110 and the loss generation limit to 100.

4.4. Basic principles of PSO

PSO is a method that was proposed around 1995 by Kennedy and Eberhart (1995), and which emulates the behavior of insects in nature. The idea underlying the operation of PSO begins with a similar start, by placing random particles in the search space, but they are given the possibility of moving through it according to certain rules that take into account the personal knowledge of each particle and the global knowledge of the swarm. We will see that by providing them with a simple capacity for movement through this landscape and allowing communication between them, they can discover particularly high values for $f\ (x, y)$ with relatively few computational resources calculations, memory and time.

Evaluations of the cost function (21) were performed to show its behavior. Firstly, three initial configurations were proposed for the penetration rates of the energies in the MG reported in the based case (Boshell and Veloza, 2008).

4.5. Objective of the PSO

Unlike the value obtained with the GA method, the PSO allows us to explore different points beyond just the minimum cost at the local minimum close to that obtained with GA. The PSO explores minimal costs away from the properties obtained in GA. If there is a lower value than the one obtained by GA, we use the coordinate value obtained by PSO to modify the key value. This method allows us to find the global minimum in the area bounded by the maximum percentage values.

The "particleswarm" function of Matlab was used to implement this algorithm. So the random is determined by the default of the software function. The total cost function was evaluated with the limitation of maximum percentage, where 100% of the demand equals the sum of the individual percentages, and the individual values are positive. Its coefficient of inertia greater than 1, 1.2 was determined; this allows the particle to accelerate in order to explore more areas of the space of the function, but makes convergence difficult. The limits of the position [0, maximum percentage] were determined in each value and velocity of the particles in maximum percentage between 2; Considering that the PSO allows a quick search only for a minimum cost that the GA has not found.

4.6. PSO design constraints

The total power must be covered, so the sum of the power percentages in the cost values must equal the power required. Percentage start values are determined by the percentage of priority power. A higher initial percentage is given to the priority power. Percentage maximum PSO input values are determined by the maximum available power of each element. The classic problem of agglomerations is enunciated in another of its edges in this manifest. Understanding the previous and subsequent in this work, is equivalent to rethinking the electrical systems, basing the efficiency of the same on the optimal consumption of the load, the positive impact of renewable energy sources and understanding that conventional resources or backup systems are elements that allow for stability of the grid. For the sizing of MGs, iterative algorithms have typically been used, including specialized software such as Homer, Ihoga, and HYBRID2. Peng used the Levi-Harmony algorithm to tripartite optimize a sizing problem for an isolated MG (Li et al., 2017).

5. Simulation results

In order to validate the effectiveness of the optimization algorithms proposed in this work, we firstly present simulation results for five specific cases for 1 year of time horizon. These configurations were empirically chosen based on the typical proportions of MG power sources. With the imposition of a cost on unsupplied energy, algorithms assign penetration percentages for each technology, looking for balance points between total cost and unsupplied energy. Then two further tests were performed

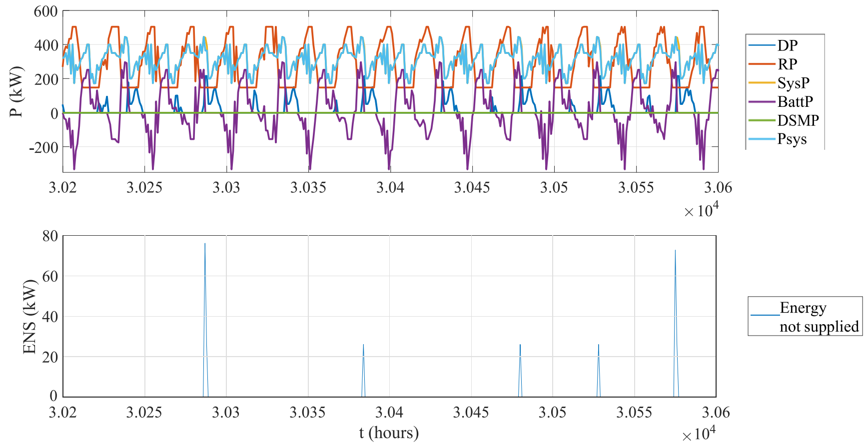

Fig. 6. Case 5: (a) Ten years microgrid operation optimized with GA, and (b) The energy not supplied without demand side management.

