Tuning Analog PID Controllers by Multi-Objective Genetic Algorithms with Fuzzy Aggregation

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Abstract: This paper deals with a procedure for adjusting the gains of a Proportional-Integral-Derivative (PID) controller. Multi-objective genetic algorithms with fuzzy aggregation are used for tuning this controller. To that end, the component values of a known topology of analog PID controller circuit are evolved by a genetic algorithm to yield acceptable performance specifications. A fuzzy aggregator allows multi-objective evaluation for the genetic algorithm. Three objectives regarding the PID reference input signal specifications were considered: overshoot, rise time and settling time. Minimizing these objectives approximates the PID controller output to the reference signal and leads the genetic algorithm to find the best controller gains. A case study is presented to illustrate the procedure.

1 INTRODUCTION

Computational intelligence is a set of computational methodologies and approaches that seek, through techniques inspired by nature, the development of intelligent systems that mimic human aspects, such as learning, perception, reasoning, evolution and adaptation. Due to the good results obtained with the use of different techniques involved in the field of computational intelligence, the number of research related has grown even more in recent years. Furthermore, the area of intelligent systems is quite broad and covers several applications (Figueiredo et al., 2014) (Luca et al., 2015) (Ignatiev et al.,2017), (Ghildiyal et al.,2019).

One of the justifications for research in the area of intelligent systems, especially in knowledge discovery, data mining, and machine learning, is the great complexity of modeling some systems and the huge volume of digital data existing today that are many times above the human analysis capability (Coello Coello, 2013). In this way, the development of these models can be done automatically through different approaches such as: artificial neural networks, Bayesian methods, graphical models and decision trees, or even through systems with more symbolic approaches, which, in addition to the ability to express the knowledge in a more comprehensible way, they allow the introduction of specialist knowledge, such as fuzzy systems. Fuzzy systems are based on fuzzy logic and are widely used, especially in decision support models and control systems. In addition, there are several related applications in the literature, such as, for example, in the area of health and the study of human locomotion, in speech signal processing, in the recognition of information and emotions, in economics and in routing systems (Luca et al., 2015). Its characteristic of expressing human inference behavior enables a high level of understanding, with interpretability being a strong point of fuzzy systems.

Among the points usually addressed in the area of intelligent systems, an important point is optimization, which consists of finding the best solution for a given problem. At this point, evolutionary algorithms are a commonly used computational intelligence technique due to their great search capability. Optimization in evolutionary algorithms consists of trying several solutions and using the information obtained in this process in order to find increasingly better solutions.

Initially, the great concentration of efforts in the area of optimization consisted in understanding, developing and applying methods for the optimization of a single objective function. However, most real optimization problems involve multiple objectives and the idea of optimizing each objective

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in isolation cannot be applied. Each objective has its degree of importance and many times the objectives are conflicting with each other (Ajith et al., 2005). In everyday situations it is common to find contexts that have different objectives. For example, the process for deciding to buy a car takes into account its size, fuel consumption and price. Another example is the job search where several points are considered to make an appropriate choice, such as starting salary, location and associated opportunities. In an industrial environment, generally, the aim is to maximize the quality of a product while minimizing its cost.

In this article, Genetic Algorithms with fuzzy aggregator for multi-objective optimization are applied as a search/optimization technique for the three gains associated with the traditional classical PID controller: Kp (proportional gain), Ki (integral gain and Kd (differential gain). Due to its widespread use in industry, the tuning of classic PID controllers is a topic of current research and several works have appeared (Pan et al., 2018) (Wang et al., 2021), including the application of Genetic Algorithms (Zhang et al., 2021) (Pu et al., 2020). The main objective of this article is to present a method capable of performing the tuning of an analog PID controller, having as a starting point the desired step response for the global closed-loop system using as objectives specifications with respect to the controller reference signal. Procedure details are described in section 2.2. Even considering that more sophisticated controllers, based on intelligent techniques, can be used in industrial controls, a great amount of the industrial controllers in use today use PID control strategies. Therefore, it is evident the importance of an approach that enables a good tuning of the PID controllers.

This paper is organized in four sections. The second section describes the basics of a PID controller and the structure of the evolutionary environment used for tuning the PID controller. Section three discusses an example and results in connection with the evolutionary analog circuits. Finally, section four ends the paper with the conclusions.

