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A Comparative Study Using Bio-Inspired Optimization Methods Applied to Controllers Tuning

Davi Leonardo de Souza¹, Fran Sérgio Lobato² and Rubens Gedraite²

¹*Department of Chemical Engineering and Statistics*
Universidade Federal de São João Del-Rei,

²*School of Chemical Engineering*
Universidade Federal de Uberlândia
Brazil

1. Introduction

The evolution of process control techniques have increased in a significant way during last years. Even so, in the industry, the Proportional-Integral-Derivative (PID) controller is frequently used in closed loops due to its simplicity, applicability, and easy implementation (Astrom & Hagglund, 1995); Shinskey, 1998; (Desborough & Miller, 2002). An extensive research concerning regulatory control of loops used in refinery, chemical, and pulp and paper processes reveals that 97% of the applications make use of classical PID structure even though sophisticated control techniques, like advanced control strategies, are also based on PID algorithms with lower hierarchy level (Desborough & Miller, 2002).

Traditionally, the controllers tuning is obtained using classical methods, such as Ziegler-Nichols (ZN), Cohen-Coon (CC) and hybridization. However, these methodologies are found to present quite satisfactory results for first-order processes, but they usually fail to provide acceptable performance for higher-order processes and especially for nonlinear ones due to large overshoots and poor regulation on loading (Hang et al., 1991; Mudi et al., 2008). In addition, it has been quite difficult to tune properly the PID parameters, during typical operation plant, due to difficulties related to production goals (Coelho & Pessoa, 2011).

Recently, optimization methods through use of information about real or synthetic data, has been used as alternative to controllers tuning (Lobato & Souza, 2008). Among these strategies, one can cite the based on evolutionary optimization techniques to controllers tuning, such as fuzzy logic (Hamid et al., 2010), genetic algorithms (Bandyopadhyay et al., 2001; Pan et al., 2011), augmented Lagrangian particle swarm optimization algorithm (Sedlaczek & Eberhard, 2006), particle swarm optimization (Kim et al., 2008; Solihin et al., 2011); differential evolution algorithm (Lobato & Souza, 2008); and differential evolution combined with chaotic Zaslavskii map (Coelho & Pessoa, 2011). Basically, the interest in evolutionary approach is due to following characteristics: easy code building and implementation, no usage of information about gradients and, capacity to escape from local optimal (Lobato & Souza, 2008; Souza, 2007).

According to this search area, biological systems have contributed significantly to the development of new optimization techniques. These methodologies - known as Bio-inspired Optimization Methods (BiOM) - are based on usage of strategies that seek to mimic the behavior observed in species of nature to update a population of candidates to solve optimization problems (Lobato et al., 2010). These systems have the capacity to notice and to modify its "atmosphere" in order to seek diversity and convergence. In addition, this capacity turns possible the communication among the agents (individuals of population) that capture the changes in "atmosphere" generated by local interactions (Parrich et al., 2002).

Among the most recent bio-inspired strategies, one can cite the Bees Colony Algorithm - BCA (Pham et al., 2006), the Fish Swarm Algorithm - FSA (Li et al., 2002) and the Firefly Colony Algorithm - FCA (Yang, 2008). The classical form of BCA is based on the behavior of bees' colonies in their search of raw materials for honey production. In each hive, groups of bees (called scouts) are recruited to explore new areas in search for pollen and nectar. These bees, returning to the hive, share the acquired information so that new bees are indicated to explore the best regions visited in an amount proportional to the previously passed assessment. Thus, the most promising regions are best explored and eventually the worst ones end up being discarded. This cycle repeats itself, with new areas being visited by scouts at each iteration (Pham et al., 2006). The FSA is a random search algorithm based on the behaviour of fish swarm which contains searching, swarming and chasing behaviour. It constructs the simple behaviours of artificial fish firstly, and then makes the global optimum appear finally based on animal individuals' local searching behaviours (Li et al., 2002). Finally, the FCA is inspired in social behaviour of fireflies and their communication through the phenomenon of bioluminescence. This optimization technique admits that the solution of an optimization problem can be perceived as an agent (firefly) which "glows" proportionally to its quality in a considered problem setting. Consequently each brighter firefly attracts its partners (regardless of their sex), which makes the search space being explored more efficiently (Yang, 2008).

In the present contribution, BiOM are used for the controllers tuning in chemical engineering problems. For this finality, three problems are studied, with emphasis on a realistic application: the control design of heat exchangers on pilot scale. The results obtained with the methodology proposed are compared with those from the classical methods. This chapter is organized as follows. Classical methods to controllers tuning are reviewed in Section 2. In Section 3 the main characteristics of BiOM are briefly presented. The results and discussion are described in Section 4. Finally, the conclusions and suggestions for future work complete the chapter.

2. Controllers tuning using classical methods

As mentioned earlier, about 97% of industrial controllers are of PID type, and implement them in practice, or even during maintenance of same, there are several technical adjustments of its parameters. In literature, there are several classical methods for controllers tuning, such as strategies based on minimization of integral error, and correlation-based methods such as ZN and CC, among others.

The majority of works involving the controllers design use the ZN and CC methods (Conner & Seborg, 2005; Lobato & Souza, 2008; Solihin et al., 2011; Xi et al., 2007). In this context, the ZN and CC methods are brief described.

2.1 Reaction curve method

The principle of this method is the correlation between controller parameters (K_c , τ_I e τ_D) with model parameters (K , τ and θ) through the temporal response of open-loop system (called the process reaction curve), compared to a step input. In open loop, leads to a unit step of input variable to obtain the reaction curve as in Fig. 1. With the parameters θ and τ , we can obtain

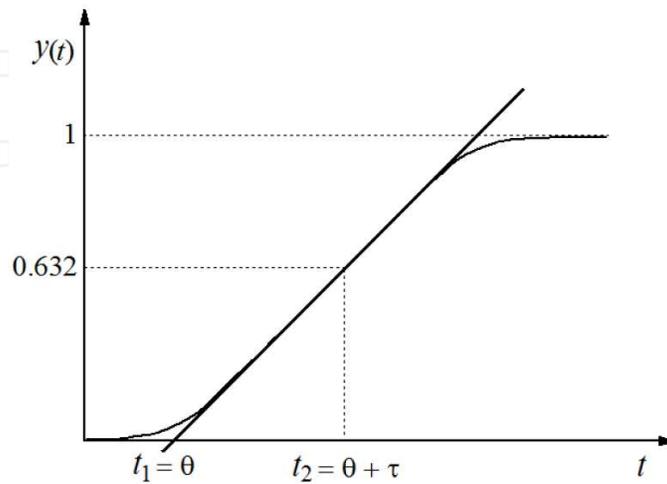


Fig. 1. Time response to open-loop system with step input $y(t)$.

the controller parameters according to Tab. 1.

