Performance analysis of optimized controllers with bio-inspired algorithms

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ABSTRACT

This article proposes tuning of PID controllers through optimization techniques known as collective intelligence algorithms: the colony of ants and cuckoo search, applied to the temperature control of a PCT-2 plant. The dynamic behavior analysis of the controllers tuned by the application of collective intelligence algorithms were performed in comparison to a controller tuned by the genetic algorithm method and a controller designed with the PID tuner tool, obtaining favorable results in the tuning of the algorithms cuckoo search and ants colony in comparison to the PID tuner method and with a faster execution speed than the genetic algorithms method.

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1. INTRODUCTION

Bio-inspired algorithms are a novel method that has been developed to solve multiple problems in the scientific field since they are based on emulating the behavior of biological systems to solve problems [1]. The genetic algorithm method is currently the most widely used in the field of evolutionary computing. This method has become one of the most popular and developed in recent years because it is inspired by genetic variation and natural selection of species [2]. However, there are methods not yet fully explored within the scope of bio-inspired algorithms, which have incredible potential and whose field of research is still young. An example of these is the ant colony method, inspired by the ability of ants to find the shortest route between the power source and its nest [3]. Another optimization method also used is the Cuckoo Search, which is a technique inspired by the lifestyle of cuckoo birds, known to be a type of "parasitic" bird that lays its eggs in other nests, and that, based on due to the environmental characteristics and migration of their societies, they seek the best habitat for the breeding and reproduction of their species [4].

Currently, the most widely used controllers at an industrial level are the so-called: proportional (P), proportional-integral (PI) and proportional-integral-derivative (PID), since these have a simple structure and relatively easy to design. However, this same simplicity usually becomes its weakness, since it limits the range of plants in which they can be used satisfactorily. This article will contribute to the analysis and application of new optimization alternatives in the design of controllers and the use of bio-inspired algorithms for the resolution of control problems based on optimization, focused on the temperature control of a PCT-2 temperature module. Available at the Universidad de las Fuerzas Armadas ESPE (Ecuador). This leads to the research development on novel robust and fast controller alternatives, which is beneficial both for the industry and for the scientific and student community.

2. BIO-INSPIRED ALGORITHMS

Bio-inspired algorithms simulate the behavior of natural systems, applied to the design of non-deterministic heuristic methods, focused on search, learning, behavior, among other qualities. For this reason, bio-inspired algorithms are often used to solve optimization problems in nonlinear systems, where conventional models have difficulty operating [5]. The interest in this novel solution is based on the fact that these algorithms recreate several intelligent behaviors in changing and complex environments, which are capable of learning, adapting, generalizing, abstracting, discovering, associating, among other qualities that we can find within nature [2]. In general, we can cover these bio-algorithms in four large groups: Evolutionary algorithms, the method of genetic algorithms being its main exponent; collective intelligence, within which are the methods of ant colony and cuckoo search; neural networks, with optimization techniques such as multilayer perception (MLP) and algorithms based on immune systems, such as clonal expansion algorithms. It should be noted that this classification is not exclusive and that some algorithms may cover more than one area of interest, depending on their objective [4].

2.1. Genetic algorithms (GA)

The optimization methods known as genetic algorithms fit into the category of evolutionary algorithms and were developed by J. Hollan in the 70s, to emulate and understand the natural adaptive process of the species and then apply it in processes of optimization in the 80s. This method is characterized by being adaptive and robust, so they can be used to solve search and optimization problems coming from different areas.

2.2. Ants colony (AC)

Ants are one of the main examples of collective intelligence that can be found in nature. These insects base their behavior on mutual collaboration to carry out multiple tasks that would be impossible to perform from an individual ant. A very important skill that many species of ants have lies in the expertise of finding the shortest route between their anthill and the nearest food source [3-7].

