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Evolutionary Tuning of a Fuzzy Controller for Electrolyte Flow Regulation in a Pulsed Electrochemical Machining Process

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Abstract. Based on Darwin's theory of natural selection and the laws of inheritance proposed by Mendel, a stochastic optimization established by a real-coded genetic algorithm is described for tuning the parameters of the membership functions of a multiple-input, single-output Mamdani-type fuzzy controller. This control is applied in modern manufacturing, which regulates the electrolyte flow in a pulsed electrochemical micromachining method. In this optimization technique, the results generated with a population crossover of 60 and 80 %, using a roulette selection, a BLX-α crossover operator, and a uniform mutation are analyzed. In addition, the electrolyte flow control response of the best-fit chromosomes according to an objective function set by the mean square error is compared to the output obtained with a PID controller tuned with Ziegler Nichols. Finally, the control space for the fuzzy controller is generated with the parameters of the membership functions that offer the best performance in flow stabilization.

Keywords: Genetic algorithm, fuzzy control, electrolyte flow, modern manufacturing.

1 Introduction

Pulsed electrochemical machining (PECM) is derived from the non-conventional manufacturing process, which uses the principle of electrolysis to wear high-strength metal parts. In general terms, the dissolution process is catalyzed by the polarization of electric energy positively at the anode and negatively at the cathode when exposed to the electrolyte flow, causing the transfer of ions from the workpiece to the tool; both are set at a constant separation.

Therefore, a pair of electrodes (anode and cathode), a mobilization system for the working tools, an aqueous solution (electrolyte), an electrolyte flow system, and a pulsed polarization source are the elementary components that allow controlled regulation of material wear [1]. Minimal tool wear, material removal on high-strength metal parts, and increased efficiency in manufacturing components with complex morphologies are part of the advantages offered by PECM.

Some of the applications of this technique are visualized in the aeronautics field for manufacturing LPC (Low-Pressure Compressor) blades, combustion chambers, diffusers, and cooling film. However, it is also used to design microtubes, micro gears, micro bushings, and scalpels [2-3].

Since the contact between the tool and the workpiece never exists in this manufacturing method, the electrolyte flow plays an important role in ensuring material wear. However, because of the detachment of metal, particles are generated that can cause an obstruction in the circulation of the solution, decreasing the flow and consequently the current transfer, thus affecting, mainly, the uniform detachment of material and the accurate estimation of the control variables [1].

Problems such as alterations in the final dimensioning of the finished part, increased electrical resistivity properties, wear of the working tool, and decreased technological stability are some of the effects identified by the deficient transfer of the solution [4].

Therefore, the correct control of the electrolyte supply is considered an essential factor in this process, which can be done through classical control methods or intelligent techniques with industrial applications such as fuzzy logic.

Fuzzy logic is a method derived from soft computing with applications in the design of industrial process control, which allows the evaluation of actual generic parameters using linguistic variables [5]. These linguistic labels are defined through a series of sets established in a universe of discourse representative of a solution space.

Therefore, being a knowledge-based system, the quality of the algorithm results will depend on the expertise expressed utilizing a knowledge base and the membership functions [6]. Additionally, the parameters that make up this type of intelligent control are classified into two groups: structural and tuning parameters [7].

The first group includes the input and output variables, the inference system, the rule base, and the defuzzification method. In contrast, the second group comprises the parameters of the membership functions, which are precisely delimited empirically or by search methods.

Genetic Algorithms are stochastic techniques helpful in searching for solutions based on evolutionary mechanisms from Darwin's theory of natural selection and the laws of inheritance proposed by Mendel [8], applicable in specialized problems from a random set of solutions called population. Some chromosomes delimit a particular solution to the problem in each population element.

After a series of iterations, commonly called generations, the algorithm evaluates the quality of the results with an objective function to subsequently select, cross, mutate and reconstruct the population with the best set of solutions found as well as with the descendants generated by them [9].

