25th ABCM International Congress of Mechanical Engineering
October 20-25, 2019, Uberlândia, MG, Brazil

COB-2019-0532
PARAMETER ESTIMATION OF THE HYDRAULIC AMPLIFIER PLUS HYDRAULIC TURBINE USING METAHEURISTICS

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Abstract. *In this paper, three metaheuristics to solve the problem of parameter estimation of nonlinear systems are studied and analyzed. These three metaheuristics (Differential Evolution, Lion Optimization Algorithm and Iterative Local Search) are evaluated using two benchmark test functions: Ackley and Rosenbrock. By using these functions, it is possible to analyze the performance of the metaheuristics, to verify its convergence and to show the similarity of its feasible solution. The metaheuristics also to be efficient in finding similar values of the global minimum of the benchmark functions. Moreover, these three metaheuristics are also applied in parameter estimation of hydraulic amplifier model plus hydraulic turbine belong to a Hydroelectric Power Plant based on actual data collected in the field. The estimated parameters by the metaheuristics are satisfactory because features a similarity with the output of the nonlinear system. In addition, the Friedman test is realized to show the degree of approximation of the feasible solutions and the statically difference between the metaheuristics applied in a nonlinear system.*

Keywords: *Parameter estimation, nonlinear systems, differential evolution, lion optimization algorithm, iterated local search.*

1. INTRODUCTION

Modelling nonlinear systems, by using system identification techniques, is a challenging task since this type of system does not share the concepts consolidated in linear theory, requiring the use of methods able to provide general solutions and acceptable and that found the literature (Billings, 2013).

The main goal of prediction error methods in the identification process is to select a mathematical model and adjust the values of parameters of this model so that the "distance" between the model output and the data becomes as small as possible. This distance is measured by the cost function that is minimized (Ljung, 2008).

In this way, the problem of adjusting the parameters of a model (parameters estimation) can be seen as an optimization problem. This optimization problem can be solved by deterministic or nondeterministic methods. The deterministic methods, such as: least squares methods; gradient based methods; and others found in the literature (Billings, 2013; Aguirre, 2015) may not be as efficient in dealing with nonlinear systems as they are in linear systems. Due to the complexities of nonlinear systems, nondeterministic methods present less than expected results when it comes to reproducing the dynamic behavior of these systems (Aguirre, 2015). Thus, several metaheuristics, referred to as nondeterministic methods, have been proposed to address the problem of parameter estimation for nonlinear systems, such as: Genetic Algorithm; Differential Evolution (Price et al., 2005); Particle Swarm Optimization (Li et al., 2010); Lion Optimization Algorithm (Rajakumar, 2012); Iterated Local Search (Lourenço et al., 2003); and others methods (Glover and Kochenberger, 2003; Doerr and Jansen, 2011). Some of these metaheuristics are discussed in following.

Parameter estimation in nonlinear systems has been attempted with nondeterministic methods. Differential Evolution and Grey Wolf Optimizer metaheuristics were used for parameter estimation of the controller in the speed regulator and hydraulic amplifier of a Hydroelectric Power Plant (UHE) (Oliveira et al., 2017).

An investigative study on the use of different metaheuristics (Genetic Algorithm, Particle Swarm Optimization and Bat Algorithm) for parameter estimation in the identification of nonlinear systems was performed by Severino et al. (2016).

Gonzalez et al. (2007), employed the Simulated Annealing metaheuristics to perform the estimation of the parameters of modeled biochemical networks. Multiobjective optimization in the estimation of kinetic model parameters of batch and fed-batch fermentation processes for ethanol production using Saccharomyces diastaticus (Wang and Sheu, 2000).

Bergamini et al. (2017), shows the efficiency of the metaheuristics: Differential Evolution; and Lion Optimization Algorithm to solve the problem of the parameter estimation of dynamic systems.

The main characteristic of metaheuristics is the randomness because they depend on randomness operators. This characteristic leaves the algorithm freer to obtain a feasible solution at each realization. In addition, they use the problem formulation to evaluate the solution set, the process is performed independently of the problem and based on available inputs and outputs (Mirjalili, 2015).

This paper presents the analysis of parameter estimation of hydraulic amplifier plus hydraulic turbine of Hydroelectric Power Plants that is part of the National Interconnected System (SIN). To solved this problem, three metaheuristics were used: the Differential Evolution (DE) is based on population, and it is a global search algorithm (Price et al., 2005); Lion Optimization Algorithm (LOA) imitates the behavior of lions and depends on two operators: territorial defense and territorial acquisition (Rajakumar 2012); and the Iterative Local Search (ILS), which is based on population type and local search (Lourenço et al., 2003).

