Turbines Allocation Optimization in Hydro Plants via Computational Intelligence

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Abstract. In the last decades, due to environmental concerns and the decentralization of the electrical systems around the world, the share of Hydroelectric Power Plants (HPP) in the electricity matrix has grown year by year. Therefore, it is necessary to determine the operational planning of the hydro plants to schedule the optimum number of turbines on operation on a daily planning horizon aiming at supplying the generation goals at the lowest possible cost. The main goal of this work is to evaluate and compare the performance of two recent computational intelligence techniques, Grey Wolf Optimizer (GWO) and the Sine Cosine Algorithm (SCA), on obtaining the optimized dispatch of hydro plants regarding the Turbine Allocation Planning (TAP) problem. Mathematically, TAP is classified as a multimodal non-linear problem with mixed-integer variables. In order to test the aforementioned metaheuristic techniques, one HPP composed of five turbines on a 24-h planning horizon was considered. The results point to a better performance of the GWO technique on the HPP daily operation.

Keywords: Dispatch optimization · Turbine allocation problem · Unit commitment · Sine Cosine Algorithm · Grey Wolves Optimization

1 Introduction

The Hydroelectric Power Plants (HPP) operation programming is an important part of the Energy Operation Planning (EOP) problem. In the very short-term planning, which corresponds to the problem investigated in this work, the determination of which hydro turbines must be in operation aiming at the optimized attendance of the hourly generation goals is a complex problem and needs to be addressed before the dispatch [1].

The use of intelligent computational techniques has grown over the last years on the hydro turbine allocation problem. Thus, the present work presents a comparison between two recent techniques, the Grey Wolf Optimizer (GWO) and the Sine Cosine Algorithm (SCA), on the EOP problem. Both optimization techniques are promising in

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solving various optimization problems because they are able to perform global and local searches efficiently. Applications of these algorithms include smart grids energy management [2], multi-robot exploration [3], inverters harmonics elimination [4], filters design [5], reactive power dispatch [6], phasor measurement unit placement in power grids [7], load demand forecast [8] and space shuttle re-entry trajectory optimization [9].

The main goal of the optimization model described in this work is to minimize the total costs of operation, which are represented by:

- Units' start-up or shut-down costs;
- Units' power losses costs.

The Brazilian electric System National Operator (ONS) provides the generation goals and forecasted demands to the power plants, so it is important that the turbines attend these goals on the planning horizon in order to avoid penalizations for not supplying energy to the consumers.

Mathematically, it is a non-linear mixed-integer optimization problem with certain particularities, such as multimodal solution region and combinatorial explosion concerning the alternatives of operation, resulting in a high computational burden.

In the technical literature, there are three large groups of algorithms used to solve this sort of problem: heuristic constructive algorithms [10–13]; classical optimization algorithms [10, 14, 15]; computational intelligence [16–18].

Heuristic Constructive Algorithms are usually fast, robust, and present low computational effort to find feasible solutions. However, they rarely reach the global optimum on large real problems. Their probability of achieving the best solution is inversely proportional to the size and modeling of the problem [10].

Classical Optimization Algorithms use decomposition techniques and generally require gradient information. This optimization class usually require a good starting point to achieve the global optimum. When dealing with large problems, they may present computational effort and convergence problems [11, 14]. They often reach the optimal solution when used in small-sized systems [10].

Computational Intelligence uses the combination of random initial solutions with historical knowledge acquired from the results obtained during the optimization process to guide their neighborhood searches on the solution region [16–18]. It usually requires more effort than the heuristic algorithms. However, over the last years, computational intelligence techniques have followed the technological evolution of computers, resulting in enhancements of existing techniques and developments of new ones.

Besides this initial section, this work has five more sections. Section 2 presents the mathematical formulation of the problem. In Sect. 3, both techniques investigated in this work, i.e., GWO and SCA, are briefly presented. Section 4 exposes the results obtained on the turbine allocation planning and their analysis. Section 5 presents the conclusions and the next steps related to this work.

2 Mathematical Formulation of the Problem

The mathematical formulation proposed in [12, 15] to optimize the operation of a particular HPP is used in this work. This model is described by Eqs. (1) to (3). It is important to note that, in this modeling, the entire set of turbines has the same nominal data, i.e., the generators and hydro turbines were considered identical to each other regarding their characteristics, such as generators' efficiency curves and hill curves.

$$Min \sum_{t=1}^{T} \left\{ c_{su/sd} \cdot |n_t - n_{t-1}| + c_e \cdot p_n(d_t) \right\} \tag{1}$$

subject to:

$$n_t \in Z \tag{2}$$

$$n_{t_{min}}(d_t) \leq n_t \leq n_{t_{max}}(d_t) \tag{3}$$

In this formulation: n_t is the number of turbines operating at hour t; $n_{t_{min}}(d_t)$ is the minimum number of turbines that can attend the generation goal at hour t; $n_{t_{max}}(d_t)$ is the maximum number of turbines that can attend the generation goal at hour t; c_e is the unitary cost of energy [US$/MWh]; T is the number of hours that compose the planning horizon; $c_{su/sd}$ is the cost of a start-up or shutdown [US$]; $p_n(d_t)$ is the function describing the total power losses for n turbines operating at hour t.

