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Resolution of the bi-objective optimization problem for the dispatch of hydroelectric plants under conditions of low inflow using the NSGA II algorithm

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Abstract: Among the consequences of climate change are the increase in temperature and changes in rainfall patterns that bring longer periods of drought. This creates limitations in the management of hydroelectric plant reservoirs, restricting in some cases the amount of electricity generated. The objective of this research is to solve the multi-objective optimization problem that seeks to minimize the electric power production of hydroelectric plants with low inflow and, at the same time, to minimize the electric rationing due to this low production. Since the objectives are opposed to each other, it was necessary to apply methodologies for solving multiobjective optimization problems, including genetic algorithms. The mathematical model was built considering the operating conditions of the reservoirs of the hydroelectric plants under study, taking into account their minimum operating levels, which are included in the model constraints. The non-dominated sorting genetic algorithm II was used to obtain the Pareto front, which resulted in a total of 78 non-dominated solutions, which were useful to manage the reservoirs considered, at the time of maximum demand. In short, it is recommended to use other multiobjective optimization algorithms for comparison purposes, selecting the appropriate indicators to evaluate the performance of each algorithm used, in addition to incorporating monetary and environmental cost restrictions to the model.

Key words: climate change; Pareto front; electricity generation; NSGA; electricity rationing

1 Introduction

Hydroelectric power plants are based on the conversion of the potential energy associated with the difference in water level stored in purpose-built reservoirs. Hydropower "is generated by the flow of water and using mechanical technology such as turbines to do the energy conversion" (Ahmad et al., 2019). This energy associated with stored or moving water is part of the well-known renewable energies. By 2022, 30% of the total electricity generation worldwide was supplied by renewable sources, with a little more than half of the electricity generation being of the hydroelectric type (REN21, 2023). Likewise, in Latin America, 45% of total electricity generation comes from hydroelectric plants (International Energy Agency, 2021).

However, climate change can generate changes in environmental temperature and rainfall patterns, affecting the availability of water for hydroelectric plants (Okoye et al., 2023). Likewise, some climatic phenomena could generate periods of drought in some parts of the planet that would negatively impact, among other things, the levels of reservoirs associated with hydroelectric plants. In countries with an energy matrix where more than 50% is composed of hydroelectric power, the impact of these climatic phenomena could lead to an increase in energy rationing for a large part of the population. For example, in the presence of the "El Niño" phenomenon, drought intensifies in some Latin American countries. According to López (2024), "El Niño" is mainly responsible for the drought experienced by Venezuela since July 2023 and, according to the Climate Prediction Center of the United States (National Oceanic and Atmospheric Administration, 2024), it is expected that the effects of this climatic phenomenon will be present until at least April 2024.

Therefore, in the presence of conditions of atypically low inflow to the reservoirs of hydroelectric plants, it is necessary to manage their use to avoid reaching minimum operating levels. This could reduce the electrical energy generated and thus increase electricity rationing, if there are no other types of generation plants to compensate for such a decrease. This situation leads to a problem of optimization of two opposing objectives in which the aim is to reduce the electrical energy generated by the plants so as not to reach the minimum operating levels of the reservoirs, but also to reduce electricity rationing in order to minimize the impact on the population. To solve this type of problem, one of the available multiobjective optimization techniques can be applied. In this sense, the purpose of this research is to apply multiobjective evolutionary algorithms to establish the dispatch of hydroelectric plants that have low inflow conditions to the reservoirs. For this purpose, the second generation non-dominated solution ranking genetic algorithm (NSGA II) is used, seeking to simultaneously minimize the electrical generation of two hydroelectric plants and the electrical rationing of the region that is supplied by these plants.

A literature review of the research related to this topic was made, and no research was found that seeks to simultaneously reduce the generation of hydroelectric plants and electricity rationing. For example, Huang et al. (2023) use the NSGA II algorithm to optimize two objective functions, the generation of a hydropower plant located in China, which serves to regulate peak demand, and the availability of navigation of the sea channel that is fed by the flow coming from the plant. Among the constraints considered are the safe levels for the reservoir, the plant's outflow, and the plant's electrical power limits. The results obtained allow programming both the plant operation and the use of the navigation channel.

Likewise, Jena et al. (2022) make use of the NSGA II algorithm to solve a two-objective optimization problem that allows scheduling the operation of hydroelectric plants, thermal plants, solar photovoltaic plants, and wind power plants, minimizing the operating costs and pollutant emissions of the system. The numerical results are compared with those of the SPEA 2 algorithm, obtaining that the use of NSGA II generates a greater decrease in cost and emissions.