Hybridization of intelligent techniques is a way to improve the results from individually applied methods. This is observed in different fields of specialized literature as described in [10] and [11], where genetic algorithms are used to tune the parameters of the membership functions of fuzzy controllers.

In the robotics area, as observed in [12, 13] the tuning of the Kp, Ki, and Kd coefficients of classical controllers such as Proportional Integral Derivative (PID) but

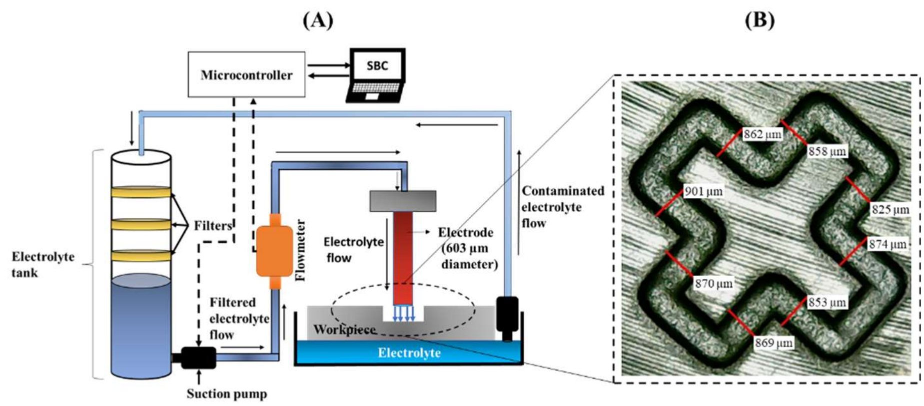

Fig. 1. General diagram of the electrolyte flow regulation system in the PECM manufacturing process (A) for micrometer-scale machining design (B).

also of fuzzy PIDs controllers is performed, validating the performance provided by the stochastic search of evolutionary algorithms.

In this sense, this paper describes the development of a genetic algorithm to tune the parameters of the membership functions of a fuzzy controller which regulates the electrolyte flow in a pulsed electrochemical machining process. This comprises two input parameters and one output, delimited by three membership functions of type Z, S, and Gaussian for each linguistic variable.

2 Methodology

The proposed evolutionary tuning is applied to an electrolyte flow regulation system implemented in a pulse electrochemical machining prototype described in [14], located in an experimental test laboratory.

It is composed of a hollow steel electrode with a diameter of 603 µm, a solution circulation system with suction pumps operating at 12 V - 1 A, and an electrolyte of Na at a molar mass concentration of 16 % per liter of H_2O. In Fig 1, the diagram of the components that make up the electrolyte circulation system in the non-conventional manufacturing process is shown.

An open-loop characterization was performed to determine the natural electrolyte flow rate Y during material removal. This relationship is described by a characteristic notation defined in equation 1, which represents the magnitude of the flow as a function of an oscillation frequency f caused by the passage of the solution in the internal mechanism of the flowmeter and a conversion factor k bounded by the volume of liquid supplied during a period:

$$Y = \frac{f}{k}. \tag{1}$$

A total of 1.182 liters of electrolyte in 60 minutes were generated in the characterization. Therefore, clearing k in equation 1 gives a conversion factor equal to

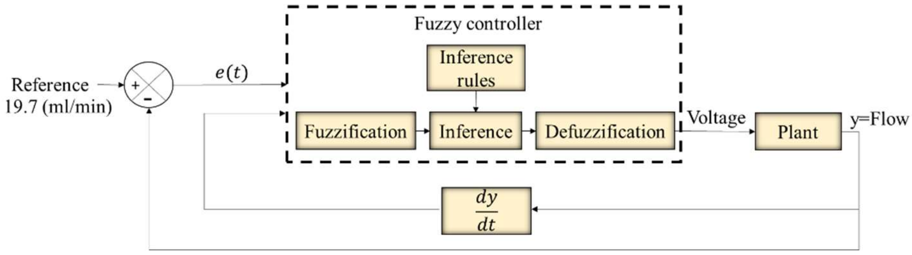

Fig. 2. Fuzzy control diagram for electrolyte control.