Equation (1) describes the objective function that aims at minimizing the total cost associated with the active power losses and the start-ups/shutdowns of turbines. Equation (2) presents the integrity of $n_t \in \mathbb{Z}$. Equation (3) presents the lower and upper bounds of n_t, i.e., respectively, the minimum and the maximum number of units that can attend the generation goal at a particular hour. As a result, the solution of this unit commitment problem aims at supplying the planner with the optimum number of units that must operate at each hour at the lowest possible cost, regarding the planning horizon.

2.1 Losses Functions Modeling

From the following set of input data, it is possible to obtain the power loss functions used in this work: n_{maq} is the total number of existent turbines on the HPP; k_p is the penstock losses coefficient; q_{min} and q_{max} are the minimum and maximum water discharge of each turbine, respectively; the generators' efficiency curve; the turbines' hill curve; n_0 represents the number of turbines operating at hour 0, i.e., the hour immediately before the first hour of the planning horizon; h_f is the forebay elevation; the level-release polynomial, which provides the tailrace elevation as a function of the total water release; g is the gravitational acceleration; ρ is the reservoir water density. The steps used to obtain the mentioned functions are described as follows:

(i) The number of operating turbines (n) is varied from 1 to n_{maq};
(ii) For each configuration, i.e., each value of n, the water discharge (q) is varied from $n \cdot q_{min}$ to $n \cdot q_{max}$;

(iii) For each configuration and for each value of q, the level-release polynomial is used to calculate the corresponding tailrace elevation (h_t);

(iv) After step (*iii*), it is possible to determine the penstock head losses (h_p) and calculate the net head (h_l) using the Eqs. (4) and (5);

$$h_p(q) = k_p \cdot q^2 \tag{4}$$

$$h_l(q) = h_f - h_t(q) - h_p(q) \tag{5}$$

(v) Regarding the prohibitive zone of operation obtained from the hill curve, the feasibility of q is verified based on the net head previously calculated;

(vi) If the current value of q is out of bounds, the process goes back to step *(ii)* with a new value of q;

(vii) However, considering that q is feasible, the efficiency of the turbines (η_{tur}) is obtained from the hill curve and the mechanical power (p_m) of one supplier unit is calculated using Eq. (6).

$$p_m = 10^{-6} \cdot g \cdot \rho \cdot \eta_{tur}(q/n, h_l) \cdot h_l(q) \cdot q/n \tag{6}$$

(viii) It is important to highlight that the generators' efficiency (η_{ger}) was not used on Eq. (6). This parameter is obtained by utilizing the generators' efficiency curve and Eq. (7) in an iterative method based on the current operating point. This equation is responsible for describing the relationship between the power output of one supplier (p_g) and p_m.

$$p_g = p_m \cdot \eta_{ger}\left(p_g\right) \tag{7}$$

(ix) Respectively, it is possible to calculate the penstock losses (p_{pn}), the losses provoked by the increase in h_t (p_{tn}), and the turbine losses ($p_{\eta n}$) with the Eqs. (8–10). In (10), η_{max} represents the maximum efficiency of the turbines, which can be extracted from the hill curve. The total losses (p_{tot}) and total generation ($p_{g_{tot}}$) for the current values of q and n are given, respectively, by the Eqs. (11) and (12);

$$p_{pn} = 10^{-6} \cdot k_p \cdot q^2 \cdot g \cdot \rho \cdot \eta_{tur}(q/n, h_l) \cdot \eta_{ger}\left(p_g\right) \cdot q \tag{8}$$

$$p_{tn} = 10^{-6} \cdot (h_t(q) - h_t(n \cdot q_{min})) \cdot g \cdot \rho \cdot \eta_{tur}(q/n, h_l) \cdot \eta_{ger}\left(p_g\right) \cdot q \tag{9}$$

$$p_{\eta n} = 10^{-6} \cdot h_l \cdot g \cdot \rho \cdot (\eta_{max} - \eta_{tur}(q/n, h_l)) \cdot \eta_{ger}\left(p_g\right) \cdot q \tag{10}$$