Controller Parameter	ZN	CC
P	$KK_c = \frac{\tau}{\theta}$	$KK_c = \frac{\tau}{\theta} + \frac{1}{3}$
PI	$KK_c = 0.9 \frac{\tau}{\theta}$ $\frac{\tau_I}{\tau} = 3.33 \frac{\theta}{\tau}$	$KK_c = 0.9 \frac{\tau}{\theta} + 0.083$ $\frac{\tau_I}{\tau} = \frac{\theta(3.33 + 0.33(\theta/\tau))}{1 + 2.2(\theta/\tau)}$
PID	$KK_c = 1.2 \frac{\tau}{\theta}$ $\frac{\tau_I}{\tau} = 2 \frac{\theta}{\tau}$ $\frac{\tau_D}{\tau} = 0.5 \frac{\theta}{\tau}$	$KK_c = 1.35 \frac{\tau}{\theta} + 0.27$ $\frac{\tau_I}{\tau} = \frac{\theta(32 + 6(\theta/\tau))}{13 + 8(\theta/\tau)}$ $\frac{\tau_D}{\tau} = \frac{0.37(\theta/\tau)}{1 + 0.2(\theta/\tau)}$

Table 1. Controllers tuning with ZN and CC methods through reaction curve (Seborg et al., 1989).

2.2 Continuous cycling method

This classical method is based on sustained oscillation, known as Continuous Cycling Method (Seborg et al., 1989). This procedure is valid only for open-loop stable plants, and conducted with the following steps: (i) establishment of parameter proportional to a very small gain, (ii) increase the gain to obtain an oscillatory response with constant amplitude and period (iii) registration of critical value (K_u), critical period (P_u) and (iv) adjustment of the parameters, as shown in Tab. 2. Although the vast majority of PID controllers design is tuned by ZN and CC methods, some difficulties can be observed, such as the need for knowledge of process dynamics in open-loop, and in the Continuous Cycling method, the need to work near of system instability limit (Seborg et al., 1989).

Controller/Parameter	K_c	τ_I	τ_D
P	$0.5K_u$	-	-
PI	$0.45K_u$	$P_u/1.2$	-
PID	$0.6K_u$	$0.5P_u$	$P_u/8$

Table 2. Controllers tuning with Continuous Cycling (Seborg et al., 1989).

3. Bio-inspired optimization methods

In the last decades, nature has inspired the development of various optimization methods. These techniques try to imitate behaviors of species found in nature, such as ants, birds, bees, fireflies, bacteria, among others, to extract information that can be used to promote the development of simple and robust strategies.

This section presents briefly three bio-inspired algorithms in nature: the Bee Colony Algorithm, the Firefly Colony Algorithm and the Fish Swarm Algorithm.

3.1 Bee colony algorithm - BCA

The algorithm proposed by Pham et al. (2006) and described in this section is based on the following characteristics observed in nature (von Frisch, 1976): (i) a bees' colony can extend itself over long distances (more than 10 km) and in multiple directions simultaneously to exploit a large number of food sources, and (ii) capacity of memorization, learning and transmission of information in colony, so forming the swarm intelligence.

In a colony the foraging process begins by scout bees being sent to search randomly for promising flower patches. When they return to the hive, those scout bees that found a patch which is rated above a certain quality threshold (measured as a combination of some constituents, such as sugar content) deposit their nectar or pollen and go to the "waggle dance".

This dance is responsible by the transmission (colony communication) of information regarding a flower patch: the direction in which it will be found, its distance from the hive and its quality rating (or fitness) (von Frisch, 1976). This dance enables the colony to evaluate the relative merit of different patches according to both the quality of the food they provide and the amount of energy needed to harvest it (Camazine et al., 2003). Mathematically this dance can be represented by following expression:

$$x = x - ngh + 2ngh \times rand \quad (1)$$

where x is the new position, ngh is the patch radius for neighbourhood search and $rand$ is the random generator.

After waggle dancing on the dance floor, the dancer (scout bee) goes back to the flower patch with follower bees that were waiting inside the hive. More follower bees are sent to more promising patches. This allows the colony to gather food quickly and efficiently. While harvesting from a patch, the bees monitor its food level. This is necessary to decide upon the next waggle dance when they return to the hive (Camazine et al., 2003). If the patch is still good enough as a food source, then it will be advertised in the waggle dance and more bees will be recruited to that source.

In this context, Pham et al. (2006) proposed an optimization algorithm inspired by the natural foraging behavior of honey bees and presented in Tab. 3.

1. Initialise population with random solutions.
2. Evaluate fitness of the population.
3. While (stopping criterion not met)
4. Select sites for neighborhood search.
5. Recruit bees for selected sites (more bees for the best e sites) and evaluate fitnesses.
6. Select the fittest bee from each site.
7. Assign remaining bees to search randomly and evaluate their fitnesses.
8. End While.

Table 3. Bees Colony Algorithm (Pham et al., 2006).

The BCA requires a number of parameters to be set, namely, the number of scout bees (n), number of sites selected for neighborhood search (out of n visited sites) (m), number of top-rated (elite) sites among m selected sites (e), number of bees recruited for the best e sites (nep), number of bees recruited for the other ($m-e$) selected sites (ngh), and the stopping criterion.

The BCA starts with the n scout bees being placed randomly in the search space. The fitnesses of the sites visited by the scout bees are evaluated in step 2.

In step 4, bees that have the highest fitnesses are chosen as “selected bees” and sites visited by them are chosen for neighborhood search. Then, in steps 5 and 6, the algorithm conducts searches in the neighborhood of the selected sites, assigning more bees to search near to the best e sites. The bees can be chosen directly according to the fitnesses associated with the sites they are visiting.