2.3. Cuckoo search (CS)

The cuckoo birds are a family of medium-sized birds characterized by several of these species practice laying parasitism, since they lay their eggs in nests of other species and leave that they raise these, thus eliminating the need to feed and care for their offspring [8-13]. To do this, the female cuckoo lays its egg in the occupied nest, and pecks or throws the host's eggs in the nest, so it does not usually notice the infiltrate in its nest. Shortly after birth, the baby of cuckoo usually throws the rest of the offspring and eggs by pushing them with their backs, to receive all the food and care of their adoptive parents, until it reaches sufficient size to leave the nest [13-15]. Based on this peculiar behavior, Xin-she Yang, a professor at the University of Cambridge, and Suash Deb developed the Cuckoo Search optimization algorithm in 2009, inspired by the laying parasitism used by cuckoo birds for reproduction [10]. Within this algorithm, each host egg in a nest represents a solution, while each cuckoo egg represents a new and better solution. Figure 1 presents the general diagram of the cuckoo search algorithm.

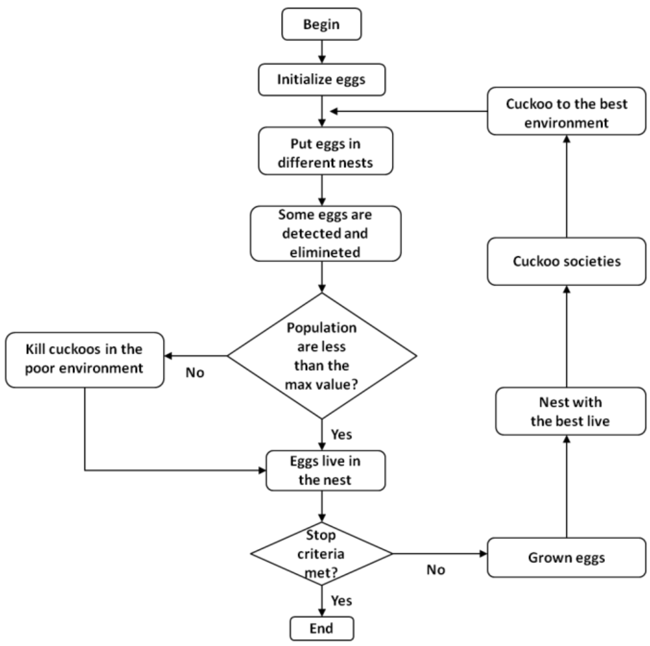


Figure 1. General diagram of the cuckoo search algorithm

Therefore, the objective is based on using new and generally better solutions (cuckoo), to replace to the not so good solutions of the nests. The algorithm can be described under three fundamental ideas [11]:
a. Each cuckoo deposits an egg in a randomly selected nest.
b. The best nests and eggs will survive and give way to the next generation.
c. There is a defined number of nests available, and each egg has a probability of being discovered. In this case, the mother will leave the nest and create a new one.

3. SYSTEM DESCRIPTION

In order to apply the optimized controller with a cuckoo search algorithm to a real case, the PCT-2 module of the DEGEM SYSTEMS´s will be used. Figure 2 represents the physical model of the system to be controlled, which consists of a solid-state temperature sensor (IC LM35) as a measuring element, a stainless steel conduit through which air controlled by a fan flows and to increase the temperature in the system is available a nickeline at the air duct inlet fed with a voltage input as the system actuator. In conclusion, the control process is based on modifying the input voltage V(t) in the plant, in order to modify the output temperature $T_o(t)$.

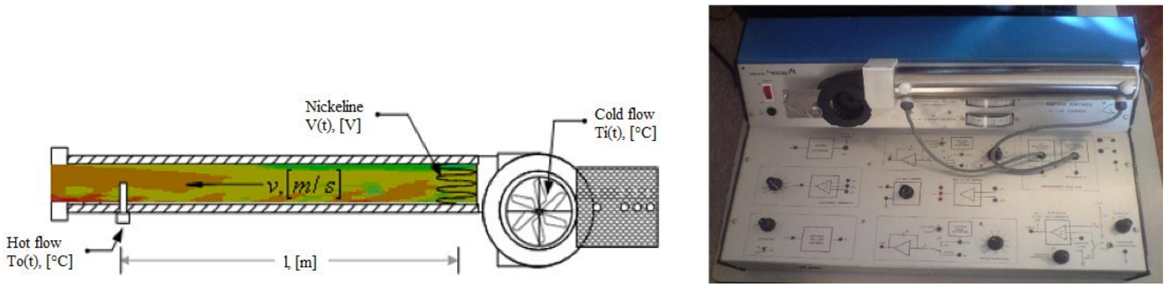


Figure 2. Module thermal process PCT-2 [16]