$$p_{tot} = p_{pn} + p_{tn} + p_{\eta n} \tag{11}$$

$$p_{g_{tot}} = n \cdot p_g \tag{12}$$

(x) For each configuration, the minimum and maximum generated powers are determined and stored. These are essentials to obtain $n_{t_{min}}$ and $n_{t_{max}}$. Furthermore, for each possibility of q different from the minimum value, the total generation is compared to the total generation provided by the previous q, aiming at observing a reduction on the generated power. This effect is justified by the drop in the turbine's efficiency, increase in tailrace elevation and/or increase in penstock losses caused by high values of water discharge. If such an effect is detected, the process is interrupted on the current configuration even if the maximum water discharge is not yet reached. Thus, the algorithm proceeds to a new configuration;

(xi) The polynomials are adjusted to the total losses and total generation points.

In this work, the HPP is modeled as a run-of-the-river plant composed of five turbines. Thus, the forebay elevation is considered constant. This consideration is valid for daily operation planning's since variations in the reservoir's level in such a small period are irrelevant, however, it should not be utilized in longer planning horizons.

Taking into account the characteristics of the downstream basin and assuming h_f as a constant, the verified net head low variation regarding the total water discharge imposes insignificant variation on the turbines' efficiency. Therefore, in this case, η_{tur} can be described as a water discharge only function. For that reason, only two points are necessary to model the prohibitive zones of operation: the minimum and the maximum water discharge values. Such an approach slightly affects the model's proximity to reality, though, for this particular HPP, it does not compromise the optimization process nor the analysis of the results.

Based on the model presented in this section, the functions that represent the total losses for each operation alternative are illustrated in Fig. 1. The losses components for the HPP operating with the maximum number of turbines are shown in Fig. 2.

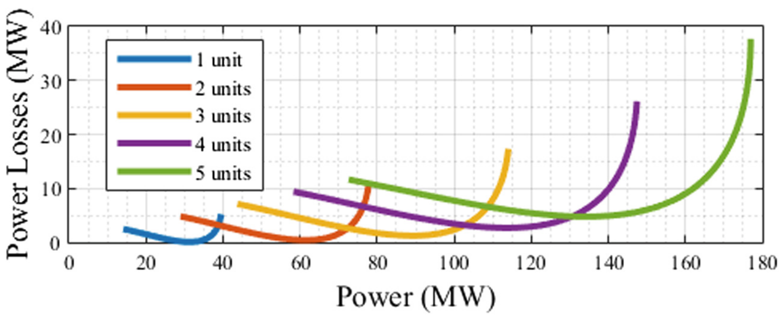

Fig. 1. Total losses curves for each configuration.

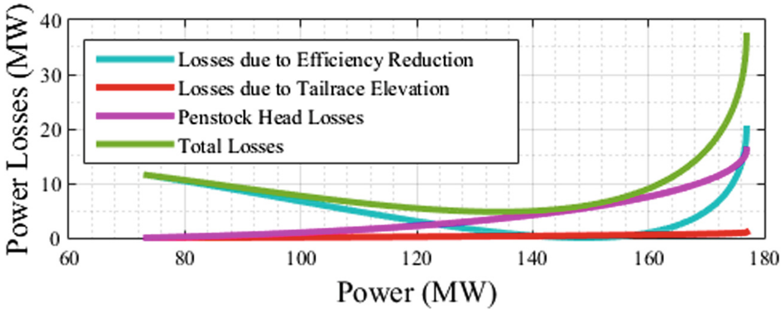

Fig. 2. Losses components for the HPP operating with five turbines.

3 Investigated Techniques

From the union of optimization concepts and artificial intelligence, it was possible to design more efficient and intelligent heuristic strategies, which were baptized as metaheuristics, also known as computational intelligence techniques. Computational intelligence is the science that seeks to develop algorithms and methodologies that emulate behaviors similar to certain aspects of intelligent behavior (human and/or inspired by nature) to solve complex problems.

Considering the described framework, numerous researchers in recent years have developed new approaches to optimize problems via computational intelligence, inspired by biological adaptation mechanisms in nature. Within this context, many algorithms were developed based on nature or human behaviors, such as: Genetic Algorithm (GA), based on the Theory of Evolution of the species; Particle Swarm Optimization (PSO), Bat Algorithm (BA), and Ant Colony Optimization (ACO), which are based on the observation of colonies searching for food; Artificial Immune System (AIS), based on the functioning of the mammalian immune systems defending the organism against invaders; and so on. These algorithms have shown great efficiency in solving numerous problems not only in engineering but also in other areas of knowledge.

In the literature, there are different classifications concerning the metaheuristics, which consider the algorithm inspiration (biology, physics, chemistry, among others) and the number of solutions involved in the optimization process (individual or population) [19].