2 BASIC FOUNDATIONS

2.1 PID Controllers

Figure 1 shows the block diagram of a closed-loop system with a PID controller in the direct path, which is the typical connection. The system's output should get as closely as manageable to the setpoint, i.e., the reference signal. The PID controller is specified by three gains, as shown in Figure 2.

In the frequency domain, the relation between the PID controller input E, i.e., error signal, and the output U, which is the input to the plant, can be described by the following transfer function:

$$G_c(s) = \frac{U(s)}{E(s)} = K_p + \frac{K_i}{s} + K_d s \tag{1}$$

The closed-loop transfer function $G_g(s)$ is given by:

$$G_g(s) = \frac{Y(s)}{R(s)} = \frac{G_c(s)G(s)}{1 + G_c(s)G(s)} \tag{2}$$

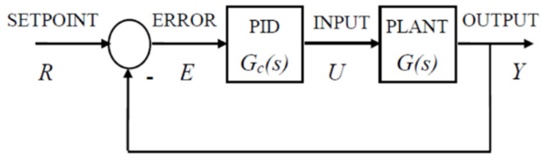

Figure 1: PID control of a plant.

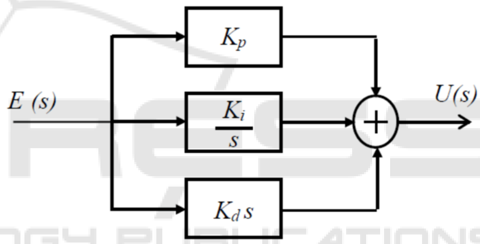

Figure 2: Structure of a PID controller.

The usual tuning of a PID controller involves selecting gains K_p, K_i and K_d so that performance specifications are satisfied. By using Ziegler-Nichols's method for PID tuning (Ogata, 2010) those gains are obtained through experiments with the process under control. The step response and the value of K_p which results in marginal stability are used as achieving points for obtaining gain values that guarantee an adequate behaviour. Finer adjustments to the gains may also be conducted which are not an easy task. It should be noted that the Ziegler-Nichols method is not applicable to all plants.

2.2 The Multi-Objective Environment

For tuning the PID controller, a procedure is used to do the evolution of component values of a known PID analog electronic circuit topology, based on a genetic algorithm and using a fuzzy system to evaluate multiple objectives. The traditional fitness assessment of genetic algorithms is changed, so that a fuzzy system is effectively responsible for the assessment, thus being able to aggregate the different objectives of the electronic design and generating a fitness value for each circuit in the population. The method was used for generating membership functions (Coelho et al, 2022).

One of the most important advantages of fuzzy systems is interpretability. This feature makes it possible to insert preferences and adapt the system to different situations using a natural and easy-to-understand language. In this way, the evolutionary environment presents a simpler and more interpretable way of inserting preferences and specifications, as it uses a fuzzy system. Such specifications are inserted before the evolution of the circuit, ensuring that it is guided in the desired direction, preventing the designer from having to choose the most appropriate solution at the end of the process. The possibility of incorporating conflicting inputs, but resulting in a single output that aims to meet both, is also a strong point that allows its use in solving problems with multiple objectives.

An implementation based solely on simulation of circuit models was selected, providing a flexible environment for case studies and enabling future applications. In this way, a method for evaluation through fuzzy systems has become attractive for the evolution of electronic circuits. The search capability of genetic algorithms motivated the choice of this intelligent technique as a basis for use in this work. A genetic algorithm was developed capable of obtaining a solution, that is, the developed circuit, according to preferences established according to the different objectives of the problem, and, for this, a fuzzy aggregation system is used. Comparing the model with the algorithms that use the Pareto concept, this fact is of great importance because it prevents several solutions from being presented for later selection of the best among them by the designer at the end of the process.

The methodology used in the present work allows the evolution of electronic circuits with characteristics to be optimized, focusing on the adjustment of the values of the components of pre-defined PID topologies and whose model is available or can be built. Basically, an evolutionary algorithm is used to search for the best circuit that meets the objectives. The evolutionary algorithm used is a genetic algorithm based on GAOT (Genetic Algorithm Optimization Toolbox) (Houck et al., 1996) and implemented in Matlab. For the simulations, mathematical models of the circuits were used. The genetic algorithm used in the work follows the model presented in Figure 3. The algorithm starts with a population normally generated randomly, but which can also be generated from a seed with potentially good solutions obtained from other methods. The traditional fitness assessment is performed from a fitness function defined by the designer.