The PCT-2 module comprises:
a. Primary and measuring element: temperature sensor-transmitter IC (linear variation). It takes the temperature at the heater outlet (20-70 [°C]) and sends an analog voltage signal (0-5 [V]) to the controller.
b. Actuator: Nickeline governed by a voltage signal in the range of 0 to 10 [V].
c. Metal Plate: Which has four holes, which determine the amount of air that will enter the process, will be used for disturbance analysis.

In order to apply the design of optimized controllers to a real case, the implementation of these controllers in the airflow Degem Systems module PCT-2 has been proposed. The mathematical model of the plant was obtained by parametric identification techniques and is represented by:

$$TF = \frac{0.055921\, s + 0.007954}{s^2 + 0.06902\, s + 0.0006519}$$

On the other hand, the characteristics described in Table 1 have been determined as a control objective to be optimized through the selected bioinspired algorithms.

Table 1. Control system specifications

Parameter	Specification
Output	30°C
Overshoot	<15%
Settling time	<20 seconds
Steady state error	<=2%

For the development of the aforementioned algorithms, a general structure has been determined to facilitate the comparison between the different optimization methods, as presented below:

3.1. Genetic algorithms

Figure 3 presents a simplified representation of the general scheme of genetic algorithms to facilitate the programming of the algorithm.

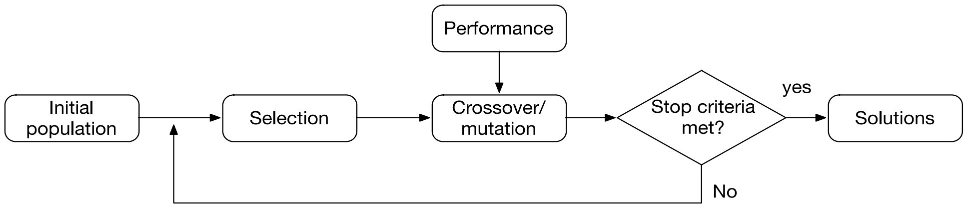


Figure 3. Simulation scheme of the GA method

3.2. Ant colony

Figure 4 presents a simplified representation of the general scheme of ant colony to facilitate algorithm programming [5].

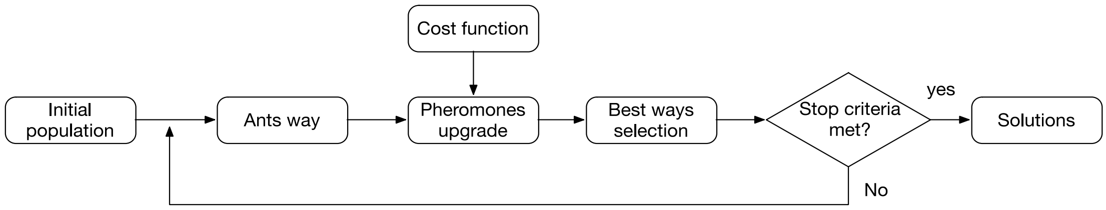


Figure 4. Simulation scheme of the ant colony method

3.3. Cuckoo search

A simplified representation of the general cuckoo search scheme is presented in Figure 5 to facilitate algorithm programming [12-20].

