Multiobjective Optimization for Microgrids Design

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Abstract: This paper addresses the multi-objective optimization problem for microgrid design, integrating various renewable energy sources and energy storage systems. The proposed framework aims to optimize the sizing of generation plants (solar, onshore wind, offshore wind) and battery storage, while simultaneously minimizing investment costs and managing the probability of power excess or deficit within the microgrid. To handle the inherent variability of wind energy, a symbolic regression method is employed for wind speed forecasting. The optimization task is tackled using two prominent metaheuristic algorithms: the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Multi-objective Particle Swarm Optimization (MOPSO) algorithm. The study details the mathematical models for all microgrid components, including their associated investment, maintenance, and replacement costs. A comparative analysis of NSGA-II and MOPSO is presented, evaluating their performance in achieving optimal Pareto fronts regarding investment costs and power balance, highlighting the trade-offs between initial investment and operational efficiency for sustainable microgrid solutions.

Key-Words: Microgrids; Multi-objective Optimization; NSGA-II; MOPSO; Renewable Energy; Solar Power; Wind Power; Battery Storage; Symbolic Regression; Energy Management; Design Optimization.

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1 Introduction

Electricity generation has evolved throughout history [1, 2]. These developments have been presented due to the need to meet end-user demand. Many times, these end users are not close to interconnected systems, therefore microgrids are an alternative solution that allows and improves the power supply in these users. These microgrids are characterized by their adaptation to the environment, taking advantage of the riches of the place where they are planned to build, in addition to their flexibility in the power generated and the power delivered to the system that are connected.

The final energy costs have associated values given by the generation, transmission, distribution and commercialization of the energy. In many parts of the world, the investment costs in the electricity grid are high then, communities cannot access the power supply, so alternatives have been sought to meet the demand of final users. One of them has been the construction of microgrids, in order to take advantage of the natural resources that are in the areas where they plan to be built. Microgrids consist of wind plants, solar plants, energy storage units among other elements, which allow to guarantee the protection and quality of energy. These elements have associated costs, so the correct planning of a microgrids takes an important role in not incurring additional expenses that can minimize the benefits of the investment.

Investment in decentralized generation would reduce energy costs because there wouldn't be costs associated with the transmission and marketing of energy; In addition, if they become surplus energy, these microgrids could supply the system to which they are connected at peak times when required at a lower price than that offered on the market during that time span [3]. Microgrids have different generation technologies, including wind generation plants and photovoltaic plants. According to [4], annually you have that 1.7 million TWh are generated by the wind. This energy can be generated with wind plants on land (Onshore) and at sea (offshore). One of the limiters of Onshore plants is land use, and geographical conditions must be favorable for electricity generation. Offshore plants have great potential around the world, but the places that have developed this type of technology the most have been on the north and west coasts of Europe and the east coast of the USA.

In [5], propose a solution to the environmental problems that arise in the world, where currently 80% of the energy is generated through fossil combustion. Therefore, the use of clean and sustainable energies would be a big gamble, in which industry and academia must be articulated to carry out a correct planning and integration of renewable energies with the current power system. Microgrids are presented as an alternative to integrate different Non-Conventional Renewable Energy Sources to gain active demand participation, in addition it would allow an implementation of intelligent technologies in your system to know energy spikes and optimize the assets of generation sources. This article proposes the optimal planning of a microgrids taking into account technical and economic constraints of solar and wind technologies.

In [6] presents a conceptual look at long-term investment in a microgrid. It is proposed that microgrids allow autonomous and self-sufficient generation of clean and sustainable energy. When deciding to invest in a microgrid, different challenges arise, for example, making this investment attractive to the market, without leaving aside the challenges of economic clearance and future expansion planning. In this article, the benefits of long-term microgrids were boosted by creating a social and economic balance sheet in the community where the investment is made, and encourage investment in efficient and innovative elements within the microgrid to improve financial and operational models.

