Evolving Analog Electronic Circuits for Fuzzy Membership Functions Generation

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Keywords: Fuzzy Systems, Genetic Algorithms, Artificial Intelligence Applications, Evolutionary Electronics.

Abstract: Recent research advances in fuzzy systems applications as controllers of increasingly complex systems motivate the consideration of analog circuits capable of implementing fuzzy logic. The purpose of this paper is to evolve the component values of known topologies of analog circuits to generate membership functions. In order to accomplish that, a hybrid model is used for the evolution of electronic circuits, based on genetic algorithms, using a fuzzy system to evaluate multiple objectives. The traditional fitness assessment of genetic algorithms is modified, 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 proposed model presents a simpler and more interpretable way of inserting preferences and specifications, as it uses fuzzy logic. 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. An implementation based purely on simulation of circuit models was chosen, providing a flexible environment.

1 INTRODUCTION

Evolutionary Electronics was conceived in 1997 and applies Evolutionary Algorithms in the development of electronic circuits. It covers the developments and issues related to the use of Evolutionary Computing in the design of electronic circuits (Haddow and Tyrrell, 2018). In addition, it enables the development of practices, methods, algorithms and software and hardware structures that allow evolving in the design of more robust circuits. This terminology covers a wide field of research on the use of evolutionary algorithms in optimization and synthesis of electronic circuits. Another point of interest is the growing demand for the synthesis of more complex analog circuits, to interact with the environment, and the need to design them more quickly for the market (Amaral et al., 2007). This imposes more dynamic design practices that can generate products in less and less time (Lohn et al., 1999).

Fuzzy systems are based on fuzzy logic and are widely used, especially in control systems and decision support models. 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, being interpretability a strong point of fuzzy systems.

Among the points usually addressed in the area of computational intelligence, optimization stands out, which consists of the search for 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 better and better solutions. Initially, the great concentration of efforts in the optimization area consisted in understanding, developing and applying methods for the optimization of a single objective function. However, most real optimization problems, such as in electronic design or component adjustments in electronic systems, involve multiple objectives and one cannot apply the idea of optimizing each objective in isolation. Each objective has its degree of importance and often the objectives conflict with each other (Ajith et al., 2005). In everyday situations it is common to find contexts that

Coelho, P., M. do Amaral, J., Bacelar, Y., N. Da Rocha, E. and Bentes, M.
Evolving Analog Electronic Circuits for Fuzzy Membership Functions Generation.
DOI: 10.5220/0011549800003332
In *Proceedings of the 14th International Joint Conference on Computational Intelligence (IJCCI 2022)*, pages 175-182
ISBN: 978-989-758-611-8; ISSN: 2184-3236

have different objectives. For example, in an industrial environment, generally, the aim is to maximize the quality of a product while the cost must be minimized.

Currently, there are several techniques and computational algorithms developed for application in multi-objective optimization (MOP) problems motivated by the vast area of application (Coello Coello, 2013). Many researches show good results obtained over the years in this field for example (Fonseca et al., 1995) (Altinoz et al., 2015) (Jiang et al., 2016). The most used methodologies include the use of genetic algorithms and are based on the Pareto optimality concept. Such an approach comprises a border with several solutions considered optimal in relation to the analyzed objectives. This methodology is characterized by having an a-posteriori articulation, that is, the search process is performed autonomously, and after obtaining the solutions, an expert must make a choice to decide which is the best solution to be used for the problem. The process of choosing the solution considered acceptable, with a large number of possibilities and variables involved, is not a trivial task and requires experience and expert knowledge. In this way, the articulation of the designer's preferences made a-priori, that is, before the execution of the algorithm, and the use of a technique capable of translating the preferences in a simpler and more understandable way are essential.

This article deals with the design of analog electronic circuits to generate fuzzy membership functions, in order to modify the traditional evaluation form of a genetic algorithm to enable the evaluation of multiple objectives. To this end, it was chosen to use a fuzzy system that aggregates the various objectives (Reiser at al., 2013), (Mardani et al., 2015). The use of fuzzy systems makes it possible to simultaneously evaluate all objectives, integrating user preferences in relation to each objective and each situation. This feature is an advantage over multi-objective methods based on Pareto optimality, as this type of model does not require user interference to choose the best solution at the end of the process, since preferences are entered before evolution, in a more efficient way, simple and interpretable, through fuzzy logic. Thus, the evolution process is guided towards pre-established preferences or specifications. The purpose of this work is to study the application of an evolutionary model, which uses genetic algorithms with the ability to evaluate multiple objectives based on a fuzzy system, to optimize the values of components of analog electronic circuits to generate fuzzy membership functions. The technique is evaluated in a purely simulation-based environment that is used for the design of electronic circuits.

