24th COBEM - 2017

24th ABCM International Congress of Mechanical Engineering
December 3-8, 2017, Curitiba, PR, Brazil

COBEM-2017-2029
IDENTIFICATION OF NONLINEAR SYSTEM USING EVOLUTIONARY DIFFERENTIAL AND GREY WOLF OPTIMIZER

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Abstract. *This paper describes the use of a grey box model to found parameters of a nonlinear system applying Grey Wolf Optimizer (GWO) and Differential Evolutionary Algorithm (DE). The system under study is a speed regulator and hydraulic amplifier from a Hydroelectric Generating Unit (UHE). Using field collected data, we were able to find the controller's gains which result in an optimized response. The time response for a load rejection situation obtained by these algorithms is very similar to the real response, which validated the estimated parameters.*

Keywords: *System Identification, Grey Wolf Optimizer, Differential Evolutionary, Hydroelectric Plant*

1. INTRODUCTION

In many engineering problems, the knowledge of the parameters which describe them is of fundamental importance for the correct modeling of the system. Among the several ways of obtaining these parameters, a field that has had enough research is the identification of systems using the grey box approach (Mirjalili *et al.*, 2014). Grey box identification assumes that some information is known from the system, such as its structure, order of the model, whether it is linear or non-linear, among others.

The estimation of the parameters is one of the most important step to the identification of a systems. Its aim is to obtain the parameters of the model, which leads to an output as close as possible to the real system output (Ljung and Glad, 2016).

Optimization is an important tool to deal with complex situations involving engineering, finance, agricultural processes, industries or in any process that involves costs, space limitations and time. Obtaining the parameters of a system through their estimation can be seen as an optimization problem, since the choice of these parameters is done by minimizing the error between the response produced by them and the real system.

Optimization is a process with the focus on obtaining better value from a measurable magnitude, the search for techniques for selecting the best alternatives, making it optimal, achieving the objectives required. It aims to obtain the best parameter setting from a mathematical or experimental process without testing all possibilities.

Generally, the optimization problem seeks to maximize or minimize an objective function of n design variables, with the possibility of lateral constraints and inequality or equality (Billings, 2013). However, an optimization problem can have several solutions and the optimal solution criterion is relative by constraints and objective function.

The objective of this paper is find the parameters of a controller belonging to the speed regulator and hydraulic amplifier of a Hydroelectric Generating Unit (UHE) belonging to the Brazilian National Interconnected System (SIN). This is a nonlinear system, which makes the optimization problem more challenging. The objective function is to minimize the value of the mean square error (MSE) (Allen, 1971) , calculate the signal generated by the identification model and the "reference signal" from the data collected in the real UHE.

For the estimation of the parameters, which can be seen as an optimization problem, it will be used two optimization algorithms: Differential Evolution (DE) algorithm proposed by (Storn and Price, 1995) (Das and Suganthan, 2011) and Grey Wolf Optimization Algorithm (GWO) proposed by (Mirjalili *et al.*, 2014) (Saremi *et al.*, 2015). The use of these algorithms is indicated for solving these types of problems, which can be applied as an algorithmic structure that allows the use in several optimization problems with relatively little changes in algorithms for application between one problem and another.

Section 2 describes the problem in which the metaheuristics will be used. In section 4 the GWO metaheuristics will be presented. In section 5 the DE metaheuristics is presented. Section 6 presents the results obtained using the different metaheuristics to solve the problem. Finally, in section 7 the conclusions are presented.

2. SYSTEM IDENTIFICATION

The system identification becomes challenging when it comes to modeling a real system, due to the representation of the temporal behavior of the system. The system identification process is composed of the following activities: Dynamic tests and data acquisition; Mathematical representation to be used; The choice of the model structure; Estimation of parameters; Validation of the model.

Some important basic concepts in the system identification is the choice of the type of model to be used, among which monovariable and multivariable models can be cited. This ensemble of models is composed of: SISO (single input, single output), MISO (multiple inputs, single output), SIMO (single input, multiple outputs) and MIMO (multiple inputs, multiple outputs). The SISO model is known from its input and output which are unique, whereas the others possess multiple input and/or output variables.

Methods of system identification are divided in three main groups: White-Box, Grey-Box and Black-Box. White-Box modeling is based on applying the laws of physics which can describe theoretically the whole system.