In the present work, the authors decided to investigate two population-based techniques. The Grey Wolf Optimizer (GWO) [20] and Sine Cosine Algorithm (SCA) [19], both developed by Mirjalili, were assessed aiming at reaching the main goal of this work: minimizing the total costs of operation on an HPP daily planning.

3.1 Grey Wolf Optimizer - GWO

The GWO is based on the social hierarchy and hunting behavior of grey wolves. The hierarchy of grey wolves is divided into alphas, betas, deltas, and omegas, respectively, in order of dominance. The alpha wolf, also called the dominant wolf, is primarily responsible for decision makings, such as hunting, sleeping, and waking times. The beta wolf is the right arm of the alpha wolf and helps him in taking decisions. The delta wolves belong to the categories of scouts, sentinels, elders, hunters, and caretakers. Finally, the omegas, the lowest level of the hierarchy, play the scapegoat role.

The wolves hunting strategy is performed in stages: (*i*) track, chase and approach the prey; (*ii*) surround the victim until it stops its movement; (*iii*) attack the prey. The pseudocode that describes the GWO framework is presented on Algorithm 1.

Regarding the GWO algorithm, the size of the wolves population is given by N_{wolves}, which represent the number of investigated solutions inside the solution region. The variables values of the solutions are randomly initialized. The solutions are evaluated by its numerical value on the fitness function and the hierarchy of the wolf pack is defined. In this work, from the best to the worst, the three best turbine allocation schedules are, respectively, the alpha (X_α), the beta (X_β) and the delta (X_δ) wolves.

After the initialization process, the iterative process, i.e., the hunting stage, begins, which results in the whole wolf pack update. For such, the search coefficients vectors $\vec{A}$ and $\vec{C}$ are necessary (from rows 7 and 8 of Algorithm 1). These coefficients propitiate local or global search during the wolves' upgrade phase in the iterative process. Local search occurs when A < 1, i.e., the best solution is refined, which, in the proposed method, represents the wolves attacks to the prey (convergence to the best solution). However, when A > 1, the global search occurs, in which the solutions (wolves) tend to seek better evaluations by exploring the solution region. Regarding vector C, C < 1 attenuates and C > 1 increases the magnitude of the best solution. The component $\boldsymbol{a^t}$ decreases a portion at each iteration ($\boldsymbol{t}$), starting at 2 and ending at 0.

Algorithm 1. Grey Wolf Optimizer

1 :	Initialization of the grey wolves population: $\boldsymbol{X_i}$ $(\boldsymbol{i = 1, 2, 3 \ldots N_{wolves}})$
2 :	Wolves fitness function: $\boldsymbol{F_f(X_i)}$
3 :	Hierarchy definition ($\boldsymbol{X_\alpha}$, $\boldsymbol{X_\beta}$ e $\boldsymbol{X_\delta}$)
4 :	While (stop criterion is not met) do:
5 :	Update the search parameter: $\boldsymbol{a^t}$
6 :	For 1 to $\boldsymbol{N_{wolves}}$
7 :	$\vec{A} = a^t.\vec{r}_1 - a^t, \qquad \vec{r}_1 \in [0, 1]$
8 :	$\vec{C} = 2.\vec{r}_2, \qquad \vec{r}_2 \in [0, 1]$
9 :	$\vec{D}_\alpha = \lvert \vec{C}_1.\vec{X}_\alpha^t - \vec{X}_i^t \rvert,\ \vec{D}_\beta = \lvert \vec{C}_2.\vec{X}_\beta^t - \vec{X}_i^t \rvert,\ \vec{D}_\delta = \lvert \vec{C}_3.\vec{X}_\delta^t - \vec{X}_i^t \rvert$
10 :	$\vec{X}_1 = \vec{X}_\alpha^t - \vec{A}_1.\vec{D}_\alpha,\ \vec{X}_2 = \vec{X}_\beta^t - \vec{A}_1.\vec{D}_\beta,\ \vec{X}_3 = \vec{X}_\delta^t - \vec{A}_1.\vec{D}_\delta$
11 :	$\vec{X}_i^{t+1} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$
12 :	Update the wolves hierarchy: $\boldsymbol{X_\alpha}$, $\boldsymbol{X_\beta}$ e $\boldsymbol{X_\delta}$
13 :	End for
14 :	End while

The positions of the wolves are updated after each iteration, i.e., after each movement of the wolf pack on the hunting process. Regarding the Algorithm 1, the rows 9 and 10 represent the behavior of the wolves surrounding the prey during hunting, whose location is identified by the alpha, beta and delta wolves. Therefore, the estimated position, $\vec{X}_i^{t+1}$, which represents the updated wolf position, is defined on row 11 by the average displacement of the dominant wolves. Finally, the wolves' hierarchy is updated and the process is repeated until it reaches the stopping criterion.