This document seeks to implement the NSGA-II and MOPSO multi-objective optimization methods for the design of a microgrids with two objectives; which are the size of the generation plants that make up the microgrids and the cost of deficiencies in the generation of energy produced by the plants to be designed. In addition, a genetic programming method will be implemented for wind forecasting of an offshore wind plant that is part of the microgrid; this microgrid will also include an onshore wind plant, a PV plant and a battery-powered power storage system.

2 State of Art

Wind generation systems have the benefit of being clean, inexhaustible and non-polluting, which is why they are a good candidate for solving environmental problems caused by power generation [7]. In this sense, offshore wind generation has emerged as an alternative among the different renewable energies that currently exist due to its growth potential, which is expected to have an installed capacity of 30 GW by 2030 [8].

To handle the uncertainty posed by sources such as wind, different approaches have been implemented over the years, such as a deterministic, stochastic, non-linear regression interpretation [9, 10] and more recently neural network-based applications and machine learning have been made [11, 12]. The time windows for wind forecasting by the afore mentioned techniques range from a few hours, days to a few months.

Moreover, recently researchers have been implementing hybrid techniques to significantly improve wind prediction. An example of this is presented in [13], where the implementation of a data set splitting mechanism is proposed in the prediction process in addition to an initial step in which the Echo State Network (ESN) technique is used to integrate the results of different hybrid models for intermediate forecasting in order to provide adaptive characteristics to the wind forecasting process.

In this sense, it has been proven that the use of recurring forecast models improves the resulting errors obtained by static methods, as obtained in [14], where the implementation of the GRPE and DEPE algorithms for training recurring forecast models improved errors obtained while decreased computational and storage requirements. This implementation sought to make wind predictions for a 72-hour time horizon. Other authors have made different implementations in which they sought to make wind forecasts for intervals from the order of a few seconds to a few days [15].

On the other hand, different multi-objective algorithms have been implemented for microgrids planning; for example, a method of configuration and coordination of protection relays for Microgrids using MOPSO is proposed. The key problem in selecting relay configuration is achieving minimum operating times while maintaining coordination between all relays. The problem of relay coordination is solved by improving the initialization and weight of the PSO algorithm and choosing the appropriate collection current, which avoids the problem of premature convergence. Optimal relay settings are determined by the PSO algorithm. The study shows that the results using the MOPSO algorithm are close to optimal solutions, and demonstrates the validity of the proposed method. [4].

Similarly, [5] proposes a new approach based on linear interval programming (ILP) that hybridized with modified particle swarm optimization (MOPSO) applied to Distributed Generation (DG) distribution systems, where current failures are fed from both ends of the line and, consequently, the currents detected by the relays at both ends are different. These variable failure currents can lead to poor coordination of overcurrent relays (DOCRs). The MOPSO algorithm is applied to overcome this coordination constraint issue.

Another algorithm implemented microgrids is the NSGA-II, an example of the implementation of this algorithm is presented in [6], where it was used to optimize the cost of programming a micro-network that implements generation with non-renewable resources and fuel generation. Moreover, it was used as a method of checking the proper functioning of the MOPSO algorithm in the management of the generation units of a microgrids where the minimization of operating costs and polluting emissions was sought. Otherwise, a case study similar to the proposed here in [7], it is proposed where wind forecasting is carried out in a first stage by means of a neural network algorithm to minimize uncertainty in wind generation to at a later stage perform economic clearance with a multi-objective optimization to minimize polluting emissions and costs.

Finally, when looking for possible solutions to a multi objective optimization problem, they can be represented through the optimal Pareto method. The Pareto method is used when we have different solutions to the multi-objective problem posed, the algorithm has as its starting a random generation which reduces its search space with the passing of each simulation, the algorithm in its initial conditions, sets how many generations will simulate and will be reduced until that condition is met and provide optimal locals after each simulation. The Optimal Pareto does not seek to solve the multi-objective problem, it seeks that the people in charge of making the decisions can understand the results and adapt them to the constraints of the optimization problem through the optimal premises of the optimization problem and simultaneously find the global optimal according to the objectives of the problem. [8, 9, 10].