Grey-Box modeling is based on applying the laws of physics to describe partially the system. Black-Box modeling is applied when nothing about the physics of the system is known (Ljung, 1999). In this work the problem will be treated as a Grey-Box, because we know some about the physical behavior of the UHE.

Due the complexity found in the modeling of a system, several types of optimization algorithms have been developed in order to improve quality of the mathematical model. Most of the optimization algorithms are based on evolutionary computing and behavioral orientation. Among evolutionary computation algorithms one can highlight Particle Swarm optimization (Zeugmann *et al.*, 2011), Differential Evolution (Storn and Price, 1995), Cuckoo Search (Yang and Suash Deb, 2009), Grey Wolf Optimizer (Mirjalili *et al.*, 2014), Genetic Algorithm (Koza, 1992).

Using these optimization algorithms, one can estimate nonlinear and linear discrete-time and continuous-time grey-box models for arbitrary ordinary differential or difference equations, using single-output and multiple-output time-domain data, or time-series data (output-only).

3. PROBLEM

The model of Hydroelectric Generating Unit used in (OSINSKI, 2017) is shown in “Fig. 1”. The speed regulator is composed by a PID controller, where Kpr, Tn, Kv are, respectively, the proportional gain, the time constant of the integrator and the derivative gain.

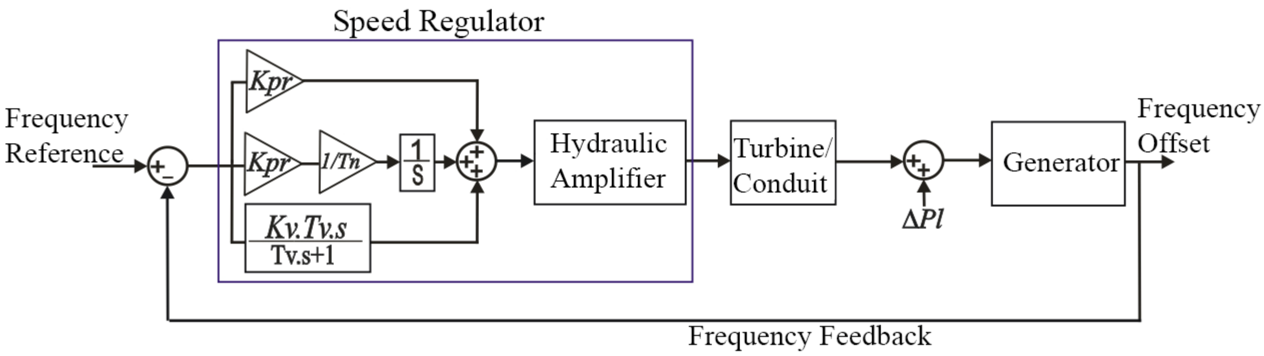

Figure 1. Hydroelectric Generating Unit Model (OSINSKI, 2017).

“Fig. 2” shows the block diagram of the hydraulic amplifier expanded. The distributor is responsible for the admission of water to the turbine and the distributor valve is what produces the distributor drive. The distributor and distributor valve gains are respectively nominated K_1 and K_2.

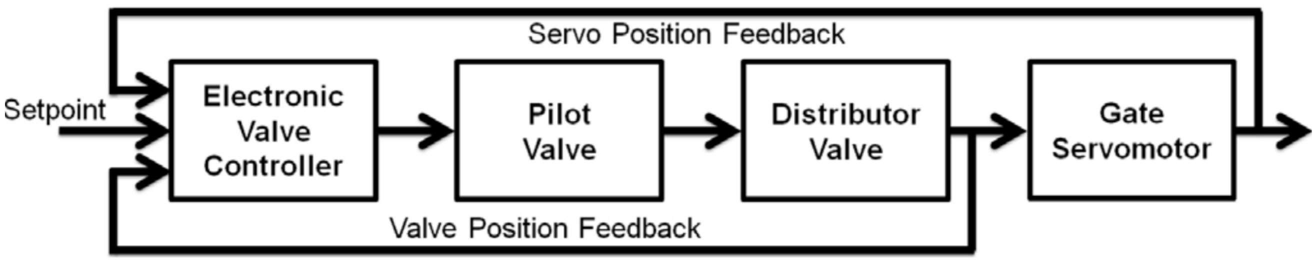

Figure 2. Block diagram of the hydraulic amplifier (Donaisky *et al.*, 2016) .

