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COMPARISON OF FUZZY TYPE-2 AND CONVENTIONAL FUZZY CONTROLLERS TUNED BY ANT COLONY OPTIMIZATION

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Abstract.*This study uses an Ant Colony Optimization (ACO) to tune two different fuzzy controllers, a conventional (FC) one and a type-2 fuzzy (FT2). These controllers provide a good representation to the imperfections of a specialist's knowledge and sensor's uncertainty. Both controllers are applied to a Quanser DC-Motor and the controllers obtained proves that ant colony is an efficient method to tune complex controllers such fuzzy type-2. The result also shows the potential of fuzzy type-2 controllers-based in comparison with conventional fuzzy ones.*

***Keywords:**: Fuzzy Controller, Fuzzy Type-2, Ant Colony Optimization, Fuzzy Tuning*

1. INTRODUCTION

Among how many control techniques in the industry, about 96 % of industrial controllers are based on PID (Rubaai *et al.*, 2008). PID controllers have a simple structure and perform well in a variety of operating conditions. Unfortunately, it was quite difficult to properly tune the gains of PID controllers because many industrial plants are often overloaded with problems such as high order, time delay, and nonlinearities (Gaing, 2004).

As an alternative to the treatment of nonlinearities of the system, fuzzy logic controllers have already proven to be more efficient than the classical controllers. This was reported by Zadeh in 1965, and in 1975, another paper presented a modification in conventional fuzzy logic, an uncertainty footprint (FOU) (Zadeh, 1975). The creation of Fuzzy Type-2 (FT2) is related to the insufficiency of the traditional fuzzy logic in the modeling of the inherent uncertainties to the definition of the antecedent and consequent pertinence functions in a system of diffuse inference (Mendel and John, 2002).

The automotive industry is a special success area for Mamdani Fuzzy Controlers (FCs). Problems and practical issues related to suspension control are discussed in Caponetto *et al.* (2003). Control of hybrid electric vehicles is discussed in Schouten *et al.* (2002). The control of anti-lock braking systems is analyzed in Mirzaei *et al.* (2005).

In dynamic systems, application of techniques that use fuzzy logic in the control has proved quite attractive from publications with efficient results in several applications. They include control of industrial weigh belt feeders (Zhao and Collins, 2003), control of machining processes (Haber *et al.*, 2003), laser tracking systems (Bai *et al.*, 2005) and vibration suppression (Marinaki *et al.*, 2010).

A complexity in the development of the diffuse system can be found at the moment of decay, what are the best parameters of the association functions, number of rules, fuzzyfication method, inference and defreition of the will for a better solution to the problem (Castillo and Melin, 2012).

One solution to this problem is an application of bio-inspired optimization algorithms for fuzzy systems. The optimization algorithm includes Genetic Algorithm (GA), particle swarm (PSO), ant colony (ACO), etc (Castillo and Melin, 2012).

The ACO is a bio-inspired heuristic in real ants. This algorithm is based on how real ants look for the shortest path between the nest and the food. This research was carried out through the exploration of pheromone trails, a chemical deposited by forms during the route.

This paper proposes an implementation and test of conventional and type-2 fuzzy controllers in order to demonstrate their efficiency and quality. These drivers are difficult to tune, so this article also proposes testing the optimization with ACO to optimize fuzzy controllers.

2. EXPERIMENTAL PROCUDURES

The fuzzy controller designed has a combination of two inputs and a single output. The inputs are: error and error derivative and the output is: variation of signal control. The inputs have three membership function, two trapezoidal and a triangular one.

2.1 Ant colony optimization

ACO is a probabilistic technique that can be used for solving problems that can be reduced in graphs. This method of find good paths is inspired on ant's behavior in finding paths from nest to food source (Dorigo *et al.*, 2006).Thus the cooperative and efficient search methodology, the ants build alternative routes to find a path between the nest and food.