On the other hand, Hojjati et al. (2018) apply and compare NSGA II and MOPSO (multi-objectiveparticle swarm optimization) algorithms to improve the operation of water reservoirs, maximizing revenues from power generation and stored water volume. Constraints associated with reservoir water balance, water flow release limits, and minimum "downstream" flow for environmental protection are considered. The researchers conclude that the NSGA II algorithm performs better with 22% and 3% improvements in revenue and volume, respectively, when compared to the MOPSO results.

In addition, Sun et al. (2018) use the multi-objective evolutionary algorithm based on decomposition with adaptive weight vector adjustment (MOEA/D-AWA) to optimize the operation of water reservoirs. Their objective functions are maximizing the power generated by the hydroelectric plant and maximizing the water flow diversion from the reservoir outlet. They consider water balance restrictions in the reservoir, electric power generation, and the design flow rate of the pumping station. The study determines that the proposed model is effective in solving the water reservoir operation optimization problem.

On the other hand, Zhou et al. (2003) make use of the non-dominated solution sorting optimization (NSBWO) algorithm to improve the operation of hydroelectric plants by considering the arrival times of the vessels at the reservoir. The constraints include the limits of reservoir elevations, plant discharge flow, unit power, rate of variation of water levels, among others. As a result, they obtained an optimal daily operation plan for the hydroelectric plant.

Similarly, Wei et al. (2022) propose a multiobjective optimization model to increase the power generation produced by a hydroelectric plant while maximizing water diversion from the system reservoir. They apply the NSGA II-SEABODE algorithm, which combines multi-objective optimization and multi-attribute decision making. The constraints considered include water balance, reservoir elevation limits, limits on power output, limits on pumping flow and limits on ecological flow. The results show that the methodology can promote the efficient use of water resources.

Additionally, Li & Qiu (2015) propose the use of a multi-objective optimization model based on the NSGA II algorithm to maximize the annual electric power generation while maximizing the firm power of the hydropower plant. The constraints considered in the model are related to reservoir elevation limits, reservoir discharge limits, water balance, among others. They conclude that the proposed methodology, besides being effective, shows a quantitative relationship between energy generation and firm power.

Finally, Marcelino et al. (2021) propose a multiobjective optimization model to maximize the generated power of a hydroelectric plant and simultaneously maximize the total volume of water in a set of reservoirs. They use the multiobjective evolutionary swarm hybridization (MESH) algorithm, and compare their results with those of the NSGA II, NSGA III, SPEA II, and MOEA/D algorithms. Their findings indicate that MESH performs better than the other algorithms in terms of efficiency and accuracy.

The rest of the article is distributed as follows. Section 2 presents the methodology used, then section 3 discusses the results obtained, followed by the conclusions derived from the research and, finally, the bibliographical references used.

2 Materials and methods

First, the objective functions to be optimized were defined, taking into account the conditions of the reservoirs, due to the increase in electricity demand and the "El Niño" phenomenon that generates drought and, consequently, low inflow. The first objective function consisted of minimizing the production of electric energy in the hydroelectric generation plants under study, corresponding to reservoirs 1 and 2, in order to reduce the consumption of stored water, since low inflow is expected in the short and medium term, and the second function was to minimize electric rationing in that region. It is evident that these two objectives are opposed, since minimizing the production of electricity generated by the hydroelectric plants implies a possible increase in electricity rationing if other sources of generation are not available to compensate for such a decrease. Electricity rationing will be given as the difference between the maximum demand in the region under study and the different contributions of electricity to that region. These inputs are the generation in the reservoir plants under study, the generation in the rest of the hydroelectric and thermal plants in the region, and the maximum transfer limit through the transmission system.

Next, the decision variables related to the objective functions were defined, which were electric generation at the reservoir 1 plant, electric generation at the reservoir 2 plant, electric generation in the rest of the region, and the limit of electric energy transfer to the study region through the transmission system. Subsequently, the limits of the decision variables were obtained, as well as the restrictions involving these variables. The operating limits for the reservoir levels were introduced in the constraints, whose equations were found using multiple linear regression.

Once the mathematical model of the multi-objective optimization problem was obtained, the appropriate technique was applied to solve this problem. In this research, the evolutionary multiobjective optimization algorithm NSGA II was used to obtain a set of non-dominated decisions that define the Pareto front, using the Python programming language.