From the recent literature, articles dealing with the subject stand out (Marlen et. al, 2018) and (Rojec et. al., 2022). The first deals with the implementation of fuzzy membership function (MF), realized as an analog electronic hardware with memristor. The other one proposes an evolution of analog circuits, including their topology, for general purposes, considering the synthesis of robust and failure-resilient electronics.

This paper is organized in four sections. The second section describes the basic structure of the evolutionary environment for generating the membership functions. Section three discusses examples and results in connection with the evolutionary analog circuits. Finally, section four ends the paper with the conclusions.

2 ELECTRONIC CIRCUITS EVOLUTION

2.1 Basic Foundations

An electronic project can be developed in an intrinsic or extrinsic way.

In the so-called intrinsic applications, the evaluation is performed based on the behavior of the circuits when loaded on programmable integrated circuits or reconfigurable platforms. In this way the real circuit is developed, although flexibility and experimentation possibilities are more limited.

On the other hand, extrinsic applications are those in which circuits are evaluated through their equivalent models. For example, a linear analog filter can be developed using its transfer function. It is also possible to use circuit simulators, such as Spice, in which case the evolutions tend to become very slow.

In this paper, we opted for the extrinsic evolution based on models of analog electronic circuits to make the experimentation of the multi-objective evaluation method more flexible.

Evolutionary algorithms are efficient in solving multicriteria optimization problems. A variety of techniques using genetic algorithms have been developed in recent decades.

The great advantage obtained in the use of genetic algorithms is the fact that they simultaneously evaluate a set of possible solutions that allows finding the total set of solutions of the Pareto frontier in a single round of the algorithm without the need to carry out several iterations as in the other methods (Coello Coello, 1999).

In addition, they present ease and flexibility of modeling, are less susceptible to non-convex and discontinuous Pareto frontier characteristics and can work in search spaces that are intractable by traditional approaches.

2.2 The Evolutionary Environment

The purpose of this work is the application of a hybrid model to enable the evolution of electronic circuits, based on a genetic algorithm and using a fuzzy system to evaluate multiple objectives. The traditional fitness assessment of genetic algorithms is modified, 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.

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, that is, a-priori, 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 including possibly 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 purely on simulation of circuit models was chosen, providing a flexible environment for case studies and enabling future applications. Thus, 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 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 executed 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 1. 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.

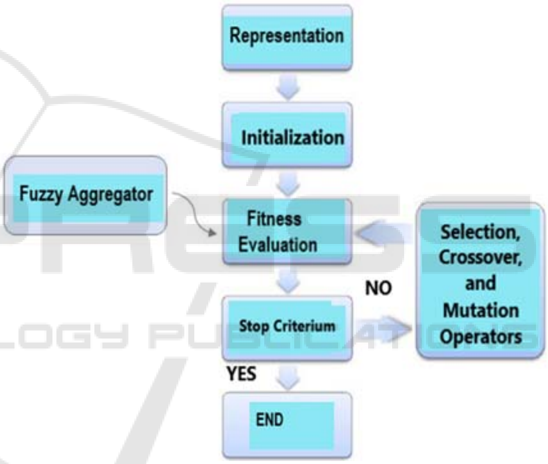

Figure 1: Hybrid Model with Genetic Algorithm and Fuzzy Aggregator.

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 work, the evaluation is performed by a fuzzy system, called fuzzy aggregator. 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 2 illustrates the proposed evaluation model.

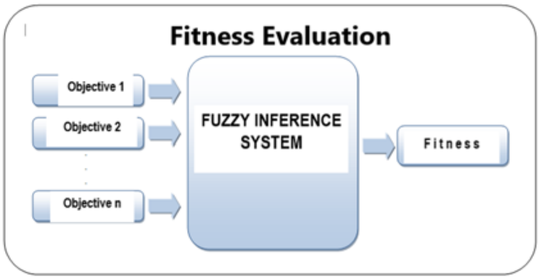

Figure 2: Fitness evaluation model with aggregator system.

A general model for aggregating two objectives was developed, which can be used as a basis for application to any 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 3.