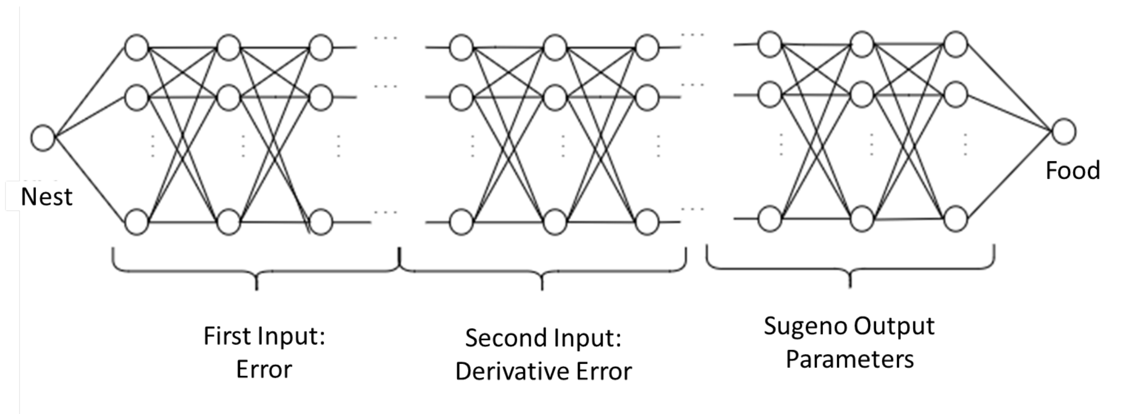

Figure 1. Fuzzy parameters as graphs

The ants start from the node representing the nest, the search for the next node for the ant takes into account the level of pheromone and the heuristic value present in each edge. The probability of transition from node i to node j is defined as the probability of an ant choosing the path i j (Dorigo *et al.*, 2006), it is calculated from equation 1.

$$p(t)_{i,j} = \begin{cases} \frac{(\tau(t)_{ij})^{\alpha}\cdot(\eta_{ij})^{\beta}}{\sum_l (\tau(t)_{il})^{\alpha}\cdot(\eta_{il})^{\beta}}, \text{ allowed path between } i \text{ and } j \\ 0, \text{ otherwise} \end{cases} \tag{1}$$

Where:

η_{ij} : Heuristic value between edges i - j;

$\tau(t)_{ij}$: Pheromone deposited at the instant t on the edge ij;

l : Population of ants;

α e β: Balanced contributions of the pheromone and the heuristic factor, respectively.

After selecting the probability, a node is selected by roulette-type draw, that is, even nodes with low probability, can still be selected for ant route.

When the ant route is complete, route cost is calculated based on a previously established function, or performance, of the found controller, which costs as the basis for calculating the pheromone that is deposited on each route. With the value of the cost of the route, the level of pheromone in each edge is updated following the equation:

$$\tau_{ij}(t) = \tau_{ij}(t) + \Delta\tau ij(t) \tag{2}$$

Thus, the amount of pheromone deposited by the ant depends on the quality of the route (Q) and the cost of each route (C (n)), as shown in equation 3 (Farias *et al.*, 2014).

$$\Delta\tau_{ij}(t) = \frac{Q}{C(n)} \tag{3}$$

In order to avoid the excessive accumulation of pheromone in a particular route, what result in stagnation of the ants by only one route, it is the rate of dissipation of the amount of pheromone, in which, for each generation of ants, a percentage of the pheromone deposited in all is dissipated. The Eq. 2 is rewrite like Equation 4.

$$\tau_{ij}(t) = \gamma\tau_{ij}(t) + \Delta\tau ij(t) \quad (4)$$

Where γ is the dissipation percentage.

2.2 Fuzzy Controller Type-1

Typically, computer programs make strict decisions by rules of decisions based only on two values: True/False, Yes/No or 0/1. Such binary sets are known as crisp sets. On the other hand, the fuzzy logic allows values that are not totally true, nor totally false, that is, partially true or partially false (Jantzen, 2007).

Zadeh proposed fuzzy logic as an option to treat inaccurate information present in human language, since expressions such as "almost", "a little" and "too" are not part of the domain of crisp sets because they can not be interpreted in the form of "all or nothing". The creation of fuzzy logic was due to the need to obtain a methodology capable of systematically expressing inaccurate, inaccurate or even uncertain quantities.

Thus, this type of logic allows to express approximate representations of pertinence of elements in sets that are being analyzed. This type of set is called Fuzzy Sets, or Fuzzy Sets (Sandri and Correa, 1999) which, in turn, determines a new domain for the logic, the fuzzy domain.

The great advantage of this type of logic is to allow rules to capture and represent the knowledge of a human expert acquired by using the plant or process over and over again. This makes the control action as good as, or even better and more consistent (Simões and Shaw, 2007). Controllers that use this type of logic are known as fuzzy controllers

The Figure 2 shows the pertinence functions obtained from the first input used.

