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Article

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A Bi-level Multi-objective Optimization Model for the Planning, Design and Operation of Smart Grid Projects. Case Study: An Islanded Microgrid

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ABSTRACT

The planning and operation of smart grid projects is an issue that has increased in complexity and requires further analysis. This is due to the increase of distributed generation sources, generation with renewable sources, storage systems, and a disarticulation of information between the different levels in the sector and the stakeholders. All these factors lead to the inherent difficulty of defining appropriate models that help decision making. This paper proposes a bi-level optimization model to solve the problem of planning and operation of microgrid projects, as these can be considered as an ideal small-scale prototype of the so-called smart grids. In this bi-level scheme, the problem of planning or design of the microgrid is formulated at the upper level, while the problem of power dispatch or operation of the units is described at the lower level. The proposed multilevel multi-objective decision model is inspired by the system of system (SoS) concept in order to integrate qualitative and quantitative decision-making tools. Likewise, key performance indicators (KPIs) are used for the detailed and continuous monitoring of any project. The presented model is applied using the information of an electrically isolated microgrid on the Colombian Pacific coast.

Keywords: Smart Grids, Bi-level Optimization, Decision Making, Key Performance Indicators, Quality Function Deployment, Energy Planning and Management

JEL Classifications: C61, D70, L94, Q42

1. INTRODUCTION

1.1. Motivation

The traditional power grid is going through one of the biggest transitions in its long history: a step towards smart energy networks. This new concept is responsible for adding a pillar of information and communication technologies - ICT and distributed generation sources to the national electricity system in order to provide sustainability, accessibility and security of supply. Given this context, microgrids appear as an ideal small-scale prototype of Smart Grids due to their capacity for expansion, management, flexibility of experimentation, acceptance of new technologies, inclusion of renewable resources, storage and demand response programs.

The adoption of microgrids has grown rapidly worldwide, becoming attractive not only to government entities but also to energy companies that implement such projects to large consumers, such as factories, supermarkets, universities and hospitals. The microgrid market is expected to grow from USD 22,220 million in 2019 to USD 39,100 million in 2023, with a compound annual growth rate of 11.97% (PRNewswire, 2018). The potential benefits and positive market projections of microgrids have mostly been obtained through simulations and academic studies, but once the project materializes companies have difficulties in perceiving these incentives and benefits (Ali et al., 2017; Pacheco and Foreman, 2017); The main reason is due to its multidimensional nature in which multiple actors (direct/indirect), multiple objectives and multiple technical, social, and environmental criteria are involved. Thus, making a decision in planning an operation of the microgrid is not an easy task (Calvillo and Villar, 2016).

In order to model this type of problem, a multilevel approach can improve the decision making in the energy sector. In the last decade, the use of these techniques has been established as a useful tool for: the conceptualization and abstraction of hierarchical organizational models, decentralized management problems and Big Data (Lu et al., 2016), Smart Energy Cities (Carli et al., 2017), Distributed Active Systems (ADS) (Zeng et al., 2016) and in general, for any Smart Grid project (Shen et al., 2017).

Specifically, two-level decision techniques (bi-level) are commonly used in studies of microgrid projects where it is necessary to consider planning and operation in a coordinated manner. In these models, decision makers try to optimize their respective objective functions independently, but decisions are affected in the decision space of the other level. Planning is the leader or the upper level problem and Operation is the follower or the lower level problem. The execution of decisions is sequential, from upper to lower level, which is consistent with the logical relationship between planning and operation. Another fundamental aspect to consider is the time scales present between long-term planning and short-term operation, being these different a bi-level decision model is capable of allowing their interaction and optimal modeling (Zeng et al., 2016).

1.2. State of Art

Most of the research papers reported in the literature on the planning and operation of microgrid projects have been addressed separately. On the one hand, in Planning, long-term formulators seek to configure and size microgrid assets. Generally, they use simple or multi-objective optimization tools. On the operation side, the authors assume that they already know a capacity or a predetermined design of the microgrid, and propose different optimization algorithms to minimize the operating cost of the systems, considering the environmental and reliability implications. The main reason why they have worked independently and not simultaneously is that the problem becomes a multilevel decision-making model of non-convex nature and NP-Hard type; Even the simplest multilevel decision making model with continuous and linear functions is a strongly NP-Hard problem and therefore difficult to solve (Hansen et al., 1992; Zhao and Gu, 2006). This gives us an idea of the complexity involved in the development of algorithms to solve multilevel problems with nonlinear, multiple objective, non-convex, discontinuous and constrained functions (Sinha et al., 2017).

Recent works have been trying to address this challenge and have coupled planning and operation in order to obtain better results. In (Quashie et al., 2017) they present a methodology for isolated or interconnected microgrid using a two-level optimization model. In (Quashie et al., 2017) and (Quashie et al., 2018) they develop a hierarchical model of two levels, where the upper level determines the optimal configuration of the microgrid that minimize the investment cost and the annualized cost of the operation; while the problem of the lower level optimizes the output of distributed energy resources (DER) through the implementation of an energy management system (EMS). In (Minciardi and Robba, 2017) they propose a two-level solution approach for the design of a system control scheme consisting of a series of micro-networks (followers): At the upper level, they minimize network losses and environmental impact, while the lower level minimizes Microgrid costs and technical losses. In (Quashie and Joos, 2016) the author proposes a two-level planning strategy that optimally configures an urban microgrid to maximize its benefits. This work uses the Karush-Kuhn-tucker (KKT) condition to transform the two-level formulation into a linear programming of mixed single-level integers. In (Poursmaeil et al., 2018; Samadi and Salehi, 2018) they formulated a two-level model where the optimal planning of the (DER) is carried out at the upper level and the problem of optimal assignment of a switch to divide the traditional distribution system into a series of microgrids is carried out at the lower level.

Some authors have addressed multi-level optimization in addition to multiple objectives considering some factors that add complexity to the problem. In (Lv et al., 2016) they present a bi-level muti-objective model to obtain the operational benefits of both the distribution network and microgrids connected to the network. In (Li et al., 2018) a multi-objective fuzzy bi-level optimization problem is proposed to model the planning of energy storage systems (ESS) in distributed generation systems. In (Gao et al., 2017) they develop an approach to the planning of distributed generation sources in a distribution network based on a multi-stage technique. Finally, in (Stojiljković, 2017) the authors present a methodology to solve energy supply problems using a multi-objective bi-level optimization model, where the upper level defines the design and energy policies, while the lower level defines the operation.

1.3. Description of the Issue

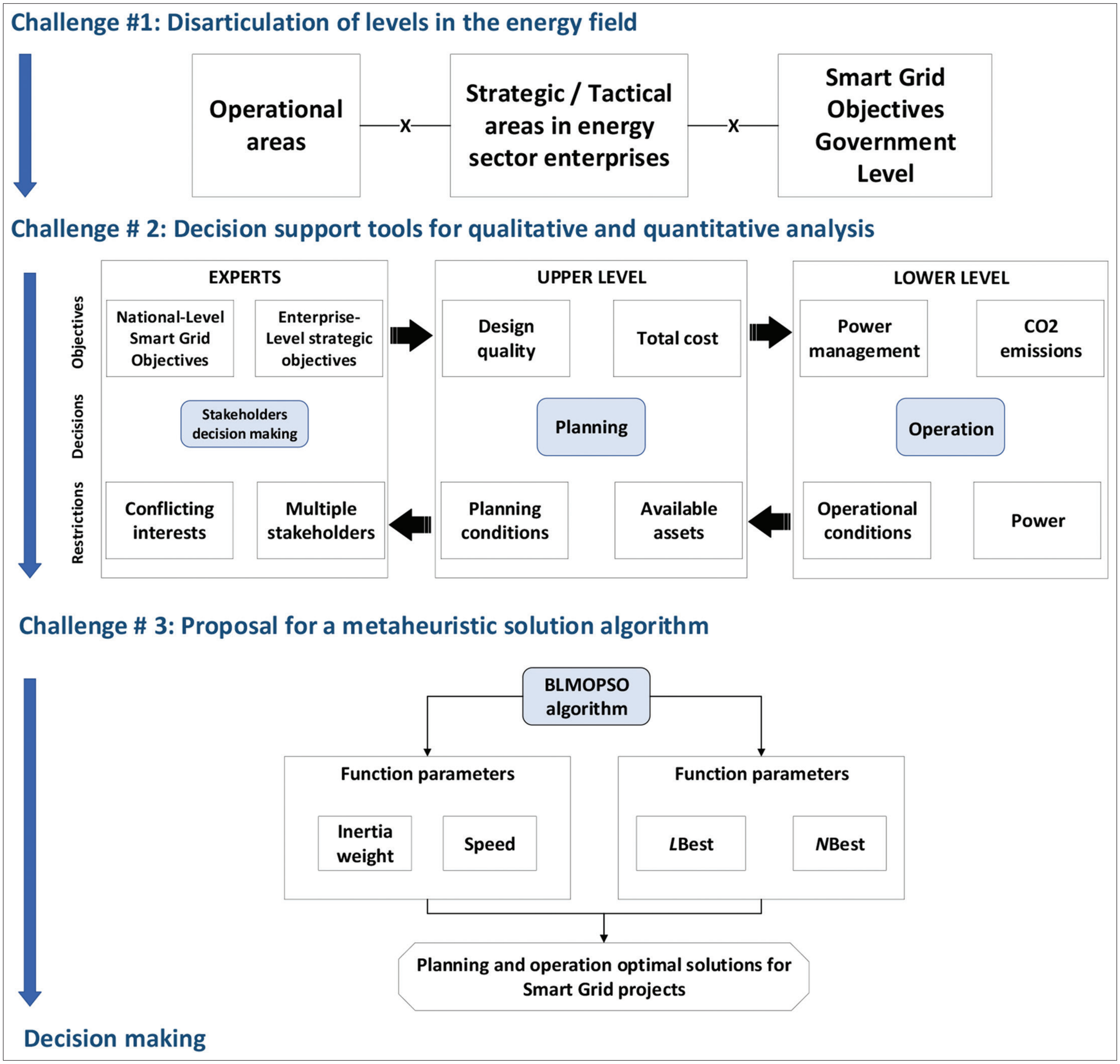
According to the literature review (Carli et al., 2017; Duncan et al., 2011a; Personal et al., 2014) three main challenges were found to overcome (Figure 1):

(1) A disarticulation between the different levels that make up the energy field. The solutions found in the literature address very specific problems and there is no linking between the enterprise-level operational and strategic objectives and the national-level objectives when designing microgrids.