The proposed mathematical model of the turbine, see block diagram in “Fig. 3”, was based on the models of (OS-

INSKI, 2017) and (Melo and Koessler, 1992), it is worth mentioning that this new model also takes into account the following simplifying hypotheses:

- No balance chimney;
- The effects of the water hammer on the pipe are neglected;
- Inelastic water column;
- The water is incompressible (no change in density during flow) in the conduit of the forced conduit;
- Hydraulic resistance is negligible.

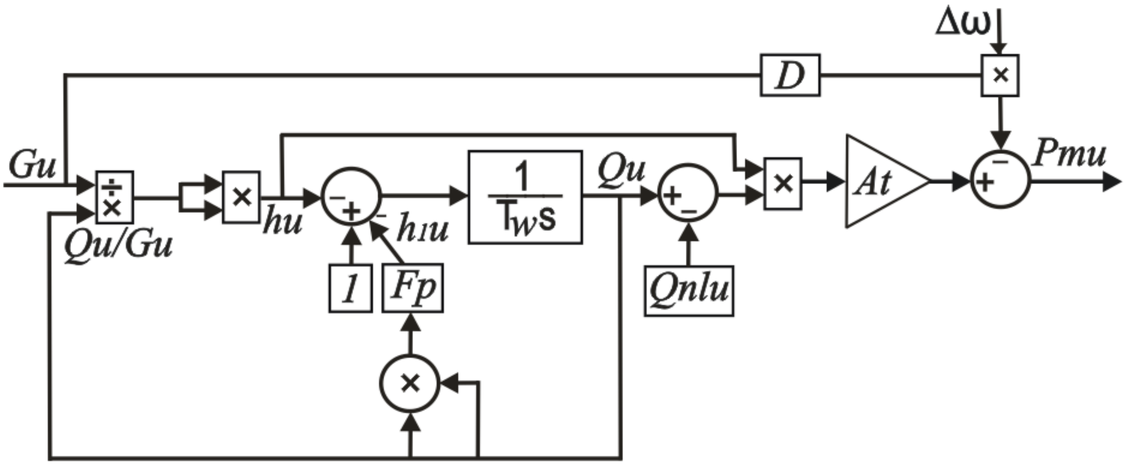

Figure 3. Block diagram penstock/turbine (Melo and Koessler, 1992).

The generator is a synchronous machine of 133 MW. This hydroelectric plant is part of the Brazilian Interconnected System (SIN).

It is noteworthy that this system is nonlinear having different operation conditions for each type of SIN load.

4. GREY WOLF OPTIMIZER

Grey Wolf Optimizer (GWO) is an algorithm that is inspired by the grey wolves (Canis Lupus) behavior of leadership hierarchy and hunting in the real habitat in nature (Mirjalili *et al.*, 2014) Saremi *et al.* (2015). In model simulation, leadership hierarchy is divided in four wolves' types as alpha, beta, delta and omega. The steps of hunting are searching, encircling and attacking prey, as shown in "Fig. 4".

4.1 Leadership Hierarchy

Wolves leadership hierarchy is divided in four levels named alpha (the higher level), beta, delta and omega (the lower level). The first level as starting best solution in alpha and decreasing position in sequence.

4.2 Encircling Prey

To represent mathematically the situation of encircling the prey, one can use the following equations: $\vec{A}$

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t))| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{2}$$

Where $\vec{A}$ and $\vec{C}$ are coefficient vectors, t is current iteration, $\vec{X}_p$ is position vector of prey, $\vec{X}$ is position vector of grey wolf as shown in (Mirjalili *et al.*, 2014).

For calculate $\vec{A}$ and $\vec{C}$:

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r_2} \tag{4}$$

The $\vec{a}$ is linearly decreased from 2 to 0 over the course of iterations and $\vec{r_1}$, $\vec{r_2}$ are random vector in [0,1].