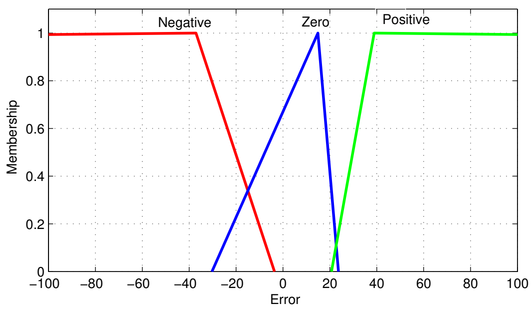

Figure 2. Pertinence functions resulting from Error input optimized by ACO

The error derivative input also resulted in configuration of pertinence functions, presented in Figure 3.

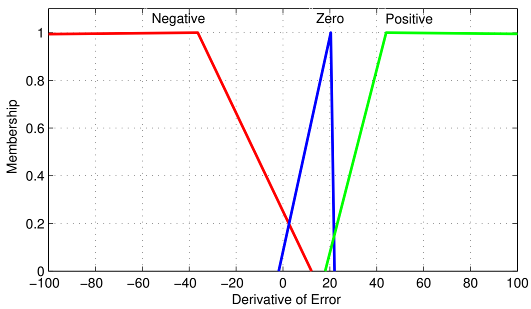

Figure 3. Pertinence function of the input: Error Derivative optimized by ACO

The Sugeno output functions obtained are shown in Table 1, where is noticed that the values of multipliers of the two inputs are closer to each other and constant output values close to zero.

Table 1. Sugeno output functions for conventional fuzzy using ACO

Name	Error Multiplier	Error Derivative Multiplier	Constant
S1	4,10	5,10	0,01
S2	7,20	5,00	0,1
S3	3,30	4,00	0,02

Table 2 gives the rules for the optimized fuzzy controller. These rules are presented in FAM form. The two inputs are associated by the AND connector and inferred by the minimum operator (MIN).

Table 2. Rules for the optimized fuzzy controller using ACO

Error/Derror	Negative	Zero	Positive
Negative	S2	S1	S3
Zero	S2	S1	S1
Positive	S3	S1	S3

2.3 Fuzzy Controller Type-2

The Type-2 Fuzzy Logic Systems was introduced in 1975 by Lotfi Zadeh as an extension of traditional fuzzy logic (Cabrera, 2014). Its emergence is related to the insufficiency of traditional fuzzy logic in modeling the uncertainties inherent to the definition of antecedent and consequent pertinence functions, in a fuzzy inference system (Mendel, 2003).

Type-2 Fuzzy sets are fuzzy sets whose pertinence degrees are type 1 and not a single value (Karnik *et al.*, 1999). These sets can be used in situations where is uncertainty about the degree of pertinence, uncertainty in the format of the pertinence functions or in some of the parameters of the pertinence functions (Karnik and Mendel, 1998).

One way to represent type-2 fuzzy sets is through the geometric form of their pertinence function. Figure 4 shows two different fuzzy sets. The first one is represented by a triangular in two dimensions, the desfocused area next to the line of the function represents the uncertainty of the boundaries of the set, this area is called *"footprint of uncertainty"* (FOU).

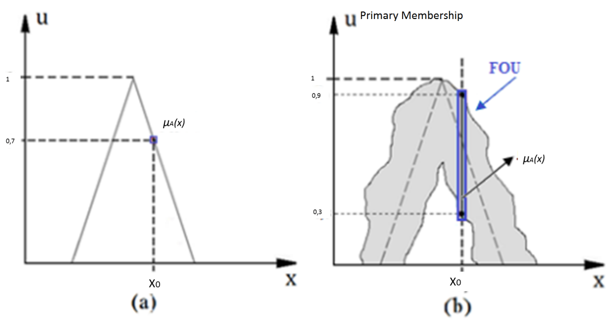

Figure 4. Fuzzy Sets (Rizol *et al.*, 2011)

Figure 5 presents the graphical representation of pertinence functions for the first input.

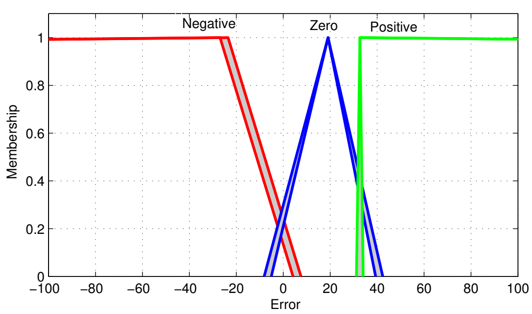

Figure 5. Pertinence functions of the input: Error optimized by ACO

Figure 6 shows the pertinence functions for the second input. It is noted that pertinence functions present small blurs of uncertainties around the pertinence functions.