Table 1. Fuzzy associative memory for electrolyte control in PECM.

Fuzzy input sets	**Minimum**	**Half**	**Advanced**
Low	Little	Little	Little /Regular
Middle	Regular	Regular	Regular
High	Much/regular	Much/regular	Much

0.964 Hz*min/ml. Finally, substituting the values obtained in equation 1, a magnitude of 19.7 ml/min is generated in the solution flow rate during material removal. This behavior was analyzed using the MATLAB system identification module, considering the flow quantified during the characterization stage and the operating voltage of the suction pumps, establishing the third order transfer function in terms of the complex variable s of equation 2, which will allow modeling the system for its implementation in the evolutionary algorithm:

$$G(s) = \frac{1.203\,s\ + 3.099}{s^2\ +\ 1.534\,s + 0.945}. \qquad (2)$$

The proposed evolutionary tuning is applied to a two-input, one-output fuzzy controller. The electrolyte flow error and the change of flow with respect to the time are the inputs evaluated in a fuzzy system composed of three stages: fuzzification, inference, and defuzzification. In the first one, a degree of membership of the actual variables to the fuzzy input is obtained.

In the second one, an inference is generated based on a series of IF-THEN type rules and the assigned sets for the output variable. Finally, in defuzzification, the fuzzy conclusion is converted to a numerical value interpreted by the non-conventional manufacturing system called "plant" according to the terminology in control. This allows the controller to modify its behavior through a closed-loop feedback system, as shown in Fig. 2.

Low, Middle, and High are the linguistic variables used to evaluate the first input variable defined by error. At the same time, Minimum, Half, and Advanced are the terms assigned to assess the change in flow with respect to time. On the other hand, the labels designated for the inference output are Little, Regular, and Much, in charge of delimiting the magnitude of the voltage applied in the plant.

In all cases, the terms are represented by Z, S, and Gaussian functions, respectively, using the fuzzy associative memory presented in Table 1. This describes the membership relationship of the fuzzy input sets located in the main column and row of Table 1 and the fuzzy output sets located in the central part of it.

Table 2. Membership functions for input variables.

Variable	Fuzzy sets		Membership function parameters
er (error)	LO	Low	μ-z (er; e_1, e_2)
	MI	Middle	μ-g (er; e_3, e_4)
	HI	High	μ-s (er; e_5, e_6)
dy (flow change)	MN	Minimum	μ-z (dy; e_7, e_8)
	HA	Half	μ-g (dy; e_9, e_{10})
	AD	Advanced	μ-s (dy; e_{11}, e_{12})

Table 3. Membership functions for the output variable.

Variable	**Fuzzy** sets		Membership function parameters
vo (voltage)	LI	Little	μ-z (vo; e_{13}, e_{14})
	RE	Regular	μ-g (vo; e_{15}, e_{16})
	MU	Much	μ-s (vo; e_{17}, e_{18})

Any function is composed of two indispensable parameters: the point of descent from 1 and the intersection at 0 for Z-type functions, the rising point from 0 and the intersection at 1 for the S-type, and finally, the standard deviation and the center for the Gaussian function. Both cases are shown in Table 2 for the input variables and in Table 3 for the output variable, set randomly initially and optimized by the evolutionary algorithm.