Table 1
Heuristic indexes versus optimized indexes.

Case	I_pSP	I_pWP	I_PDSM	I_PBP	I_pDP	ENS (kWh)	CT (USD) e^{+06}
Base	0.53	0.75	0.97	0.77	0.25	5133	2.19
Base2	0.49	0.76	0.77	0.10	0.54	43 096	1.69
Heu.	0.87	0.82	0.87	0.18	0.80	$2.3e^{-13}$	2.10
PSO	0.80	0.73	0.90	0.18	0.86	$1.1e^{-13}$	2.09
GA	0.83	0.75	0.94	0.20	0.85	$5.7e^{-14}$	2.12

Table 2
Penetration index of system for a time stamp of 10 years.

Case	I_pSP	I_pWP	I_PDSM	I_PBP	I_pDP	ENS (kWh)	CT (USD) e^{+06}
Case 1	0.68	0.87	0.00	0.54	0.48	0	4.845
Case 2	0.89	0.37	0.67	0.88	0.59	0	3.514
Case 3	0.89	0.37	0.67	0.88	0.54	91	3.483
Case 4	0.86	0.40	0.83	0.78	0.67	0	3.477
Case 5	0.89	0.37	0.00	0.59	0.54	290 840	3.399

using the proposed heuristic algorithms to minimize the cost function (21) for 5 and 10 years.

In the first case, Table 1 shows the values of the penetration indexes for each technology (I_pSP, I_pBP, I_PDSM, I_PBP *and* I_pDP), as well as the total cost and ENS for the system. A decrease in ENS as a function of cost growth can be clearly observed. However, if we compare the costs and ENS for the base, optimized and heuristic scenarios, better performance is evident in the optimized scenario.

Table 2 shows results for a time horizon of 10 years, where all the indexes are optimized. Next considerations are done:

1. The system operates without restrictions of any kind and does not use DSM.
2. This case incorporates management but does not prioritize it, and does not require that renewable energy is a predominant element.
3. In this case, DSM is not used to regulate the ENS, which presupposes an increase in cost and a minimization in the operation of the system.
4. The main objectives are to minimize the ENS and the total cost of the system by minimizing the function of the area described by Eq. (21).

A general analysis is described next:

Table 2, shows the interdependence and proportional relationship of various index configurations found using GA. The Table relates the cost and the energy not supplied over a period of 10 years. Case 1 shows a system where demand management is not used. We can compare it with scenarios where management is used to meet the objective of minimizing cost without affecting system performance. Case 2 shows a combination that allows significant returns to be obtained through the cost/ENS. This is achieved using a high but not critical DSM value. Cases 1 and 2 presented here were chosen with the intention of observing two scenarios where the ENS is zero, with and without DSM. Case 3 shows a scenario that includes ENS. Although the total cost is a bit lower than Case 2, supply of the total demanded power is not guaranteed. The difference when the DSM is a little higher can be seen in Case 4. It reduces the total cost of the system and reduces ENS to zero. In Case 5, the DSM block was completely deactivated, and although this approach seems to be the least expensive, it is the only one in which there are large interruptions in the load.

A deeper analysis of results presented in Table 2 is described below:

Comparing Cases 2 and 3, it is highlighted that although both systems have the same penetration rates, with the exception of the diesel technology. If its penetration index is reduced, the total cost decreases, but the ENS increases smoothly. On the other hand, if we compare Cases 2 and 4, the cost of the latter is reduced by increasing the penetration rate of the DSM from 0.67 to 0.83, making the system more economical and sustainable, by reducing the storage system. Case 2 shows a higher cost associated with a proportionally large backup system. If we compare Cases 1 and 4, we see that the cost reduction is approximately 28%. In both cases, the system operates without electrical service failures; however, in Case 4, the use of DSM allows the system to be both economical and sustainable too.

In order to illustrate the results for the five studied scenarios, in the Figs. 6 and 7 show the simulation results from Cases 5 and 4, respectively. It is important to mention that in these figures, a sample of only 400 h is shown to allow the behavior of the energy supply from the different sources to be clearly seen. The variables *DP*, *RP*, *SysP*, *BP*, *DSMP* y *TotalP* denote diesel power, renewable power, system power, battery power, DSM power, and system size, respectively.