The Pareto method works as follows: [11, 12]

- An initial population is chosen randomly and should uniformly cover the entire space solution based on consideration of the population diversity requirement.
- The evolutionary method based on Pareto differs from the basic algorithm, mainly in the selection procedure used to select later generations of the population. Low quality solutions (individuals) are removed from the population, while high quality individuals are reproduced.
- Then the generation of descendants can be generated according to the algorithm carrying out mutation and crossing operations in parental individuals.
- Then boundary treatment must be performed, because the MOP workspace is limited, that is, the Pareto solution is a constraint to the boundary problem, it is essential to ensure that the parameter of the test vector values is within its allowed ranges after the crossover operation.
- Combine the new population with the existing parental population to generate a combined population.
- Evaluate each individual in the combined population and perform classification and select un denominated individuals to form a Solution Set.
- Finally, the solutions are presented that allow to analyze the results of the algorithm addressed to the objectives initially raised.

3 Methods

In this work, it is proposed to carry out a forecast of wind speeds for offshore generation through the application of symbolic regression based on historical winds (subsection 3.1). On the other hand, the NSGA-II (subsection 3.2) and MOPSO (subsection 3.3) multi-objective optimization algorithms will be used to solve the problem microgrid planning problem (section 4).

3.1 Symbolic Regression

Symbolic regression (SR) applied to prognostic problems is an application of genetic programming that results from the combination of evolutionary computing and nonlinear regression. Symbolic regression provides mathematical expressions that model a series of data and has the advantage of being flexible over incomplete information and non-assumption [8]. For data prediction, the representation of mathematical expressions corresponding to different models is used as a tree structure; where the inner nodes (union between terminals and other operators) would become the mathematical operators and the leaves of the tree would be the variables and parameters. The algorithmic process is based on the exploration of a field of possible equations through the use of genetic operators such as: crossover, mutation and reproduction [9]. For tree creation this relates genes to arithmetic expressions (+,-,/,*) and trigonometric functions (sine, cosine, tangent). The population is then organized by hierarchies and creates a new generation based on the principle of genetic recombination [10] The RS seeks to find a mathematical expression that adapts to the observed data with some degree of precision through relationships between a dependent variable (y) and other dependent variables (x). The algorithm starts with a population of individuals composed of a single tree structure gene through which a mathematical expression is encoded. The adjustment of the values of the above variables is calculated by the mean quadratic error (RMSE) on the full set of observations. According to the result, each individual is likely to participate in genetic operations such as recombination, reproduction, selection and crossing; in this way a new population is created which is iteratively reassessed until the maximum number of generations established by the user is reached. Finally, the symbolic model will be one that generates a lower degree of approach error throughout the process; where each individual is considered as a set of genes whose weighted linear combination generates the result of inference [11].

$$\hat{y} = a_0 + a_1 gen_1 + a_2 gen_2 + a_3 gen_3 \tag{1}$$

$$\hat{y} = a_0 + a_1(\sin(x_1) - x_3) + a_2 \tan(7.3x_2) + a_3(x_1(x_2 - x_3)) \tag{2}$$

Equations (1) and (2) present the estimate given by the individual, where (x_i) they are values of independent variables, a_i are values of weights and is the value of inference.$(\hat{y})$

3.2 Non-dominated Sorting Genetic Algorithm (NSGA-II)

Multi-objective optimization (MOP) problems consist of a set of n decision variables, k objective functions, and sets of m inequality constraints and p equality constraints, where constraints and objective functions are functions of decision variables. Of this, it has to be that an MOP can be expressed as: Function to optimize