A structure of 18 genes for each chromosome in the population of the evolutionary algorithm is proposed based on the above. In this sense, each pair of genes will represent the parameters of the membership functions to be optimized, keeping the form of equation 3:

$$\text{Chromosome} = [e_1, e_2, e_3, e_4, \dots, e_{18}]. \tag{3}$$

In addition, an initial population with 100 randomly generated chromosomes was established, maintaining a universe of discourse from -25 to 25 ml/min for the error genes. On the other hand, gene initialization for flux change were trained under the same method with a universe of discourse from -30 to 30 ml/min^2. Finally, a population was randomly set from 0 to 12 V for the elements of the output variable. Once the population was generated, an objective function was established considering the mean square error of the electrolyte flow described in equation 4:

$$f_{obj} = \max\left(\frac{1}{1 + \sqrt{\frac{1}{T}\int_0^T (reference - output)^2}}\right). \tag{4}$$

The roulette operator is proposed for the selection of the chromosomes with the best fitness. At the same time, the generation of offspring is performed with a BLX-α cross, which allows creation a random offspring from the combination of the genes of two-parent chromosomes and a uniform parameter between 0 and 1 called alpha, as shown in equation 5:

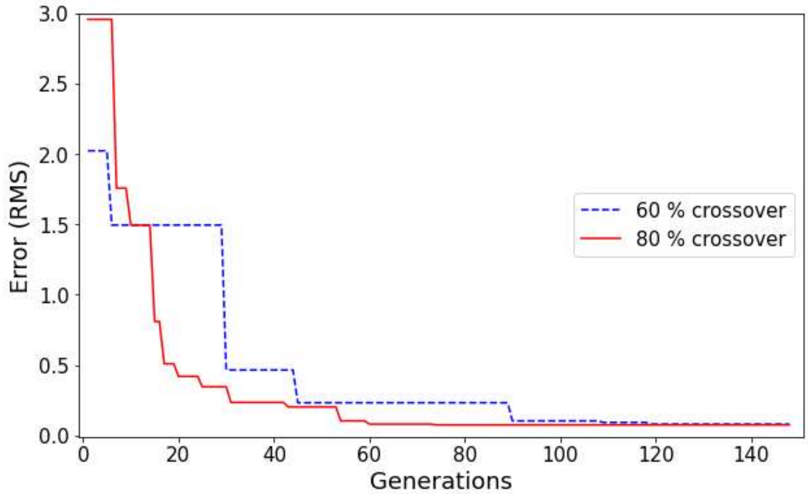

Fig. 3. Convergence of the algorithm with 60 and 80 % crossover of the population.

Table 4. Statistical analysis of the genetic algorithm with the 60 and 80 % crossover treatments in the population.

Technique	Crossover %	Error average	Standard deviation	K-S test (P-value)
GA	60	0.0825	0.008156	.09395
GA	80	0.0743	0.010847	.37194

$$D_n = \text{random}[(G_{min} - R * \alpha), (G_{max} + R * \alpha)], \quad (5)$$

where D_n is the chromosome generated as offspring, G_{min} is the minimum gene value of the parents $[G^1, G^2]$, G_{max} is the maximum gene value of the parents $[G^1, G^2]$, R is the difference of $G_{max} - G_{min}$ and α a random value between [0-1]. Finally, a uniform 5% mutation is applied on a randomly selected population during each generation of the algorithm, applying a comparative study between the results generated with a 60 and 80 % cross, verifying their distribution with the Kolmogorov-Smirnov test and, if necessary, applying the ANOVA test to demonstrate if they present significant differences between the two treatments. This is also contrasted with the results obtained with a PID controller tuned with the Ziegler Nichols method, establishing the value of the parameters $K_p = 0.61895$, $K_i = 0.60241$ and $K_d = -0.0036784$.