2.1 Multi-objective optimization

A multiobjective optimization problem is one that has a set of objective functions to be optimized, properly adjusting the values of the decision variables, which are subject to a set of constraints that must be satisfied simultaneously. Coello et al. (2007, p. 5) indicate that "these objective functions form the mathematical description of the performance criterion, which are usually in conflict with each other". Given the conflicting characteristic between the functions to be optimized, there is no single solution that can improve them simultaneously, so the solution to the problem consists of finding the values of the objective functions that are acceptable to the decision maker. Additionally, Hussain & Kim (2021, p. 3) speak of multiobjective optimization as the process of simultaneously optimizing a set of objective functions, and posit that "in most cases the objective functions are conflicting in nature and optimizing one of them implies the deterioration of the other, and vice versa. Therefore, the goal is to find a balance between these conflicting objectives".

The constraints of the problem are imposed by the environment or by limitations of available resources, so they must be met for a given solution to be considered acceptable or feasible. On the other hand, they describe dependencies between the decision variables and constants or parameters involved in the particular problem.

As stated by Al Shidhani et al. (2020), if one sets the vector of decision variables: $\boldsymbol{X} = (x_1, x_2, \dots, x_n)^T$, such that they satisfy J inequality constraints, K equality constraints and are bounded between an upper bound and a lower bound, and optimize the vector of objective functions, the generic mathematical model is:

$$minimizar/maximizar \quad f(\boldsymbol{X}) = [f_1(\boldsymbol{X}), f_2(\boldsymbol{X}), \dots, f_k(\boldsymbol{X})]^T \tag{1}$$

Subject to:

$$g_i(x) \le 0, i = 1,2, \dots, J \tag{2}$$

$$h_j(x) = 0, j = 1,2, \dots, K \tag{3}$$

$$x_i^L \le x_i \le x_i^U, \quad i = 1,2, \dots, n \tag{4}$$

2.2 Pareto optimal front

For each multi-objective optimization problem, several equilibrium or compromise solutions could be found, which are known as Pareto optimal solutions. Karami & Dariane (2022) indicate that the Pareto front is the graph of the objective functions considering non-dominated solutions, i.e., solutions that are superior to the rest of the components of the decision space. A solution, such as the decision vector, is optimal if it is not dominated by any other solution in the decision space. When a solution is not dominated, it is not worse in any of the objectives, and is better in at least one of the objectives. The non-dominated solution is called Pareto optimal, and the set of such optimal compromise solutions is known as the Pareto optimal set, while its image in the objective space is known as the Pareto front.

Figure 1 presents both the decision space and the objective space for the case of an optimization problem for which two objective functions need to be minimized, and two decision variables are available. For illustration purposes, only three points are represented in the decision space, which are mapped to the objective space. In this case, point p3 represents a dominated solution, and points p1 and p2 are part of the Pareto optimal set, and their images in the objective space fall within the Pareto front.

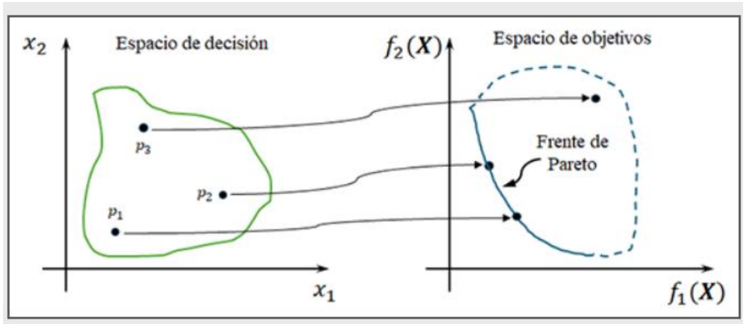

Figure 1. Decision and target spaces

On the other hand, Figure 2 shows the graph of a generic Pareto front in which there are three characteristic points: the utopia point at which the two functions reach their individual optima, but which is not really part of the front, and the two anchor points, at which each function reaches its optimum and which do form part of the Pareto front. These three points are defined in Yeung & Zhang (2023), who also incorporate the nadir point, which simultaneously represents the worst values of the objective functions.

Currently, a variety of techniques exist for finding the Pareto front. In the research of Emmerich & Deutz (2018) they classify these techniques into three categories: scalarization techniques, numerical algorithms, and evolutionary algorithms. The first group consists of grouping the objective functions into one (or reformulating all but one as constraints), and the problem is solved restricted to a single objective. The second group consists of combining scalarization methods with mathematical numerical methods to solve a single-objective optimization problem. Finally, the third group lies in using evolutionary algorithms, such as genetic algorithms, to solve the multiobjective optimization problem. This third group is the one used in this research, since, as indicated by Zitzler et al. (2004), the generation of the Pareto front could be computationally very costly, and may not even be feasible to obtain, depending on the complexity of the application. For this reason, use has been made of evolutionary algorithms to obtain the approximation of the Pareto front.