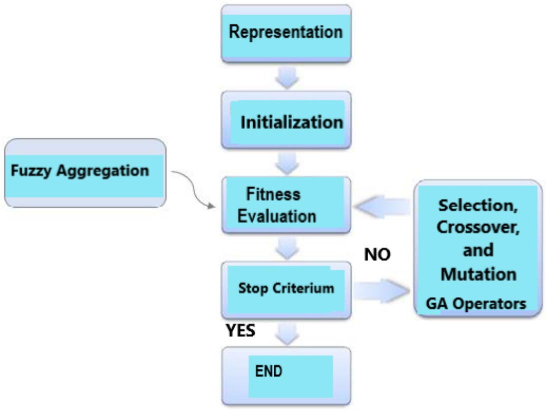

Figure 3: Basic structure with genetic algorithm and fuzzy aggregation.

Such a function generates a scalar number for each evaluated individual, which corresponds to the individual's aptitude in relation to the objective established by the defined function. In this paper, the evaluation is performed by a Fuzzy Inference System (FIS), called fuzzy aggregation. The fuzzy aggregator system makes it possible to evaluate all objectives simultaneously, integrating the user's preferences and specifications in relation to each objective and each situation, in a natural way. Figure 4 shows the proposed evaluation model.

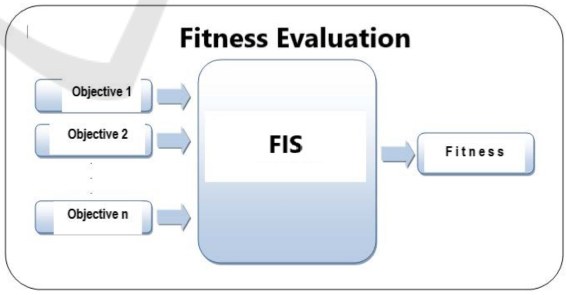

Figure 4: Fitness evaluation model with aggregator system

A general model for aggregating two objectives, as an example,was developed, which can be used as a basis for application to any multi-objective problem. The model has five triangular membership functions uniformly distributed within the range from 0 to 1 for the inputs, corresponding to the variation limits of each input that must be normalized to facilitate and generalize the application, as shown in Figure 5.

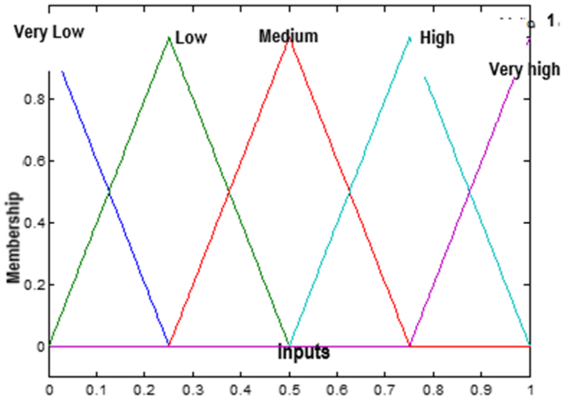

Figure 5: Typical membership functions for inputs.

The defuzzified output of the fuzzy system represents the general fitness assessment of the individual being evaluated. For the membership functions of the output, the format shown in Figure 6 is used as standard, consisting of five membership functions.

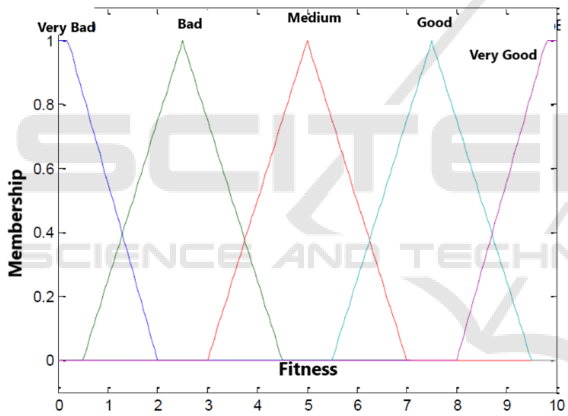

Figure 6: Typical membership functions for the output.