The paper is divided into two case studies, that is: the metaheuristics pass by a set of benchmarks or test functions (Jamil and Yang, 2013) of optimization to evaluate the algorithms and the metaheuristics are applied to the problem parameter estimation of the hydraulic amplifier system plus hydraulic turbine. Tests and simulations were performed with the software Matlab® and Anatem®. The results were statistically analyzed using mean square error (MSE) compared with the results provided by the SIN (measurement data). An analysis of the degree of approximation of the data obtained by MSE is performed using the Friedman Test.

This paper is organized in 5 sections. Section 1 introduces system identification and optimization methods. Section 2 describes the methodology of parameter estimation in the identification of nonlinear systems. Section 3 presents the types of optimization methods used to solve the problem of parameter estimation. In Section 4 the obtained simulations shows the efficiency of these optimization methods. Finally, Section 5 highlights the conclusions.

2. PARAMETER ESTIMATION

System identification is the area of science that studies how to obtain mathematical models of dynamic systems through data obtained from the system under study (Ljung and Glad, 2016).

Obtaining the model of a system is a challenging task because when omissions and simplifications of relevant dynamics occur, the result can be much lower than expected (Wang and Zhu, 2015; Rannen and Ghorbel, 2017).

Figure 1, shows the steps of the system identification process.

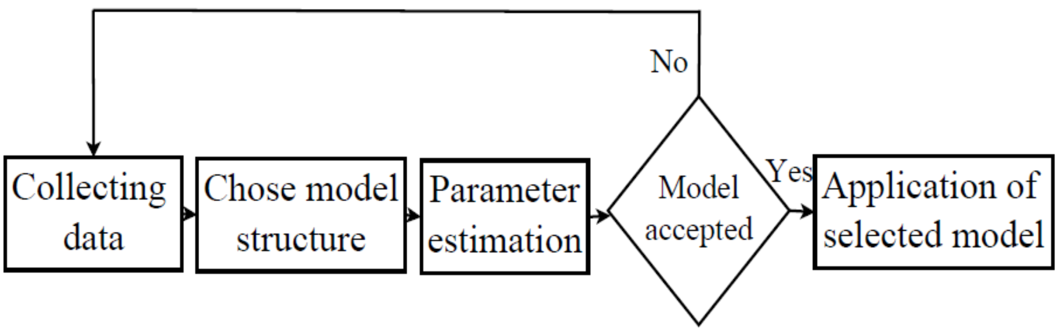

Figure 1. Block diagram the step of the system identification.

The input and output data are obtained during an experiment performed with the system. In some cases, it is necessary to filter the input and output data, to eliminate noise that impairs the estimation of the parameters of the model (Aguirre, 2015).

The choice of the structure of the model is hard, however, is the most important and at the same time the most difficult of the steps of the identification process. If a model is built from basic physical laws and other well-established relationships, it is called white box, otherwise the model is constructed using the input and output data can be called the black box In this case, the model parameters fit the data collected and do not reflect the physical considerations of the system (Corrêa and Aguirre, 2004).

The parameter estimation step aims to find values for the adjustable parameters in order to approximate the model output to the measured system output (Freitas and Macau, 2004; Gomes et al., 2009). Obtaining the parameters of a system through its estimation can be seen as an optimization problem since the choice of these parameters is made by minimizing the error between the data generated by the simulated system and the measured system's data.

Optimization problems maximize or minimize the objective function of n variables (dimension of the problem) with the possibility of lateral constraints from the problem to be solved (Abraham and Jain, 2005). However, an optimization problem may have several solutions, that is, different combinations of estimated parameters generating the same results, and the criterion for obtaining the feasible solution is related to the constraints and the objective function.

The last step of the system identification process is the validation of the model. A model is only valid when it results in a good approximation, that is when it reproduces the approximate or exact characteristics of the real system.

The parameter estimation requires efficient methods to find the values of the nonlinear parameters of the system, because when wrong estimates causing injury, this is: shorten the useful life of the components (sensors, motors, vane, etc) of the nonlinear system.