Alternatively, the fitness values are used to determine the probability of the bees being selected. Searches in the neighborhood of the best e sites, which represent more promising solutions, are made more detailed by recruiting more bees to follow them than the other selected bees. Together with scouting, this differential recruitment is a key operation of the BCA.

However, in step 6, for each patch only the bee with the highest fitness will be selected to form the next bee population. In nature, there is no such a restriction. This restriction is introduced here to reduce the number of points to be explored. In step 7, the remaining bees in the population are assigned randomly around the search space scouting for new potential solutions.

In the literature, various applications using this bio-inspired approach can be found, such as: modeling combinatorial optimization transportation engineering problems (Lucic & Teodorovic, 2001), engineering system design (Lobato et al., 2010; Yang, 2005), transport problems (Teodorovic & Dell’Orco, 2005), mathematical function optimization (Pham et al., 2006), dynamic optimization (Chang, 2006), optimal control problems (Afshar et al., 2001), parameter estimation in control problems (Azeem & Saad, 2004), estimation of radiative properties in a one-dimensional participating medium (Ribeiro Neto et al., 2011), among other applications (<http://www.bees-algorithm.com/>).

3.2 Firefly colony algorithm - FCA

The FCA is based on the characteristics of fireflies’ bioluminescence, insects notorious for their light emission. Although biology does not have a complete knowledge to determine all

the utilities that firefly luminescence can bring to, at least three functions have been identified (Lukasik & Zak, 2009; Yang, 2008): (i) as a communication tool and appeal to potential partners in the reproduction, (ii) as a bait to lure prey for the firefly, (iii) as a warning mechanism for potential predators reminding them that fireflies have a bitter taste.

It were idealized some of the flashing characteristics of the fireflies so as to develop firefly-inspired algorithms. The following three idealized rules were used (Yang, 2008):

- all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;
- attractiveness is proportional to their brightness, thus for any two flashing fireflies the less bright will move towards the brightest one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brightest one, than a particular firefly will move randomly;
- the brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function.

According to Yang (2008), in the firefly algorithm there are two important issues: the variation of light intensity and the formulation of the attractiveness. For simplicity, it is always assumed that the attractiveness of a firefly is determined by its brightness, which in turn is associated with the encoded objective function.

This swarm intelligence optimization technique is based on the assumption that the solution of an optimization problem can be perceived as agent (firefly) which “glows” proportionally to its quality in a considered problem setting. Consequently, each brighter firefly attracts its partners (regardless of their sex) which make the search space being explored more efficiently.

The algorithm makes use of a synergic local search. Each member of the swarm explores the problem space taking into account results obtained by others, still applying its own randomized moves as well. The influence of other solutions is controlled by the value of attractiveness (Lukasik & Zak, 2009).

According to Lukasik & Zak (2009), the FA is presented as follows. Consider a continuous constrained optimization problem where the task is to minimize the cost function $f(x)$. Assume that there exists a swarm of N agents (fireflies) solving the above mentioned problem iteratively, and x_i represents a solution for a firefly i at the algorithm’s iteration k , whereas $f(x_i)$ denotes its cost. Initially, all fireflies are dislocated in S (randomly or employing some deterministic strategy). Each firefly has its distinctive attractiveness β which implies how strong it attracts other members of the swarm. As the firefly attractiveness, one should select any monotonically decreasing function of the distance $r_i=d(x_i,x_j)$ to the chosen firefly j , e.g., the exponential function:

$$\beta = \beta_0 e^{-\gamma r_j} \quad (2)$$

where β_0 and γ are the following predetermined algorithm parameters: maximum attractiveness value and absorption coefficient, respectively. Furthermore, every member of the swarm is characterized by its light intensity, I_i , which can be directly expressed as the inverse of a cost function $f(x_i)$. To effectively explore the considered search space S , it is assumed that each firefly i changes its position iteratively by taking into account two factors: attractiveness of other swarm members with higher light intensity, e.g., $I_j > I_i, \forall j=1, \dots, m$,

$j \neq i$, which is varying across the distance and a fixed random step vector u_i . It should be noted as well that if no brighter firefly can be found only such randomized step is being used.

Thus, moving at a given time step t of a firefly i toward a better firefly j is defined as:

$$x_i^t = x_i^{t-1} + \beta (x_j^{t-1} - x_i^{t-1}) + \alpha \left(rand - \frac{1}{2} \right) \quad (3)$$

where the second term on the right hand side of the equation inserts the attractiveness factor, β while the third term (governed by the parameter α) governs the insertion of certain randomness in the path followed by the firefly, $rand$ is a random number between 0 and 1.

In the literature, few works using the FCA can be found. In this context, the application of the technique is emphasized in continuous constrained optimization task (Lukasik & Zak, 2009), multimodal optimization (Yang, 2009), solution of singular optimal control problems (Pfeifer & Lobato, 2010) and load dispatch problem (Apostolopoulos & Vlachos, 2011).

3.3 Fish swarm algorithm - FSA

In the development of FSA, based on fish swarm and observed in nature, the following characteristics are considered (Madeiro, 2010): (i) each fish represents a candidate solution of optimization problem; (ii) food density is related to an objective function to be optimized (in an optimization problem, the amount of food in a region is inversely proportional to value of objective function); and (iii) the aquarium is the design space where the fish can be found.

As noted earlier, the fish weight at the swarm represents the accumulation of food (e.g., the objective function) received during the evolutionary process. In this case, the weight is an indicator of success (Madeiro, 2010).

Basically, the FSA presents four operators classified into two class: "food search" and "movement". Details on each of these operators are shown as follows.

3.3.1 Individual movement operator

This operator contributes for the movement individual and collective of fishes in swarm. Each fish updates its new position using the Eq. (4):

$$x_i(t+1) = x_i(t) + rand \times s_{ind} \quad (4)$$

where x_i is the final position of fish i at current generation, $rand$ is a random generator and s_{ind} is a weighted parameter.

3.3.2 Food operator

The weight of each fish is a metaphor used to measure the success of food search. The higher the weight of a fish, the more likely this fish be in a potentially interesting region in design space.