(2) The need for qualitative and quantitative decision support tools. The solutions found in the literature only have quantitative decision support tools (mathematical optimization models), leaving aside tools that allow considering and transforming the judgments of those directly responsible for the project into numerical assessments.

(3) The difficulty of developing efficient algorithms. There are two main classes of algorithms applied to bi-level problems: the classical and the metaheuristic (Sinha et al., 2018). In classical algorithms, the problem is supposed to behave mathematically well, i.e. contains functions that are linear, quadratic or convex. In most of the literature consulted the authors make strong assumptions to apply reduction techniques at a single level due to the high degree of difficulty of the problem, such as the Karush-Kuhn-Tucker (KKT conditions method) (Cervilla et al., 2015; Esmaeili et al., 2019; Quashie and Joos, 2016; Quashie, Bouffard, et al., 2017). Moreover, there are

Figure 1: Proposed strategy overview



metaheuristic algorithms such as evolutionary algorithms and swarm intelligence like differential evolution (DE), genetic algorithms (GE), particle swarms (PSO) and the algorithm of colony of artificial bees (ABC). When these two kinds of algorithms are compared, the classical methods present high levels of uncertainty and easily suffer the "curse" of dimensionality on a large scale. This involves a large amount of computation time to solve problems (Sheikhi et al., 2016). Evolutionary algorithms have the advantage of balancing computational efficiency and accuracy, and that is why they are considered in this study (Jung et al., 2014).

This paper proposes a bi-level planning model that combines problems of Planning/Design at the upper level (Leader) and Operation at the lower level (Follower) with the development of a multi-objective bi-level metaheuristic algorithm by particle swarm (BLMOPSO). The model allows planners, managers and/or policy makers to make optimal or close to optimal decisions on the use of a microgrid asset, ensuring adequate solutions to strategic and operational objectives set by the energy company. One of the advantages of this work is the use of KPIs (up to twelve for this study), which are closely linked to strategic objectives and allow answering critical business questions set before the proposed optimization model.

1.4. Contribution

The main contributions of this work are the following:

1) A proposal for a multi-objective optimization strategy in organizational hierarchical decision problems, where a central

decision model (Leader) is responsible for making strategic decisions and a low-level decision model (Follower) is responsible for making tactical or operational decisions.
2) A planning model used in the construction of a microgrid as a case study. This model delivers the information for designing conventional and unconventional energy sources and the operational considerations of project assets.
3) The implementation of a PSO metaheuristic algorithm that yields adequate solutions at both levels.
4) The model consists of qualitative and quantitative decision support tools, as well as key performance indicators (KPI) and a systemic approach (System of Systems).

1.5. Article Organization

The following part of this paper is organized as follows: Section 2 presents the proposed general model, the mathematical representation of assets and KPIs. Section 3 shows the metaheuristic solution algorithm. Section 4 presents the application of the model in a case study. Finally, section 5 presents the conclusions of the work.

2. PROPOSED GENERAL MODEL

In order to model the bi-level optimization problem a new systemic approach (System of Systems) is considered in this work. This allows to obtain a conceptual overview and to describe the stages and tasks in each development phase (Aljohani, 2018; Arasteh et al., 2016; Cavalcante et al., 2016; Duncan et al., 2011b; Garvey, 2018; Pacheco and Foreman, 2017) The model considers three stages of the life cycle of a system, these are: Definition of the technical process, planning/design and operation (Figure 2).

In the technical process definition phase qualitative methods are used for decision-making assistance in order to make a coherent assignment of the weights that each of the KPIs must have. It is very important to determine which of these indicators has the greatest impact according to the area and project to be implemented. In this work, the decision-making techniques Hierarchical Analytical Process (AHP) and the Quality Function Deployment (QFD) both of diffuse representation are considered. These techniques allow to transform the human judgments of experts to mathematical representations; in (Chang, 1996; Osorio-Gómez et al., 2018) the theorems, axioms and mathematical foundations that must be taken into account for the realization of both techniques are presented in greater detail. Also, in this phase are defined the stakeholders, interests and objectives, both the Smart Grid and the strategic-levels objectives of the company.

The Planning/Design and Operation phases are addressed as a multi-objective bi-level optimization problem. The Planning/Design phase represents the leader or the upper level problem and the Operation acts as the follower or the lower level problem. The Planning/Design problem should be considered on a larger time scale (years) compared to the operation problem (days). The top level or leader receives input information (from technical process definition phase) about the planning time horizon, the maximum load, available assets and economic parameters, and the valuations or preferences given by the stakeholders. After selecting a design option, i.e. the number of power units based on the input information and restrictions, the lower level problem is addressed. Data obtained on the upper level serve as parameters for the lower level problem whose solution determines the set points of the assets that minimize all of the considered KPIs (emissions, operational cost, SAIDI, SAIFI, etc.). This solution is returned to the upper level to assess the total cost along the planning time horizon. This process is repeated until a more efficient design and operational combination is determined.

2.1. Mathematical Modeling Considered in the Development of a Microgrid Project

The first fundamental step is to mathematically represent the models that govern the case study. Three models are considered to do so: mathematical models of microgrid assets, mathematical models of key performance indicators (KPIs) and mathematical models of objective functions.

2.1.1. Mathematical models of system assets

An accurate representation of the operating restrictions of the formulation is essential, and therefore, the asset outputs of the system must be modeled correctly. The assets considered for the purposes of this study include diesel power generation units, photovoltaic generation systems, wind turbine generation systems and battery energy storage systems.

1) Photovoltaic model: The available photovoltaic power P_{PV} is estimated as

$$P_{PV}(t) = G(t) * A * \eta_{PV} \tag{1}$$

Where $G(t)$ is the irradiance (kW/m^2), A is the area of the solar panel and η_{PV} is the efficiency of the solar panel and the DC/DC converter.

2) Wind turbine model: The power generation of a wind turbine P_{WT} is calculated with equation 2 and depends on the speed and power of the wind at the installation site.

$$P_{WT} = \begin{cases} P_R * \dfrac{V - V_C}{V_R - V_C} & V_C \le V \le V_R \\ P_R & V_R \le V \le V_F \\ 0 & V < V_c \text{ ó } V > V_F \end{cases} \tag{2}$$

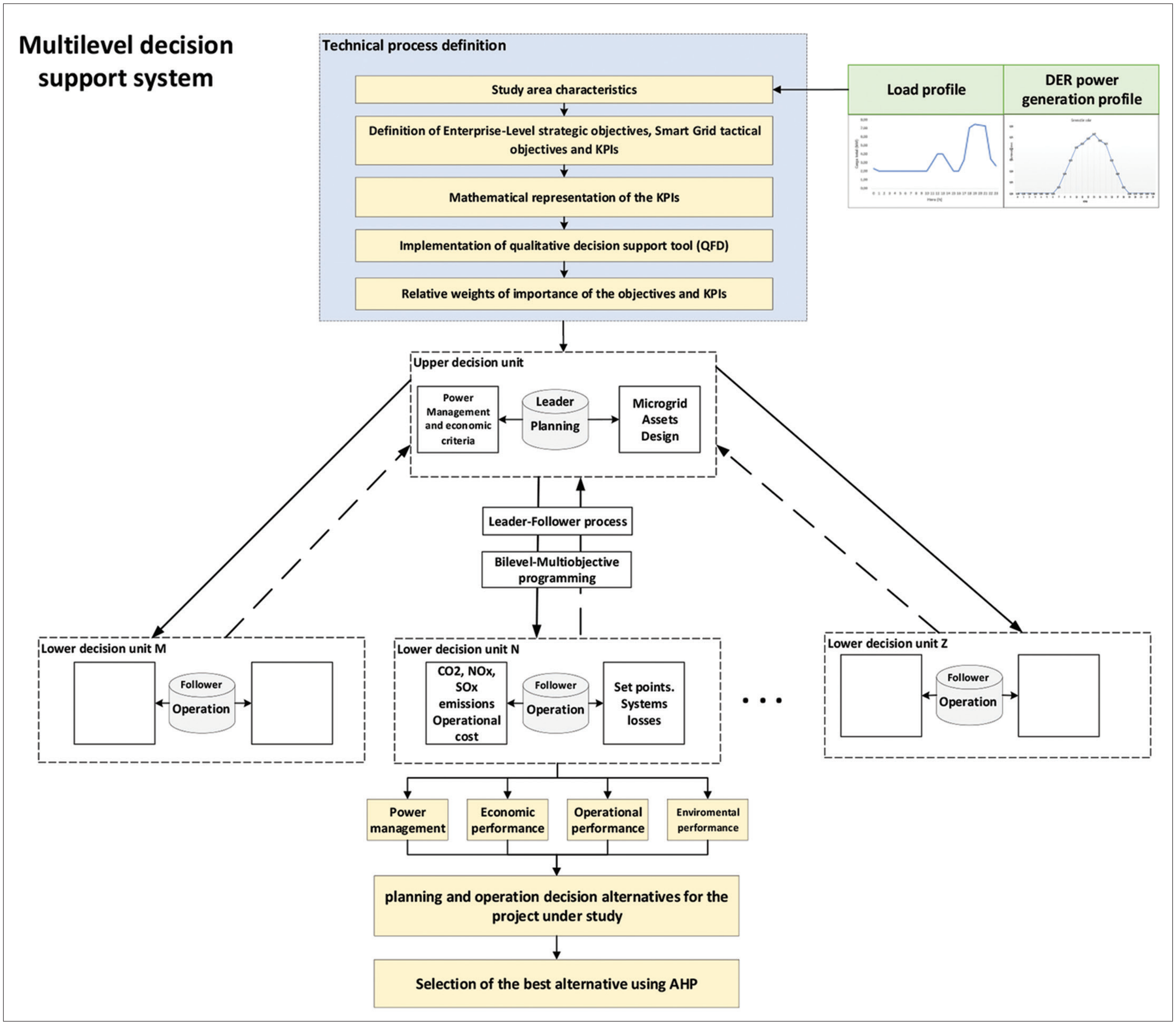
Where P_R is the rated power output, V_C is the wind cut-in speed, V_R is the rated speed, and V_F is the furling speed.