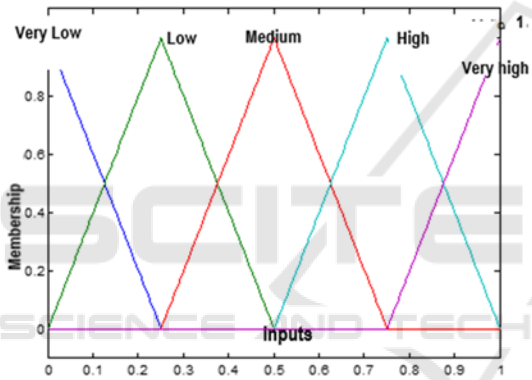

Figure 3: Base membership functions for inputs.

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 4 is used as standard, consisting of five membership functions.

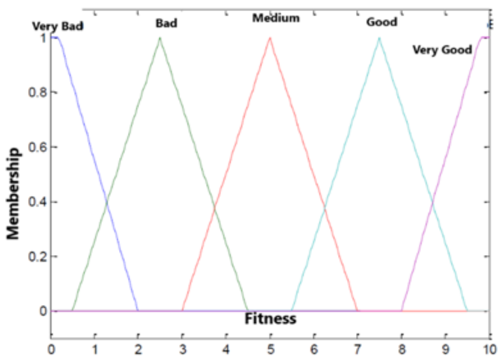

Figure 4: Base membership functions for the output.

The fuzzy aggregator system is of the Mamdani type, characterized by being simpler and more interpretable than TSK-type systems and all rules have the same degree of importance, that is, a weight equal to one. 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 5 shows a block diagram of the proposal, illustrating in general the interconnections between the components used.

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 are evaluated through computer simulations.

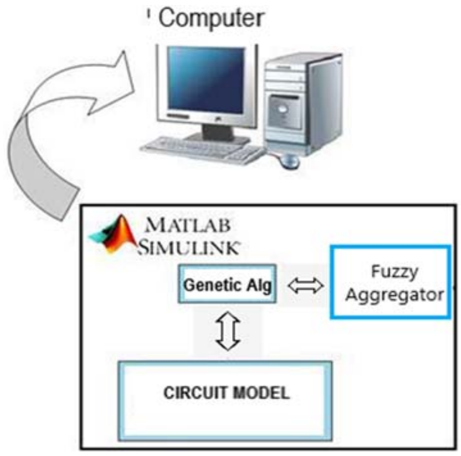

Figure 5: Basic Structure Used.

3 CASE STUDIES

With the great advance in research related to fuzzy systems applications as controllers of increasingly complex systems, it becomes interesting to enable the production of analog circuits capable of implementing fuzzy logic. The objective here was to evolve the values of the components of topologies of circuits known to perform membership functions.

3.1 Case Study 1: S Membership Function (MF)

For the evolution of a S membership function circuit, it is necessary a topology capable of generating at its output a voltage similar to that shown in Figure 6.

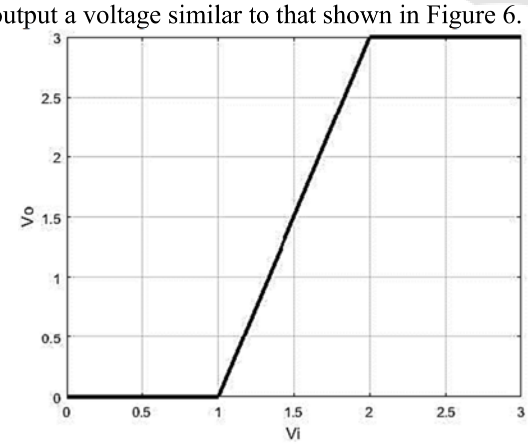

Figure 6: Vo x Vi for the S Membership Function.

Thus, to proceed with the proposal, it was necessary to use a circuit that behaves linearly when its input was contained in the interval [1, 2], in addition to providing 0V at the output when the voltage applied to the input were at [0 , 1] and 3V in the range [2 , 3]. A suitable circuit that has these characteristics can be seen in Figure 7. One of the objectives for the search for resistor values will be to minimize the Root Mean Square Error (RMSE) in relation to the straight line on figure 6, where Vi varies from 1V to 2V. The other objective will be to minimize the power consumption in the +3V source, for that it is enough to maximize the value of resistor R2, since the current supplied by the source is inversely proportional to the value of R2.

Table 2 shows the possible values of resistors R1, R2 and R3 as well as their ideal values, according to the previously defined objectives.