According to Madeiro (2010), the amount of food that a fish eats depends on improvement in its objective function in current generation and the value of greatest value considering the swarm. The weight is updated according to Eq. (5):

$$W_i(t+1) = W_i(t) + \frac{\Delta f_i}{\max(\Delta f)} \quad (5)$$

where $W_i(t)$ is the fish weight i at generation t and Δf_i is the difference of objective function between the current position and the new position of fish i . It is important to emphasize that $\Delta f_i=0$ for the fishes in same position.

3.3.3 Instinctive collective movement operator

This operator is important for the individual movement of fishes when $\Delta f_i \neq 0$. Thus, only the fishes whose individual execution of the movement resulted in improvement of their fitness will influence the direction of motion of the school, resulting in instinctive collective movement. In this case, the resulting direction (I_d), calculated using the contribution of the directions taken by the fish, and the new position of the i th fish are given by:

$$I_d(t) = \frac{\sum_{i=1}^N \Delta x_i \Delta f_i}{\sum_{i=1}^N \Delta f_i} \quad (6)$$

$$x_i(t+1) = x_i(t) + I_d(t) \quad (7)$$

It is important to emphasize that in the application of this operator, the direction chosen by a fish that located the largest portion of food to exert the greatest influence on the swarm. Therefore, the instinctive collective movement operator tends to guide the swarm in the direction of motion chosen by fish who found the largest portion of food in it individual movement.

3.3.4 Non-Instinctive collective movement operator

As noted earlier, the fish weight is a good indication of search success for food. In this way, the swarm weight is increasing, this means that the search process is successful. So, the "radius" of the swarm must decrease for that other regions can be explored. Otherwise, if the swarm weight remains constant, the radius should increase to allow the exploration of new regions.

For the swarm contraction, the centroid concept is used. This is obtained by means of an average position of all fish weighted with the respective fish weights, according to Eq. (8):

$$B(t) = \frac{\sum_{i=1}^N x_i W_i(t)}{\sum_{i=1}^N W_i(t)} \quad (8)$$

If the swarm weight remains constant in the current iteration, all fish must update their positions using the Eq. (9):

$$x(t+1) = x(t) - s_{vol} \times rand \times \frac{x(t) - B(t)}{d(x(t), B(t))} \quad (9)$$

where d is a function that calculates the Euclidean distance between the centroid and the current position of fish, and s_{vol} is the step size used to control the displacement of fish.

In the literature, few works using the FSA can be found. In this context, feed forward neural networks (Wang et al., 2005), parameter estimation in engineering systems (Li et al, 2004),

combinatorial optimization problem (Cai, 2010), global optimization (Yang, 2010), Augmented Lagrangian fish swarm based method for global optimization (Rocha et al., 2011), forecasting stock indices using radial basis function neural networks optimized (Shen et al., 2011), and hybridization of the FSA with the Particle Swarm Algorithm to solve engineering systems (Tsai & Lin, 2011).

4. Applications

For evaluating the methodology proposed in this work for controllers tuning, some practical points should be emphasized:

- the objective function (Sum Quadratic Error - *SQE*) considered in all case studies is given by Eq. (10):

$$\min SQE = \sum_{k=1}^{np} Error = \sum_{k=1}^{np} \left(X^{setpoint} - X^{calculated} \right)^2 \quad (10)$$

where $X^{setpoint}$ and $X^{calculated}$ are the values of variables considered at *setpoint* and calculated using the mathematical model, respectively, and np is the points number used to formulate this objective function (np equals to 1000).

- in all case studies the following parameters used are presented in Tab. (Li et al., 2002; Pham et al., 2006; Yang, 2008).
- it should be emphasized that is necessary, with the parameters listed in this table, 1510 objective function evaluations in each algorithm.
- all case studies were run 20 times independently to obtain the values and standard deviations shown in the upcoming tables.
- the stopping criterion used was the maximum number of iterations (generations).
- to compare the results obtained by the BiOM, the following strategies were used: Ziegler-Nichols Sensibility-Limiar Method (ZN-SL), Ziegler-Nichols Reaction Curve Method (ZN-RC) and Cohen-Coon Reaction Curve Method (CC-RC).

4.1 Distillation column

This first study proposed by (Skogestad & Morari, 1987) considers a distillation column of high purity consisting of 25 plates, a condenser and a reboiler. The reflow ration and the composition of distillate are the input and output system, respectively. The dynamic model that describes this system is given by following transfer function (Skogestad & Morari, 1987):

$$G(z) = \frac{-0.75448z + 0.149199}{z - 0.6386913} \quad (11)$$

The objective is to maintain the composition of distillate in 0.99 by manipulating the reflow ratio, which has a nominal value of 1.477 Kmol/min. In this case, the following ranges to controllers tuning are considered: $0 \leq K_c \leq 150$, $0 \leq \tau_I \leq 50$ and $0 \leq \tau_D \leq 50$.

Table 5 presents the best value and standard deviation for the distillation column case study.

In this table can be observed that both the algorithms presented good estimates for the unknown parameters. When the results are analyzed in terms of the objective function (*OF*),

BCA	
Number of scout bees	10
Number of bees recruited for the best e sites	5
Number of bees recruited for the other selected sites	5
Number of sites selected for neighbourhood search	5
Number of top-rated (elite) sites among m selected sites	5
Neighborhood search	10^{-6}
Generation Number	50
FCA	
Number of fireflies	15
Maximum attractiveness value	0.9
Absorption coefficient	0.9
Generation Number	50
FSA	
Number of fishes	15
Weighted parameter (s_{ind})	0.01
Weighted parameter (s_{vol})	1
Generation Number	50

Table 4. Parameters used by the BiOM.

Method	K_c	τ_I (min^{-1})	τ_D (min^{-1})	OF (Eq. 10)
ZN-SL	67.2000	12.500	3.1250	8.10×10^{-3}
ZN-RC	2.6578	2.0000	0.5000	1.24×10^{-2}
CC-RC	3.2890	2.1154	0.3364	1.09×10^{-2}
BCA	24.282 (36.265)	0.008 (12.12)	43.103 (12.710)	8.102×10^{-3} (3.026×10^{-6})
FCA	77.412 (37.324)	0.003 (0.037)	26.955 (15.926)	8.100×10^{-3} (6.834×10^{-8})
FSA	128.009 (28.260)	0.009 (0.237)	7.176 (18.779)	8.101×10^{-3} (3.145×10^{-8})

Table 5. Results obtained by the BiOM - distillation column case study.

is clear that the combination of control parameters lead us to very close values, also seen in the value of standard deviation presented.