$$y = f(x) = \{f_1(x), f_2(x), ..., f_k(x)\} \tag{3}$$

Restrictions

$$g(x) = \{g_1(x), g_2(x), ..., g_m(x)\} \geq 0 \tag{4}$$

$$h(x) = h_1(x), h_2(x), ..., h_p(x) = 0 \tag{5}$$

Where

$$x = \{x_1, x_2, ..., x_n\} \in X \tag{6}$$

$$y = \{y_1, y_2, ..., y_n\} \in Y \tag{7}$$

X represents the decision space, x represents the decision vector, y represents the target vector, and Y denotes the target space. Each decision vector has the shape $x = \{X_1, X_2, ..., X_n\}$, and the target vector is shaped $y = \{f_1(x), f_2(x), ..., f_k(x)\}$. Given this, the problem is to find the value of x that as a result the best value for f(x). However, there is no single solution generally, but you have sets of better solutions that are known as not mastered. Proposed in [13], the Non-dominated Sorting Genetic Algorithm (NSGA-II) emerged to eliminate defects in its predecessor by incorporating an elitist approach, decreasing computational complexity, and incorporating a comparison parameter [14]. The algorithm starts by performing a population classification on different fronts. Each individual is assigned a rank equivalent to their level of non-dominance. Additionally, the algorithm involves a crowding distance, as an operator to preserve the diversity of the population. The selection is made through a binary tournament, by means of the operator's comparison criterion $(\prec_n)$; By this criterion the winner of the tournament is the lowest- ranking individual; in case there are multiple individuals of the same rank, the individual with the least distance from Crowding wins. The input parameters for the NSGA-II algorithm are: population size, elite population size, probability of crossing, probability of mutation, (P_{cruce}) $(P_{mutación})$ maximum number of generations (and g_{max} maximum number of generations of convergence.(g_{conv})

Algorithm 1 Pseudocode of the NSGA-II. (Taken from [15])

Inicio
for cada $t \in T$ **do**
    while existe un ruta del nodo s a nodo t **do**
        Conjunto_Rutas Ruta desde s hasta t;
    end while
end for
Generar aleatoriamente P_0
Hacer ordenamiento rápido no dominado de P_0
Aplicar los operadores de selección, cruce y mutación para generar una población hija Q_0
Hacer $t = 1$
Hacer $R = \emptyset$
while $t < \delta$ y Cont_Convergencia $< \epsilon$ **do**
    Hacer $R_t = P_t \cup Q_t$
    Calcular el número de saltos y el retardo de los miembros R_t
    FB Ordenamiento Rápido NoDominado (R_t)
    $i = 1$
    $P_{t+1} = \emptyset$
    while $|P_{t+1}| < N$ **do**
        Calcular DistanciaCrowding (F_i)
        $P_{t+1} = P_{t+1} \cup F_i$
        $i = i + 1$
    end while
    Ordenar P_{t+1} en forma descendente, utilizando el operador $>$
    Escoger los N primeros elementos de P_{t+1}.
    Generar Q_{t+1} aplicando los operadores de selección cruce y mutación sobre P_{t+1}
    $t = t + 1$
end while
Fin

3.3 Modified Particle Swarm Optimization - MOPSO

MOPSO is an algorithm inspired by nature which is the evolution of PSO. Particle Swarm Optimizing is a population-based stoic optimization. PSO takes into account two populations: the population of the current positions of the particles (i.e. Pbest) and a population of the best particle positions (i.e. Gbest) reached so far. The first is considered as the candidate solutions in the search space, while the latter is to guide the update of the first one. In the PSO system, each particle is associated with two properties (velocity vector V and X position vector) and moves in the search space with a speed that dynamically adjusts according to the particle experience and the particles companion experience simultaneously [16].

Mathematically, the velocity and position of the particles are updated according to the following formulation:

$$V_i(k) = WV_i(k){+}C_1R_1(P_{besti}{-}x_i(k)){+}C_2R_2(G_{best}{-}x_i(\quad (8)$$

$$x_i(k+1) = x_i(k) + V_i(k+1) \quad (9)$$

Where V_i is the velocity of particle i, x_i is the position of particle i, W is the random inertial weight, k is the iteration number, C_1 and C_2 are the social and cognitive coefficients of the population, R_1 and R_2 are the random numbers between 0 and 1. When PSO applied to large or multimodal problems, it tended to get stuck in optimal premises and provide premature convergence, finding a local optimal and not an overall optimal. [7]

4 Problem formulation and Case Study

The case study is based on the planning of a microgrid that integrates different renewable energy sources, where a multi-lens optimization problem is solving. The first objective is related to the investment costs of the different technologies to be implemented (subsection 4.1-4.4) while the second objective is the excess or power deficiency generated in the microgrid (subsection 4.5). The technologies to be taken into account are photovoltaic, wind of two types: onshore and offshore and by storage in battery systems. In general, the importance of these objectives is that through this one can have an estimate of the feasibility of building a micro-network by minimizing investment resources and optimizing the generation necessary to meet the adapted demand for [10]. The overall approach of the system will then be made and the costs associated with each technology will be specified; which will be used in the next section for the approach of the two objectives to be optimise [17].