3) Battery model: The power stored and managed by a battery E_{Bat} is defined by the following equation:

$$E_{Bat}(t) = E_{Bat}(t-1) * (1-\sigma) + \left[\left(E_{PV}(t) * \eta_{Inv} + E_{WT}(t) * \eta_{Inv}^2 \right) - \frac{E_{Load}(t)}{\eta_{Inv}} \right] * \eta_{Bat} \tag{3}$$

Where σ is the self-discharge rate per hour, E_{PV} is the power of solar panels, E_{WT} is the power of wind turbines, η_{Inv} is the inverter efficiency, E_{Load} is the power demand, and η_{Bat} is the efficiency of the battery.

Figure 2: Decision-making process



4) Diesel generator: The following equation calculates the power of the diesel generator $P_G(t)$:

$$P_G(t) = \eta_G * P_{Gi}(t) \tag{4}$$

Where η_G is the efficiency of the generator, and P_{Gi} is the rated power.

2.1.2. KPI mathematical models

The KPIs in this study are constructed based on the following sequence: transform the functionality of the assets of the microgrid project into benefits, and then transform these into measurement parameters (KPIs). This type of procedure guarantees at least one decision variable (for example, the power generated by the source) to optimize the cost function of the objectives of the project. The KPI equations are the following:

1) Increase distributed generation capacity

$$KPI_1 = \gamma_{re} = \frac{P_{wt}^M * N_{WT} + P_{PV}^M * N_{PV}}{P_{wt}^M * N_{WT} + P_{PV}^M * N_{PV} + P_{Gi} * N_{Diesel}} \tag{5}$$

Where γ_{re} is the penetration of the renewable sources, P_{wt}^M is the wind turbine power, N_{WT} is the number of turbines, N_{pv} is the number of solar panels, P_{PV}^M is the power of the solar panels, P_{Gi} is the rated power of the diesel unit, and N_{Diesel} is the number of diesel units.

2) Reduction in hours of power not supplied by renewable sources

$$KPI_2 = LPSP = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} P_{Load}(t) * \Delta t} \tag{6}$$

Where *LPSP* is the number of hours of power not supplied by renewable sources, and *LPS*(*t*) is defined by the following equation:

$$LPS(t) = P_{Load}(t)*\Delta t - \begin{pmatrix} (P_{PV}(t) + P_{wT}(t))*\Delta t \\ +C_{Bat}(t-1) - C_{Bat\,min} \end{pmatrix} \quad (7)$$

Where P_{Load} is the power demanded by the load, Δt is the time interval (1 h in this paper), $P_{PV}(t)$ is the power supplied by solar panels, $P_{wT}(t)$ is the power supplied by wind turbines, C_{Bat} is the charge of the battery, and $C_{Bat\,min}$ is represented as

$$C_{Bat\,min} = (1 - DOD)*S_{Bat} \quad (8)$$

Where *DOD* is the maximum depth of discharge, and S_{Bat} is the rated capacity of the battery.

3) Reduction in hours of power not supplied by renewable sources

$$KPI_3 = \%H_{DG} = \frac{H_{DG}}{H_T} \quad (9)$$

Where $\%H_{DG}$ is the factor of hours in which renewable source power is supplied (solar panels, wind turbines and batteries), and H_T is the total number of analysis hours.

5) System average interruption duration index (SAIDI) reduction

$$KPI_4 = SAIDI = \frac{U*N_u}{N_{uTot}} \quad (10)$$

Where *U* is the offline time, N_u is the number of users affected by the outage, and N_{uTot} is the total number of users (Hong et al., 2018).

6) System average interruption frequency index (SAIFI) reduction

$$KPI_5 = SAIFI = \frac{\lambda*N_u}{N_{uTot}} \quad (11)$$

Where λ is the interruption rate, N_u is the number of users affected by the outage, and N_{uTot} is the total number of users (Hong et al., 2018).

7) Power not supplied reduction

$$\begin{aligned} KPI_6 = ENS = U_{PV}*P_{PV} + U_{WT}*P_{WT} + \\ U_{BAT}*C_{BAT} + U_{Diesel}*P_{Diesel} \end{aligned} \quad (12)$$

Where *U* is the offline time, *P* is the load of each source within the system, C_{BAT} is the battery charge, and the subscripts (*PV*, *WT*, *BAT* and *Diesel*) refer to each source (Ansari et al., 2016).

8) Technical losses reduction

According to (Bhuiyan and Yazdani, 2014), there is a load considered as the "*dump load*" that absorbs surplus energy and is used when the produced power cannot be used or stored in the system. The formula to calculate it is the following:

$$KPI_7 = P_{Loss} = P_{Total} - P_{Load} \quad (13)$$

Where P_{Loss} is the dump load, and P_{Total} is the total power.

9) Investment and maintenance costs minimization

Equation 14 defines the total costs:

$$KPI_8 = C_T = C_{CP} + C_{mt} + C_{Diesel} + w_E*E_T \quad (14)$$

Where C_{CP} is the annual investment cost, C_{mt} is the operation and maintenance cost, C_{Diesel} is the cost of power generation using diesel, w_E is the emissions cost factor, and E_T is the total amount of emissions. C_{Diesel} is calculated as

$$C_{Diesel} = \left[\sum_{t=1}^{T_C}\left(G_{Diesel}(t)*C_{cd} + G_l*C_l\right)\right]*\frac{T}{T_C} \quad (15)$$

With G_{Diesel} being the hourly diesel fuel consumption in a year, C_{cd} is fuel cost, G_l is the diesel generator lubricant expenses, C_l is the lubricant cost, T_C is the calculation scope and *T* is 8760, which is equivalent to the number of hours in a year. Each element in equation 15 also has its own calculation as follows:

$$G_{Diesel} = CC_{Diesel}*P_{Diesel} \quad (16)$$

$$G_l = FG_l*P_{Gi} \quad (17)$$

$$C_{CP} = CRF*\left[N_{PV}*C_{PV} + N_{WT}*C_{WT} + N_{BAT}*C_{UB} + C_{Tr} + C_{re}\right] \quad (18)$$

Where CC_{Diesel} is the fuel consumption rate, P_{Diesel} is the power of the diesel generators, FG_l is the lubricant expenditure factor, P_{Gi} is the rated power of the diesel generator, *CRF* is a capital recovery factor, N_{PV} is the number of solar panels, C_{PV} is the solar panel cost, N_{WT} is the number of wind turbines, C_{WT} is the cost of the wind turbines, N_{BAT} is the number of batteries, C_{UB} is the cost of the batteries, C_{Tr} is the land cost, and C_{re} is the equipment replacement cost. The recovery factor *CRF* and the replacement cost C_{re} are obtained with the following equations:

$$CRF = \frac{i*(1+i)^{Tc}}{(1+i)^{Tc} - 1} \quad (19)$$

$$C_{Tr} = ips*(N_{PV}*A_{PV} + N_{wt}*A_{wt} + N_{BAT}*A_{BAT}) \quad (20)$$

$$C_{re} = N_{BAT}*\left(C_{re}^{BAT} + C_{re-co}^{BAT}\right) + N_{PV}*C_{re-in}^{PV} \quad (21)$$

Where T_c is the asset life time in years, *i* is the interest rate, *ips* is the land price index, A_{PV} is the area occupied by solar panels, A_{wt} is the area occupied by wind turbines and A_{BAT} is the area occupied by batteries (Ruiz, 2016); C_{re}^{BAT} is the replacement cost of each battery, C_{re-co}^{BAT} is the replacement cost of battery converters, and C_{re-in}^{PV} is the cost of the inverter of each solar panel. In addition, taking depreciation into account,

$$C_{re}^{BAT} = C_{UB}*\left(1 + \frac{1}{(1+i)^5} + \frac{1}{(1+i)^{10}} + \frac{1}{(1+i)^{15}}\right) \quad (22)$$

Where C_{UB} is the battery cost, with replacement every 5 year.

$$C_{re-co}^{BAT} = C_{CO}^{BAT}*\left(1 + \frac{1}{(1+i)^{10}}\right) \quad (23)$$

C_{CO}^{BAT} is the price of the converter of each battery, with replacement every 10 years.

$$C_{re-in}^{PV} = C_{in}^{PV} * \left(1 + \frac{1}{(1+i)^{10}}\right) \quad (24)$$

C_{in}^{PV} is the price of the inverter of each solar panel, with replacement every 10 years.

Additionally, using equation 25 again, the operation and maintenance cost C_{mt} is

$$C_{mt} = \begin{pmatrix} N_{PV} * C_{mt}^{pv} + N_{wt} * C_{mt}^{wt} + N_{BAT} * C_{mt}^{BAT} \\ + N_{Diesel} * C_{mt}^{Diesel} \end{pmatrix} * T_c \quad (25)$$

Where C_{mt}^{pv} is the annual maintenance cost of the panel, C_{mt}^{wt} is the annual wind turbine maintenance cost, C_{mt}^{BAT} is the annual cost of batteries, N_{Diesel} is the number of diesel units, C_{mt}^{Diesel} is the maintenance cost of each diesel unit, and T_C is the calculation scope of the optimization.