The fuzzy aggregator system is of the Mamdani type, characterized by being simpler and more interpretable than TSK-type fuzzy systems and all rules have the same degree of importance. The rules of the fuzzy aggregator system are designed to meet the problem specifications considering each of the objectives. To exemplify the process of creating rules, Table 1 shows basic rules for minimizing two objectives without preference between their minimization, that is, the minimization of both is sought equally. Thus, when the entries correspond to a Very Low value, they generate a Very Good aptitude assessment. Likewise, entries with a Very High value have a Very Bad aptitude rating.

Table 1: Base model for minimization rules.

INPUT 1 / INPUT 2	Very Low	Low	Medium	High	Very High
Very Low	Very Good	Very Good	Good	Medium	Bad
Low	Very Good	Good	Medium	Medium	Bad
Medium	Good	Medium	Medium	Bad	Very Bad
High	Medium	Medium	Bad	Very Bad	Very Bad
Very High	Bad	Bad	Very Bad	Very Bad	Very Bad

In case where it is desired to prioritize the minimization of one objective in relation to the other, the rules must be modified to meet this preference. Likewise, if the problem involves maximization, the same rules can be used by inverting only the linguistic terms of the antecedents, or the designer can create a new set of rules. The operators used in the system are the minimum and maximum operators and defuzzification is performed using the center of gravity method. After the evaluation of all the individuals of the population of the current generation, the genetic algorithm continues the evolution process in the traditional way, until the evaluation of the next generation, where the evaluation process through the fuzzy aggregator system is executed again for all the individuals, until the stopping criterion is reached. To carry out the evolution of circuits with multiple objectives and the fuzzy aggregator, the project must be carried out in a simulated environment. Figure 7 shows a block diagram of the proposal, illustrating in general the interconnections between the components used.

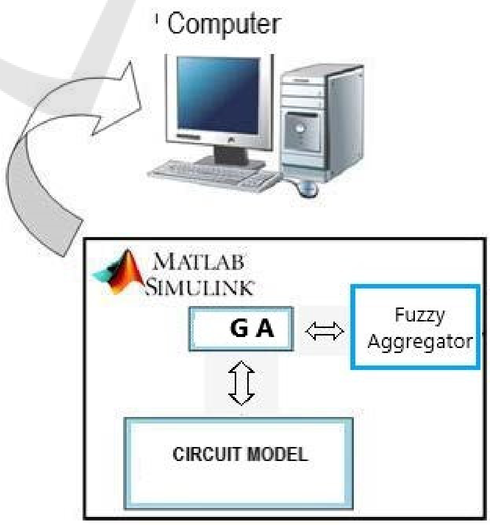

Figure 7: Fundamental used structure.

An implementation based purely on simulation of circuit models was chosen, providing a flexible environment for case studies and enabling future applications. Evolutions of analog electronic circuits in different application areas can be evaluated through computer simulations.

3 CASE STUDY

Control systems are needed in many fields of activity. Obtaining a stable process implies more efficient results, better quality products, reduced reprocessing, raw material savings, among other highly important factors, whether in an industry, laboratory or any environment that demands efficient control. Classic PID controllers (Proportional Integral Derivative) have general applicability in most control systems and correspond to most industrial controllers. In this way, a fine adjustment of their control parameters is essential for a stable process.

Since the appearance of the first tuning method for controllers, proposed by Ziegler & Nichols (Ziegler et al., 1942), several PID tuning techniques have been proposed in the literature, among them, intelligent control techniques, such as fuzzy logic, neural networks and genetic algorithms (Amaral et al., 2001), (Zhou, 2022), (Ding et al., 2022), (Lakmesari et al., 2022). Based on this need, a case study applied to the tuning of analog PID controller was developed in this work in order to obtain an adequate control performance. For this, the search technique of a genetic algorithm is used to find the best controller gains, that is, the proportional, integral and derivative gains (Kp, Ki and Kd). Multi-objective optimization is applied to this problem in order to obtain the best system according to each project need. The first step in designing control systems is to obtain a mathematical model of the system and from that it is possible to analyze its performance.