4.3 Hunting

In hunting, the behavior of grey wolves is encircle and find the prey, that is guided by alpha, but beta and delta can participate occasionally (Mirjalili *et al.*, 2014). This is mathematically represented by:

$$\vec{D_\alpha} = |\vec{C_1} \cdot \vec{X_\alpha} - \vec{X}| \tag{5}$$

$$\vec{D_\beta} = |\vec{C_2} \cdot \vec{X_\beta} - \vec{X}| \tag{6}$$

$$\vec{D_\delta} = |\vec{C_3} \cdot \vec{X_\delta} - \vec{X}| \tag{7}$$

$$\vec{X_1} = \vec{X_\alpha} - \vec{A_1} \cdot (\vec{D_\alpha}) \tag{8}$$

$$\vec{X_2} = \vec{X_\beta} - \vec{A_2} \cdot (\vec{D_\beta}) \tag{9}$$

$$\vec{X_3} = \vec{X_\delta} - \vec{A_3} \cdot (\vec{D_\delta}) \tag{10}$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \tag{11}$$

4.4 Attacking Prey

The finish of the hunting process happens when the prey is stopped, resulting mathematically in minimizing values of $\vec{a}$ and $\vec{A}$.

4.5 Search for prey

The geographical position of each Grey Wolf diverges when searching for a prey and converges to attack the prey. The search process can be represented mathematically by allocating to each wolf hierarchical level random values, which are bigger than 1 or smaller than -1. These values force search agent to diverge from the prey, resulting in better behavior for the global search (Mirjalili *et al.*, 2014).

When $\vec{A} > 1$ the prey will force to diverge and $\vec{A} < 1$ will converge, the $\vec{C}$ has random values 0 to 2.

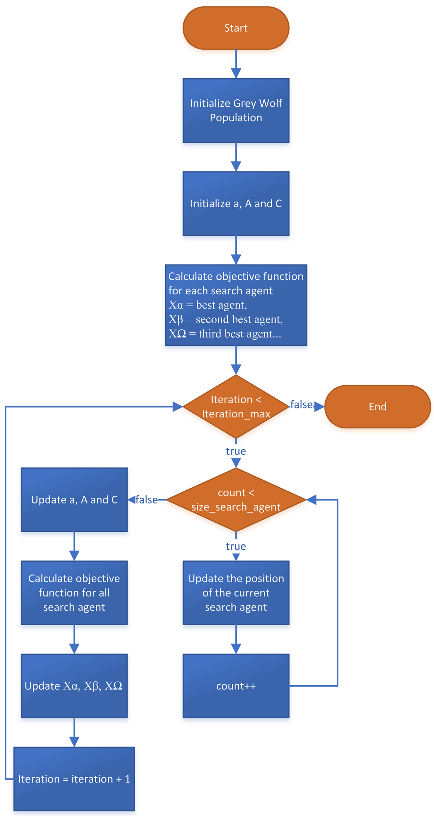

Figure 4. Flowchart Grey Wolf Optimizer.

5. DIFFERENTIAL EVOLUTION

Differential Evolution (DE) has developed (Storn and Price, 1995) to be reliable and robust for solving various optimization problems. The stage of DE are initialization, mutation, recombination, selection and validation of convergence as demonstrated in "Fig. 5".

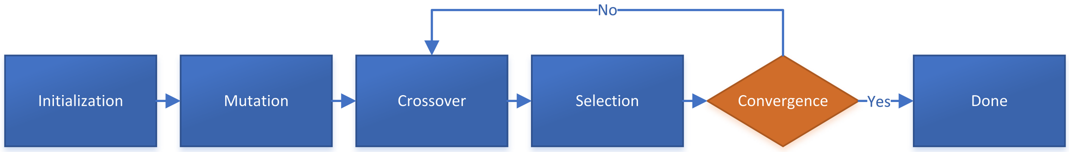

Figure 5. Flowchart Differential Evolution Algorithm.

According by (Storn and Price, 1995) and (Price, 1996), at the of initialization of DE is generated vector of uniformly distributed random values, which correspond to the population,

$$\{X_{1,i,0} = (x_{1,i,0}, x_{2,i,0}, ..., x_{D,i,0}) | i = 1, 2, ..., NP\} \tag{12}$$

$$x_j^{low} \leq x_{j,i,0} \leq x_j^{high} \; where \, j = 1, 2, ..., D \tag{13}$$

Corresponding,
NP = population size,
D = problem dimension,
x_j^{low} = lower bound of vector j,
x_j^{high} = upper bound of vector j.
In the mutation process, each generation g is created a mutation vector $V_{i,g}$ based on the current population of the parent. To perform the mutation the techniques frequently used are:
DE/best/1:

$$V_{i,g} = X_{best,g} + F_i(X_{r1,g} - X_{r2,g}) \tag{14}$$

DE/rand/1:

$$V_{i,g} = X_{r0,g} + F_i(X_{r1,g} - X_{r2,g}) \tag{15}$$

DE/current-to-rest/1:

$$V_{i,g} = X_{i,g} + F_i(X_{best,g} - X_{i,g}) + F_i(X_{r1,g} - X_{r2,g}) \tag{16}$$