3 Results

This section shows the results obtained from the search for the parameters of the membership functions using the genetic algorithm. First, Fig. 3 shows the convergences obtained from the crossover with 60 and 80 % of the population in a total of 150 generations, showing that the evolutionary algorithm converges earlier in generation 76

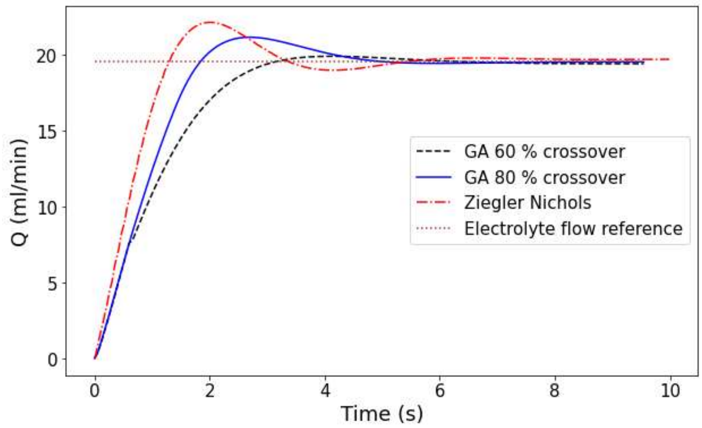

Fig. 4. Stabilization of electrolyte flow with the chromosomes with the best fitness in the search with 60 and 80 % crossover of the population, in addition to the response generated by the PID controller tuned with Ziegler Nichols.

Table 5. Performance criteria of the tuned controller with a genetic algorithm and Ziegler Nichols.

Test	Technique	% Crossover	RMS error	% Overshoot	Stablishment time (s)	Stable state error
1	GA	60	0.07988	1.50	5.8	0.14118
2	GA	80	0.07448	7.88	4.6	0.11997
3	PID (Ziegler)	-	0.10465	12.87	7.2	0.42549

for the criterion with the highest crossover percentage with a mean square error of 0.07448, while the convergence obtained for 60 % of the population was established in generation 121 with an RMS error of 0.07988.

As a result of the above, a statistical analysis was performed to determine the characteristics of the genetic algorithm when implementing both treatments in the proposed optimization. The results obtained are described in Table 4.

As shown in Table 4, the result of the Kolmogorov-Smirnov analysis indicates a normal distribution behavior for both experiments because the significance value is greater than 0.05.

Therefore, after applying the ANOVA test, a value of 0.006 is obtained, establishing that there are statistically significant differences between the treatment with different percentages of crossover between populations.

Subsequently, the chromosomes with the best aptitude from the previous experiments were extracted to be applied to the plant, and the response in the electrolyte flow control was analyzed. Furthermore, these results are contrasted with the stabilization of the controller tuned with the Ziegler Nichols method.

This is observed in Fig. 4, which describes each case for regulating the flow rate to a reference 19.7 ml/min. In addition, Table 5 describes the evaluation criteria defined

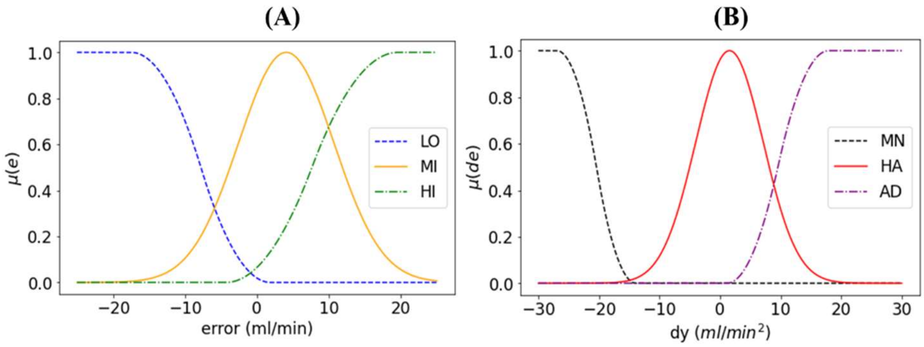

Fig. 5. The membership functions generated with the chromosome with the best fitness for evaluation of (A) error and (B) flux change with respect to time.