In the analysis of the control system, input signals are used as a reference to allow a performance comparison based on certain specifications. Among the main specifications considered in the time domain, the overshoot or maximum overshoot value (Mp), the rise time (tr), the settling time (ts) and the delay time (td) stand out. Figure 8 shows these four parameters. The overshoot corresponds to the maximum point obtained beyond the reference signal. The rise time is the time required for the output signal to vary from 10 to 90% of the final value. Settling time corresponds to the time taken for the value to settle within a range (ess), usually 2% or 5%, of the final value and the settling time delay is the time taken for the signal to reach 50% of the final value. In this work, it was decided to analyze three objectives: the overshoot, the rise time and the settling time. Thus, the implemented fuzzy aggregator has three inputs and one output. The membership functions used for evaluation were created from the required specifications. For example, the overshoot is measured in percentage, so a scale from 0 to 100% was used as shown in Figure 9. For values above 45% the overshoot is considered Very High and above 55% is no longer acceptable. Values below 12% are considered ideal and therefore characterize the linguistic term Low. Values in intermediate ranges are considered Medium or High.

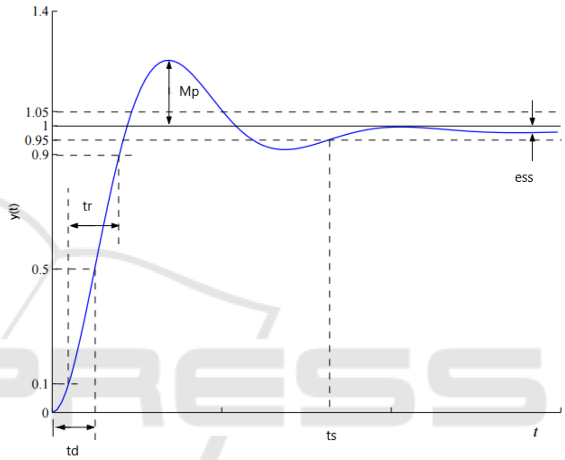

Figure 8: Control system step response.

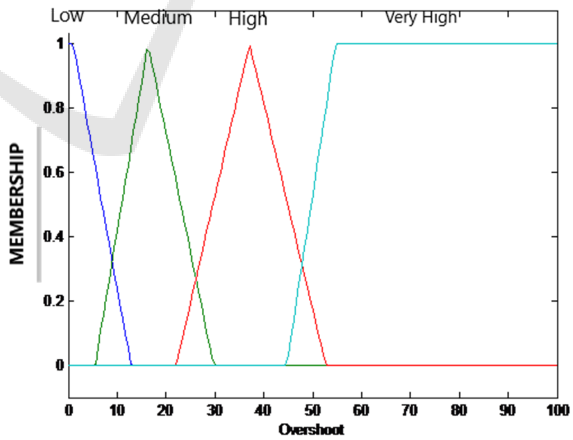

Figure 9: Membership functions of input variable Overshoot.

For the rise time, it was considered that a time above 1 second is Very High, as well as a time below 0.4 seconds is Low and desirable, as shown in Figure 10.

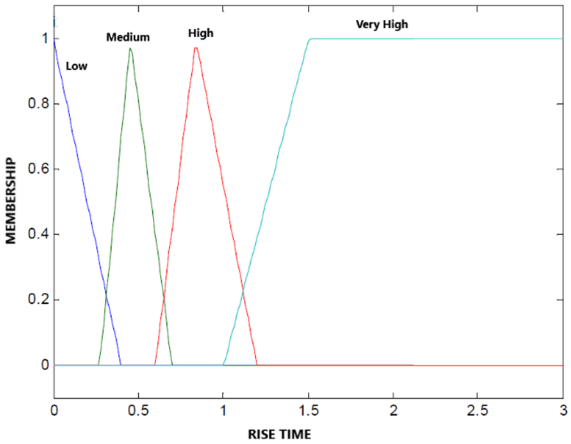

Figure 10: Membership functions of input variable rise time.

The settling time was represented by three sets: Low, Medium and High. The Medium set was centered on 2 seconds, the Low for values up to 1.5 seconds and High above 2.5 seconds, as shown in Figure 11.