3.2 Sine Cosine Algorithm - SCA

The SCA is considered a population optimization technique, which is based on the sine and cosine mathematical functions. In SCA, the local and global searches are performed according to random and adaptive variables integrated into the algorithm. Algorithm 2 describes the SCA framework.

Algorithm 2. Sine Cosine Algorithm

1 :	Initialization of the solutions: $\boldsymbol{X_i}$ $(\boldsymbol{i = 1, 2, 3 \ldots N_{sol}})$
2 :	Evaluation of the solutions by the fitness function: $\boldsymbol{F_f(X_i)}$
3 :	Definition of the best solution $(\boldsymbol{P}^*)$
4 :	While (stop criterion is not met) do:
5 :	Update the search parameter : $\boldsymbol{r_1^t} = \boldsymbol{a - t\frac{a}{T_{max}}}$
6 :	For 1 to $\boldsymbol{N_{sol}}$
7 :	$\boldsymbol{X_i^{t+1}} = \begin{cases} \boldsymbol{X_i^t + r_1^t.sin(r_2).\lvert r_3.P^* - X_i^t \rvert,\ r_4 < 0,5} \\ \boldsymbol{X_i^t + r_1^t.cos(r_2).\lvert r_3.P^* - X_i^t \rvert,\ r_4 > 0,5} \end{cases}$ $\boldsymbol{r_2 \in [0, 2\pi], r_3 \in [0, 2], r_4 \in [0, 1]}$
8 :	Update the best solution $(\boldsymbol{P}^*)$
9 :	End for
10 :	End while

As in the GWO, in the SCA, the total number of solutions is predefined and these solutions are randomly dispersed in the solution space. They are evaluated by the fitness function and the best one, P^*, is selected. Then, the search process begins. The exploration of the search space is determined by "movements" of the current solutions, X_i^t, towards the best solution. Regarding the Algorithm 2, at row 7, the solutions are updated according to the random component r_4, which determines whether it will be a sinusoidal or cosinusoidal update.

The parameter r_1 is a function subject to the maximum number of iterations (T_{max}), the current iteration (t), and the exploration constant (a). In fact, analyzing Algorithm 2, row 5 shows that r_1 decreases during the iterative process. This variable's behavior privileges the global search at the beginning of the optimization process and the local search at the end of the process. If $r_1 < 1$, it is estimated that the solution's new position may be between the current solution, X_i^t, and the best one, P^*, or outside this region, considering $r_1 > 1$. The parameter r_2 is the pitch towards or outwards the best solution. $r_3 < 1$ attenuates and $r_3 > 1$ increases the weight of the best solution in the position update process. Finally, the algorithm updates the position of the best solution, P^*. That process is repeated until it reaches the stopping criterion.

4 Simulations, Results, and Analysis

In order to evaluate the methodologies here investigated, their efficiencies in obtaining the optimum turbine allocation planning of an HPP on a daily operation planning were analyzed[1]. This HPP is composed of five turbines. Despite the short number of turbines, the Number of Possible Combinations (NPC) of operating turbines during the planning horizon, given by Eq. (13), is equal to 6^{24}, making it impossible to execute the exhaustive enumeration as a definitive solving method.

$$NPC = (n_{maq} + 1)^T \tag{13}$$

The generation goals (MW) are shown in Fig. 3. It is important to highlight that each turbine is able to supply up to 39.4 MW as nominal power. The main result consists of the determination of the optimal hourly schedule of turbines that must be in operation during the 24-h planning.

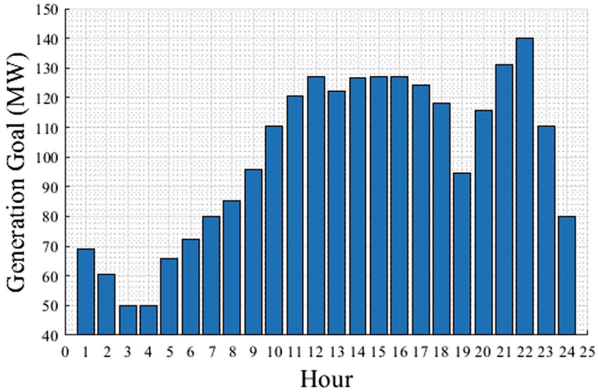

Fig. 3. Hourly generation goals throughout the day.