3. OPTIMIZATION TECHNIQUES : METAHEURISTICS

Some optimization problems can be solved by deterministic methods, but these methods are unformalized problems that take a long time to find the only feasible solution. In this way, the metaheuristics are an alternative to these situations. However, there is no guarantee the method will find the optimal global solution, but they could provide a feasible solution is obtained in a shorter space of time (Rajakumar et al., 2016).

According to Ribeiro and Hansen (2002), the choice of a method to solve a given optimization problem depends on of the quality of the feasible solution generated by that method and the cost time it takes to find the feasible solutions (processing time used by the algorithm).

There is currently a wide variety of optimization methods, each with its advantages and disadvantages, depending on the characteristic of the problem defined. In this research, the metaheuristics DE, LOA and ILS will be analyzed and applied for an actual system and for benchmark problems.

3.1. Differential Evolution

Differential Evolution (DE) is a population-based metaheuristic that solves problems of continuous time optimization and global solution. Because of its simplicity, effectiveness and robustness has gradually become known and is applied in several fields. Its performance is directly linked to its strategy of generating the experimental vector, which depends on two operators: mutation rate (F) and crossover rate (Cr) (Price et al., 2005). Pseudocode 1 illustrates the steps of the DE algorithm.

Pseudocode 1: **Differential Evolution**
Initialization: Generate an array with the population size and the problem size ($NP\,x\,Dim$) of individuals over the specified search space (Bu, Bl). Set $j=1$ to the first population vector. Mutation: Select two vectors randomly from the population. The vector difference between the last two vectors is multiplied by the mutation rate (F) and added to the first vector to result in the mutant vector. $V_{NP,Dim}=X_{best}+F.(X_{NP,Dim}-X_{NP,Dim})$ Evaluate the fitness of each individual of the new population. Crossover: For the experimental vector (U_{NP}, Dim), each variable value comes from the mutant vector or target vector j. The probability of the value of the variable of the mutant vector is Cr. Selection: The vector that has the best value of the objective function ($min.\ f(X_{NP,Dim})$) is chosen to generate the next generation. $j=j+1$ If $j=NP$ End Else Back to start

3.2. Lion Optimization Algorithm

The Lion Optimization Algorithm (LOA) is based on the social behavior of lions and is formulated to find optimal solutions in a relatively large search space and to deal with $Np-hard$ problems (polynomial degree problems).

This algorithm depends on the operators: territorial dispute; and territorial acquisition, to find feasible solutions (Rajakumar 2012). Pseudocode 2 shows the LOA steps.

Pseudocode 2: **Lion Optimization Algorithm**

Initialization: Generate an array with the population size and the problem size ($NP x\ Dim$) of individuals over the specified search space (Bu, Bl).
Separate population: 15% of individuals are lions and 85% lioness.
$Lioness_{NP,Dim} = X_{NP,Dim} > (r = 15\%)$;
$Lion_{Np,Dim} = X_{NP,Dim} \leq (r = 15\%)$.
Selection: determines whether the individual population is eligible or not through the Roulette method. By means of a roulette move, it processes the number of times the individuals $X_{NP,Dim}$ and returns the index of the best individual who has the highest chances of being selected.
Mating: It consists of mutation and crossover operators.
Crossover: For the best $Lion_{NP, Dimj}$ chosen by selection is multiplied by randomly chosen β and summed by multiplication of (β-1) with the individual randomly selected from the lion population, producing two cubs.
$Cub_{NP}=\beta((Lion_{NP, Dim}) + (1-\beta).(Lion_{NP, Dim}))$;
$Cub_{NP+1}=(1-\beta).(Lion_{NP, Dim}) + \beta((Lion_{NP, Dim}))$.
Mutation: Modifies one or more of the cub genes with a probability of mutation rate (F).
Territorial Defense: Nomad Lion version Lion pride

```
Age = 4
 For i = 1 to Dim
   Nomad Lion
     If X_{nom,i} = Age
        X_{i,NP+1} = X_{nom}
     Else
        X_{i,NP+1} = X_{NP, Dim}
     End if
 End for
     If f(X_{nom}) < f(X_{Lion})
        f(X_{NP, Dim}) = f(X_{nom})
        count = 1
     Else
        f(X_{NP,Dim}) = f(X_{Lion})
        count = 0
   End if
```

Territorial Takeover: With the exclusion of the worst individuals, the population ($X_{NP, Dim}$) goes through the evaluation process by the objective function ($min.\ f\ (X_{NP, Dim})$) to record only the best solutions of the population.
If the algorithm satisfies the stopping criterion (best individual > stop criteria = 0.001), finalize the realization.
Otherwise, go back to the selection process and redo all processes until you find a solution that meets the criteria.