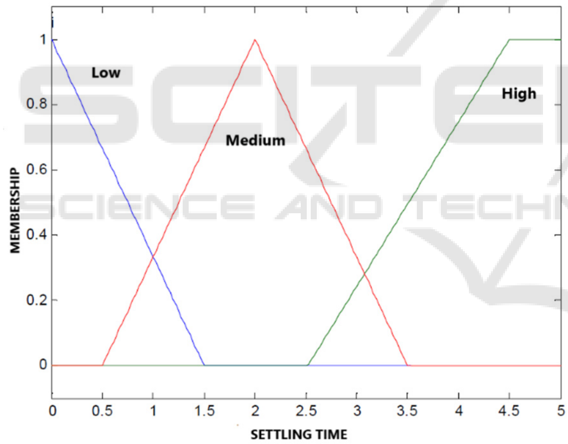

Figure 11: Membership functions of input variable settling time.

The membership functions for the output are the same as those illustrated in figure 6, which are the typical ones considered in section 2.2. The rules were created in order to minimize the three objectives. A High value in any of the objectives is considered Bad and likewise a Very High value is considered Very Bad. The 11 rules created for the fuzzy aggregator applied to control systems are shown in Table 2.

Table 2: Fuzzy aggregator rules for control systems.

Overshoot	Rise Time	Settling Time	Fitness
Low	Low	-	Very Good
Low	Medium	-	Good
Medium	Low	-	Good
Medium	Medium	-	Medium
High	-	-	Bad
Very High	-	-	Very Bad
-	High	-	Bad
-	Very High	-	Very Bad
-	-	Low	Very Good
-	-	Medium	Good
-	-	High	Very Bad

The electronic implementation for the topology of the analog PID controllers used in this work can be found in (Ogata, 2010) and is illustrated in Figure 12.

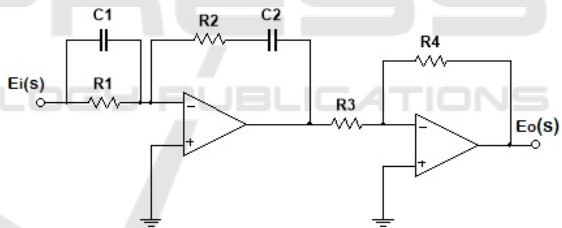

Figure 12: Base Circuit Topology for Analog PID Controllers.

The transfer function of this circuit is given by:

$$\frac{E_o(s)}{E_i(s)} = \frac{R_4 R_2}{R_3 R_1} \frac{(R_1 C_1 s + 1)(R_2 C_2 s + 1)}{R_2 C_2 s} \quad (3)$$

The evolution is performed considering the chromosome representing the six components used to calculate the transfer function (3). The chromosome is illustrated in Figure 13. From these parameters, it is possible to calculate Kp, Ki and Kd, as shown in equations 4, 5 and 6.

R_1	R_2	R_3	R_4	C_1	C_2

Figure 13: Chromosome for the Evolution of PID Controllers.

$$K_p = \frac{R_4(R_1C_1 + R_2C_2)}{R_3R_1C_2} \quad (4)$$

$$K_i = \frac{R_4}{R_3R_1C_2} \quad (5)$$

$$K_d = \frac{R_4R_2C_1}{R_3} \quad (6)$$

The search interval used is between 0 and 100kΩ for resistors and from 1 kpF to 100 µF for capacitors. The parameters used to configure the evolution of the genetic algorithm are in Table 3.

Table 3: Fuzzy aggregator rules for control systems.

Parameter	Value
Number of Generations	100
Number of individuals in the population	100
Crossing Rate	70 %
Mutation Rate	1 %

For the analyzed plant, comparisons were made with the results of a genetic algorithm with traditional evaluation and with results of traditional techniques for parameter tuning. A 2nd order plant (7) was used as a case study (Ogata, 2010).

$$G(s) = \frac{4}{s^2 + 0{,}5s} \quad (7)$$

Figure 14 illustrates the control system implemented in Simulink, with the application of a unit step at the input and it is desirable that the controller obtain a response as close as possible to this applied input signal.

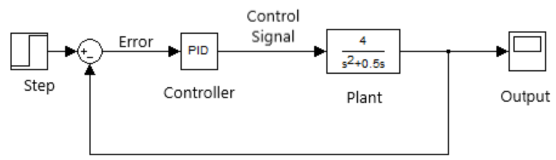

Figure 14: Block diagram of the 2nd order control system.