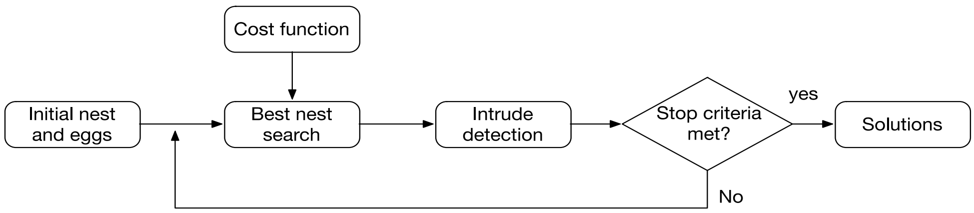


Figure 5. Simulation scheme of the cuckoo search algorithm

a. Generation of nests with eggs

The first phase of the algorithm corresponds to the generation of initial solutions, that is, the first set of nests containing cuckoo eggs. For this, a solution matrix has been proposed under the following configuration:

$$Nests = \begin{bmatrix} Solution_1 & performance_1 \\ Solution_2 & performance_2 \\ Solution_3 & performance_3 \\ \cdot & \cdot \\ \cdot & \cdot \\ Solution_n & performance_n \end{bmatrix} = \begin{bmatrix} Egg_1 \\ Egg_2 \\ Egg_3 \\ \cdot \\ \cdot \\ Egg_n \end{bmatrix}$$

where n represents the number of nests to be used for the optimization. Each solution can be represented by the concatenation of the gains obtained for the PID controller:

$$Solutions = \begin{bmatrix} Kp_1 & Ki_1 & Kd_1 \\ Kp_2 & Ki_2 & Kd_2 \\ Kp_3 & Ki_3 & Kd_3 \\ . & . & . \\ . & . & . \\ Kp_n & Ki_n & Kd_n \end{bmatrix} = \begin{bmatrix} Solution_1 \\ Solution_2 \\ Solution_3 \\ . \\ . \\ Solution_n \end{bmatrix}$$

b. Search for the best nests

This step takes place at the moment when the cuckoo eggs laid in the first generation of nests have grown and are ready to give rise to a new generation of eggs. For this, the optimization algorithm cuckoo Search requires the application of scanning techniques for the best nests within the search space. This process has been carried out using the Lévy Flights search technique [11]. This procedure generates a set of random values (with a normal distribution) interacting with each other, which are related to the measured distance between each element of the solution and the elements of the best nest identified, and are added to the current values of each nest. As a result, a set of newly available nests is obtained whose location within the search space has been found based on random values and influenced to some extent by the best nest of the previous generation [21-30].

$$Solution_d = Solution_d + ss_d \text{ x } Rand(norm)$$

where d corresponds to the number of elements within the solution, that is, the gains Kp, Ki, and Kd treated individually, and Rand (norm) corresponds to a random value generated with a normal distribution. Also, ss_d can be calculated from:

$$ss_d = st_d \text{x}(Solution_d - S_d)$$

Being ss_d the elements of the nest with the best performance identified in the first place, and st_d can be obtained from the following equation:

$$st_d = (u_d \text{x}[v_d])^{\frac{2}{3}}$$

Being u_d and v_d calculated as:

$$u_d = Rand(norm) \text{ x } sigma$$
$$v_d = Rand(norm)$$

where sigma controls the size of the steps traveled during the search process.

c. Intruder detection

In [6], an intruder discovery technique based in Pa probability is proposed, with which an alteration process of the selected nests is carried out and its performance is verified to know if the cuckoo is discovered or not. The mentioned process is executed within the algorithm based on the following formulas:

$$new\ population = Nest\ matrix + (ss \text{ x } mpa)$$

where *ss* is calculated from:

$$ss \ \ = rand(0\ to\ 1)\text{x}(N1 - N2)$$
$$N1 = permutation(Nest\ matrix)$$
$$N2 = permutation(Nest\ matrix)$$

Being *rand* (0 to 1) a random value generated between 0 and 1, *mpa* is an array with binary elements determined by:

$$mpa = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ . & . & . \\ . & . & . \\ b_{n1} & b_{n2} & b_{n3} \end{bmatrix}_{nx3} \quad where\ b_{ij} = \begin{cases} 1 & with\ P_a\ probability \\ 0 & with\ 1 - P_a\ probability \end{cases}$$

If the new nests show better results, the cuckoo egg originally deposited in the nest is eliminated and the nest is maintained with the new solution [21-30].