10) Levelized cost of electricity (LCOE) minimization

$$KPI_9 = LCOE = \frac{I_o + \sum_{t=1}^{n} \frac{A_t}{(1+i)^t}}{\sum_{t=1}^{n} \frac{M_{el}}{(1+i)^t}} \quad (26)$$

Where I_o is the initial investment, M_{el} is the power generated in year t, A_t is the total annual cost in year t, and i is the interest rate.

11) CO_2 emissions minimization

$$KPI_{10} = E_T = N_{PV} * P_{PV}^{M} * E_C^{PV} + N_{wt} * P_{wt}^{M} * E_c^{wt} + N_{BAT} * S_{BAT} * E_C^{BAT} + \left[\sum_{t=1}^{T} E_{op}^{Diesel} * G_{Diesel}(t)\right] \quad (27)$$

Where $G_{Diesel}(t)$ is defined by equation 16, P_{PV}^{M} is the peak power of each solar panel, E_C^{PV} is the emissions produced in the construction phase of each panel, P_{wt}^{M} is the maximum power of each wind turbine, E_C^{wt} is the emissions produced in the construction phase of the wind turbines, S_{BAT} is the maximum power of each battery, E_C^{BAT} is the emissions produced in the construction phase of the batteries, and E_{op}^{Diesel} is the emissions from diesel generators.

12) SO_x emissions minimization

$$KPI_{11} = E_{SOx} = F_{PV}^{SOx} * P_{PV} + F_{WT}^{SOx} * P_{WT} + F_{Diesel}^{SOx} * \sum_{t=1}^{T} P_{Diesel} \quad (28)$$

Where F_{PV}^{SOx} is the SO_x emissions factor of the solar panels, P_{PV} is the power of the solar panels, F_{WT}^{SOx} is the SO_x emissions factor of each wind turbine, P_{WT} is the power of the wind turbines, F_{Diesel}^{SOx} is the SO_x emissions factor of the diesel generator, and P_{Diesel} is the power of the diesel generators (Benitez-Leyva, 2015).

13) NO_x emissions minimization

$$KPI_{12} = E_{NOx} = F_{PV}^{NOx} * P_{PV} + F_{WT}^{NOx} * P_{WT} + F_{Diesel}^{NOx} * \sum_{t=1}^{T} P_{Diesel} \quad (29)$$

Where F_{PV}^{NOx} is the NO_x emissions factor of the solar panels, P_{PV} is the power of the solar panels, F_{WT}^{NOx} is the NO_x emissions factor of each wind turbine, P_{WT} is the power of the wind turbines, F_{Diesel}^{NOx} is the NO_x emissions factor of the diesel generator, and P_{Diesel} is the power of the diesel generators.

2.1.3. Mathematical model of the objective functions

To optimize the leader (planning/design) and follower (operation) problems in a coordinated manner, equation 30 shows the formulation of the bi-level problem. Figure 3 shows this process graphically.

$$\max F\left(P_{Diesel}, C_{BAT}, N_{PV}, N_{WT}, N_{Diesel}, N_{BAT}\right) = \left[F_{AU}, F_{Comp}\right]$$
$$s.t. \begin{cases} H\left(N_{PV}, N_{WT}, N_{Diesel}, N_{BAT}\right) \le 0 \\ G\left(N_{PV}, N_{WT}, N_{Diesel}, N_{BAT}\right) = 0 \end{cases}$$
$$(30)$$

$$\max f\left(P_{PV}, P_{WT}, P_{Diesel}, C_{BAT}, N_{PV}, N_{WT}, N_{Diesel}, N_{BAT}\right) = [f_{SC}, f_S]$$
$$s.t. \begin{cases} h\left(P_{Diesel}, C_{BAT}\right) \le 0 \\ g\left(P_{Diesel}, C_{BAT}\right) = 0 \end{cases}$$

From the equation, P_{Diesel} and C_{BAT} are obtained from the optimization process in the follower. In addition, x=[P_{Diesel}, C_{BAT}, N_{PV}, N_{WT}, N_{Diesel}, N_{BAT}] is the decision vector at the upper level, [F_{AU}, F_{Comp}] are the objective functions of the optimization problem called Universal Access to Power and Competitiveness, and H(.) and G(.) are the restrictions of the planning problem located at the upper level. In the lower level, y=[P_{PV}, P_{WT}, P_{Diesel}, C_{BAT}, N_{PV}, N_{WT}, N_{Diesel}, N_{BAT}, t] is the decision vector at an operation time t, [f_{sc}, f_s] are the objective functions called Security-Quality and Sustainability to be optimized, and h(.) and g(.) are the problem constraints. Therefore, [F_{AU}, F_{Comp}, f_{sc}, f_s] are the four smart grid strategic objectives established under the Colombian National Energy Plan for 2030 (PEN-2030). The equations for the four objective functions are below.

Universal access to power objective function

$$F_{AU} = \sum_{n=1}^{12} Q2_{n1} * \frac{\left(KPIn - KPIn_{BS}\right)}{KPIn_{BS}} \quad (31)$$

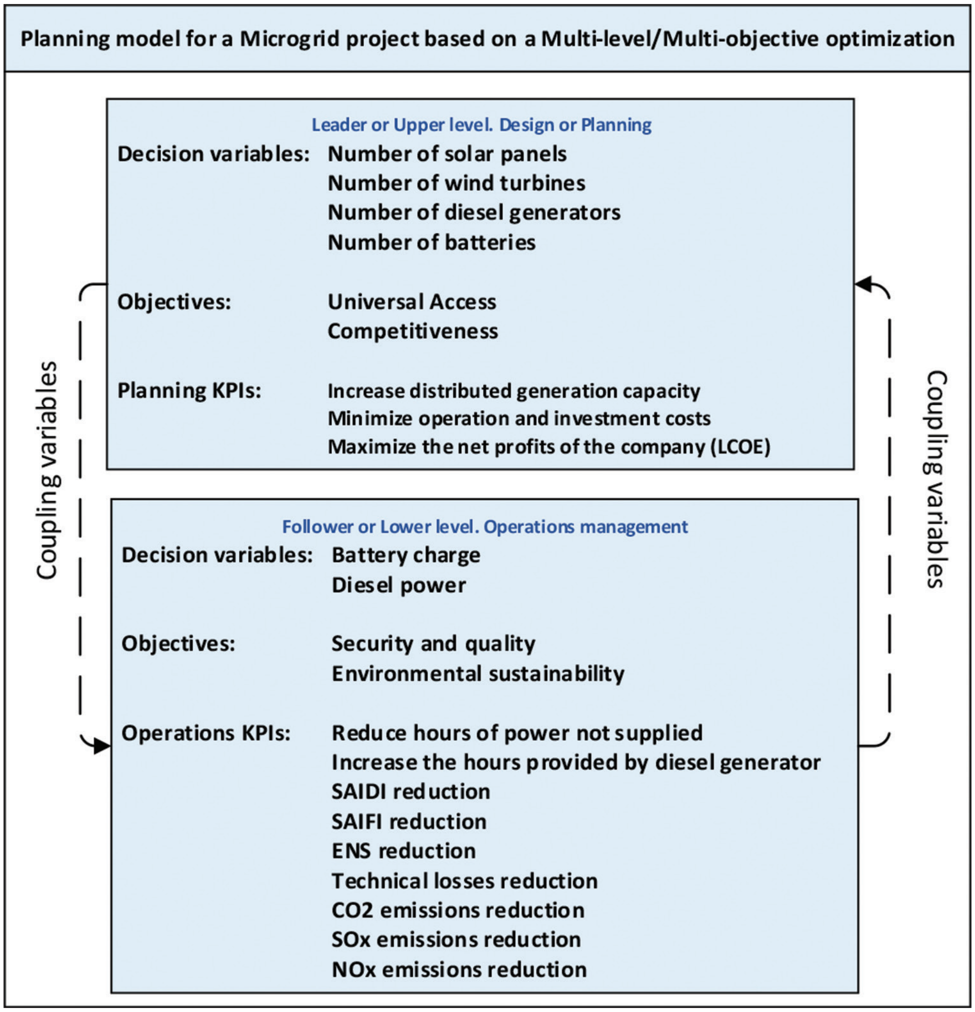
Competitiveness objective function

$$F_{COMP} = \sum_{n=1}^{12} Q2_{n2} * \frac{\left(KPIn - KPIn_{BS}\right)}{KPIn_{BS}} \quad (32)$$

Supply security and quality objective function

$$F_{AU} = \sum_{n=1}^{12} Q2_{n3} * \frac{\left(KPIn - KPIn_{BS}\right)}{KPIn_{BS}} \quad (33)$$

Figure 3: General power planning structure based on a bi-level optimization model



Sustainability objective function

$$f_S = \sum_{n=1}^{12} Q2_{n4} * \frac{\left(KPIn - KPIn_{BS}\right)}{KPIn_{BS}} \quad (34)$$

Where $KPIn$ is the n-th KPI and $KPIn_{BS}$ is its value. This step is critical in the evaluation of smart grid projects (Giordano et al., 2012). The main reason is the possibility of comparing new scenarios with the current scenario and finding the difference between the costs and benefits generated. The importance weights, $Q2_{nm}$, were obtained using the fuzzy quality function deployment (QFD) technique. The results in Tables 1 and 2 were obtained considering the work of (Osorio-Gómez, 2011; Osorio-Gómez et al., 2018) with the modification and addition of fuzzy logic, which easily helps to determine the ranking in linguistic terms and prioritize smart grid goals. It is necessary to preliminarily find stakeholders with expertise in this field and energy companies that are willing to implement the project.