It is easy to observe from Fig. 6 that as time passes and the power of the battery cannot provide enough energy in conjunction with intermittent renewable energy, the diesel generator is triggered. This in order to prevent in a certain interval of time turn off the loads to obtain the least amount of ENS. Fig. 6 shows the behavior of the MG described above over a period of 400 h,

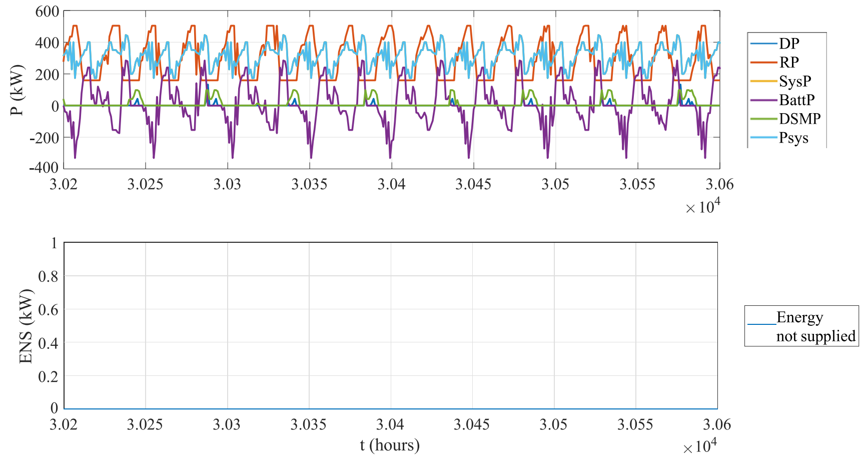

Fig. 7. Case 4: (a) Ten year microgrid operation optimized with GA, and (b) The energy not supplied with demand side management.

where the total power that can be delivered to the system is sometimes lower than the power required by the system, and at this moment, ENS appears. In Fig. 6b, we can see the behavior of the ENS. The ENS over the 10-year period for the system was 42 422 kW, and over a 400-h period was approximately 226 kW. In this period, five service disruptions were noted: the first was from hour 30 290 to hour 30 291, with a magnitude of 76 kW, and the second occurred between time intervals 30 380 to 30 381, with a value of 26 kW. This behavior is also observed in other intervals in Fig. 6

Fig. 7 shows our simulation results for a case with identical conditions to those in Fig. 6 except that DSM is incorporated. It creates a substantial change in this case. From these results, it is evident that when the load is controlled by means of systematic shutdowns, both fixed and variable costs are decreased, as is the ENS. The simulation in the previous figure was based on values output by the GA algorithm for a 10-year interval.

It can be observed from Fig. 8 that despite a reduction in both the fixed and variable costs, the ENS is reduced, the stability of the system increases, and the indexes of MG penetration of the characterized technologies are appreciated. The cost of operation and installation of the elements of the system is displayed used as a GA. The graphs (a), (b), (c) represent the fixed costs associated with the system derived from the implementation, the variable costs associated with the maintenance and operation, and the penetration index of the energy resources for this case study. The variables are the fixed cost DSM power (FCDSM), the fixed cost diesel power (FCDP), the fixed cost battery power (FCBP) and the fixed cost renewable power (FCRP). In this work, the variable costs are represented by the variable cost of DSM power (VCDSM), the variable cost of diesel power (VCDP), the variable cost of battery power (VCBP), the variable cost of renewable power (VCRP), the penetration index of DSM (IpDSM), the penetration index of diesel power (IpDP), the penetration index of battery power (IpBP) and the penetration index of renewable power (IpRP). These variables are represented as percentages with respect to the total.

Figs. 8, and 9 show what happens when the system is sized without and with DSM, respectively. It can clearly be observed that for a similar cost, the energy supplied is considerably greater if the demand is not managed. Of course, it is possible to ask why the size of the system should not be increased geometrically, and the answer lies in the finite system of resources of our planet.

Finally, a third scenario is presented in Table 3. Results were obtained using GA and PSO optimization algorithms, and over two time periods: the values marked with ($*$) and ($+$) corresponds to 10 year and 5 years, respectively.

Table 3
Penetration index comparison between optimization with a time stamp of 10 year* and 5 years+.