Figure 2 present the distillation top and the control action (reflow profile), respectively, using the classical methods and the BiOM. The behaviour observed in this simple case study is practically the same for all strategies used.

4.2 Heat exchanger

Consider a heat exchanger type shell-tube counter-current as illustrated in Fig. 3 (Garcia, 2005). In this figure, $Q_{c,i}$ and $T_{c,i}$ represent, the flow rate and inlet temperature of the hot fluid, respectively, $Q_{t,e}$ and $T_{t,e}$, the flow rate and inlet temperature of cold fluid, respectively. T_c is the fluid temperature on the side of hull and T_t is the fluid temperature in the side of pipe. The objective of this system is to heat a water stream at 40°C to 41°C manipulating a hot water stream ($Q_{t,e}$) with nominal flow rate $0.0004 \text{ m}^3/\text{s}$. The thermal exchanges are

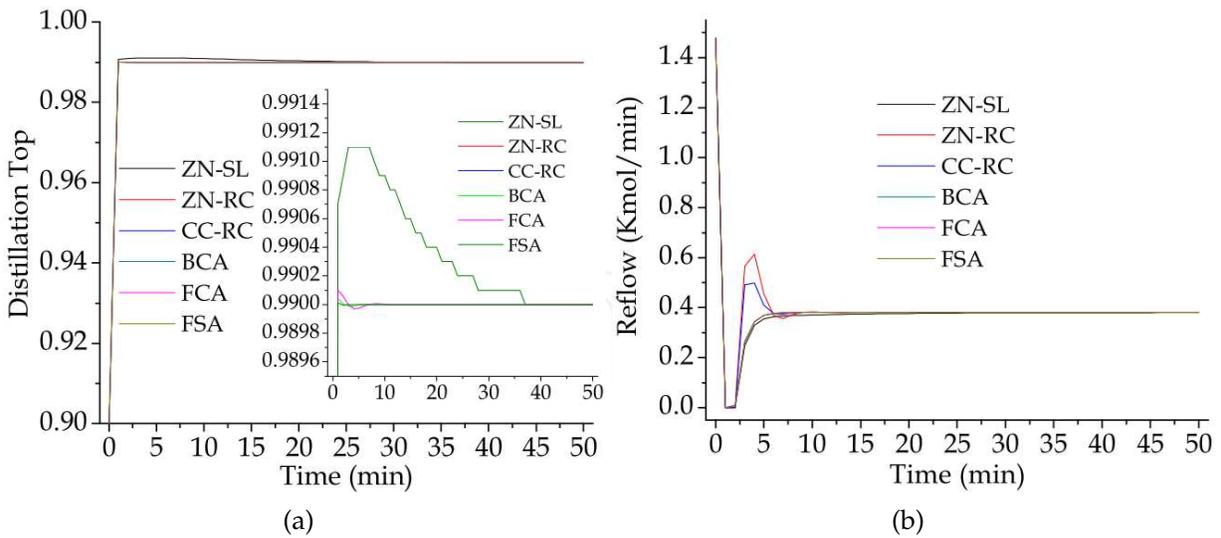


Fig. 2. Distillation top profile (a) and reflow profile (b) using classical and BiOM.

considered: heat transfer fluid circulating between the tubes and the hull, heat transfer fluid circulating between the hull and its walls, and transport of energy (enthalpy) due to fluid flow in pipes and shell. More information about the design and the considerations are in Garcia (2005).

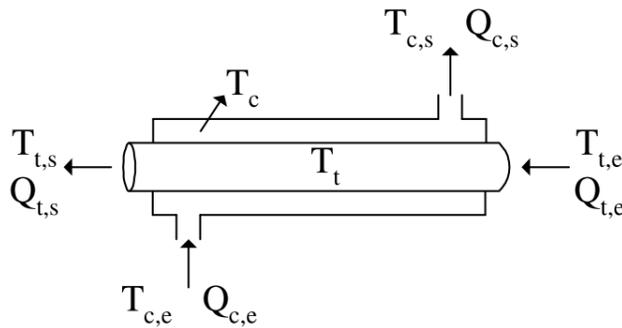


Fig. 3. Schematic heat exchanger.

The dynamic model that describes this system is given by transfer function:

$$G(s) = \frac{0.0189}{10s^3 + 5.114s^2 + 0.825s + 0.041} \tag{12}$$

In this case, the following ranges to controllers tuning are considered: $0 \leq K_c \leq 150$, $0 \leq \tau_I \leq 50$ and $0 \leq D \leq 50$.

Table 6 presents the best value and standard deviation for the heat exchanger case study.

As observed in the previous case, that both the algorithms presented good estimates for the unknown parameters, but the best results were obtained by the BiOM. It is possible to observe the fluctuation of control parameters, found in the value of standard deviation.

Figure 4 present the temperature and flow profiles using the classical methods and the BiOM. It should be emphasized the oscillatory behaviour observed with the application of the BiOM, even for a short period of time (see Fig. 4(a)).

Method	K_c	τ_I (s^{-1})	τ_D (s^{-1})	OF (Eq. 10)
ZN-SL	5.8800	30.0000	7.5000	0.6206
ZN-RC	3.3600	27.0000	6.7500	2.1733
CC-RC	4.4300	26.0200	4.2500	0.9025
BCA	26.289 (10.949)	10.086 (5.845)	17.120 (4.467)	0.0219 (0.0202)
FCA	48.638 (13.425)	6.577 (5.146)	24.354 (4.898)	0.0228 (0.033)
FSA	47.274 (9.751)	9.012 (7.209)	17.508 (5.409)	0.0238 (0.0157)

Table 6. Results obtained by the BiOM - heat exchanger case study.