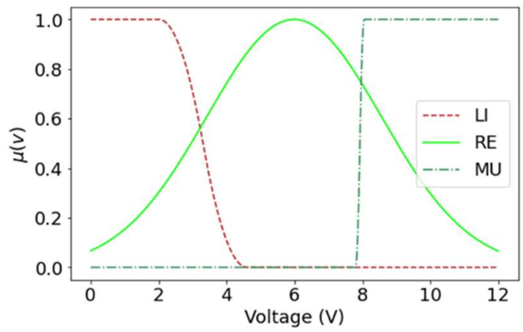

Fig. 6. Membership functions for the output variable.

according to the percentage of overshoot, steady-state error, and settling time for every tuning method.

As shown in Table 5, the genetic algorithm with a crossover percentage of 80 has a lower steady-state error and RMS than in the other cases. It requires less time to reach the flow establishment in error +/- 2 %.

Although the genetic algorithm of test 1 presents less over impulse, it is considered less significant than the response of test 2 since the establishment time with the lowest error is prioritized. In this sense, the membership functions generated with the chromosome with the best fitness in the optimization with 80 % crossover for the input variables are visualized in Fig. 5 and Fig. 6 for the output variable.

Finally, Fig. 7 shows the control space obtained with the membership functions resulting from the genetic algorithm. This image shows the behavior of the voltage variable according to the knowledge base represented by the fuzzy associative memory in Table 1, emphasizing that the voltage applied to the plant is set in the 10 V interval when the error is in the High set, and the flow change is established in the Minimum set.

Conversely, when the governing set of the error is Low, and the flow change is Minimum, the output result is established in the Little set. However, when the electrolyte flow remains stable, the governing output set remains Regular.

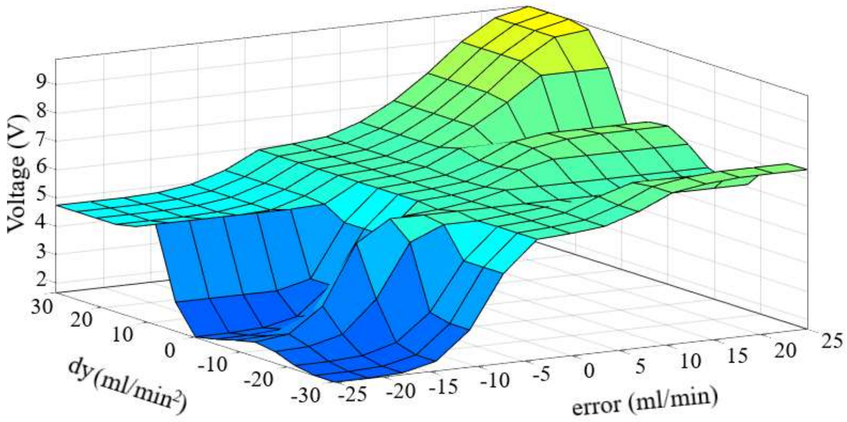

Fig. 7. Control space resulting from the fuzzy regulator obtained with the best-fit chromosome.

4 Conclusions

An evolutionary tuning was developed to establish the optimal parameters of the membership functions of a multiple-input, single-output electrolyte flow controller. Studies were carried out with 60 and 80 % crossover in the population, observing that convergence is obtained earlier when the population that generates offspring is larger. In addition, after performing statistical analysis with the Kolmogorov-Smirnov test, it is demonstrated that a normal distribution behavior and significant differences exist according to the ANOVA test.

On the other hand, regarding the response of the electrolyte flow control system, the tuning of the parameters with the genetic algorithm with 80 % crossover presents a settling time 1.2 s faster than that obtained in the test with 60 % crossover and a difference of 2.6 seconds with the PID controller. Finally, a smaller steady-state error is generated in both evolutionary optimizations as opposed to the classical control obtained with Ziegler Nichols, demonstrating that the heuristics coming from the bio-inspired algorithms are applicable to the optimization of fuzzy control parameters.

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