Case	I_pSP	I_PWP	I_PDSM	I_PBP	I_pDP	ENS (kWh)	CT (USD) e^{+06}
DSM-GA*	0.83	0.75	0.94	0.20	0.85	$5.7e^{-14}$	2.122
NoDSM-GA*	0.83	0.75	0.00	0.20	0.85	$2.3e^{+5}$	2.086
WCR-GA*	0.87	0.80	0.98	0.56	0.85	$5.7e^{-14}$	2.424
PSO$*$	0.80	0.73	0.90	0.18	0.86	$1.1e^{-13}$	2.092
PSO+	0.94	0.73	0.90	0.20	0.84	$1.7e^{-13}$	2.153
GA+	0.96	0.95	0.96	0.20	0.18	$5.1e^{-14}$	2.070

First, we analyze the results for the first four cases, corresponding to a horizon of 10 years. In the third case, without cost restriction (WCR-GA*), the total cost it the highest, due to a significant increase of storage capacity. Case 2 (NoDSM-GA*) is cheaper than Case 1 (DSM-GA), but, the ENS is high. Case 4 (PSO*) is a little higher than Case 2, but it considers DMS, reducing the installed power of renewable energies and batteries.

The best result is obtained for a horizon of 5 years, showed in Case 6 (GA+), with the lowest investment and an ENS near to zero. Case 5 (PSO+) has a slightly higher cost, due to an increase in the penetration indexes of almost all the technologies.

Using DSM as a control element, a reduction in the fixed and variable costs associated with the sizing process is favored, and it becomes evident that by using demand controls the amount of initial investment for the development of a generation project is optimized.

6. Conclusions

The importance of this work lies mainly in the fact that we propose and optimized penetration indexes that favor the regulation of the supplied power and allow to reduce the energy not supplied, without duplicating the installed powers and reducing the total cost of the system. Nevertheless, the optimal sizing of an MG, by means of demand control, will not be successful without the implementation of energy management systems and a change in the paradigm of energy consumption. We must remember that modern energy systems aim to achieve low fossil fuel consumption economies and high resilience.

It is important to mention that, when comparing the cost for the evaluations, regardless of the morphological nature, there is a

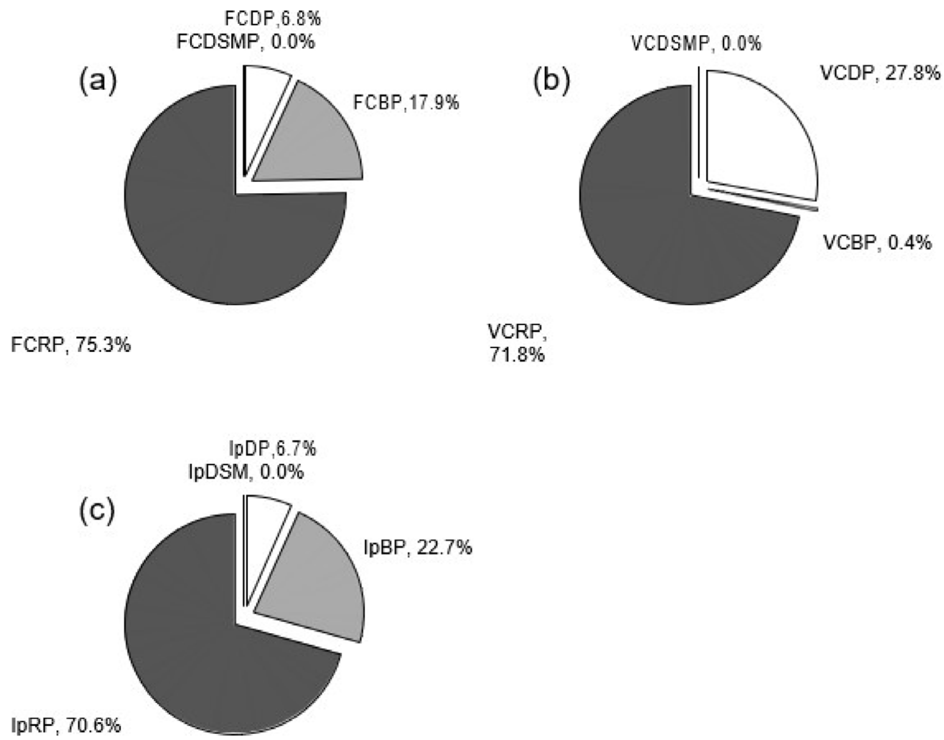

Fig. 8. Variables in a system without demand side management. (a) Fixed costs, (b) Variable costs, (c) Penetration indexes.