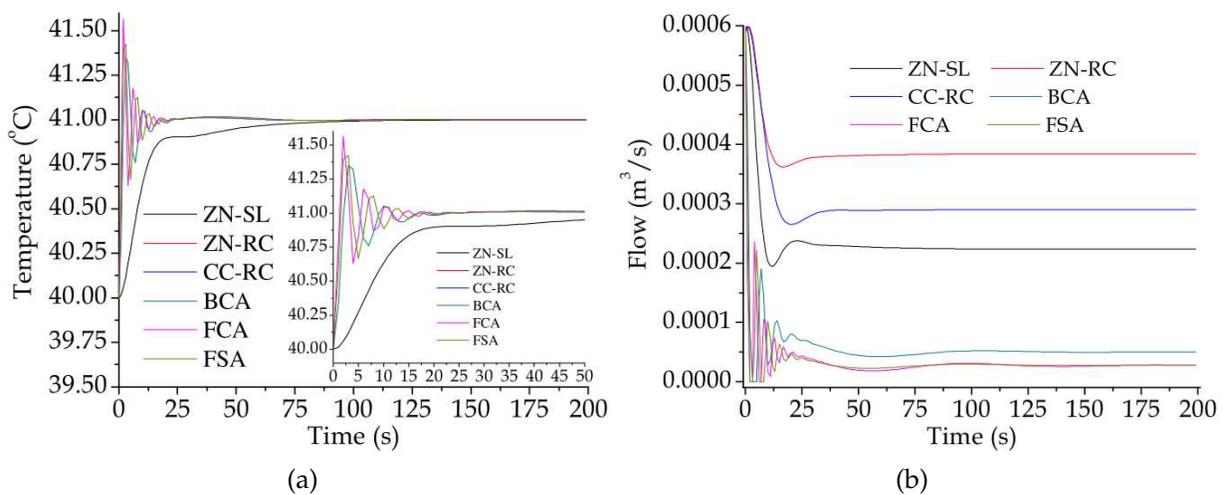


Fig. 4. Temperature and flow (control action) profiles.

4.3 Shell and tube heat exchanger

Finally, consider the real system shown in Fig. 5 for analysis and application of the previously studied concepts. This system consists essentially of: (i) the main tank (P5) in stainless steel with a capacity of approximately 0.250 m^3 , (ii) stainless steel shell and tube heat exchanger (P1), (iii) positive displacement pump for movement of food products (P3), (iv) centrifugal pump for the heating agent movement (P2) and (v) vertical cylindrical storage tank water heater (P4) (Gedraite et al., 2011).

The Vettore-Manghi heat exchanger is responsible for heating the liquid food product that flows inside the tube bundle, considering four passes. The displacement of the process fluid inside the tubes of the heat exchanger is driven by a model RE50-110 Robuschi positive displacement pump (pump 2). The heating of the heat exchanger is done by hot water which flows through the shell side of the exchanger. Hot water is transported by Robuschi, model RE50-160 centrifugal pump (pump 3). Hot water is heated at the expense of saturated steam produced in the H. BREMER steam generator, installed in suitable and safe environment. The temperature of the process fluid is controlled by manipulating the flow of steam fed to the system, whose setting is done by the Fluxotrol model PK2117 control valve (P4), with reverse action. The hot water removed from the shell of the heat exchanger returns to the vertical tank, that is equipped with a safety valve. For cooling the product, the procedure is reversed, ie, the

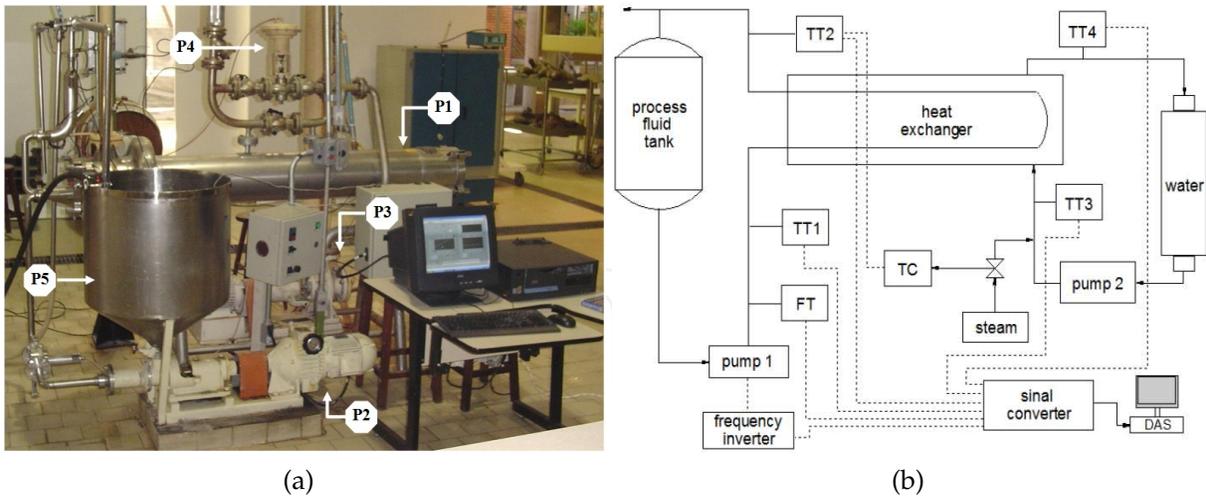


Fig. 5. Process and instrumentation diagram for the system studied (Gedraite et al., 2011).

flow control valve used for manipulate the value of heating steam flow is gradually closed. In this process, the response time is slower when compared with heating time. Cooling only occurs as a result of the heat exchange between the body of the heat exchanger, the process fluid and the environment.

The data acquisition and control system is composed by an PC based DAS (Data Acquisition System), working also as a computer control. This system consists of the following items: (i) PC microcomputer for the collection and storage of process data, (ii) LabVIEW[®] version 2009 application to perform monitoring, data acquisition and process control in real-time, (iii) data acquisition board, National Instruments (NI) PCI-6259 model, with 4 analog output channels and 32 analog input channels with both operating range of -10 V to +10 V and resolution of 16 bits, and 48 channel digital input/output programmable, (iv) set of cables to acquisition board NI model SHC68-68-EPM, (v) a connections terminal NI model CB-68LP, (vi) signal conditioners INCON model CS01-1360 to match the signals from the sensing elements of temperature, (vii) temperature sensors IOPE model 49312 type Pt 100, (viii) METROVAL flow meter model OI-2-SMRX/FS, (ix) ENGINSTREL model 621-IPB electrical current to pressure signal converter, (x) pneumatic control valve Fluxotrol model PK2117 and (xi) Micronal model B474 pH meter.