4. RESULTS AND DISCUSSION

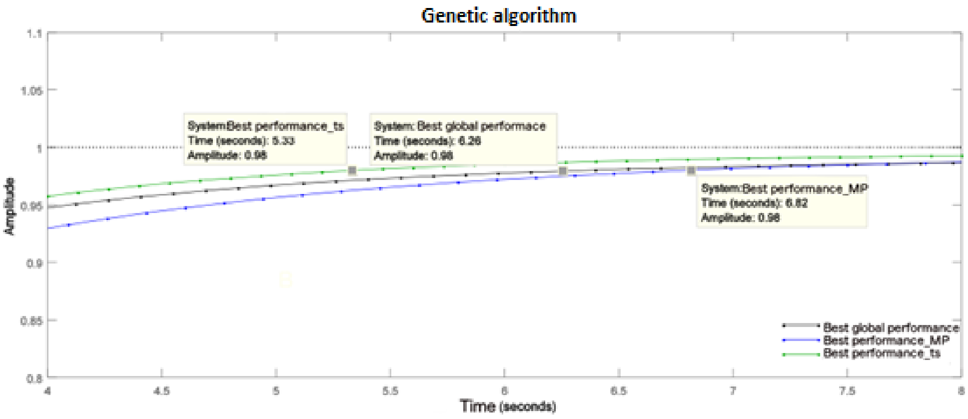
Based on the MATLAB PID tunner tool, preliminary tuning of the standard PID controller has been carried out as shown in Table 2, which has determined a series of base parameters on which a search range has been established for the proposed algorithms.

Table 2. Initial parameters for algorithm development

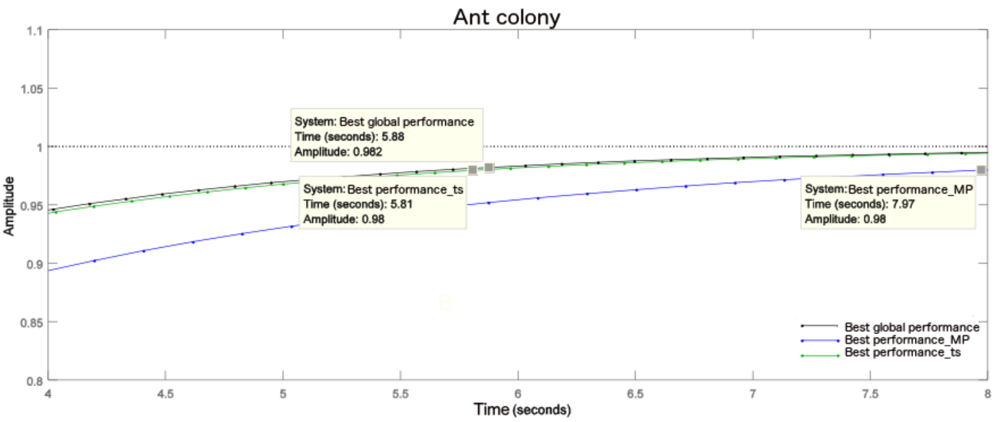
Parameters	Values
Kp gain	0-12
Ki gain	0-5
Kd gain	0-2
Maximum overshoot percentage	15%
Maximum settling time	20 s
Steady state error	2%
Population size	20
Number of iterations	50
Reference voltage	1V

4.1. Results obtained

In the first place, an analysis of results in the transitory regime has been carried out, obtaining the following results in the execution of each applied algorithm. Figure 6 presents the step response of the controllers tuned by the described methods. In section a) we find the response of the controller tuned by the method of genetic algorithms. In section b) we find the response of the controller tuned by the ant colony method. In section c) we find the response of the controller tuned by the cuckoo search method. Table 3 presents the controllers tuned by the described methods. On the other hand, Table 4 presents the iteration number in which each of the algorithms found the best individual of each execution performed.