4.1 Solar Panels

These solar panels have the following associated values: Power supplied by solar panels

$$P_{ps} = \frac{eff_{ps} * A_{ps} * RS}{1000} \text{ [W]} \quad (10)$$

Where eff_{ps} is the efficiency of solar panels, A_{ps} is the area occupied by solar panels and RS is the solar radiation. The irradiance value taken into account for the case study is presented in Figure 1 and was taken from [11]. This equation results in the power generated by solar panels for one day.

Investment costs

$$CI_{ps} = I_{ps} * A_{ps} \quad (11)$$

Where I_{ps} is the initial investment per square meter and C_{ps} is the investment cost for solar technology.

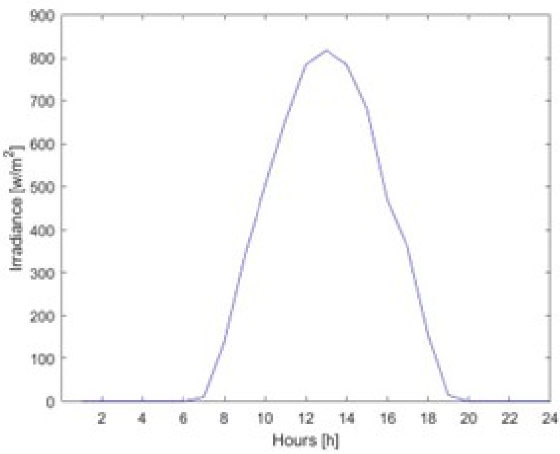

Figure 1: Irradiance Level

Total cost of maintenance

$$\sum CM_{ps} = CMO_{ps} * A_{ps} * \frac{1+TC}{1+TI} \quad (12)$$

Where CMO_{ps} is the cost of operation and annual maintenance, TC is the exchange rate, TI is the interest rate, t is the projected time that is 20 years and $\sum CM_{ps}$ is the total cost of maintenance in the 20 years. Replacement cost

$$CR_{ps} = CR_{ps} * A * \frac{1+TIF}{1+TI} \quad (13)$$

Where CR_{ps} is the resale cost per square meter, TIF is the inflation rate and t_I is the amount of time it takes to use.

4.2 Onshore Wind Generation

Wind generation has the following associated values: Power delivered by wind generators

$$P_{on} = \frac{0.5 * eff_{on} * A_{on} * CP_{on} * D_a * V_{on}^3}{1000} \text{ [W]} \quad (14)$$

Where eff_{on} is the efficiency of the wind generator is, A_{on} is the area occupied by Onshore generators, CP_{on} is the power coefficient, D_a is the density of the air and V is the wind speed.

Investment costs

$$C_{on} = I_{on} * A_{on} \quad (15)$$

Where I_{on} is the initial investment per square meter and C_{on} is the investment cost for Onshore wind generation. Total cost of maintenance

$$\sum CM_{on} = CMO_{on} * A_{on} * \frac{1+TC}{1+TI} \quad (16)$$

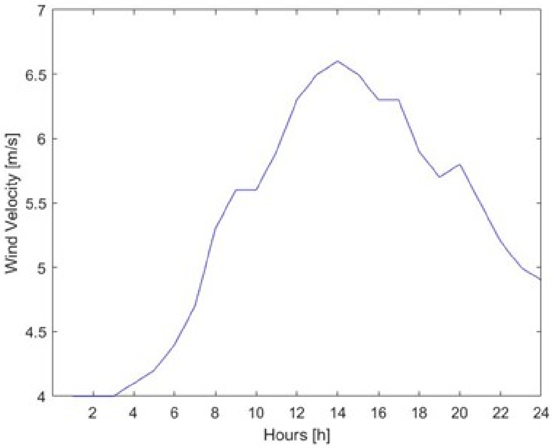

Figure 2: Wind speeds onshore.