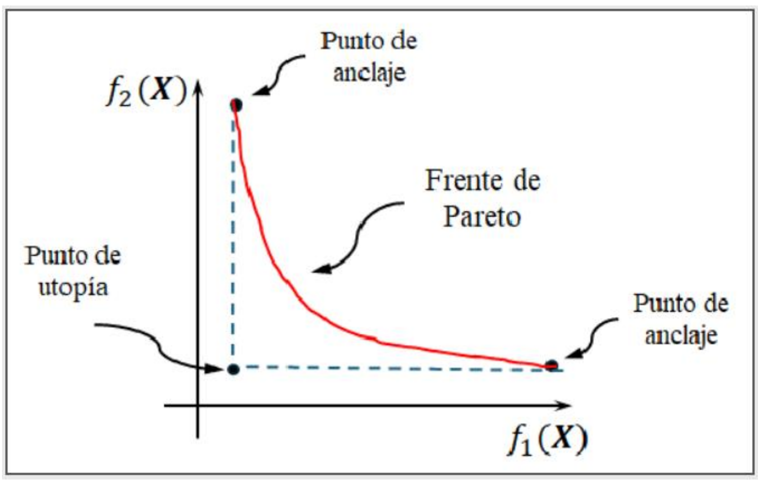

Figure 2. Generic Pareto Front

2.3 Evolutionary multi-objective optimization

Multi-objective evolutionary algorithms (MOEA) are a type of stochastic optimization methods that simulate the process of natural selection. Since the 1970s, a variety of evolutionary methodologies have been proposed, and according to Zitzler et al. (2004) these methodologies work on a set of candidate solutions, which is modified through two basic principles: selection and variation. Selection mimics the competition for reproduction and resources among living things, and variation mimics the natural ability to create "new" life forms through recombination and mutation.

The aforementioned authors establish that an evolutionary algorithm is characterized by having three main elements: a set of candidate solutions, a selection process (mating) applied to the set of candidate solutions, and a recombination process to generate new solutions. Making analogy with natural evolution, candidate solutions are called individuals, and the set of candidate solutions are called population. The selection process usually consists of two stages: adaptability (fitness) and sampling (sample).

In the first stage, individuals in the current population are evaluated in the objective space and then assigned a scalar value called fitness, which reflects their quality. Subsequently, the sampling stage occurs, in which individuals are selected from the population according to their fitness values and placed in a mating pool. A commonly used sampling method involves randomly selecting two individuals from the population, and the one with the best fitness value is copied into the pool. This procedure is repeated until the pool is full.

The variation operators are then applied to the individuals located in the pool; these are generally the mutation and recombination operators. The recombination operator takes a certain number of individuals (parents) and creates a predefined number of offspring by combining parts of the parents. Associated with this operator is a crossover probability. On the other hand, the mutation operator modifies the individuals by changing small parts of them in the associated vector, according to a given mutation rate. It may be the case that some individuals are merely copies of the previously generated solution due to the random effect of the process.

Finally, there is the environmental selection process, which determines which individuals from the population and the modified pool will form the new population. One approach is to use the modified pool as the new population; another approach is to combine both sets and then select the best individuals, although these are not the only two approaches commonly used.

Coello et al. (2007) classify MOEA algorithms into three types: clustering functions, population-based approaches, and Pareto-based approaches. The Pareto-based approach consists of a selection scheme based on the concept of Pareto optimality. It uses the concept of fitness to maintain diversity and prevent the genetic algorithm from converging to a simple solution. According to Coello et al. (2007), this approach can be divided into two generations: a first generation characterized by the use of adaptive capacity combined with a Pareto ranking; and a second generation that emerges with the introduction of the concept of elitism. Elitism usually refers to the use of an external population to retain non-dominated solutions. This population is also called a secondary population. Some of the most representative MOEAs of this second generation are: Force Pareto Evolutionary Algorithm (SPEA), Force Pareto Evolutionary Algorithm 2 (SPEA2), Non-dominated Sorting Genetic Algorithm II (NSGA II), Niche Pareto Genetic Algorithm 2 (NPGA II).