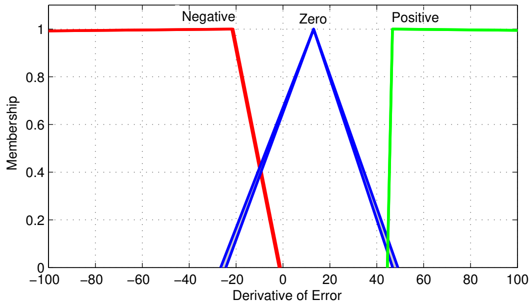

Figure 6. Pertinence functions of the input: Error Derivative optimized by ACO

The Sugeno output functions for the optimized controller are presented in Table 3. As other controllers, the constant of Sugeno function approaches 0, also the values that multiply the first input are bigger than those values that multiplies the second input (for S2 and S3 functions).

Table 3. Sugeno function for Type-2 Fuzzy using ACO

	Error	Error Derivative	
Name	Multiplier	Multiplier	Constant
S1	1,4	3,9	0,2
S2	10,9	3,7	0,1
S3	18,9	0,6	0,4

Rules of Type-2 Fuzzy controller are shown in Table 4.

Table 4. Rules of Type-2 Fuzzy controller using ACO

Error/Derivative of Error	Negative	Zero	Positive
Negative	S2	S1	S3
Zero	S2	S1	S1
Positive	S2	S3	S3

3. RESULTS AND DISCUSSION

Based on Ant Colony Optmisation algorithm, the controllers shown in the following subsections were obtained. The processing time for the conventional fuzzy controller was 160,63 seconds, for type-2 fuzzy was 217,63 seconds. The increase of the FOU causes an increase in the complexity of the algorithm, due to the increase in the number of possible routes for the ants to travel.

3.1 Conventional Fuzzy Controller

The graph in Figure 7 shows the behavior of a plant for the conventional fuzzy controller optimized by ACO. In the figure, its noticed that the system response presents small overshoots for 10 and 15 steps in the reference. However, in the descent steps, the system response became slow and without overshoot.

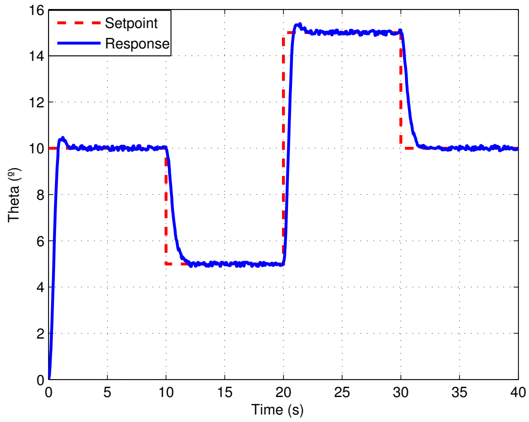

Figure 7. Resposta para o controlador fuzzy convencional com ACO System response for Conventional Fuzzy Controller by ACO

It can be analyzed that the control signal presents high voltage peaks when occur a change of *setpoints* occurs and small oscillations because of the noise.

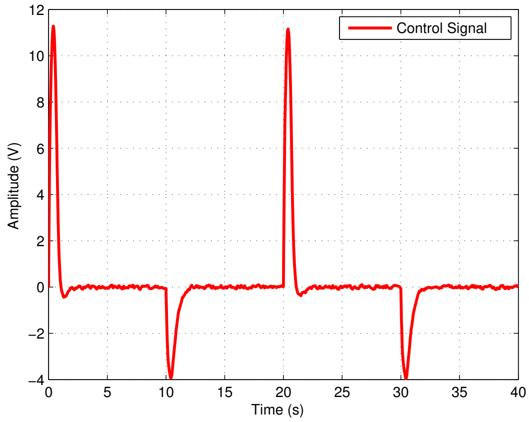

Figure 8. Control signal for conventional fuzzy controller using ACO

3.2 Type-2 Fuzzy Controller

Figure 9 shows the behavior of the system for the ACO-optimized type-2 fuzzy controller. It is note that for this controller, the response of the system showed small rise time, but large overshoots for 10 and 15 steps, and small *overshoots* for the descent steps. In this case, the signal was oscillating due to the presence of noise, but the controller rejected these noises.