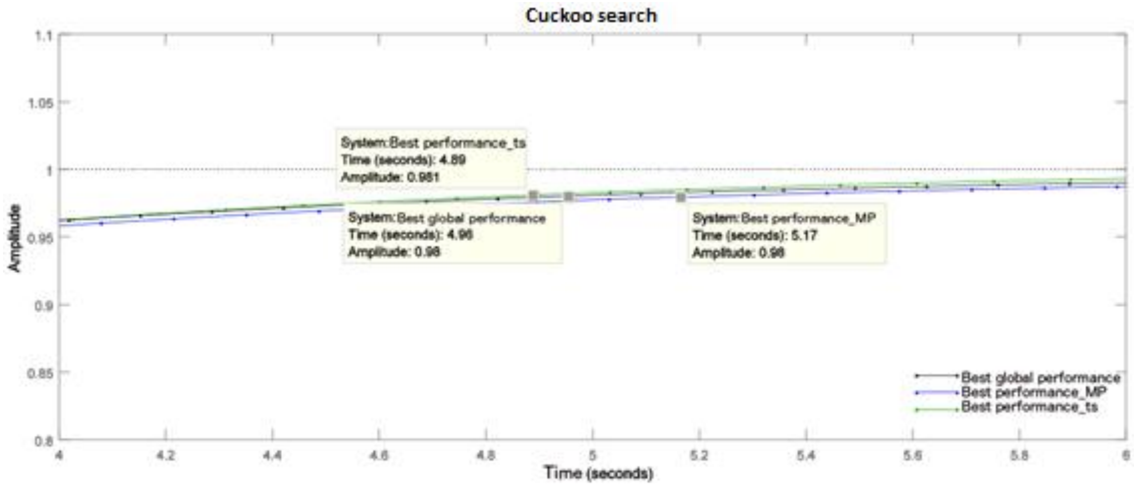


(a)



(b)

Figure 6. Response of the best controllers to step function, (a) Genetic algorithms, (b) Colony ants



(c)

Figure 6. Response of the best controllers to step function, (c) Cuckoo search *(continue)*

Table 3. Controllers tuned by genetic algorithms, ant colony, and cuckoo search

System	Genetic algorithms		Ant colony		Cuckoo search	
	Measure	Controller	Measure	Controller	Measure	Controller
System with the best overall performance	6.26 seconds	$1.5216\,s + 11.717 + \frac{0.4706}{s}$	5.88 seconds	$0.5265\,s + 10.3652 + \frac{0.5683}{s}$	4.96 seconds	$0.2712\,s + 11.8192 + \frac{0.6485}{s}$
System with better performance by overshoot	6.82 seconds	$1.2549\,s + 9.7412 + \frac{0.4706}{s}$	7.97 seconds	$0.0697\,s + 7.3847 + \frac{0.3929}{s}$	5.17 seconds	$0.4102\,s + 11.6760 + \frac{0.6021}{s}$
System with better performance by settling time	5.33 seconds	$0.5176\,s + 11.9059 + \frac{0.5686}{s}$	5.81 seconds	$1.2370\,s + 10.4244 + \frac{0.5690}{s}$	4.89 seconds	$1.3884\,s + 11.9131 + \frac{0.7417}{s}$

Table 4. Iterations needed to find the best solution

System	Best global performance	Better overshoot	Best settling time
Genetic algorithms	24	21	23
Ant colony	23	4	8
Cuckoo Search	24	24	6

When considering the controllers that obtained the best overall performance in each applied method, we obtained the described results in Table 5. Table 6 shows the result of measurements obtained in rejection of disturbances and illustrated in Figure 7. For the analysis in the permanent regime, a disturbance of -0.2V has been simulated, obtaining the following results in response of the controllers, as shown in Figure 8.

Table 5. Summary of parameters measured in controllers

Controller	Overshoot	Settling time
PID Standard	6%	12.3 s
Genetic algorithms	-	6.26 s
Ant colony	-	5.88 s
Cuckoo Search	-	4.97 s

Table 6. Measurements obtained in rejection of disturbances

Controller	Settling time
PID Standard	7.6 s
Genetic algorithms	3.8 s
Ant colony	3.8 s
Cuckoo Search	3.4 s