Where CMO_{on} is cost of annual operation and maintenance, and $\sum CM_{on}$ is the total cost of maintenance in the 20 years. Replacement cost

$$CR_{on} = CR_{on} * A * \frac{1 + TIF}{1 + TI} \tag{17}$$

Where CR_{on} is the cost of resale per square meter.

4.3 Offshore Wind Generation

Wind generation has the following associated values: Power delivered by wind generators

$$P_{off} = \frac{0.5 * eff_{off} * A_{off} * CP_{off} * D_{off} * V_{off}^3}{1000} \text{ [W]} \tag{18}$$

Where eff_{off} is the efficiency of the wind generator, A_{off} is the area occupied by Offshore generators, CP_{off} is the power coefficient, D_{off} is the density of the air and V_{off} is the wind speed. To determine wind time speeds for wind generation simulation, a genetic programming-based wind forecasting method with symbolic regression implementation was implemented through the use of historical values. The data were taken from [13]. Values of 14 days were taken for algorithm training and 12-day time data were used to check the results of the executed forecast. The training results of the symbolic regression algorithm are shown in Figure 3 and the one-day wind time rate values taken from the forecast to be used in the offshore wind generation calculation are presented in Figure 4.

Investment costs

$$C_{off} = I_{off} * A_{off} \tag{19}$$

Where I_{off} is the initial investment per square meter and C_{off} is the investment cost for Offshore wind generation. Total cost of maintenance

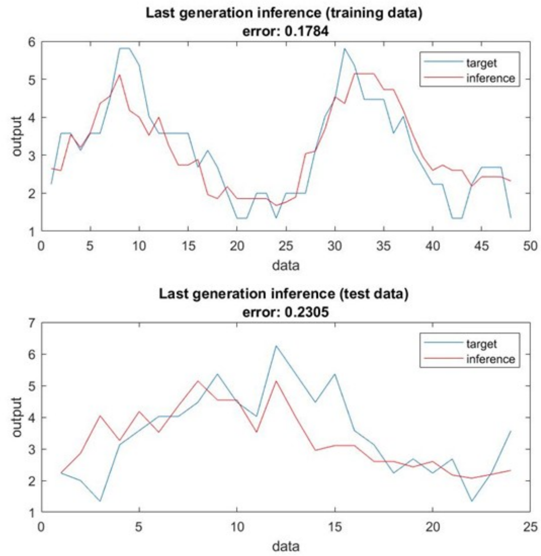

Figure 3: Algorithm result for forecasting hourly wind speeds.

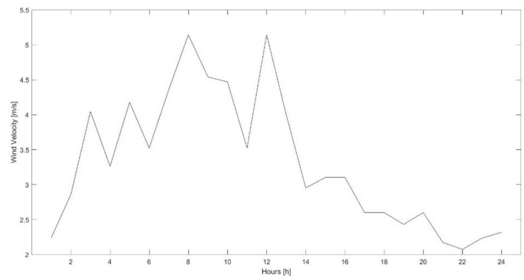

Figure 4: Wind speeds taken from the forecast performed.

$$\sum CM_{off} = CMO_{off} * A_{off} * \frac{1 + TC}{1 + TI} \tag{20}$$

Where CMO_{off} is cost of annual operation and maintenance, and CM_{off} is the total cost of maintenance in the 20 years. Replacement cost

$$CR_{off} = CR_{off} * A * \frac{1 + TIF}{1 + TI} \tag{21}$$

Where CR_{off} is the cost of resale per square meter.