In order to compare the methodologies (GWO and SCA), they were both initialized with identical solutions in order to guarantee a nonbiased comparison. Both algorithms were implemented in Matlab® and simulated in the same CPU[2]. Regarding the size of the population and the maximum number of iterations (stopping criterion of all simulations), the initial configurations of all simulations contained in this work are

[1] The detailed HPP data used in all simulations presented here, such as efficiency curves and plant parameters, can be consulted at http://bit.ly/HPPdata.

[2] All tests were performed using Matlab R2016a on a standard computer with the following characteristics: Intel® Core i3 CPU M 350 @ 2.27 GHz; 4 GB of RAM using Windows 7 Pro 64 bits.

presented in Table 1. For each configuration, fifty simulations were performed aiming at evaluating both methodologies regarding:

- Running time;
- Quality of the obtained solutions;
- Convergence features.

Table 1. Simulations parameters.

Configuration	Size of the population	Stopping criterion
I	20	50 iterations
II	50	50 iterations

4.1 Results Analysis

The first analysis concerns the operation planning costs obtained on fifty executions of both techniques: GWO and SCA. The variations of the better scheduling regarding the operational costs for configurations I and II are depicted by boxplot graphs on Figs. 4 and 5.

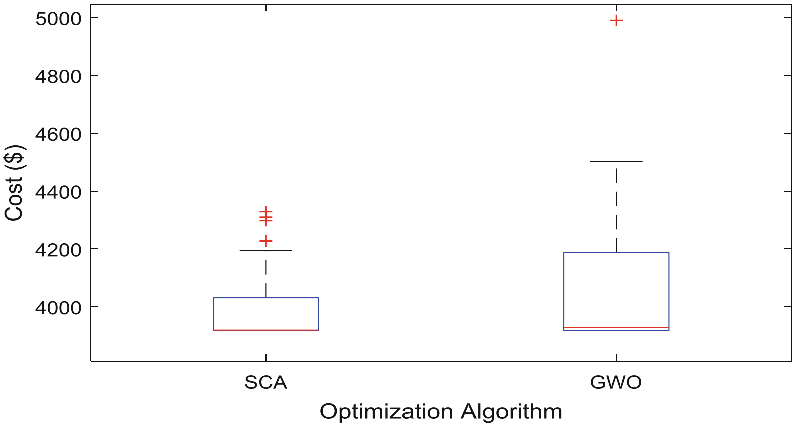

Fig. 4. Configuration I - Optimal solutions obtained by SCA and GWO.

From Fig. 4, it is possible to observe that, even though GWO and SCA have obtained the same optimal solution (3,917 $\times$ 10^3 \$) and practically the same median solution, GWO presented more dispersed solutions than SCA. It should be noted that the (+) in Fig. 4 corresponds to the discrepant planning's obtained, also known as outliers. These discrepant solutions occurred in both methods, although with larger amplitudes on GWO results.

Regarding Fig. 5, which represents larger population simulations, both methods presented similar results regarding the best solution found and the dispersion of the set of solutions. For that configuration, it is possible to admit that both techniques provided practically the same results in the light of the operational costs.

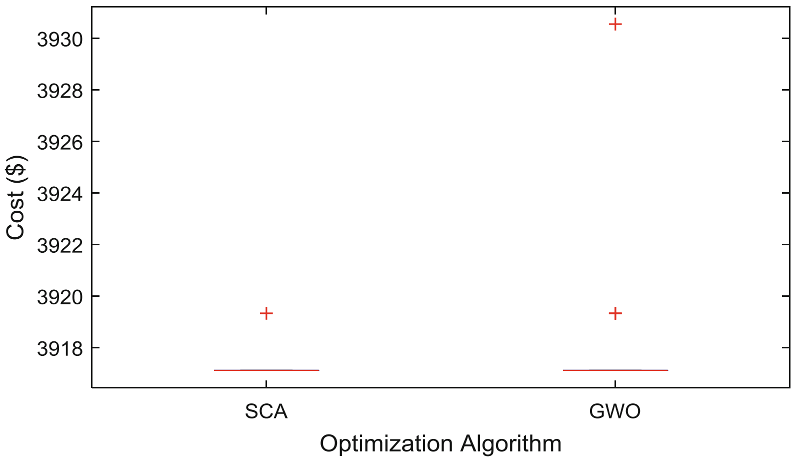

Fig. 5. Configuration II - Optimal solutions obtained by SCA and GWO.