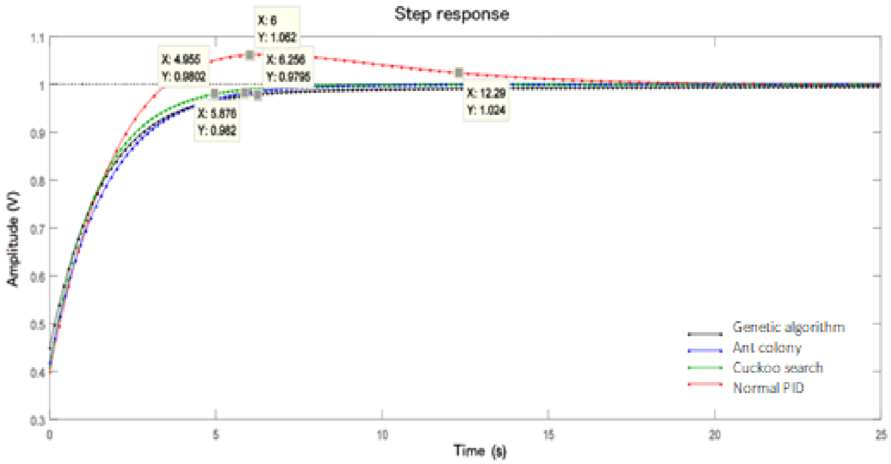


Figure 7. Comparison of simulated results

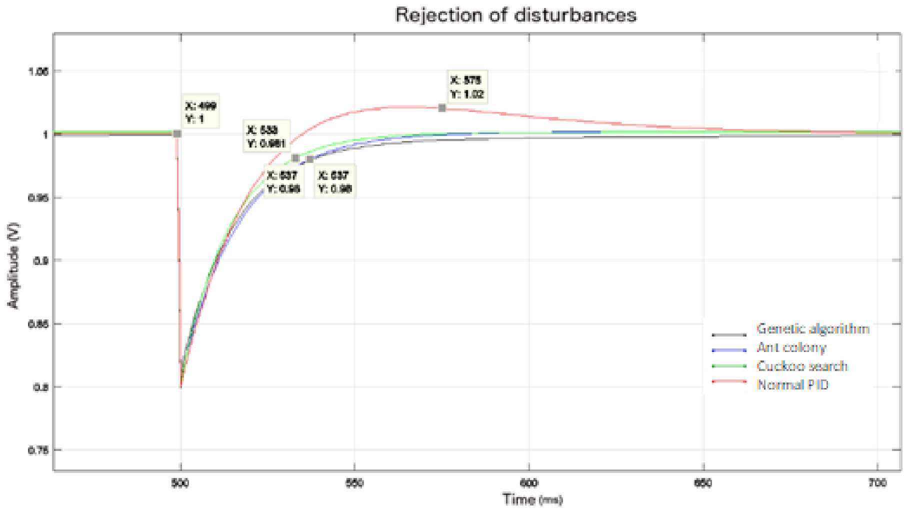


Figure 8. A comparative graph of controllers performance in rejection of disturbances

As shown in Figure 8, the responses obtained by the controllers tuned by bio-inspired algorithms maintain a similar behavior and reaction values in response to the applied disturbance and without overlining the signal and highlighting the controller tuned by cuckoo search, which recovers 12% faster. In summary, the results obtained by each of the controllers can be compared in Table 7.

Table 7. Summary of features of each controller

Tuning method	Genetic algorithms	Ant colony	Cuckoo Search
Measured settling times [s]	6.26	5.88	4.96
Percentage of overshoot	0%	0%	0%
Population size	20	20	20
Generations to achieve the best result	24	23	24
Maximum number of iterations performed	50	50	50
Simulation time measured	157.88	59.93	104.92

4.2. Measured results

After the implementation of the best controllers obtained from the execution of the bio-inspired algorithms designed, the response shown in Figure 9 was obtained. Figure 8 shows the behavior of the controllers applied to the PCT-2 temperature plant. It should be noted that the measures presented have been taken with a sampling period of 50 ms. The measurements obtained in the signals corresponding to the controllers optimized by genetic algorithms, ant colony, and cuckoo search, do not exceed 2%

of the measured signal, despite the increase in oscillation obtained by the instability of the plant, unlike the controller optimized by PID Tunner, and whose measurements are summarized in Table 8. According to the taken measures, we can notice better performance concerning the time of settling in the controller tuned by ant colony (as in simulated case) with 10.95 seconds, however, since on this occasion, the measured signals do show overshoot, that the response obtained by the controller tuned by cuckoo search delivers the least overshoot of all with 3.9%.