2.2. Solution Algorithm

This study implements a particle swarm optimization (PSO) algorithm that refers to a metaheuristic that evokes the behavior of birds flocking and fish schooling in nature (Kennedy and Eberhart, n.d.). This algorithm has been used to solve complex problems with multiple objectives in different scientific areas, including the energy sector (Kheshti and Ding, 2018). The proposed algorithm uses a scheme similar to that used in (Sinha et al., 2017) to solve bi-level multi-objective optimization problems (BLMOPSO).

1) Initial and adjustment parameters: The first elements to establish are the number of particles and the n dimensions of the problem. Subsequently, each particle $i \in s$ is assigned a velocity vector $v_i \in R^n$ that indicates the direction of the movement of the particle caused by the combination of the inertial velocity, the best position reached by the particle p_i^{best} and the best position reached by the entire population g^{best}. Each particle i moves to a new position $p_i^{k+1} \in R^n$ in each iteration k according to the following equation:

$$v_i^{k+1} = wv_i^k + c_1R_1\left(p_i^{best} - p_i^k\right) + c_2R_2\left(g^{best} - p_i^k\right) \quad (35)$$

$$p_i^{k+1} = p_i^k + v_i^{k+1},\ i = 1,2,\ldots,s \quad (36)$$

Where w is the inertial weight, c_1 and c_2 are the cognitive and social parameters, and $R_z \in U[0,1]$: z ={1,2} are uniformly distributed random values in the range of [0,1]. Each of these parameters are configured at both the upper and lower levels.

2) Evaluation: The BLMOPSO algorithm starts with an initial population located randomly in the search space R^n; namely,

Table 1: QFD matrix for determining the relative weights of enterprise-level strategic objectives

QFD matrix smart grid tactical objectives (What)	Enterprise-level strategic objectives (How)				
	ObjE1	ObjE2	ObjE3	ObjE4	ObjE*m*
OTSG 1	$Q1_{11}$	$Q1_{12}$	$Q1_{13}$	$Q1_{14}$	$Q1_{1m}$
OTSG 2	$Q1_{21}$	$Q1_{22}$	$Q1_{23}$	$Q1_{24}$	$Q2_{1m}$
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
OTSG *n*	$Q1_{n1}$	$Q1_{n2}$	$Q1_{n3}$	$Q1_{n4}$	$Q2_{nm}$
Relative weights of enterprise-level strategic objectives	Weight 1	Weight 2	Weight 3	Weight 4	Weight *m*

Table 2: QFD matrix for ranking the KPIs of the project

QFD matrix	Enterprise-level strategic objectives (How)					Ranking KPIs
	ObjE1	ObjE2	ObjE3	ObjE4	ObjM	
KPI1	$Q2_{11}$	$Q2_{12}$	$Q2_{13}$	$Q2_{14}$	$Q2_{1m}$	KPI1
KPI2	$Q2_{21}$	$Q2_{22}$	$Q2_{23}$	$Q2_{24}$	$Q2_{1m}$	KPI2
KPI *n*	$Q2_{n1}$	$Q2_{n2}$	$Q2_{n3}$	$Q2_{n4}$	$Q2_{nm}$	Ranking KPI *n*

the control parameters are initialized at both levels for each particle $I \in s$, including positions p_{xi} and p_{yi}, with particle velocities v_{xi} and v_{yi} at both levels. Population size s assumes that the current positions of the particles at the upper and lower levels are the best positions locally p_{xi}^{best} and p_{yi}^{best}. Similarly, the best global positions of the upper and lower levels are estimated for the entire population. The algorithm performs the iterations of the upper level problem, in each iteration, searches for optimal solutions and removes the nondominated solutions. The above procedure updates the repository and checks the maximum limit that transfers as input parameters to the lower level problem. The lower level routine performs iterations, and the algorithm searches for solutions to determine a leader and extract the nondominated particles. Finally, the repository is updated, and the limits are checked; the solutions from this level return to the upper level to evaluate the cost functions again and adjust the parameters with the new conditions. This process is repeated until the maximum number of iterations has been completed. Figure 4 shows the steps of the BLMOPSO algorithm.

3. CASE STUDY

To verify the effectiveness of the proposed optimization model, a microgrid was simulated assuming a non-interconnected zone of the National Electricity System. The goal is to illustrate how the proposed model can be used to support planners, managers and/or energy policy makers to make optimal decisions in an uncertain environment. An islanded microgrid is modeled with four main assets: a diesel generator, a photovoltaic system, a wind generator and batteries (Figure 5).

3.1. Area Studied

The Colombian government aims to install sustainable energy projects in areas that are not connected to the National Electricity System. To do so, the Miramar Communitarian Counsel, located in Bahía Málaga in the Colombian Pacific region, was studied. This area has an N_{UTot} of 34 houses and 165 inhabitants, and fishing is the main economic activity. The construction of an islanded microgrid to provide electricity service to meet the basic needs of the population and a cooling system for the conservation of fish are being considered.

3.2. Data Acquisition and Processing

Numerical data on the population and electricity demand and meteorological, technical and economic data are obtained from two sources: Colombian governmental energy agencies, such as the "Institute of Planning and Promotion of Energy Solutions" (Instituto de Planificación y Promoción de Soluciones Energéticas - IPSE), and various technical references found in the literature. Figures 6-8 show the load profile, solar radiation per hour and daily wind speed, respectively. The average daily energy demand considered in the study is 78.77 kWh/day, of which 48.0 kWh/day corresponds to the fishing activity and the remaining 30.77 kWh/day is the consumption of the community in other activities. The projected maximum load is 7.46 kW at 19:00 h. The average daily solar radiation is 3.5 kWh/day, and the maximum daily solar radiation is 4.0 kWh/m^2 in the summer season. The NREL-NASA database was used to calculate the peak number of sun hours, considering the chosen inclination and orientation and the location data of the site. The peak number of sun hours in the worst months is 3.67 h. The average wind velocity ranges from 7.8 km/h to 10.8 km/h.

The tables below show some technical factors. Table 3 shows the surface area of the assets, Table 4 shows the costs, and Table 5 shows the emissions and environmental factors.

Table 6 shows the power, failure rates and other technical data of the microgrid.

The fuzzy QFD method was used to obtain the KPIs weights with respect to the smart grid tactical objectives. To do so, a survey was conducted with five experts from a major company in the energy sector interested in building the microgrid. They gave their evaluation, which is shown in Table 7 with its respective triangular fuzzy number (TFN). The linguistic labels indicate the following: VL = a very low relationship; L = a low relationship; M = a medium relationship; H = a high relationship; and VH = a very

Figure 4: Flow diagram of the bi-level multi-objective particle swarm optimization algorithm (BLMOPSO)

Table 3: Technical considerations for the case study

Name	Value	Unit	Description
A_{Bat}	0.14	m^2	Area occupied by each battery
A_{PV}	1.68	m^2	Area occupied by each solar panel
A_{WT}	14.5	m^2	Area occupied by each wind turbine

high relationship. Finally, Table 8 shows the obtained evaluations. Two evaluation scenarios were established; in the first scenario, the environmental factor (*KPI*1, *KPI*2, *KPI*3 and *KPI*10) is given greater importance; in the second scenario, the security of the supply with a minimum cost(*KPI*3, *KPI*5, *KPI*6, *KPI*7 and *KPI*8) is given greater importance.

