Genetic Algorithm for the Optimization of an Electrolyte Flow Controller in a Non-conventional Manufacturing Method

Algoritmo genético para optimizar un controlador de flujo de electrolito en un método de manufactura no convencional

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Abstract

This work describes the optimization of a fuzzy controller using a genetic algorithm based on Darwin's principle of natural selection and Mendel's inheritance laws. An elitist selection, blend alpha crossover, and uniform mutation are implemented, with crossover rates of 60 and 80%, evaluating its performance statistically. The chromosome with the best fitness is implemented in an electrolyte flow controller for an electrochemical machining process. The result is compared with a classical Proportional-Integral-Derivative controller tuned with Ziegler-Nichols, showing that the optimized regulator achieves better performance, with a 7.95% overshoot, a steady-state error of 0.1151, and a settling time of 4.8 s.

Keywords: electrolyte flow control, fuzzy logic, genetic algorithm, modern manufacturing.

Resumen

Se describe la optimización de un controlador difuso utilizando un algoritmo genético basado en el principio de selección natural de Darwin y las leyes de herencia de Mendel. Se implementa una selección elitista, cruce alfa mixto y mutación uniforme, con tasas de cruce del 60 y 80%, evaluando su desempeño de manera estadística. El cromosoma con mejor aptitud se implementa en un controlador de flujo de electrolito en un proceso de maquinado electroquímico. El resultado se compara con un controlador Proporcional-Integral-Derivativo clásico sintonizado con Ziegler-Nichols, lo que demuestra que el regulador optimizado alcanza un mejor rendimiento, con un sobreimpulso de 7.95%, un error en estado estacionario de 0.1151 y un tiempo de estabilización de 4.8 s.

Palabras clave: control de flujo de electrolito, lógica difusa, algoritmo genético, manufactura moderna.

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Introduction

Pulsed Electrochemical Machining (PECM) is an advanced manufacturing process in the metalworking industry that uses non-conventional techniques to remove material from electrically conductive workpieces. This strategy establishes the tool and workpiece at a constant separation (a gap or interelectrode distance), polarized in anode-cathode form through a pulsed electrical energy source and a continuous conductive solution called an electrolyte flow. Under these conditions, the mass transfer is catalyzed to remove material until the desired geometric characteristics of the workpiece are achieved, governed by the fundamental principles of electrolysis (Grzesik, 2017).

The essential components required for controlled material removal using the PECM technique are a mechanical system for electrode mobilization, a work tool, a workpiece, a conductive solution, an electrolyte flow system, and a polarization source. Some of the main applications of PECM are found in the metal mechanical industry for the development of technological components in the field of aeronautics, medicine, and precision tools, highlighting advantages over conventional manufacturing methods such as minimum tool wear, greater precision, manufacturing of complex structures, and material removal on high-resistance materials (Natsu, 2018). This is the case in producing components for aircraft engines such as LPC (Low-Pressure Compressor) blades, diffusers, cooling films, combustion chambers, or tools such as scalpels, micro-bushings, micro-tubes, and micro-gears (Xu & Wang, 2021).

On another note, the electrolyte flow employed in the pulsed electrochemical machining process is essential because it connects the tool and the workpiece, allowing the transfer of ions produced by the electric current. However, during the electrolysis process, residual particles are generated that can interfere with the constant circulation of the solution, decreasing the flow and conductivity. Consequently, this affects the electric current transfer, reduces the material removal rate, and hinders the proper estimation of control parameters. In this sense, some possible consequences of the improper stability of the electrolyte flow are an increase in the electrical resistance, damage to the working tool, a change of the final dimension, and a decrease in the technological stability of the produced tool (Qin, 2015; Liu *et al*., 2020). Therefore, proper control of the solution supply is considered an indispensable factor to maintain the quality of the process. In this strategy, classical feedback control techniques such as PID (Proportional Integral Derivative) or intelligent strategies with industrial applications such as Fuzzy Logic are valuable tools for integrating flow control into the PECM process.