Table 2: Range of values for Values of R1, R2, R3 and Vi for the S Membership Function.

Parameters	Range of Values	Ideal Value
R1	1 kΩ - 10 kΩ	10 kΩ
R2	1 kΩ - 10 kΩ	10 kΩ
R3	1 kΩ - 10 kΩ	10 kΩ
Vi	0V – 3V	------

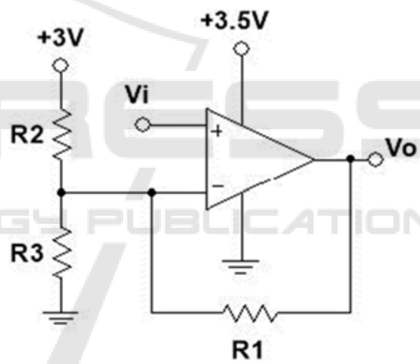

Figure 7: Selected topology for the S Membership Function.

For this evolution, the used parameters are shown in Table 3.

Table 3: Parameters of Genetic Algorithms.

Parameters	Value
Number of Generations	100
Number of individuals per generation	100
Crossover Probability	0.8
Probability of mutation	0.01

The rules were laid down so to minimize RMSE and maximize R2. The matrix of rules is presented in the Table 4. For the multi-objective Genetic Algorithm with weighted aggregation, the following fitness evaluation was adopted:

$$\text{Fitness} = 0{,}5 \times \frac{1}{1 + RMSE} + 0{,}5 \times \frac{R2}{R2_{max}} \quad (1)$$

Table 4: Rules Matrix for S MF Circuit.

INPUT RMSE / INPUT R2	Very Low	Low	Medium	High	Very High
Very High	Very Good	Very Good	Good	Medium	Bad
High	Very Good	Good	Medium	Medium	Bad
Medium	Good	Medium	Medium	Bad	Very Bad
Low	Medium	Medium	Bad	Very Bad	Very Bad
Very Low	Bad	Bad	Very Bad	Very Bad	Very Bad

For the fuzzy aggregator system, the objectives were normalized between 0 and 1 as follows:

$$\text{Input} \quad \text{RMSE} = \frac{RMSE}{RMSE + 1} \quad (2)$$

$$\text{Input} \quad R2 = \frac{R2}{R2_{max}} \quad (3)$$

Figure 8 depicts an evaluation graph of the best individual and the average of individuals per generation of the Multiobjective genetic algorithm with fuzzy aggregator.

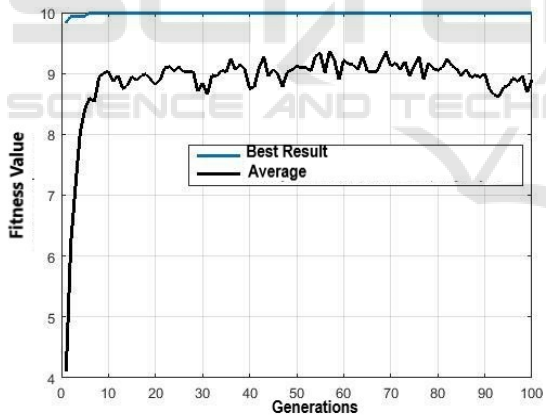

Figure 8: S MF circuit evolution.

The results of the evolutions are presented in Table 5.

Table 5: Results for the S membership function circuit.

	Mono obj. G.A.	Multi obj. G.A.	Multi obj. G.A. with Fuzzy Aggregator
RMSE	0	0	0
R1	3,3 kΩ	8,2 kΩ	10 kΩ
R2	3,3 kΩ	8,2 kΩ	10 kΩ
R3	3,3 kΩ	8,2 kΩ	10 kΩ

3.2 Case Study 2: Triangular Membership Function (MF)

The triangular membership function circuit topology should provide an output voltage relative to the input voltage as illustrated in Figure 9.

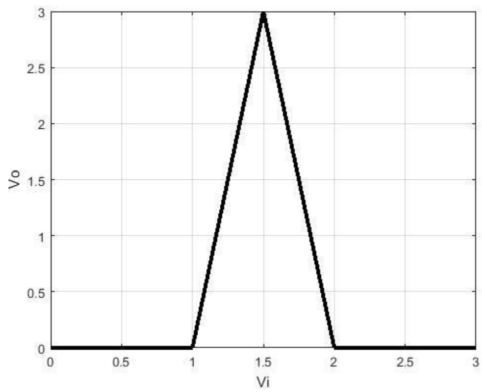

Figure 9: Vo x Vi for the triangular MF circuit.