4.3.1 Approximate model system

The non-parametric identification process employs basically the response curves of the system when excited by input signals like step, impulse or sinusoidal. From these curves, one can extract approximate models of low order, which describe the dynamic behavior of the process (Aguirre, 2007). These models are reasonably accurate and can be assumed to be good enough to represent the system studied. In this work, they were used to perform the pre-tuning PID controllers and to mathematically model the dynamic behavior of pH versus time.

The input most commonly used as non-parametric excitation to identify a process dynamics is the step (Aguirre, 2007). These tests usually can generate by means of graphical representation, empirical dynamic models that consists of low order transfer functions (1st or 2nd order, possibly including a dead time) with a maximum of four parameters to be determined experimentally.

Astrom & Hagglund (1995) state that many of the processes can be represented in an approximate way, by combining four elements typically found in industrial processes, namely: (i) gain, (ii) transport delay, (iii) transfer delay and (iv) integrating element. The approach of overdamped systems of order 2 or higher for transfer delay plus dead time (transport delay) can be represented by the transfer function shown in Eq. (13) (Aguirre, 2007):

$$G(s) = \frac{K.e^{-\theta s}}{1 + \tau s} \quad (13)$$

where K is the gain, τ is the transfer delay and θ is the dead time (or transport delay).

4.4 Plant reaction curves

Tests were made to obtain the process parameters related to plant response to changes in flow and temperature. In this test, the equipment was put into operation with steady flow of 7 Lmin⁻¹ and applied positive step 3 Lmin⁻¹ at time 32 s, waiting for the system stabilization. In the sequence, a negative step of 3 Lmin⁻¹ at time 203 s was applied. The first step (7 to 10 Lmin⁻¹) was adopted to obtain the process parameters, whose results are presented below. Figure 6 shows the system behavior to the situation examined.

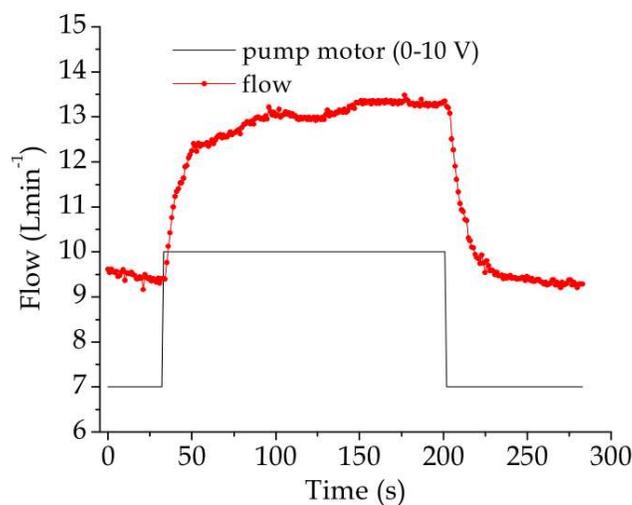


Fig. 6. Step test at flow of process fluid.

In the assay realized for the temperature, whose response time is illustrated in Fig. 7, a constant flow of 9 Lmin⁻¹ was used. The outlet temperature of process fluid was adjusted equal to 60 °C and a step into the control valve installed at the steam line stem position was applied at the time 50 s, starting from the condition of fully closed until 50% opening. Following the instant 1430 s, we applied a second step of amplitude equal to 10%. The analysis to obtain the process parameters were calculated considering the first step (50%).

The process parameters K (process gain), τ (process time constant) and θ (process dead time) were calculated using the method proposed by Aguirre (2007). The transfer functions obtained are presented in Eqs. (14) and (15):

i) flow: $K=1.3 \text{ Lmin}^{-1}\text{V}^{-1}$, $\tau=14 \text{ s}$ and $\theta=2 \text{ s}$

$$G(s) = \frac{1.3 \exp(-2s)}{1 + 14s} \quad (14)$$

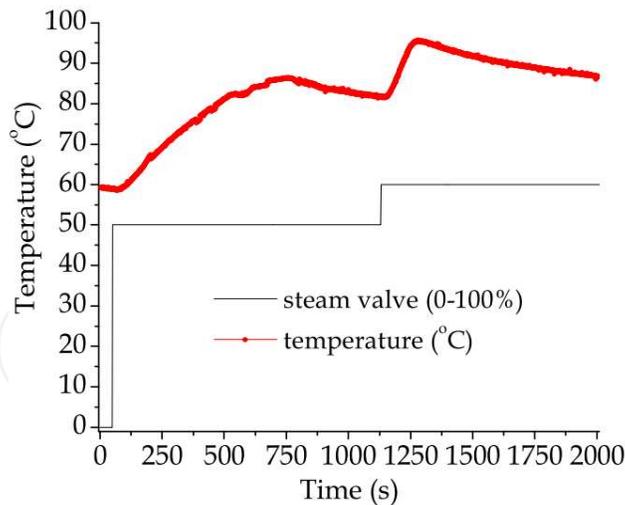


Fig. 7. Step test at temperature position at steam line.

ii) temperature: $K=7.22$ °C, $\tau=378$ s and $\theta=78$ s

$$G(s) = \frac{7.22 \exp(-78s)}{1 + 378s} \quad (15)$$

In these simulations, the following ranges to design parameters are considered: $0 \leq K_c \leq 50$, $0 \leq \tau_I \leq 248$ and $0 \leq \tau_D \leq 50$.

Tables 7 and 8 present the average and standard deviation for the flow and the temperature case studies.

Method	K_c	τ_I (s ⁻¹)	τ_D (s ⁻¹)	OF (Eq. 10)
ZN-SL	6.9240	3.25	0.8125	0.0119
ZN-RC	3.1185	8.0000	2.0000	0.0629
CC-RC	3.7162	8.9937	1.3972	0.0366
BCA	9.4859 (1.6760)	3.7011 (0.5122)	0.6687 (0.1531)	1.0707×10^{-5} (0.0055)
FCA	9.1635 (1.2686)	3.9305 (0.7119)	0.7154 (0.1616)	2.2288×10^{-7} (0.0021)
FSA	9.3345 (0.8472)	3.8780 (0.7640)	0.7149 (0.2455)	3.3536×10^{-7} (0.0001)

Table 7. Results obtained by BiOM - Flow case study.