4.4 Battery bank

The battery bank has the following model: Maximum charging status

$$EC_{max} = 0.8 * A_{bat} * C_{bat} \tag{22}$$

Where C_{bat} is the nominal capacity of the battery. Minimum charging status

$$EC_{min} = 0.8 * A_{bat} * C_{bat} \tag{23}$$

If the power generated is greater than the power of the charge, at that time, the batteries will be in charge. In that case you will get the charging status of the batteries as follows:

$$EC = [EC_{min} * (1 - THA)] + \frac{P_g - P_{ct}}{eff_i} * ECB \tag{24}$$

Where THA is the Auto-Discharge Time Rate, P_g is the total power generated, P_{ct} is the total power of the charge, eff_i is the efficiency of the inverter and ECB is the efficiency of battery charge. As the battery is charging, a formulation will be in place to measure the excess power generated and is associated with the following formulation:

$$EPG = P_g - \frac{P_{ct}}{eff_i} + \left[\frac{EC_{max} - EC_{min}}{ECB}\right] \tag{25}$$

If the power generated is less than the power of the charge, at that time, the batteries will be in discharge. In that case you will get the charging status of the batteries as follows:

$$EC = [EC_{min} * (1 - THA)] - \left[\frac{P_{ct}}{eff_i} - P_g\right] * EDB \tag{26}$$

Where EDB is the battery discharge efficiency. As the battery is in discharge, a formulation will be available to measure the power deficiency delivered and is associated with the following formulation:

$$DPE = \frac{P_{ct}}{eff_i} - P_g \tag{27}$$

Investment costs

$$C_{bat} = I_{bat} * A_{bat} \tag{28}$$

Where I_{bat} is the initial Investment for each battery and C_{bat} is the investment cost for the battery bank Battery replacement cost

$$CRB = C_{bat} * A_{bat} * \frac{1 + TC}{1 + TI} \tag{29}$$

Total cost of maintenance Battery maintenance cost is a fixed cost (CMB) The main objective of the problem is to minimize investment costs and further minimize the chances of excess and power deficit generated in the microgrid. Since the above poses a multiobjetive optimization problem, the NSGA-II and MOPSO algorithms will be implemented for the solution of this.

$$\min\{F_1, F_2\} \tag{30}$$

Where the objective function 1 is: F_1

$$F_1 = CT \tag{31}$$

The total investment cost of the microrred consists of the sum of the costs associated with each of the technologies to be implemented.

The second target function is given by equation (32)

$$F_2 = PDE \tag{32}$$

And it's equal to: PDE

$$PDE = PDPE + PEPG \tag{33}$$

Where PDPE is the probability of having a deficit in the power delivered to the system and PEPGis the probability of having an excess of power generated. The purpose of the second objective function is to carry out a correct energy management strategy, which seeks to know the deficit or excess power generated by the microgrid. In cases where higher than required power is generated, it is stored in the battery banks, this scenario is the most favorable for the proper functioning of the micro-reed. The next scenario is when the power generated is less than the power required by the system, in that case the battery banks come to meet the demand to the point where the system may need less power. For this reason, it is very important to know the load profile of the system that will be fed by the micro-reed, in this way you can carry out a correct planning of each generation source used in the micro-area. The load profile of the system based on which the comparison of compliance with the above will be made are presented in Figure 5.

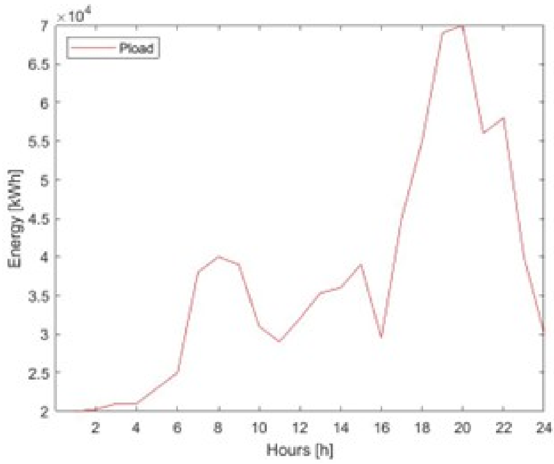

Figure 5: Micro-network load profile.