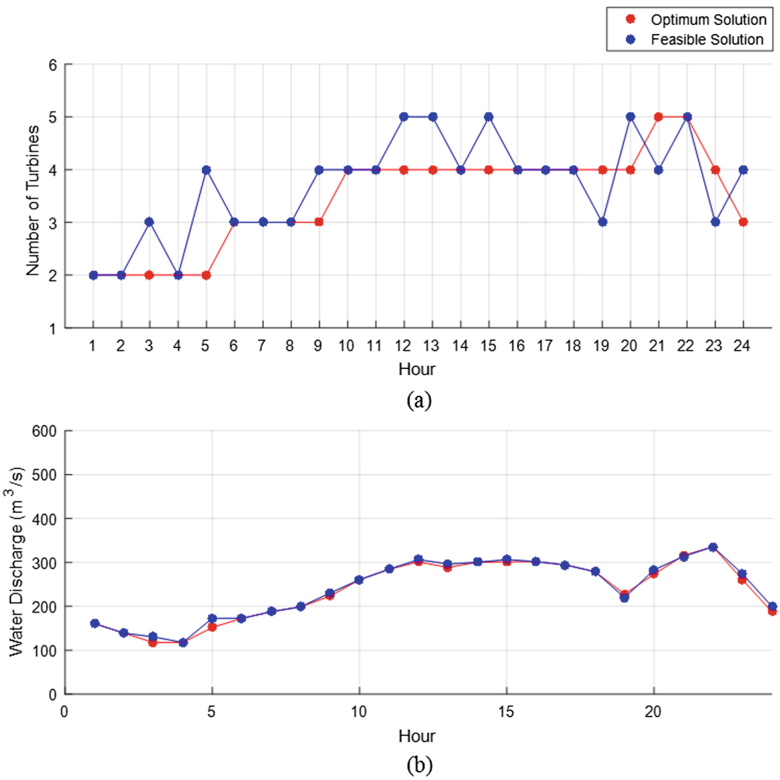

Fig. 6. (a) Number of operating turbines and (b) Total water discharge.

Figure 6 depicts how hydraulic turbines allocation optimization plays a fundamental role in the use of hydric resources. To do so, a comparison was made between the optimal solution obtained by GWO/SCA ($3{,}91 \times 10^3$ \$) and a feasible solution ($1{,}48 \times 10^9$ \$) with respect to the number of operating turbines (Fig. 6a) and water discharge (Fig. 6b) over the twenty-four hours of operation.

Based on the obtained results shown in Fig. 6b, the total water discharge was 5765,777 m^3/s for the feasible solution and 5681,699 m^3/s for the optimal solution. This difference represents a reduction of 84,0776 m^3/s, which results in a saving of 0,3 hm^3 of water in the 24-h period (in certain conditions, this amount can be converted to a 75 MW power generation during an hour). This factor is even more expressive if considering the potential of optimized use of water during longer periods (weeks, months and/or years).

4.2 Convergence Curves Analysis

The second analysis concerns the convergence trajectory of the methodologies. The convergence curves represent the behavior of the best individual on the population over the iterations of the GWO and the SCA. Figures 7 and 8 depict the convergence curves of configurations I and II, respectively, in one particular simulation.

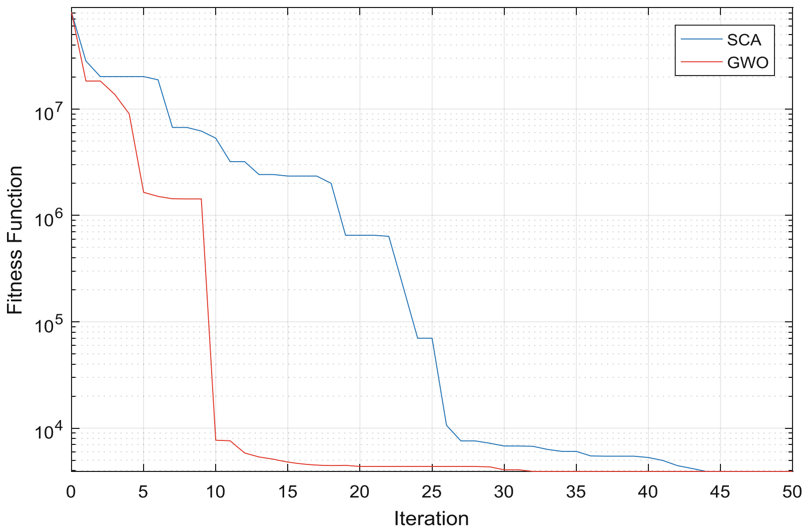

Fig. 7. Configuration I – Convergence curve for both techniques.

According to Fig. 7, SCA's iterative process required 44 iterations to reach the optimal planning. On the other hand, GWO found the same solution in 32 iterations.

Comparing the convergence trajectories of both methodologies, it can be seen that, in both configurations, GWO reached the optimality in fewer iterations than SCA.