The NSGA algorithm ranks the population based on non-dominance before selection. All non-dominated individuals are classified into a category with a fitness value proportional to the population size, thereby providing identical reproductive potential for these solutions. To maintain population diversity, fitness is partitioned among these classified individuals using arbitrary fitness values previously defined. This group of classified solutions is then ignored, and another layer of non-dominated individuals is considered. This process is repeated until all individuals in the population are classified. NSGA II is a revised version of the first-generation NSGA algorithm. It is computationally more efficient, uses elitism, and a fill-in comparison operator to maintain diversity without specifying any additional parameters. It does not use external memory; its elitism mechanism consists of combining the best relatives with the best offspring obtained.

2.4 Multiple linear regression

This is a supervised machine learning algorithm, and it uses a series of explanatory or regressive variables that define the behavior of a target variable. The model is said to be linear in the parameters (coefficients) and not necessarily in the variables. If there are k explanatory variables, as proposed by Gujarati & Porter (2010), the expression for the target variable is presented below:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \epsilon_i \quad (5)$$

In equation (5) it is true that Y_i is the target variable, $X_{1i} \ldots X_{ki}$ are the explanatory or regressive variables, ϵ_i is the stochastic disturbance term, and i is the ith observation of the data set. Likewise, β_0 is the average value of the target variable when all predictors are equal to zero, and $\beta_1 \ldots \beta_k$ are the regression coefficients.

According to Gujarati & Porter (2010), there are generally three methods for estimating regression coefficients, also known as parameter estimation: ordinary least squares, maximum likelihood, the method of moments, and its extension, the generalized method of moments. The first of these, the ordinary least squares method, is usually used.

Additionally, they argue that the linear regression model is based on certain assumptions; for example: there is no exact or quasi-exact collinearity between the explanatory variables, the stochastic disturbance term is normally distributed, the number of observations must be greater than the number of parameters to be estimated, the regression model is linear in the parameters, the mean value of the stochastic disturbance is zero, among others.

3 Results and discussion

The results obtained are presented and discussed below, including the development of the multi-objective optimization problem model and the Pareto front obtained after applying the NSGA II algorithm using the Python programming language.

3.1 Multi-objective problem model

Function F1 minimizes the generation of the hydroelectric plants associated with reservoirs 1 and 2 (see equation 6); that is, it minimizes the sum of the generation of both reservoirs. Function F2 minimizes electricity rationing in the region where the reservoirs are located (see equation 7). The historical maximum demand, corresponding to the 20th hour of the day, is considered.

Regarding the operation of the generators at Reservoirs 1 and 2, historical operating limits were assumed for the 2021-2023 period. For the Reservoir 1 plant, generation ranged from 0 MW to 185 MW, and for the Reservoir 2 plant, generation ranged from 0 to 201 MW. For the remaining hydrothermal generation plants in the area, overall generation is expected to be between 300 MW and 700 MW. For the transfer limit to the area, the values are set between 200 MW and 400 MW.

For reservoir elevations, the minimum operating limit of each reservoir is considered a constraint. To this end, a linear relationship is generated between the respective elevation as the target variable and the decision variables as the explanatory variables, using a multiple linear regression model. Two constraint equations associated with the reservoir elevations are obtained: see equation 12 for reservoir 1 and equation 13 for reservoir 2. The regression model for reservoir 1 elevation had an R^2 of 59% and a mean absolute percentage error (MAPE) of 1.1% on the test data. The regression model for reservoir 2 elevation had an R2 of 53% and a MAPE of 0.43% on the test data.

Finally, the model would be as follows:

$$F_1: min\ (x_1 + x_2) \quad (6)$$

$$F_2: min\ (1400 - x_1 - x_2 - x_3 - x_4) \quad (7)$$

Subject to:

$$0 \leq x_1 \leq 185 \quad (8)$$

$$0 \leq x_2 \leq 201 \tag{9}$$

$$300 \leq x_3 \leq 700 \tag{10}$$

$$200 \leq x_4 \leq 400 \tag{11}$$

$$0{,}0813 \cdot x_2 - 0{,}013 \cdot x_3 - 0{,}055 \cdot x_4 + 32{,}67 \geq 0 \tag{12}$$

$$0{,}0316 \cdot \mathrm{x}_1 - 0{,}007 \cdot \mathrm{x}_3 - 0{,}025 \cdot \mathrm{x}_4 + 15{,}08 \geq 0 \tag{13}$$

Where：

x1: Power generated by plant 1, in MW.

x2: Power generated by plant 2, in MW.

x3: Average hourly power generated by the remaining plants, in MW.

x4: Transfer limit through the transmission system, in MW.