3.3. Iterated Local Search

Iterative Local Search (ILS) is a metaheuristic that explores feasible solutions within the given search space, performing a scan around the solutions. This saves the path you have taken so that you do not walk the same path more than once.

In addition, ILS depends on local search operators and disruption. The disturbance is applied to the feasible solution found to see if it has a better solution in its vicinity (Lourenço et al., 2003). The pseudocode 3 shows the ILS steps.

Pseudocode 3: **Iterative Local Search**

Initialization: Generate an array with the population size and the problem size ($NP x\ Dim$) of individuals over the specified search space (Bu, Bl).
Local search ($X^*_{NP, Dim}$): Individuals of the population already evaluated by the objective function ($min.\ f(X_{NP, Dim})$) go through a local search of the size of NP to find the local optimal.
Disturbance: The solutions are modified Dim times throughout the routine, diverting them from the great places already found in ($X^*_{NP, Dim}$).
Local Search: Refresh the population by doing a new local search in an attempt to exclude bad solutions.
If the algorithm satisfies the stopping criterion, finalize the realization.
Otherwise, go back to the local search process and redo all processes until you find the solution that meets the criteria.

4. RESULTS

Initially benchmark tests with: Ackley and Rosenbrock functions; Then, estimation of parameters of a speed control system (hydraulic amplifier plus hydraulic turbine of type Kaplan) of a Hydroelectric Power Plant was carried out, using data collected in from this plant, which is located in the southeast region of Brazil.

4.1 Ackley and Rosenbrock Test Function

The first test was used for validation of the performance of each algorithm in the optimization of benchmark functions. These functions can represent Np-hard or small-sized problems. The larger the dimension (Dim – number of parameters to be estimated), the more it will be require from the algorithm in use, because it increases the computational effort, delaying the convergence. Each function depends on the set of upper (Bu) and lower (Bl) initial parameter limits. Table 1, shows the characteristic of each test function.

Table 1. Test Function Settings.

Function test	Bu	Bl	Global minimum	Equation
Ackley	32	-32	$f(x^*)=0$	$f(x)=-a\exp(-b\sqrt{\frac{1}{Dim}\sum_{i}^{Dim} x_i^2}) - \exp(\frac{1}{d}\sum_{i=1}^{Dim}\cos(cx_i)) + a + \exp(1)$
Rosenbrock	10	-5	$f(x^*)= 0 \text{ or } \neq 0$	$f(x)=\sum_{i=1}^{Dim}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$

Variable values were: a = 20; b = 0.2; c = 2π; $x_i \in [Bu, Bl]$ and i = 1, …, Dim, these values can be found in the literature Molga and Smutnicki, (2005). The function test have global minimum $f(x^*) = 0$. The algorithms having the following settings: dimension size (Dim) is 100; population size (NP) is 1000; the maximum number of iterations is 10000; stop criterion is 0.001; and a maximum number of executions is 500. The initial population was the same for all methods. Table 2 shows other settings.

Table 2. Settings values for the algorithms.

Setting	DE	LOA	ILS
Mutation rate	F = 0.5	F = 0.3	-
Crossover rate	Cr = 0.7	Cr = 0.6	-
Size local search	-	-	NP/2
Perturbation	-	-	Dim

After, the minimum, maximum, mean and standard deviation values found for each metaheuristic and shown in Table 3.

Table 3. Error for solutions obtained by the algorithms.

Algorithms	Ackley Test Function				Rosenbrock Test Function			
	Min	Max	Mean	Std. deviation	Min	Max	Mean	Std. deviation
DE	2.08	5.05	3.50	0.90	9.02	730.5	157.54	118.17
LOA	0.004	10.74	4.21	3.18	0.005	$3.62e^4$	$3.83e^3$	$6.51e^3$
ILS	0	2.86	1.85	0.21	0	17.17	4.78	4.28

The ILS metaheuristic has the least dispersion around the mean value, which means that the results found are always close to each other (good repeatability). The LOA metaheuristic present smaller mean error and smaller dispersion since it could provide solutions close to the global minimum of both test functions.