Corresponding,
$r0, r1, r2$ = different values uniformly and chosen from the vector,
$X_{r1,g} - X_{r2,g}$ = difference of the vector to mutate father,
$X_{best,g}$ = best vector from current generation,
F_i = mutation factor.
Mutation factor corresponds to a constant that defines the size of the step to be given in the direction defined by the difference vector $(X_{r1,g} - X_{r2,g})$.
Crossover process is performed after mutation performed a binomial combination that generates the final experimental vector in order to increase the diversity of the mutated parameter vectors.

$$u_{i,g} = (u_{1,i,g}, u_{2,i,g}, ..., u_{D,i,g}) \tag{17}$$

If $rand_j(0, 1) \leq CR_i \vee j = j_{rand}$

$$u_{j,i,g} = u_{j,i,g} \tag{18}$$

else

$$u_{j,i,g} = x_{j,i,g} \tag{19}$$

$rand_j(a, b)$ = random numbers in the interval (a, b) and newly generated for j, j_{rand} = random integers from 1 to D and again generates for each i, the crossover rate $CR_i \in [0, 1]$, corresponding to approximately the average fraction of vectors inherited in the mutation process.
The selection process determines the best from the parent vector $X_{i,g}$ and the experimental vector $u_{i,g}$ according to the fitness values $f_{(x)}$.

6. RESULTS AND DISCUSSION

Among the various disturbances that a UHE can suffer, the most severe is the load rejection, because if the controllers are not well adjusted the possibility of a motorization is great. When this happen, there will be a need to take out the generating unit of the system, which will cause financial losses for the concessionaire (Kundur *et al.*, 1994).

"Table 1" and "Table 2" show the values used in the respective optimization algorithms for the estimation of the parameters of the controllers. "Table 1" shows the parameters used for the differential evolution algorithm configuration.

Table 1. Parameters of DE

	Differential Evolutionary
Number of population members	50
Iteration maximum	20
Crossover probability	0.5
F	0.8
Strategy	DE/rand/1/bin

"Table 2" shows the parameters used to configure the Grey Wolf Optimizer algorithm.

Table 2. Parameters of GWO

	Grey Wolf Optimizer
Number of population members/ Number of Search agents	50
Iteration maximum	20

"Fig. 6" and "Fig. 7" present the values obtained from the controller's parameters at each round. For a better analysis of the results obtained by the optimization algorithms, we used the boxplot tool belonging to Matlab©.

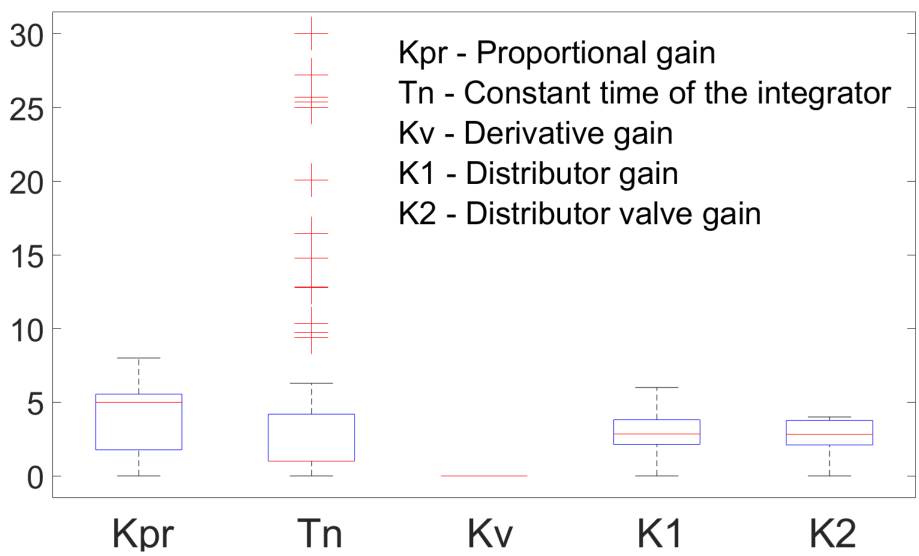

Figure 6. Boxplot of the controller and distributor parameters obtained by the DE algorithm.