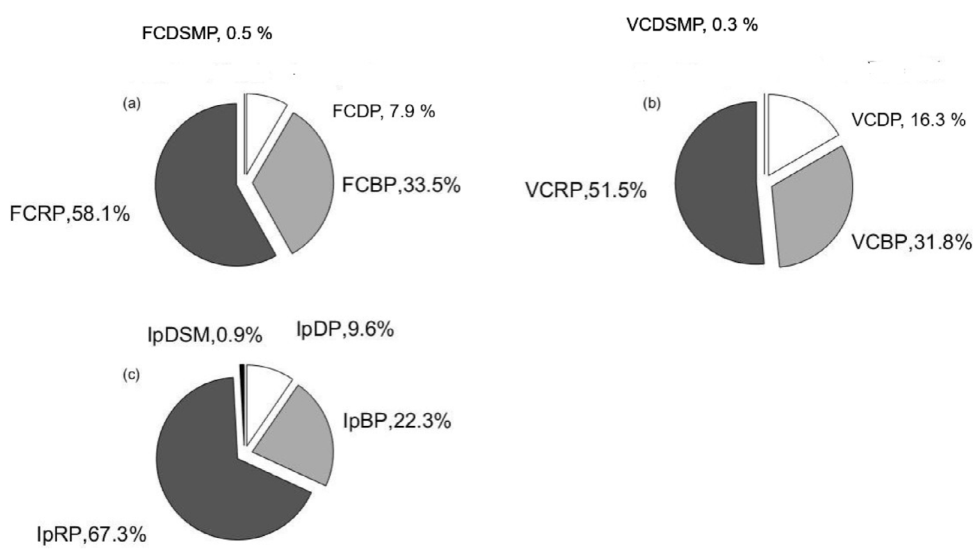

Fig. 9. Variables in a system with demand side management. (a) Fixed costs, (b) Variable costs, (c) Penetration indexes.

marked response to the use of diesel and batteries in short periods of time. However, the use of the optimization algorithms over prolonged periods can find solutions with a higher penetration of renewable energies due to lower variable costs.

The sizing process of all variables is a function of cost minimization. The main reason for incorporating DSM is to amortize the total cost, reduce Dp in the system, support renewable generation and allow for a paradigm shift.

Incorporating a cost into the ENS allows DSM to become highly effective in different time scenarios, since this scheme penalizes not delivering the necessary power to the system. DSM implementation has a low cost and it is responsible of the renewable power management and costs reductions. When DSM is considered in the sizing process, the total renewable power, the storage and diesel systems capacities can be reduced and therefore, also the total cost, with a less pollution.

The limiting factors of technologies have two natures: technical and economic. They are directly influencing the penetration index, because the optimization algorithm seeks both to reduce the cost of the system and to minimize the amount of energy not supplied. It is such that the system will always try to be as small as possible, but satisfying the critical loads.

The study is currently presented as an alternative solution to the optimal sizing of MGs. This work is supported by a project in collaboration with the National Autonomous University of Mexico and the University of Sonora. The name of the project is: generation of models for the sustainable development of "magical towns". This initiative is financed by the Mexican Council for Innovation in Solar Energy (CEMIESOL). It is intended as future work to stagger the demand with proportional increases, the stochastic variation of resources and their repercussions on the electrical network capacities.

CRediT authorship contribution statement

L.F. Gonzalez Gabriel: Conceptualization, Software, Validation, Investigation, Data curation, Writing – original draft, Writing – review & editing. **R. Ruiz-Cruz:** Validation, Writing – review & editing. **H.J. Coss y Leon Monterde:** Investigation, Visualization. **V. Zúñiga-Grajeda:** Software, Resources. **K.J. Gurubel-Tun:** Formal analysis, Resources. **A. Coronado-Mendoza:** Conceptualization, Methodology, Validation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

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

Data availability statement

All data are specified in the article.

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Sample availability

Samples of the compounds are available from the authors

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