4.2 Estimation of Parameters of a Speed Control System

This real system belongs to the UHE of the SIN, this model is of the gray box type because the input and output data are using and priori knowledge this system. The speed controller regulates the flow of water passing through the vane to the hydraulic turbine, which rotates the rotor of the electric generator (IEEE, 2011).

The speed control system consists of the following elements: hydraulic amplifier and the Kaplan turbine assembly as shown in Figure 2.

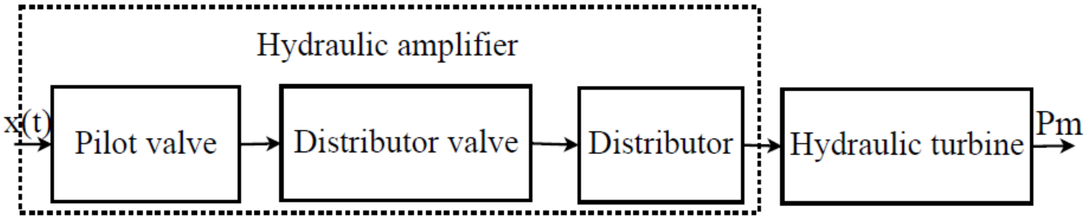

Figure 2. Block diagram of the Hydraulic amplifier and Hydraulic turbine.

The input *x(t)* (controller signal) and output *Pm* (mechanical power). The system structure and some of its parameters are known and the parameters to be estimated can be visualized in Figure 3.

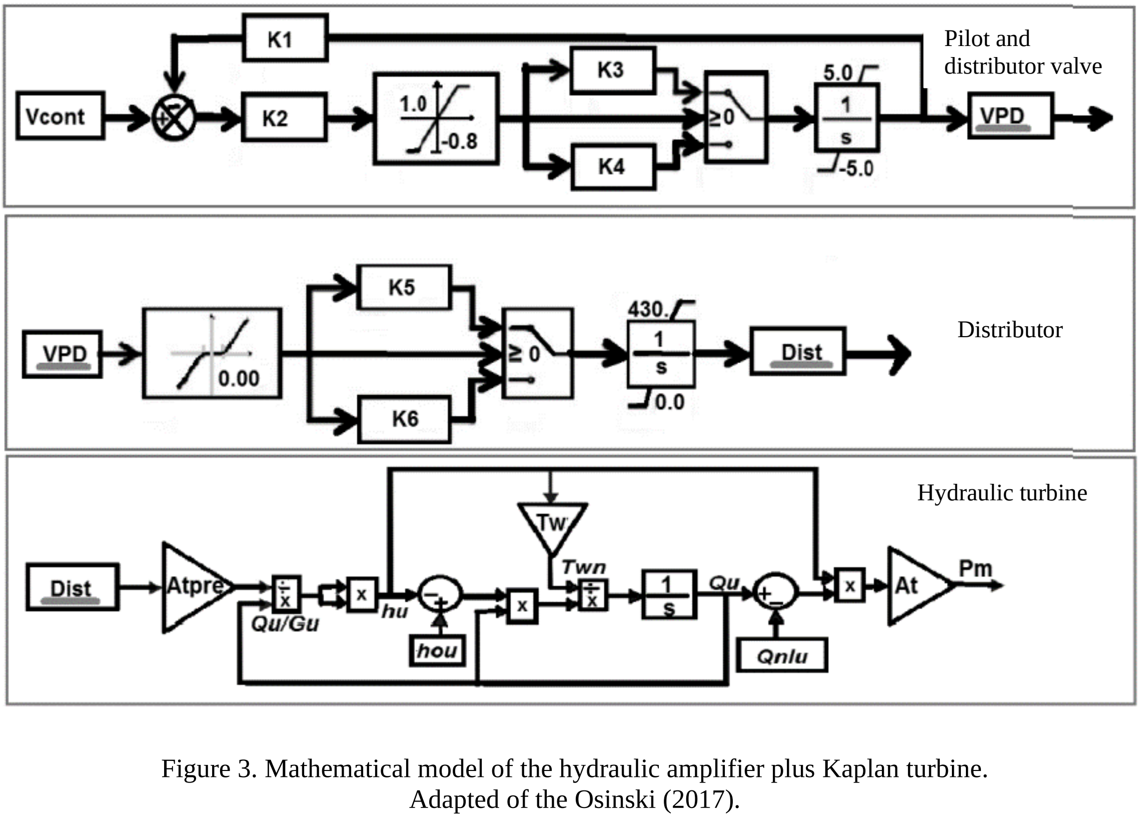

Figure 3. Mathematical model of the hydraulic amplifier plus Kaplan turbine.
Adapted of the Osinski (2017).