Figure 5: Proposed microgrid scheme

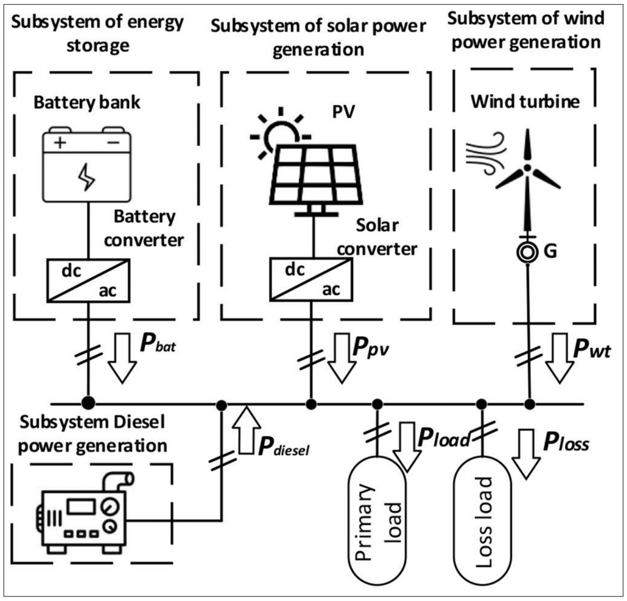


Figure 6: Daily power demand of the Miramar population

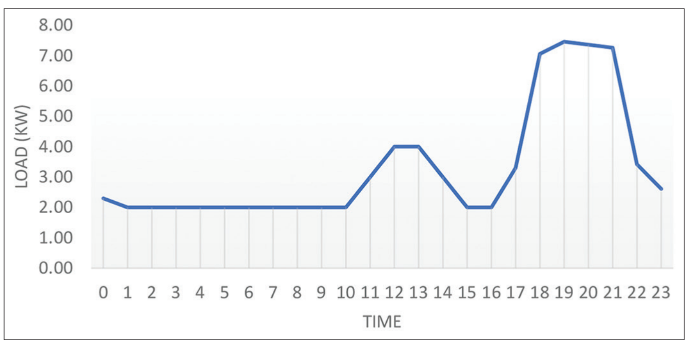


Figure 7: Solar panel power per hour per PV considered in the study area

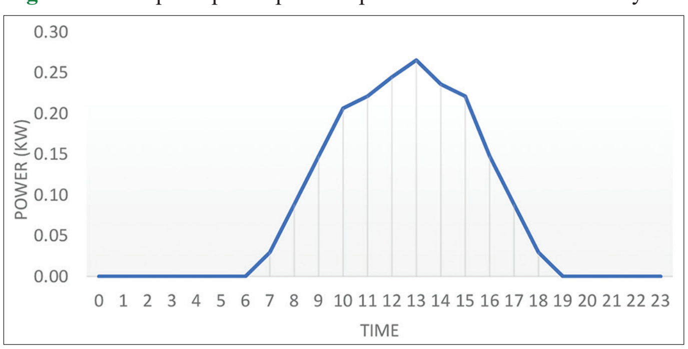


Figure 8: Annual wind speed average in the study area

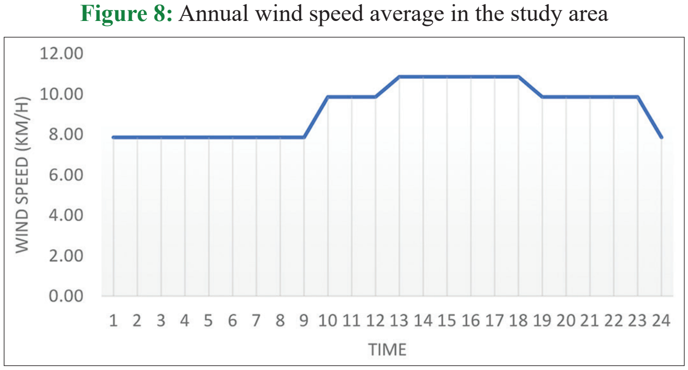


Table 4: Costs considered for the case study

Name	Value	Units	Description
C_{CO}^{BAT}	731.18	USD	Cost of the converter of each battery
C_{Energy}	0.24	USD/kWh	Energy price
C_{PV}	158.01	USD	Cost of each solar panel
C_{UB}	436.57	USD	Cost of each battery
C_{WT}	1,261.68	USD	Cost of each wind turbine
C_{cd}	2.67	USD/gal	Fuel cost
C_{in}^{PV}	121.88	USD	Cost of the inverter of each solar panel
C_{l}	3.96	USD/gal	Lubricant cost
C_{mt}^{BAT}	54.17	USD/Year	Maintenance cost of each battery
C_{mt}^{Diesel}	151.36	USD/Year	Maintenance cost of each diesel unit
C_{mt}^{PV}	8.13	USD/Year	Maintenance cost of each solar panel
C_{mt}^{WT}	45.70	USD/Year	Maintenance cost of each wind turbine

Table 5: Emissions and environmental factors considered for the case study

Name	Value	Units	Description
E_{C}^{BAT}	0.059	tCO_2/kWh	Emissions due to the construction of each battery
E_{C}^{PV}	1.392	tCO_2/kW	Emissions due to the construction of each solar panel
F_{Diesel}^{SOx}	0.675	tCO_2/kW	Emissions due to the construction of each wind turbine
E_{op}^{Diesel}	0.012	tCO_2/gal	Emissions due to the operation of each diesel unit
F_{Diesel}^{NOx}	21.8	gNO_x/kWh	NOx emissions factor of the diesel generator
F_{Diesel}^{SOx}	0.45	gSO_x/kWh	SOx emissions factor of the diesel generator
F_{PV}^{NOx}	0.1462	gNO_x/kWh	NOx emissions factor of the solar panels
F_{PV}^{SOx}	0.2580	gSO_x/kWh	SOx emissions factor of the solar panels
F_{WT}^{NOx}	0.0343	gNO_x/kWh	NOx emissions factor of the wind turbines
F_{WT}^{SOx}	0.0430	gSO_x/kWh	SOx emissions factor of the wind turbines

3.3. Solution of the Planning and Operation Problem

The BLMOPSO algorithm was run on a PC with the Windows 10 operating system, with 8 GB RAM and an Intel Core i3 2.3 GH processor. MATLAB R2018 software was used to perform the simulation. The control parameters in each level were set as follows: upper level iterations $iter_x = 50$; lower level iterations $iter_y = 90$; number of swarms $s = 40$; number of particles $I = 150$; inertia weight $w = 0.7$; and cognitive coefficients c_1=1.2 and c_2=1.3.

Table 9 and Figure 9 show the 15 solutions from the optimization algorithm, where the level of planning delivers the optimal design (number of assets of the microgrid) according to the smart grid tactical objectives and KPIs established for case study 1. In the Operations level the smart grid tactical objectives from this level

Table 6: Power values and other factors

Name	Value	Units	Description
P_{Gi}	10	kW	Rated power of the diesel units
P_{PV}^{M}	0.295	kW	Peak power of each solar panel
P_{Total}	10.07	kW	Power required by the load
P_{WT}^{M}	1	kW	Peak power of each wind turbine
S_{BAT}	2.49	kWh	Rated capacity of the battery
U_{BAT}	1	h/Year	Time offline of the batteries
U_{Diesel}	12	h/Year	Time offline of the diesel generators
U_{PV}	72	h/Year	Time offline of the solar panels
U_{WT}	60	h/Year	Time offline of the wind turbines
W_{E}	8.34	USD/tCO_2	Cost factor of the emissions
λ_{BAT}	0.12	Event/Year	Failure rate of the batteries
λ_{Diesel}	0.18	Event/Year	Failure rate of the diesel generators
λ_{PV}	0.12	Event /Year	Failure rate of the solar panels
λV	0.22	Event/Year	Failure rate of the wind turbines
CCV	0.14	gal/kWh	Rate of fuel consumption
DOD	0.8	-	Depth of discharge
FG_{l}	0.001226	gal/kW	Lubricant expense factor
ips	11.80	USD/m²	Land price index

For the upper capacity limits, $N_{PV}^{Max} = 100$, $N_{WT}^{Max} = 50$, $N_{Diesel}^{Max} = 5$, and $N_{BAT}^{Max} = 100$.
The service life of the project is 30 years, and the interest rate is 13%

Table 7: Linguistic rating and its triangular fuzzy number

Rating	Triangular fuzzy number (TFN)		
Very low (VL)	1	1	1
Low (L)	2	3	4
Medium (M)	4	5	6
High (H)	6	7	8
Very high (VH)	8	9	10

are optimized and an optimal management of the proposed design at the planning level is suggested.

The algorithm focused its solutions on the sustainability objective due to the fuzzy QFD weightings given by the stakeholders. Only in the first six solutions is diesel used moderately for the power supply, which represented the load of refrigerators from 7:00 pm until 7:00 am in most cases. The other solutions are strictly the use of nonrenewable energy sources and batteries for power generation. Table 10 shows the KPI values optimized in the model and the baseline KPIs. Figure 10 shows the percentage difference of the two KPIs, which reveals that, for example, *KPI*9 (reduction in CO_2 emissions) increases in the first six solutions compared to the baseline, and in the next nine solutions, there are solutions with up to a 50% reduction in emissions.

Table 11 shows the upper level solutions for case study 2. Unlike case 1, each of these solutions consider at least one diesel generator based on the weightings given by the stakeholders of the project, who in the fuzzy QFD matrix gave greater importance to the security of the supply with a minimum cost. Figure 11 shows that diesel generation is always active during operations and combines with nonrenewable generation sources and batteries. Table 12 shows the optimized KPI values and baseline KPIs for case 2. Likewise, the percentage difference of the two KPIs is taken as an example, and in the nine solutions, *KPI*9 (reduction in CO_2 emissions) increases from 6.09% to 60.97% compared to the baseline, and the operations and investment cost KPIs increase up to 85% due to the low investment and maintenance costs of diesel generation. This difference is shown in Figure 12.

Table 8: Evaluation of the existing relationship between KPIs and smart grid objectives

	*KPI*1	*KPI*2	*KPI*3	*KPI*4	*KPI*5	*KPI*6	*KPI*7	*KPI*8	*KPI*9	*KPI*10	*KPI*11	*KPI*12
Universal Access	$Q2_{11}$	$Q2_{12}$	$Q2_{13}$	$Q2_{14}$	$Q2_{15}$	$Q2_{16}$	$Q2_{17}$	$Q2_{18}$	$Q2_{19}$	$Q2_{110}$	$Q2_{111}$	$Q2_{112}$
Case 1	H	H	VH	VL	VL	VL	VL	VL	VL	H	L	M
Case 2	H	H	H	H	H	H	M	M	M	M	M	M
Competitiveness	$Q2_{21}$	$Q2_{22}$	$Q2_{23}$	$Q2_{24}$	$Q2_{25}$	$Q2_{26}$	$Q2_{27}$	$Q2_{28}$	$Q2_{29}$	$Q2_{210}$	$Q2_{211}$	$Q2_{212}$
Case 1	M	H	VH	VL	VL	VL	VL	VL	VL	H	L	VL
Case 2	H	H	H	VH	VH	VH	H	H	M	M	M	M
Security and Quality	$Q2_{31}$	$Q2_{32}$	$Q2_{33}$	$Q2_{34}$	$Q2_{35}$	$Q2_{36}$	$Q2_{37}$	$Q2_{38}$	$Q2_{39}$	$Q2_{310}$	$Q2_{311}$	$Q2_{312}$
Case 1	VH	L	H	VL	VL	VL	VL	L	L	M	M	M
Case 2	L	L	L	H	H	H	VH	VH	VH	VL	VL	VL
Sustainability	$Q2_{41}$	$Q2_{42}$	$Q2_{43}$	$Q2_{44}$	$Q2_{45}$	$Q2_{46}$	$Q2_{47}$	$Q2_{48}$	$Q2_{49}$	$Q2_{410}$	$Q2_{411}$	$Q2412$
Case 1	VL	VH	H	VL	VL	VL	VL	VL	VL	VH	VH	VH
Case 2	VL	VL	H	M	L	L	M	M	M	VH	VH	VH