Moreover, the decision variables K_1 to consider for the multiobjetive solution of the problem are 4, and they are associated with the area required for photovoltaic, onshore wind, offshore wind and the amount of batteries required for energy storage.

$$K_1 = A_{ps} \tag{34}$$

$$K_2 = A_{on} \tag{35}$$

$$K_3 = A_{off} \tag{36}$$

$$K_4 = A_{bat} \tag{37}$$

5 Multi-objetive Optimization for Microred Planning Results

5.1 NSGA-II

Figure 6 the optimal Pareto obtained through the optimization implemented to the multi-objective problem posed through the implementation of the NSGA-II algorithm considering a population size of 20 and 150 generations. From the simulations carried out, Table 1 presents the values of the decision variables obtained for multi objective optimization with NSGA-II

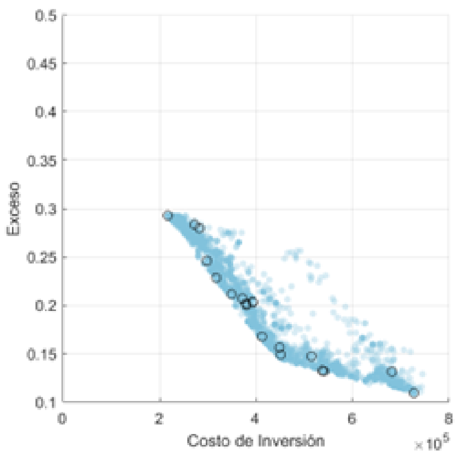

Figure 6: Optimal pareto obtained with NSGA-II algorithm.

5.2 MOPSO

Figure 7 the optimal Pareto obtained through the optimization implemented to the multi-objective problem posed by the implementation of the NSGA-II algorithm for a population of 20 and 150 generations. From the simulations performed, Table 2 presents the values of the decision variables obtained for multi-target optimization with MOPSO.

The results of the first target function raised are presented in Table 2 of which investment costs can be

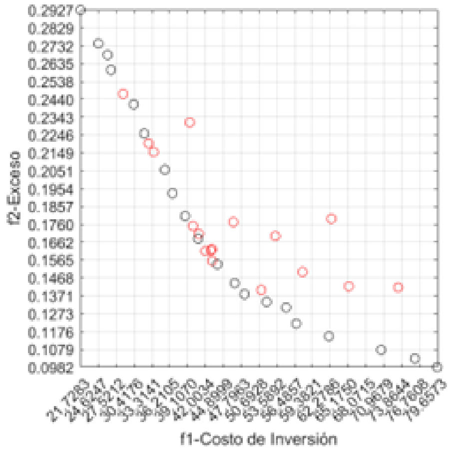

Figure 7: Optimal pareto obtained with the MOPSO algorithm.

observed to be lower with the results of the MOPSO algorithm.

On the other hand, Table 3 can be observed that the probability of excess or power deficit generated by the microgrid is lower in the results obtained from the NSGA-II algorithm.

6 Conclusions

This article proposed the implementation of the NSGA-II and MOPSO multi-objective optimization algorithms to solve the problem of planning a microgrid that integrates different distributed generation resources. After implementing each algorithm to the proposed system, it was found that particular solutions are reached for each, but with consistent results. This is because the NSGA-II will have a more efficient probability of system operation since it has a lower PDE value; however, it results in higher upfront investment being required as the total calculated cost is higher for this algorithm. On the contrary, with MOPSO the operation of the system has to be more likely to be inefficiencies, but the initial investment cost will low.

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Table 1: Optimized decision variable results

Algorithm	PV panels $[m^2]$	Onshore Wind Turbines $[m^2]$	Offshore Wind Turbines $[m^2]$	Number of Batteries
NSGA-II	157,0826	246,523	157,4642	23
MOPSO	100	262,1669	102,4032	22

Table 2: Objective function results 1.

Algorithm	PV cost [$]	Wind Onshore Cost [$]	Cost of Wind Offshore [$]	Battery Cost [$]	TOTAL COST [$]
NSGA-II	87927	163575	67715	123865	393740
MOPSO	55975	173955	80552	17596	328080

Table 3: Probability of excess or power deficit generated in the microgrids.

	Pde
NSGA-II	0,2033
MOPSO	0,2199