The input of the model is the data obtained from the controller signal (Vcont). All signal are in pu. The pilot and distributor valve gains are K1, K2, K3 and K4. The output VPD is the input to distributor valve. The second block, the distributor valve gains are K5 and K6; and the output is distributor signal (Dist). The last block, the gain of Kaplan turbine is Atpre, water start time is Tw, relation to base change is At and the output is the mechanical power (Pm). The parameters (K1, K2, K3, K4, K5, K6, Tw and At) of this nonlinear mathematical model will be estimated by metaheuristics: DE; LOA; and ILS. The settings of the metaheuristics used for this case study. Were the same presented in Table 2. Population size was 80 (*NP* = 80); dimension size is number of parameters to be found (*Dim* = 8); the maximum number of iterations is 250; stop criterion is 0.001; and maximum number of executions is 250.

Some restrictions were imposed to the parameters. Table 4 shows these constraints where in terms of the lower and upper bounds. Atpre gain was not left as a free parameter, but set to a fraction of the At gain.

Table 4. Constraints of the parameters of the real system.

Parameter	Constraints
K1	[0.5, 0.8]
K2	[2, 2.2]
K3	[2.5, 2.9]
K4	[2, 2.7]
K5	[14, 26]
K6	[0.1, 6.5]
Tw	[2, 3]
At	[1.1, 1.8]
Atpre	*267.5 * 0.0023*At*

After several rounds, the results minimum, maximum, mean and standard deviation values of the obtained parameters were calculated. The results are shown in Table 5.

Table 5. Performance of the parameters.

Comparison		K1	K2	K3	K4	K5	K6	Atpre	At	Tw
Minimum	DE	0.5005	2.1602	2.6517	2.5005	21.0017	3.3012	0.4389	0.4389	1.6018
	LOA	0.5524	1.900	2.0057	2.0002	20.0761	0.1463	0.4662	0.4662	1.5001
	ILS	0.5513	1.9001	2.0025	2.0118	20.0099	0.1275	0.4664	0.4664	1.5018
Maximum	DE	0.5999	2.1899	2.7993	2.6999	21.9854	3.9972	0.4562	2.9993	1.7989
	LOA	0.7953	1.9997	2.7996	2.6936	25.9634	6.5375	0.5427	2.6982	1.6994
	ILS	0.7994	1.9996	2.7931	2.6987	25.9018	6.5970	0.5432	2.6912	1.6989
Mean	DE	0.5504	2.1750	2.7296	2.6014	21.4656	3.6917	0.4480	2.9062	1.7042
	LOA	0.6644	1.9545	2.3968	2.3184	23.0123	3.2938	0.5020	2.4231	1.5960
	ILS	0.6762	1.9508	2.3778	2.3424	23.0887	3.3929	0.5010	2.3988	1.6029
Std. deviation	DE	0.0289	0.0088	0.0435	0.0600	0.2823	0.2112	0.0050	0.0576	0.0567
	LOA	0.706	0.0278	0.2345	0.2209	1.7685	1.8121	0.0208	0.1697	0.0573
	ILS	0.0768	0.0278	0.2410	0.1977	1.6814	1.9691	0.0219	0.1827	0.0543

Using the data collected from real turbine (Vcont) the outputs (Pm) was calculated with the mean values of obtained parameters. Figure 4 shows the output (Pm) as function of time for each metaheuristic.

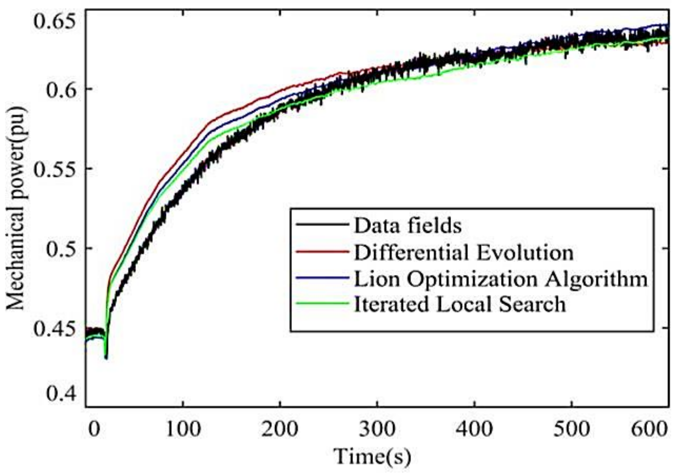

Figure 4. Output of the hydraulic amplifier plus Kaplan hydraulic turbine model using real data as input.