In (Ogata, 2010) an analytical compensator is developed for this system whose transfer function is:

$$G_C(s) = \frac{10(2s+1)(5s+1)}{(0{,}1992s+1)(80{,}19s+1)} \quad (8)$$

In this work, a single objective genetic algorithm was also implemented in order to minimize the RMSE and the multi-objective algorithm using the fuzzy aggregator to minimize the overshoot, the rise time and the settling time. The analytical compensator presented in (8) was used for comparison with the PID controllers obtained by the genetic algorithms. Table 4 presents the gain values found by the two genetic algorithms.

Table 4: Comparison of gains for 2nd order plant.

PID Gains	Mono-objective G.A.	3 Objective G.A. with Fuzzy Aggregator
Kp	100	99.9996
Ki	0.0001	0.2436
Kd	4.7514	8.3985

Table 5 presents the values for the overshoot, the rise time and the settling time that were obtained by the three analyzed methods.

Table 5: Evaluation parameters for 2nd order plant.

Parameters	Analytical Comp.	Mono-objective G.A.	3 Objective G.A. with Fuzzy Aggregator
Overshoot %	21.1612	17.1186	0.4982
Rise Time (s)	0.3159	0.0806	0.1342
Settling T. (s)	3.4010	0.4041	0.2123

Figure 15 presents the response obtained as a function of time in a 15-second simulation carried out in Simulink with the application of a unit step at the input. The three analyzed methods are shown in the figure.

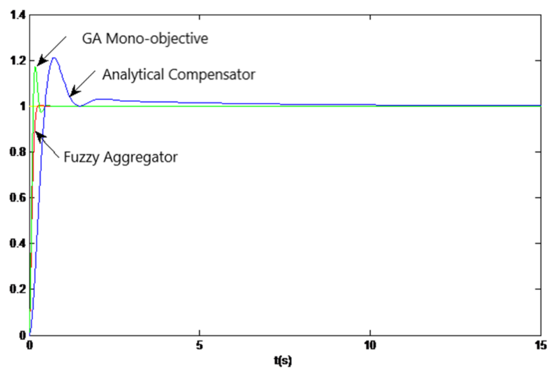

Figure 15: Response to a unit step by the three analyzed techniques.

Through Figure 15 and the values presented in Table 5, it can be seen that the response obtained by the GA with fuzzy aggregation obtained the lowest overshoot and settling time. The rise time achieved by the single objective GA was the lowest, but the overshoot was much greater than that obtained by the fuzzy aggregator, which is not desirable. The analytical compensator obtained higher values in the three analyzed parameters. Thus, the obtained results show that the fuzzy aggregation method was able to minimize the three parameters adequately and satisfactorily, obtaining good results compared to the other controllers. The evolved circuit is shown in Figure 16.

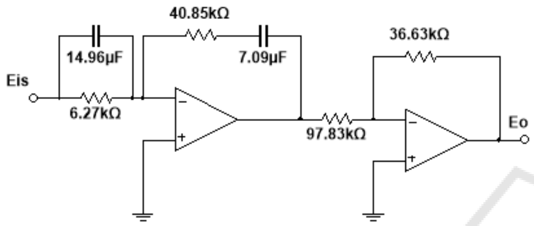

Figure 16: Evolved analog PID controller.

4 CONCLUSIONS

In this work, an evolutionary model was used for the development of a PID analog electronic circuit, which uses a method for evaluation that considers more than one objective and uses, for that, a process of aggregation of objectives through a fuzzy system. This method was called fuzzy aggregator and was applied in the evaluation process of genetic algorithms, modifying the traditional method of these algorithms and including, in this way, the feature of multi-objective evaluation to such evolutionary algorithms for obtaining the gains of a PID controller. The obtained results show that the fuzzy aggregation method managed to minimize the three parameters adequately. Compared to the other methods, it obtained the lowest overshoot and settling time. The shortest rise time was obtained by the single objective AG, but it was very close to the time obtained by the fuzzy aggregator. The analytical compensator method obtained the highest values for the three analyzed parameters. In this way, it is concluded that the fuzzy aggregation method was able to obtain good values for the gains of a PID controller, generating an adequate control system.

Future work will include comparisons with other PID tuning methods, when applicable, and also investigations with more complex plants.

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