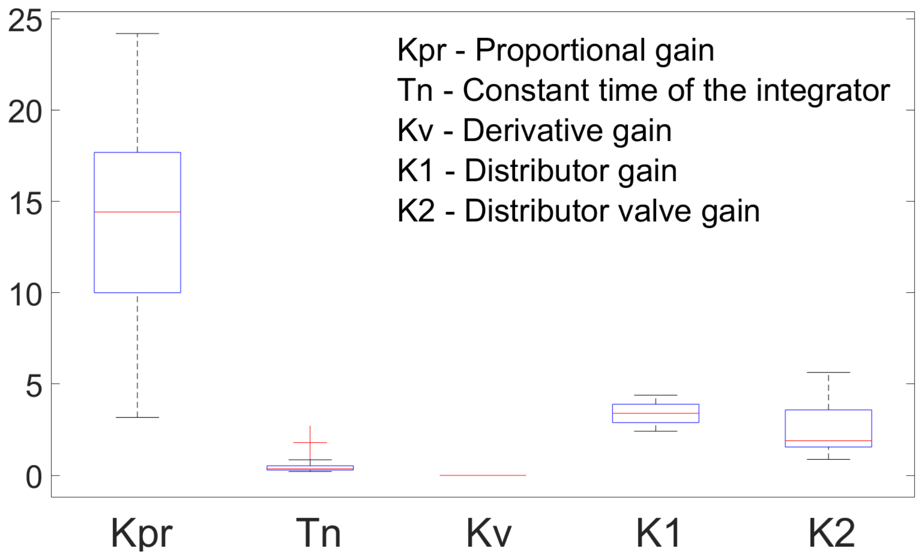

Figure 7. Boxplot of the controller and distributor parameters obtained by the GWO algorithm.

"Table 3" shows the best parameters estimated by the algorithms used in this work. They have been executed eighty times with a maximum number of twenty iterations. For the first iteration, the population has been randomly generated and its solution was incorporated as the initial population for the next round.

Table 3. Better parameters obtained from optimization

	Differential Evolutionary	**Grey Wolf Optimizer**
MSE	33.7383	31.2640
K_1	2.7063	4.1510
K_2	4	1.6431
K_{pr}	8	24.1916
K_v	0.7129	0.7879
T_n	0.6637	0.2155

"Fig. 6" shows the time response of the UHE output frequency, when it is subjected to a load rejection, in which the output power goes from 75% to 0% of its nominal capacity.

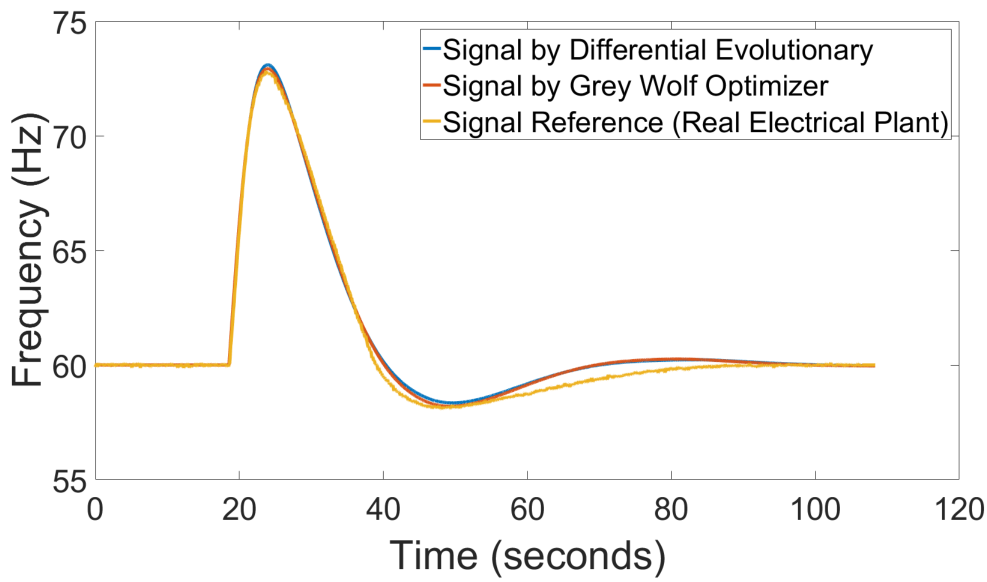

Figure 8. Graph of comparison between signal generated by GWO, DE and reference.