To compare the performance of the algorithms, the mean square error (MSE) related to real output data from the hydraulic turbine was calculated as

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (|a_i^{referenced} - a_i^{estimation}|)^2 \quad (1)$$

where n is the number of time samples, $a_i^{referenced}$ is the measured signal, $a_i^{estimation}$ is the output of the model. Table 6 shows the resulting MSE for each algorithm.

Table 6. Comparison of MSE of feasible solutions for each algorithm.

Comparison	DE	LOA	ILS
Minimum	61.03	23.21	23.55
Maximum	80.61	83.82	81.91
Mean	69.39	50.10	48.07
Standard deviation	4.95	14.49	14.01

Additional statistics tests were performed. Table 7 shows the results of the Friedman test (Kanji, 2006). The degree of freedom (Df = number of samples - 1), the observed difference (Do), the critical difference (Dc), Friedman is nonparametric test, where is used to detect possible differences in the data from the test experiments. The procedure involves the classification of each row, then considering the values of the column posts. The value of the Friedman test has as based in the null hypothesis where $p < 0.05$ to accept (Wong *et al.*, 2016).

Table 7. Friedman test.

Comparison	DE – LOA	DE – ILS	LOA – ILS
Df	1	1	1
Do	38.4615	44.8615	0.061
Dc	38. 4615	44.8615	0.06154
p	$1.77748\ e^{-18}$	$2.73941\ e^{-21}$	0.7257
Rejected	No	No	Yes

The Friedman test in MSE can not point out the best metaheuristic, just to say whether it performs similar or different because feasible solutions are similar. But the one that has the lower MSE, is a minimization problem. That is, ILS is better, and statistically different from LOA.

The performance of the feasible solutions was also analysed using boxplot with 250 executions. In Figure 5, the similarity between LOA and ILS can be confirmed.

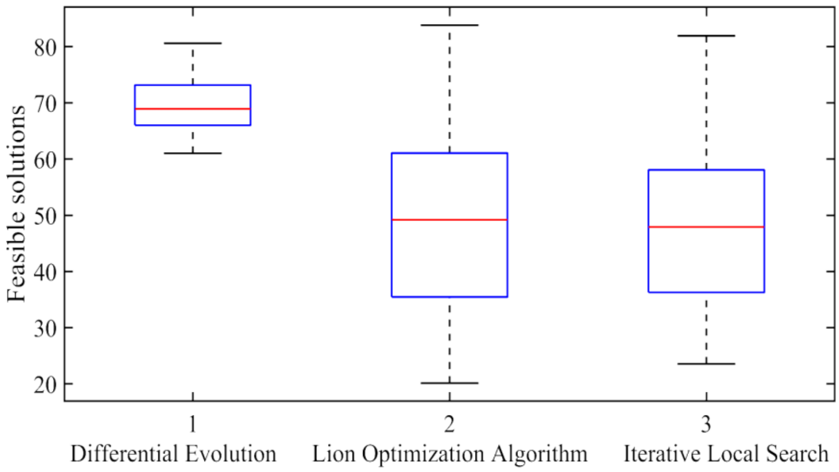

Figure 5. Performance of feasible solutions**.**

5. CONCLUSION

The goal of this research was to verify the ability of metaheuristics Differential evolution (DE), Lion optimization algorithm (LOA) and Iterative local search (ILS) to solve parameter estimation problem of real systems. These metaheuristics were tested with benchmark functions and applied in the problem of parameter estimation of at real Hydroelectric Power Plant. The presented method appeared as viable alternatives for the proposed problem and can could accurately provide values for the parameters of nonlinear systems. The Friedman test showed that LOA has no visible performance difference compared to ILS, but there is statistical difference between DE – ILS and between DE – LOA. The observed MSE variations also confirms that LOA feasible solutions are close to the ILS feasible solutions.

6. ACKNOWLEDGMENTS

This research was developed in Laboratory of Simulation, Control and Optimization of the Systems (LaSICO) of the Electrical Engineering Department at Federal University of Parana (UFPR) and financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES).

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