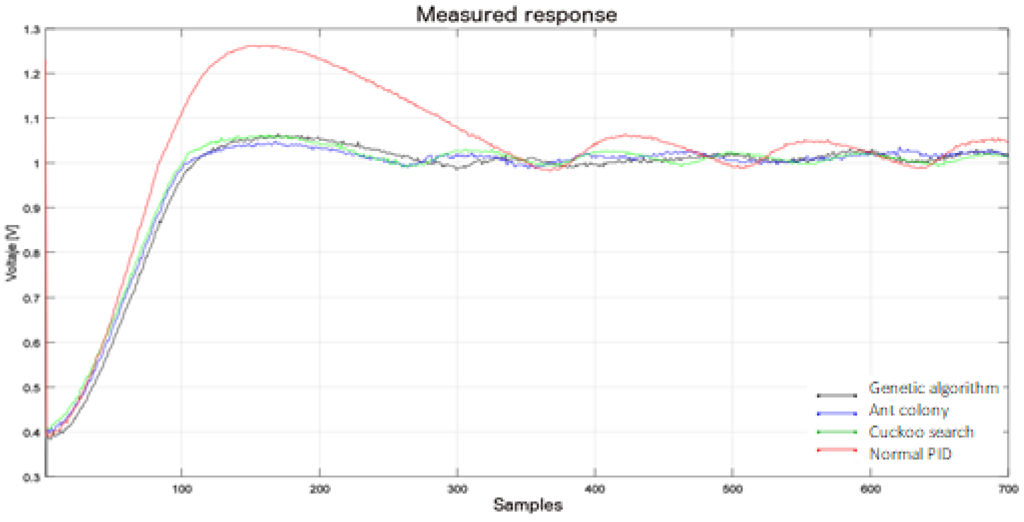


Figure 9. Measured response of controllers in transitory regime

Table 8. Summary of characteristics measured in controllers

Controller	Maximum voltage [v]	Overshoot percentage	Establishement time [s]
PID	1.261	26.1%	-
Genetic algorithms	1.064	6.4%	12.65
Ant colony	1.061	6.1%	10.95
Cuckoo Search	1.039	3.9%	11.3

5. CONCLUSIONS

After performing the respective analysis of results, some fundamental parameters have been determined to make the comparison between the designed algorithms. The settling time measured in the simulated cases determines that the controller optimized by the CS algorithm is stabilized by 14.7% faster than the controller optimized by GA and 11.76% faster than the controller optimized by AC, whereas in the case of the controller implemented on the temperature module a higher settling speed could be measured in the controller optimized by AC, being this is 15.52% faster than that optimized by GA and 3.19% faster than the controller optimized by CS. In the second parameter, it was possible to measure the best performance in terms of the percentage of overshoot in the controller designed by CS, this being 56.41% smaller than the controller optimized by AC and 64.1% smaller than the controller optimized by GA. Similarly, the recovery time in rejection of disturbances in the three optimized controllers has been measured, concluding that the CS algorithm recovers 12.5% faster than the other two implemented algorithms. And finally, an execution time of the implemented algorithms has been measured, observing a faster execution speed and a lower computational cost in the AC algorithm, which is executed 75.07% faster than the CS algorithm and 163.34% than GA.

Regarding the implementation in the PCT-2 temperature plant, the rapid control action can be evidenced before the temperature changes measured in the controllers designed based on bio-inspired algorithms, unlike the slow behavior of the standard PID controller that resulted in a signal unable to stabilize in a range less than 2%. The obtained results show a better performance in the controllers tuned by the bioinspired algorithms in comparison to the PID Tuner tool. Likewise, the ant colony and cuckoo search present similar performance to the controller tuned by the genetic algorithms method, but a better response in terms of computational cost.

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