A suitable circuit that has these characteristics is depicted in Figure 10.

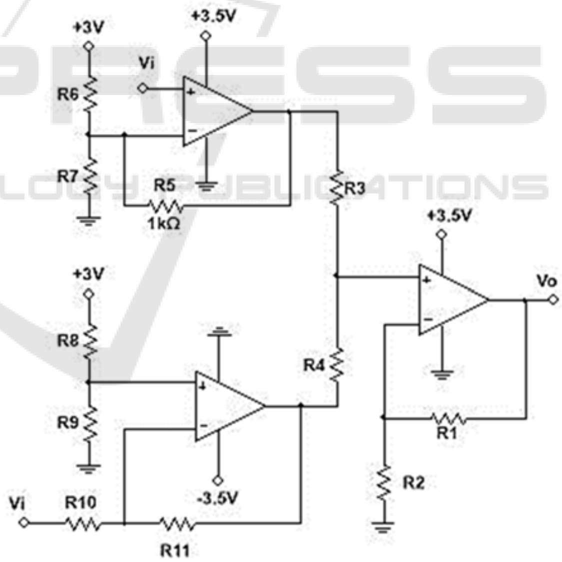

Figure 10: Topology for the evolution of the triangular Membership Function.

The first objective of this evolution is to minimize the RMSE of the voltage curve given by the circuit that generates the triangular MF in relation to the objective function that represents the target triangular function. The second objective is to minimize the sum of the resistor values in the circuit. The range of each value of the 11 resistors in the circuit are between

1kΩ and 10 kΩ. The used parameters of the GA are the same as in case study 1.

The configuration of the fuzzy aggregator system was similar to that used for the S MF circuit but following the rules according to Table 1. For this system the objectives were normalized between 0 and 1 as follows:

$$\textbf{Input} \quad \text{RMSE} = \frac{RMSE}{RMSE+1} \tag{4}$$

$$\textbf{Input} \quad \left(\sum R\right) = \frac{\sum R}{\sum R_{max}} \tag{5}$$

For the multi-objective GA with weighted aggregation, the following aptitude assessment was used:

$$\textbf{Fitness} = 0{,}5 \times \frac{1}{1+RMSE} + 0{,}5 \times \frac{\sum R_{max} - \sum R}{\sum R_{max}} \tag{6}$$

The obtained results are shown in Table 6:

Table 6: Results for the triangular MF circuit.

	Mono obj. G.A.	Multi obj. G.A.	Multi obj. G.A. with Fuzzy Aggregator
RMSE	0.16	0.21	0.13
$\sum R$	51.7 kΩ	24.2 kΩ	9.02 kΩ

4 CONCLUSIONS

In this work, an evolutionary model was used for the development of analog electronic circuits, 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 some circuits were successfully evolved. The fuzzy aggregator 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.

Case studies of MF circuit evolution were carried out to analyze the effectiveness of the method. 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 are evaluated through computer simulations. The work developed for evolution, evaluation and implementation showed good performance in the analyzed case studies, and can be used as a basis for new applications and implementations of other circuits. Compared to the other methods studied, the evaluated method yielded consistent results, with the advantages of inserting the designer's preferences and specifications in a simple and interpretable way at the beginning of the project, in addition to not requiring the designer's interference, either during or after the evolution process. In this way, the work developed for the evolution of analog electronic circuits with multi-objective evaluation through a fuzzy system constitutes a contribution to the design studies and implementation of electronic systems that can be used in several applications.

For future work, studies in different lines of action may be suggested. It would be important to implement the evaluation of circuits in a Spice-type circuit simulator, thus facilitating the experimentation and design of new circuits with models closer to the real thing. The use of the GPGPU (General Purpose Graphics Processing Unit) technique deserves to be investigated because it will certainly contribute to faster evaluations in the simulators and, consequently, the evolved circuit will be obtained in a shorter time. After implementing an evolutionary platform with a Spice simulator that uses GPGPU, it is worth investigating chromosomal representations to enable the search for circuit topologies and not just the values of the components.

In addition, comparisons with other algorithms such as Coyote optimization algorithms, Particle Swarm Optimization (PSO) (Mekhmoukh Taleb et al, 2022), Quantum Butterfly Optimization algorithm (Li et al, 2022), etc. are anticipated possibilities in future works.

ACKNOWLEDGEMENTS

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001, and FAPERJ.

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