Table 9: Optimum solutions from the planning /design phase for case 1

# of smart grid assets	Solutions															Baseline
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
	4	8	10	14	19	26	29	30	30	34	35	37	39	40	41	84
	2	30	47	45	30	2	50	41	43	26	22	15	12	9	5	0
	1	2	1	1	1	1	0	0	0	0	0	0	0	0	0	3
	37	35	21	33	49	50	25	41	17	33	26	34	34	32	34	72

Figure 9: Case 1. Microgrid operation solutions: Power generated by each source

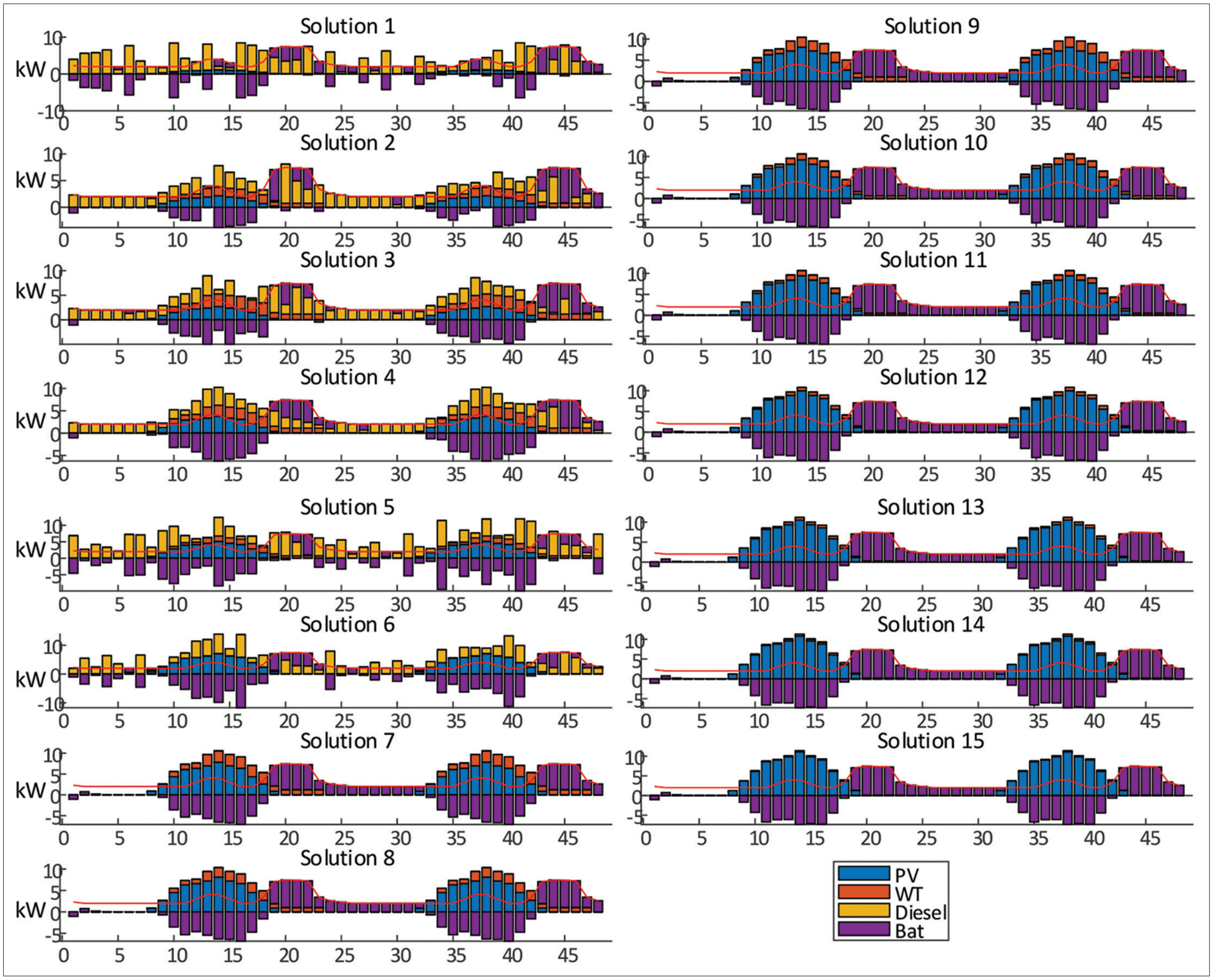
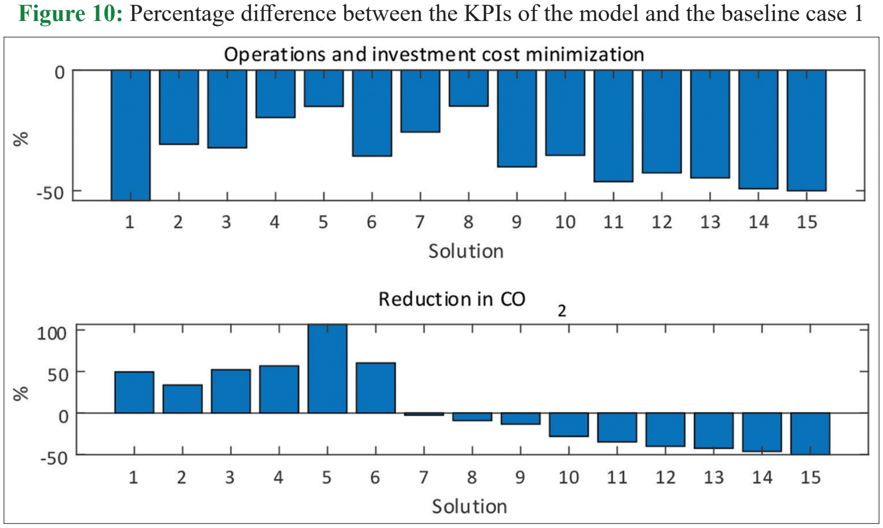


Figure 10: Percentage difference between the KPIs of the model and the baseline case 1



Finally, to obtain the solution of each case study, the fuzzy analytical hierarchy process (AHP) method was used to aid in strategic decision making. With this tool, decision makers (the panel of experts) methodically evaluate all the elements to compare them with each other; these comparisons are carried out to determine the importance of each solution attained (Heo

Figure 11: Case 2. Microgrid operation solutions: Power generated by each source

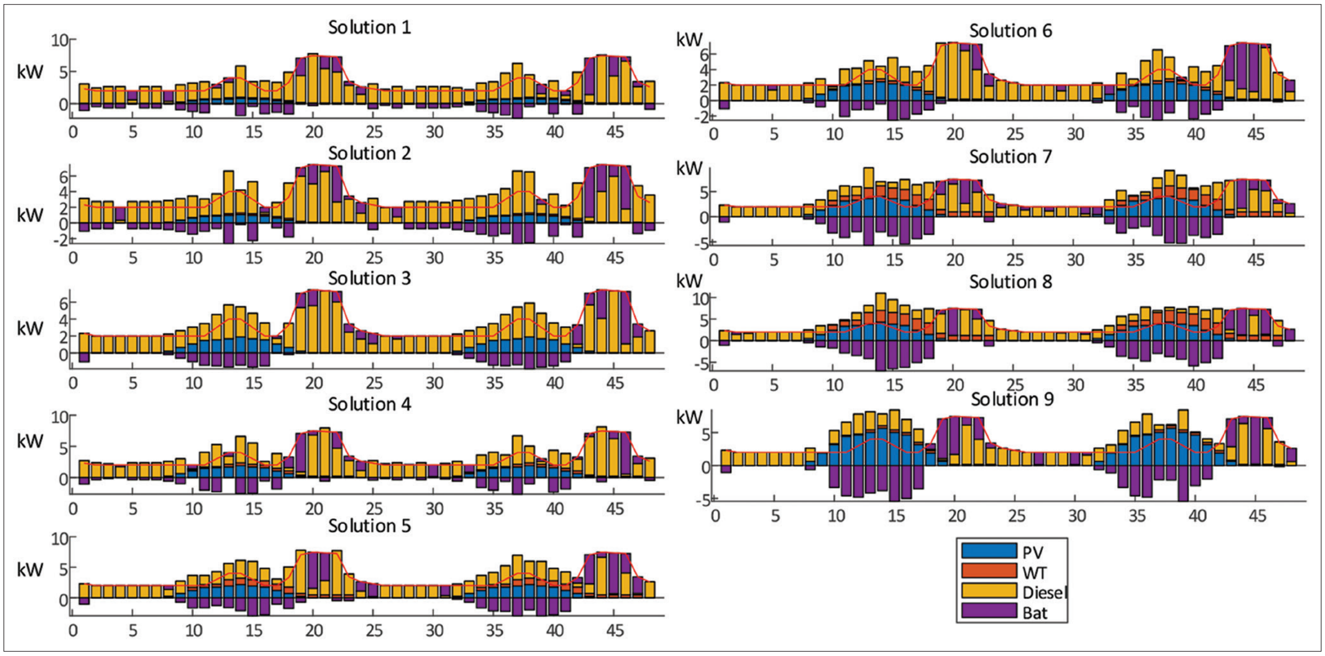
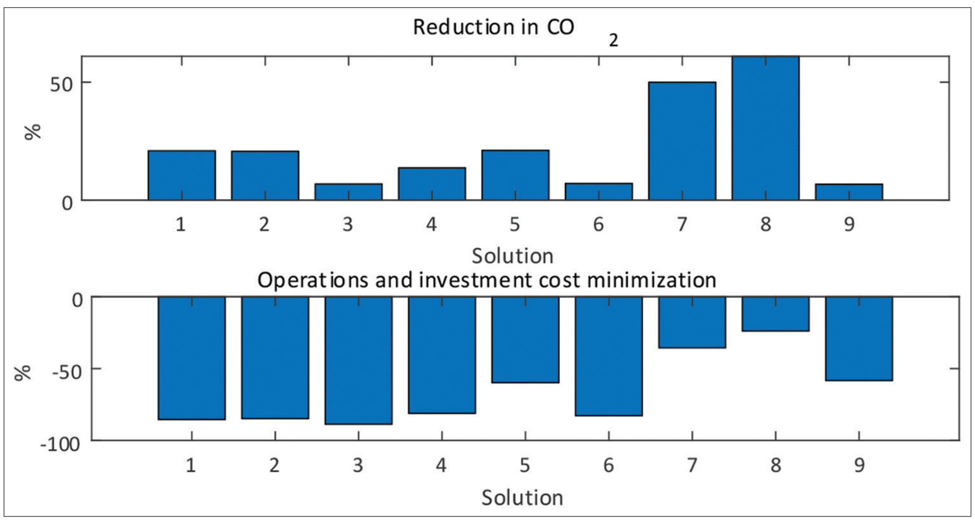


Figure 12: Percentage difference between the KPIs of the model and the baseline case 2



et al., 2010). The comparisons made in pairs are evaluated by preference indices if alternatives are compared or by indices of importance if criteria or objectives are compared; subsequently, the comparisons are then evaluated using the numerical scale proposed by Saaty, as shown in Table 13.