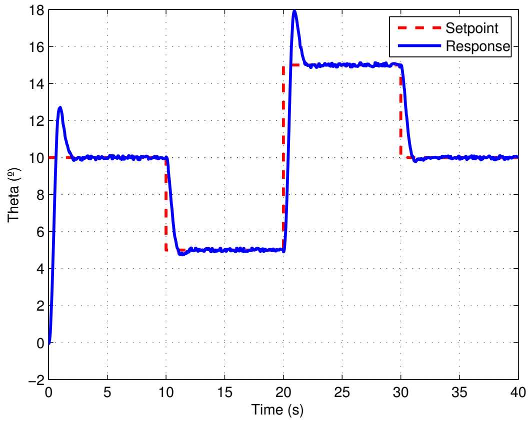

Figure 9. Resposta para o controlador FT2 com ACO FT2 Controller response using ACO

The control signal generates the system response that is presented in Figure 10. For rising steps, the control signal shoes voltage peaks that do not reach the saturation of the controller. The control signal also displays the oscillations resulting from noise.

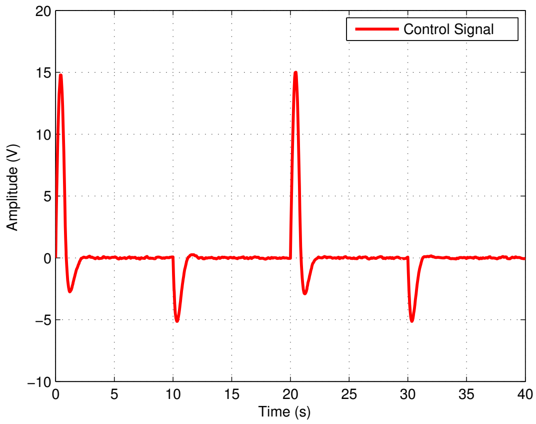

Figure 10. Sinal de controle para o controlador FT2 com ACO Control Signal for FT2 controller using ACO

In order to evaluate the controllers, this study used three criteria: Integral Absolute Error (IAE), Integral Time-weighted Absolute Error (ITAE) and Goodhart Index (GI) (Table 1)

Table 5. Controlled System Performance Criteria.

Controller	IAE	ITEA	GI
Fuzzy Conventional	7.23×10^{-1}	3.78×10^{0}	1.24×10^{1}
Fuzzy Type 2	6.05×10^{-1}	3.05×10^{0}	1.18×10^{1}

The quality of the controllers of obtained by optimization comes proved with the graphics and performance criterions. It is observed that FT2 controllers and the FC have differents responses. The FT2 have a smaller overshoot and steady error than the conventional one. The control signal of FT2 is less aggressive than the conventional one.

For the setpoint changes, the type-2 fuzzy controller presents smaller voltage peaks in the control signal than conventional fuzzy. Regarding the response, the setpoint changes cause larger overshoot for the type-2 fuzzy controller than for the conventional controller.

Because of this relation among overshoot and reference tracking speed, for the fuzzy controllers, the IEA index values are very close.

In the setpoint changes, the type-2 fuzzy controller presents smaller voltage peaks than the conventional fuzzy controller. However, the conventional controller presents smaller overshoots than type-2. Therefore, the values of the IEA, which weighs the error equally by the time, are very close to the two controllers with the type-2 fuzzy controller behaving better for the system.

In the Goodhart index, it is observed that the type-2 fuzzy controller has a better result than the conventional fuzzy controller, this is due to the greater weighting of the control signal. Conventional fuzzy presented higher voltage peaks than the type-2 fuzzy controller.

4. CONCLUSIONS

The work presents a strategy of tuning conventional and type-2 fuzzy using ant colony optimization. The algorithm proved to be effective in finding parameters of complex controllers such as FT2, despite being a recent optimization method when compared to optimization methods as particle swarm or a genetic algorithm.

The FT2 controller presented better response than the conventional one, but it has more computational cost. This controller allows to better treat the plant nonlinearity and the knowledge impression.

The ACO optimization presents a good computational performance. The execution time for each ant to this algorithm is short but requires a large memory in the computer to store the graph where the artificial ants travel.

5. ACKNOWLEDGEMENTS

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