In these tables is possible to observe that both the algorithms presented good estimates for the controllers tuning, but the best results were obtained by the BiOM (this represent a reduction of approximately 97% in comparison to ZN-SL method). In addition, it is important to comment that if a larger range for the design variables was used, the value of the objective function would reduce. However, in spite of this reduction, the design found cannot be physically viable, e.g., can represent an infeasible condition in industrial context, as illustrated in Fig. 11(a) for the classical methods.

Figures 8 and 9 present the flow and temperature profiles using the classical methods and the BiOM. Also can be observed in these figures the control action (motor pump signal (8(a)) and valve steam signal (9(b))).

Method	K_c	τ_I (s^{-1})	τ_D (s^{-1})	OF (Eq. 10)
ZN-SL	0.8880	112.5	28.125	87303
ZN-RC	0.7453	124.0000	31.0000	64056
CC-RC	0.8758	142.8046	21.9605	77922
BCA	1.3713 (0.0010)	248.0000 (0)	38.1768 (0.0307)	1929.1287 (0.2111)
FCA	1.3708 (0.0018)	248.0000 (0.0008)	38.1905 (0.0518)	1929.1073 (0.1990)
FSA	1.3725 (0.0015)	248.0000 (0.0023)	38.1428 (0.0438)	1929.1481 (0.1501)

Table 8. Results obtained by BiOM - Temperature case study.

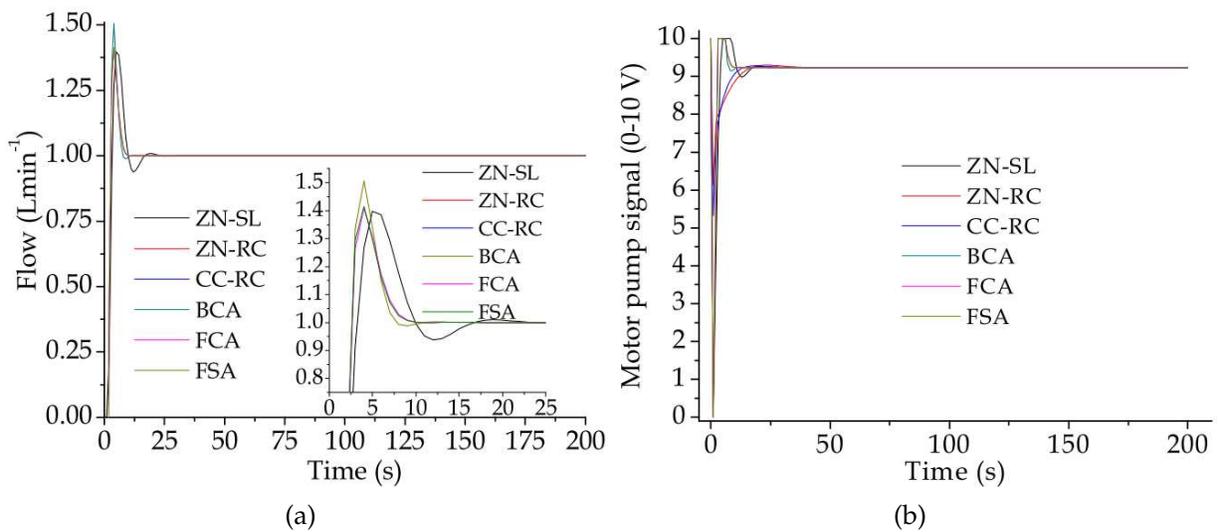


Fig. 8. Flow profile and control action (motor pump signal).

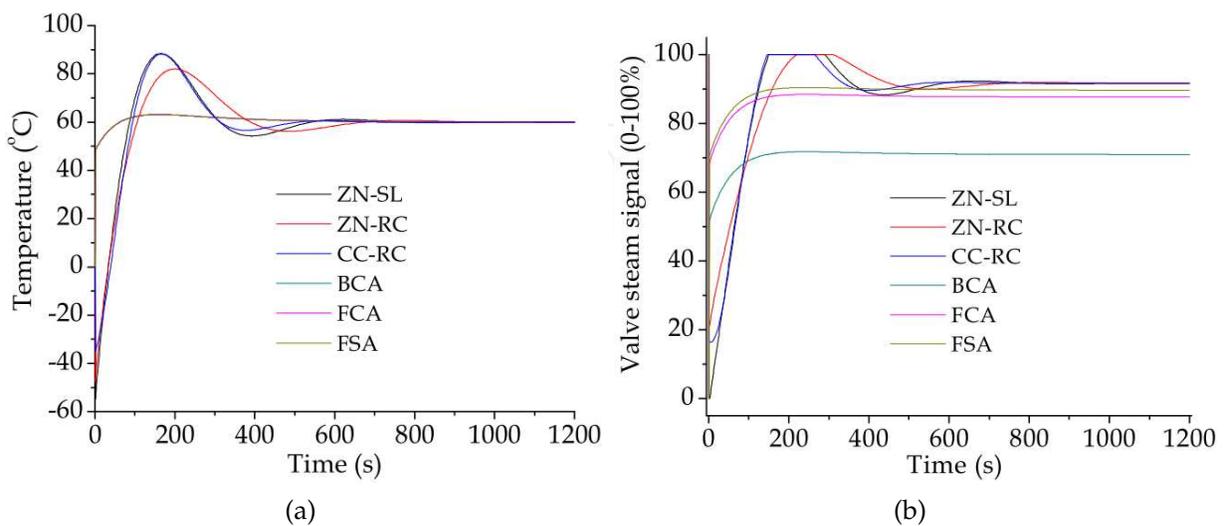


Fig. 9. Temperature profile and control action (valve steam signal).

5. Conclusions

In the present contribution, the effectiveness of using the BiOM for controllers tuning through formulation of an optimization problem was analyzed.

In this sense, three cases were studied and it was possible to conclude that both bio-inspired algorithms led to good results for an acceptable number of generations (1510) when compared to the classical methods. It should be pointed out that the quality of solution obtained is dependent of design space considered, e.g., if other ranges were used, other results can be found. Besides, also can be observed that the combination of control parameters, can take to values close, in terms of the objective function.

It is important to emphasize that the use of the BiOM not have the pretension of substituting the classical techniques for the controllers tuning, but to represent an interesting alternative for this purpose.

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