3.2 Pareto front

Prior to running the NSGA II algorithm, its parameterization was carried out, leaving a population size equal to 100, a total of 1000 generations, a crossover probability equal to 0.9, a mutation probability equal to the inverse of the number of decision variables, the crossover operator of the "simulated binary" type, a polynomial mutation operator, and the initialization of the "Latin hypercube" type.

After applying the algorithm, the Pareto front shown in Figure 3 was obtained. It can be seen that the utopia point corresponds to the trivial solution when there is zero generation in the plants of reservoirs 1 and 2, and all the demand is satisfied with the generation of the rest of the plants, plus what is transferred through the transmission system.

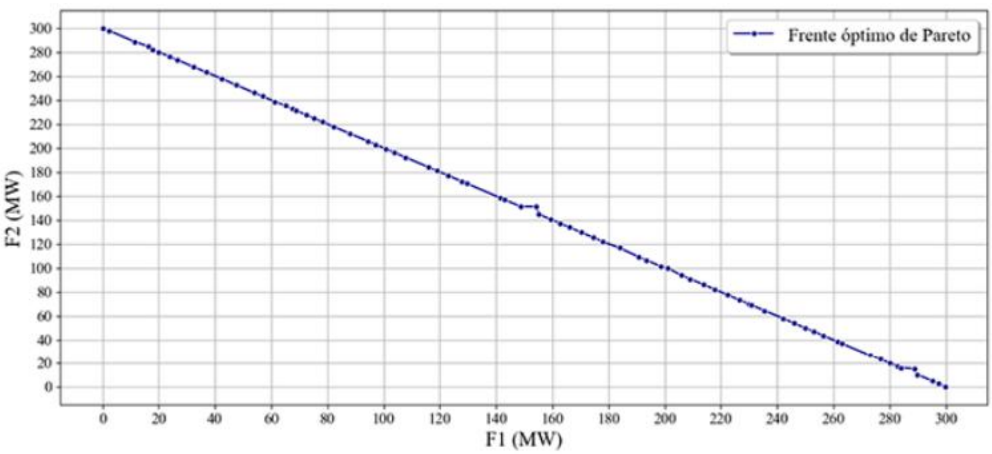

Figure 3. Pareto Front

Figure 3 also shows that the upper anchor point corresponds to zero generation in reservoirs 1 and 2 and rationing of 300 MW, as well as generation from the rest of the plants of 700 MW and a transfer limit of 400 MW. The lower anchor point comprises a generation of 298.12 MW in the reservoir plants and a rationing of 2.01 MW. The generation of the reservoir 1 plant would be 118.51 MW, that of reservoir 2 of 179.6 MW, that of the rest of the plants 700 MW, and the transfer limit at 400 MW.

Between the two anchor points, there are an additional 76 non-dominated points that complete the Pareto front. This is a considerable number of non-dominated solutions, which provides flexibility for reservoir management. For example, in Jena et al. (2022), only 20 non-dominated solutions are obtained using the NSGA II algorithm, as is the case in Hojjati et al.'s (2018) study when using the same optimization algorithm.

To apply the NSGA II algorithm to the optimization problem, the Platypus evolutionary computing framework was used with the Python language, and the time to obtain the Pareto front was approximately 4.55 seconds.

4 Conclusion

A multi-objective optimization model was developed to minimize the electricity production of the hydroelectric plants associated with two reservoirs, while simultaneously minimizing electricity rationing in the region partially supplied by the plants at the aforementioned reservoirs. The model considers compliance with the minimum and maximum operating limits of the reservoirs as model constraints, whose mathematical expressions were found using the machine learning algorithm multiple linear regression.

After applying the NSGA II algorithm, the Pareto front of the multi-objective optimization problem was found. This front has a total of seventy-eight non-dominated solution points, including the two anchor points. These solutions can be considered for the operation of the plants associated with the reservoirs under study, during the hours of the day when electricity demand is expected to be highest. The time taken to obtain the Pareto front using Python and the Platypus framework was only 4.55 seconds.

It is recommended to compare the results obtained using other multi-objective optimization algorithms and select the appropriate indicators to evaluate the performance of each algorithm used. It is also recommended to incorporate monetary and environmental cost constraints associated with thermal plants and the rest of the region's electricity generation. Finally, it is advisable to incorporate a multi-criteria decision-making technique to select the best point on the Pareto front obtained.

Conflicts of interest

The author declares no conflicts of interest regarding the publication of this paper.

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