It is observed in "Fig. 8" that the output frequency obtained by both DE and GWO algorithms are in very good agreement to the real frequency, validating the algorithms used in this work.

For a numerical analysis of the results of the metaheuristics and consequently for a comparison between them, it was used the Mean Square Error (MSE) (Allen, 1971).

$$MSE = \bar{X} = \frac{1}{n}\Sigma_{i=1}^{n}(X_i) \tag{20}$$

Which X_i is each value of signal, n is size of signal.

"Table 4" shows the maximum, minimum, mean and standard deviation of the MSE's of the results obtained by the optimization algorithms used in this work.

Table 4. Statistical analysis MSE

	Differential Evolutionary	**Grey Wolf Optimizer**
Mean	114.2158	32.4430
Standard deviation	142.9130	2.2120
Maximum	745.7016	50.6940
Minimum	33.7560	31.2640

"Fig. 9" shows the global results of the statistical analysis comparing the MSE of both DE and GWO algorithms.

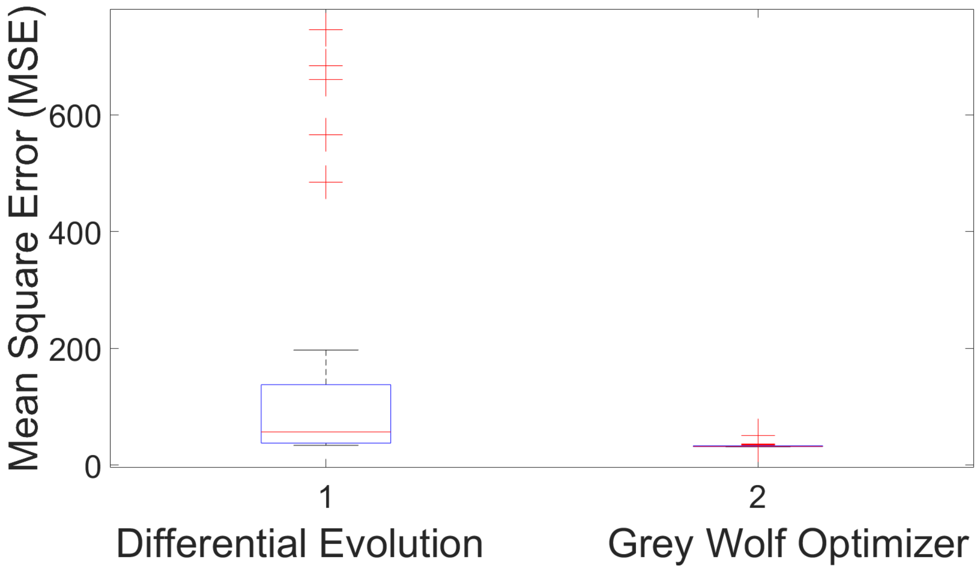

Figure 9. Boxplot of MSE obtained by the GWO algorithm and DE.

It is observed in "Fig. 9" that the GWO algorithm presents a greater robustness, since the MSE has a small variation around its average value, in which it can be seen that the GWO algorithm has a smaller dispersion, i.e. there is a greater degree of repeatability.

7. CONCLUSIONS

In this paper two metaheuristics are used to obtain the gains of the speed regulator and the gains of the distributor valve and distributor of a Hydroelectric Generating Unit. Observing the graph of "Fig. 8" it is shown that the curves obtained through the metaheuristics present satisfactory results compared to the response obtained in real field, which means that the estimated parameters are very close to the real values. "Table 3" shows that the MSE for the two metaheuristics are close, although the parameters K_1,K_2 show a small difference in each method and the parameter K_{pr} is the one that has the biggest difference between the methods. "Table 4" shows that the Grey Wolf metaheuristic presents a lower variation of the MSE being close to the average value of the best result, while in the metaheuristic DE the variation of the MSE is higher, being an average value far from the best result. With this it can be inferred that the Grey Wolf metaheuristic presents a greater repeatability of the optimal solutions, showing to be a good method for parameter estimation.

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9. RESPONSIBILITY NOTICE

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