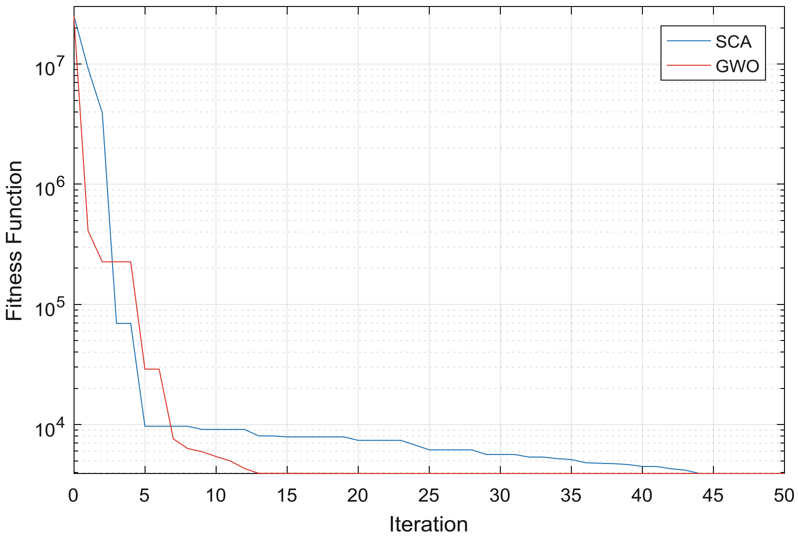

Fig. 8. Configuration II – Convergence curve for both techniques.

Furthermore, in both figures, it is possible to see the dominance of GWO regarding the trajectories.

Regarding the configuration II, Fig. 8 shows that SCA required 44 iterations to find the optimal solution in that particular simulation, whereas GWO required 14 iterations.

For all fifty simulations, the convergence curves' behaviors presented the same pattern shown on Figs. 7 and 8, i.e., GWO's global and local search procedures have shown to be more efficient in obtaining the optimal solution. This algorithm consistently obtained the best solution within a smaller number of iterations compared to the SCA.

Table 2 summarizes the results obtained for all simulations. This table depicts the minimum cost, average cost, maximum cost, and average simulation time required. It should be noted that the discrepant values of the outliers were not considered for statistical analysis.

Table 2. Summary of obtained results for GWO and SCA.

Configuration	SCA		GWO	
	I	II	I	II
Minimum cost ($10^3 \times$ US$)	3,917	3,917	3,917	3,917
Average cost ($10^3 \times$ US$)	3,988	3,917	4,059	3,918
Maximum cost ($10^3 \times$ US$)	4,329	3,919	4,990	3,930
Average elapsed time (sec)	11	26	11	26

5 Conclusions and Further Works

The main goal of the present work was to compare the performance of two recent computational intelligence techniques, Grey Wolf Optimizer (GWO) and Sine Cosine Algorithm (SCA), at solving the turbine allocation planning problem aiming at optimizing the dispatch of hydroelectric plants.

Considering the obtained results, it can be verified that with the increase of the population size (configuration II), the performances of both methodologies were similar. However, the GWO method performed better than SCA since it required fewer iterations to obtain the optimal solution, which is justified by how its balanced global (exploration) and local (intensification) procedures work inside the solution region.

Regarding the operation of the hydraulic turbines, both techniques achieved the overall optimum schedule, which was confirmed through the exhaustive enumeration method. The optimum operation schedule enables not only the reduction of involved costs but also a better use of water resources.

As shown in Table 2, both algorithms required relatively short times to reach the stopping criterion. Therefore, even if utilized on a larger HPP, i.e., a plant with more turbines, they can be executed with increased numbers of solutions and/or maximum number of iterations while still being viable regarding execution time. Thus, the authors consider GWO and SCA efficient in solving TAP problems.

For future works, it is intended to:

- Include spinning reserve constraints, which guarantees that a predetermined amount of power generation is rapidly available for possible sudden, urgent and/or unpredicted power demands;
- Study the insertion of hydro pumps, which store hydric resources for high demand periods. Although non-existing in this work's HPP, other ones may possess such equipment;
- Add turbine maintenance constraints, which aims at operating the turbines in a way that as many as possible turbines are available over time;
- Research GWO's and SCA's performances on formulations that consider turbines with different data, e.g., different efficiency curves, on the same HPP since the researched model does not allow such characteristic;
- Research GWO and SCA performances on formulations designed for short, medium and long-term operation schedules, i.e., longer planning horizons than the one studied in the present work;
- Investigate forebay elevation variation approaches during the planning horizon since storage HPPs enable this consideration and longer planning horizons require it;
- Test the algorithms in larger systems models. For instance, systems with more HPPs and/or more turbines.

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