Figure 13 shows the priority of the Smart Grid objectives of Colombia obtained using the fuzzy AHP tool to evaluate 67 stakeholders from the energy sector and experts on the topic.

It is observed that the F_{AU} (Universal Access to Power) objective was the most important with 50%, followed by f_{sc} (Security and Quality of Power Supply) with 30% and finally F_{Comp} (enterprise competitiveness) and f_s (environmental sustainability) with 10% each. After the KPIs and smart grid tactical objectives are weighted, a possible solution can be determined. Using case 1 (environmental factor) as an example, solution 15 produces the lowest carbon dioxide CO_2 emissions, which means that it is a potential candidate for selection. However, the importance

Figure 13: Priority of smart grid objectives using fuzzy AHP

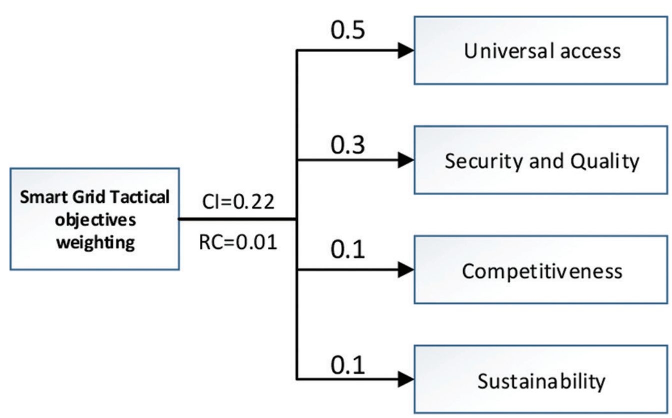


Table 10: Optimized KPIs in the model of case 1

KIPs	KPI1	KPI2	KPI3	KPI4	KPI5	KPI6	KPI7	KPI8	KPI9	KPI10	KPI11	KPI12
Units	(%)	(%)	(%])	Hours/ Year	Events/ Year	kWh/ Year	kWh/ Year	$ in 30 years	$/ kWh	tCO_2/30 years	gSO_x/30 years	gNO_x/30 years
Optimized KPIs	100	1.11	100	2.10	0.0001	0.10	10.0	97,100	$ 0.45	75.58	18,922.6	871,946.3
	16	0.65	73	1.10		1.16		146,533	$ 0.68	67.62	12,569.9	506,618.9
	23	0.64	79	4.10		1.26		143,333	$ 0.67	76.95	12,958.4	495,174.4
	23	0.64	75	1.10		1.16		169,865	$ 0.79	79.26	13,921.2	499,036.6
	100	1.15	100	1.10		0.10		179,719	$ 0.83	104.51	23,204.6	901,459.6
	100	1.03	100	4.10		1.47		136,135	$ 0.64	81.03	22,476.6	803,413.8
	100	0.10	100	8.10		15.53		157,216	$ 0.81	49.33	7,144.6	4,168.2
	100	0.10	100	8.10		15.50		179,991	$ 0.93	46.02	7,280.0	4,223.3
	100	0.10	100	8.10		15.15		126,582	$ 0.65	43.84	7300.0	4,239.86
	100	0.10	100	8.10		15.38		136,747	$ 0.70	36.36	8,038.8	4,617.5
	100	0.10	100	8.10		15.35		113,681	$ 0.58	33.04	8,225.9	4,713.9
	100	0.10	100	8.10		15.29		121,381	$ 0.62	30.31	8,610.5	4,915.1
	100	0.10	100	8.10		15.23		116,945	$ 0.60	29.11	9,036.4	5,149.3
	100	0.10	100	8.10		15.20		107,482	$ 0.55	27.20	9,233.9	5,254.1
	100	0.10	100	8.10		15.17		105,717	$ 0.54	25.21	9,421.0	5,350.5
Baseline KPIs	11	0.09	100	0.1	0.2	0.1	20,405	211,496	0.98	50.56	20664,6	82,045.7

Table 11: Optimum solutions for the planning/design phase of case 2

# of smart grid assets	Solutions									Baseline
	1	2	3	4	5	6	7	8	9	
	3	4	7	7	8	9	15	16	21	84
	4	4	0	8	19	7	39	49	7	0
	2	1	3	3	1	1	1	1	1	3
	7	8	6	7	19	7	25	28	27	72

Table 12: Optimized KPIs in the model of case 2

KIPs	KPI1	KPI2	KPI3	KPI4	KPI5	KPI6	KPI7	KPI8	KPI9	KPI10	KPI11	KPI12
Units	(%)	(%)	(%)	Hours/ Year	Events/ Year	kWh/Year	kWh/30 years	$ in 30 Years	$/kWh	tCO_2/30 years	gSO_x/30 years	gNO_x/30 years
Optimized KPIs	7	0.93	100	1.10	0.0001	0.40	10.00	30,341	0.14	61.09	15,763.73	728,869.24
	14	0.92	100	1.10		0.32		31,853	0.15	60.99	15,813.14	720,322.28
	9	0.80	100	1.10		0.74		39,400	0.19	57.45	14,578.61	625,720.52
	2	0.84	71	1.10		1.16		23,589	0.11	53.99	15,057.60	652,870.09
	39	0.71	77	1.10		1.16		83,793	0.40	61.20	13,354.73	550,063.80
	23	0.75	75	1.10		1.16		83,796	0.17	54.09	14,087.83	580,555.79
	57	0.66	79	1.10		1.16		134,322	0.64	75.79	14,448.62	516,606.04
	62	0.63	81	1.10		1.16		134,330	0.75	81.38	14,240.51	490,651.65
	29	0.61	77	1.10		1.16		86,787	0.41	53.93	14,678.71	477,889.24
Baseline KPIs	11	0.09	100	0.1	0.2	0.1	20,405	211,496	0.98	50.56	20,664.6	82,045.7

Table 13: Saaty scale and its fuzzy representation

Linguistic proposal and its corresponding triangular fuzzy number		
Saaty scale	Linguistic variable	Fuzzy number
1	Equally important	(1,1,1)
3	Somewhat important	(2,3,4)
5	Moderately important	(4,5,6)
7	Very important	(6,7,8)
9	Absolutely important	(8,9,10)
2,4,6,8	Intermediate opinions	(1,2,3); (3,4,5); (5,6,7); (7,8,9)

weight given by the experts with the AHP to the environmental sustainability objective was relatively low at 10%; therefore, if these importance weights are introduced into the algorithm, then solution 12 is the best for case 1. In case 2 (minimum cost), solution 1 was the most economical, which, for purposes of the case, would be the best solution. As with case 1, the relative importance weights obtained with the AHP method cause the solution to tend to associate more with the Universal Access objective, which was the most important objective with an importance weight of

50%. Therefore, by introducing these importance weights into the algorithm, solution 4 is the best for case 2.

4. CONCLUSIONS

This article proposes a bi-level multi-objective optimization model for planning and operating smart grid projects, using the construction of a microgrid in an area that is not electrically interconnected as a case study.

The model considers the development of a metaheuristic PSO algorithm. The model also demonstrates the importance of using qualitative decision-making tools such as fuzzy QFD and AHP, which can transform the judgments of experts into mathematical representations to introduce relative importance weights into the optimization algorithm. Solutions for two scenarios were identified in the context of the smart grid tactical objectives in accordance with the Colombian National Energy Plan 2030.

At the upper level, the algorithm aims to find the optimal dimensions of the assets of the project in the planning horizon and maximize the Universal Access and Competitiveness objectives of the energy company. At the lower level, the operating points are determined at an interval of 48 h given the maximization of the Environmental Sustainability and Security and Quality of Power Supply objectives. Compared to other similar methods, the proposed method is innovative because it uses KPIs, which are widely used in industry and business environments, to quantify and evaluate the progress and performance related to the goals and objectives of the organization.

The results show that the focus of the solutions depends on the QFD weights given by the decision makers. For case 1, the model provided 15 solutions and gave priority to power generation using nonrenewable energy sources and batteries. The reason is mainly that the experts gave greater relative importance weight to KPIs 1, 2, 3 and 10. For case 2, the decision makers gave more importance to the security of the supply with a minimum cost (KPIs 3, 5, 6, 7 and 8), which caused the algorithm to consider at least one diesel generator in all the solutions and use nonrenewable generation sources and batteries to a lesser extent. Finally, using the AHP tool, the proposed model selected the best solution for both case studies. The most convenient scenario for case study 1 was solution 15, and for case study 2, it was solution 4, in conformity with the smart grid tactical objectives using fuzzy AHP.

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