Fuzzy logic is a method derived from artificial intelligence with applications in process flow control in the industry, as observed in Frota *et al*. (2022) and Errouha *et al*. (2019). It can evaluate real, imprecise, or ambiguous numerical data and transform them into fuzzy terms called linguistic variables or labels (Dumitrescu *et al*., 2021). These labels are generally formed by sets established within a limit of probable solutions, known as the discourse universe. Moreover, the ability to control offered by Fuzzy Logic is based on expertise expressed through inference rules and the establishment of membership functions. These characteristics facilitate the generation of robust control models capable of handling complex, nonlinear, and imprecise processes for which classical methods are typically ineffective (Dumitrescu *et al*., 2021). The features of their architecture also allow them to be integrated with other techniques to enhance performance. This is made possible by the fuzzy composition, which is divided into two groups: structural parameters and tuning parameters (Zangeneh *et al*., 2022). The first group consists of a set of input-output variables, the knowledge base, the inference system, and the defuzzification function. The second group consists of a set of parameters of fuzzy functions that can be determined empirically or through search methods.

Genetic algorithms are stochastic techniques derived from the evolutionary principle of natural selection proposed by Darwin and the laws of inheritance described by Mendel. These techniques are employed to search and optimize solutions to a diverse array of specialized problems. The solution space is populated with a random assortment of potential solutions called chromosomes and collectively constitute a population (Abbas *et al*., 2020). These solutions are evaluated and modified through a series of generations, analyzing their fitness in each one through selection, crossover, mutation, and population reconstruction, generating new alternative responses based on the criterion that only the fittest individuals can survive and generate future offspring.

The combination of intelligent methods is a strategy widely adopted in various fields of specialized literature to improve search methodologies and problem-solving approaches, as observed in Kant *et al*. (2021), and Reddy *et al*. (2018), where genetic algorithms are employed to establish optimal parameters for fuzzy controllers. Despite the existence of different strategies, such as the Mamdani and Takagi-Sugeno systems, evolutionary algorithms have demonstrated excellent results in optimizing both inference methods (Yazid *et al*., 2019). Genetic Programming has been used in Dogruer & Can (2022), *Piraisoodi et al*. (2018), and Ghaleb *et al*. (2023) for the optimization of classical PID control, where the proportional, integral, and derivative coefficients are calculated, and also for the optimization of fuzzy PID control, where the fuzzy parameters are determined using evolutionary algorithms.

In this sense, the present document describes the development of a genetic algorithm to tune the fuzzy function parameters of the controller for regulating the electrolyte flow supply in a pulsed electrochemical machining process. This model is defined by two inputs and one output, using Z, S and Gaussian membership functions for each variable, which are optimized to improve the controller performance.

1. Methodology

The electrolyte flow is a critical variable in the PECM process, as it affects the conductivity of the electrolyte, which in turn serves as the medium for eliminating machining residues from the workpiece (Grzesik, 2017). For this reason, this section provides an overview of the equipment used in this work for experimentation, the procedure for characterizing the flow behavior, the design of a fuzzy controller tuned using a genetic algorithm, and the validation process of its operation compared to that of a classical controller.

1. 1. Electrochemical machining prototype

The proposed evolutionary tuning is intended for an electrolyte flow control system in a pulsed electrochemical machining prototype, previously described in (Nopalera, 2021). The diagram in figure 1 provides a schematic representation of the PECM prototype, and in figure 2, the control (1), monitoring (2), and electrolyte recirculation system (3) are described.

This device comprises a Raspberry Pi 3 single-board computer (SBC), responsible for coordinating the manufacturing process, controlling the mechanical mobilization system, and executing the artificial intelligence programs used to manage the prototype. In addition, the motion system consists of a rectangular platform, endless screws, and NEMA23 stepper motors operating at 24 V, 10 A. This allows the electrode to be moved linearly along the (x-y-z) axes. On the other hand, a PIC18F46K22 microcontroller is used for data monitoring via an internal 10-bit ADC, communication with the SBC via the Serial Peripheral Interface (SPI) protocol, and voltage control for the suction pump that supplies electrolyte to a steel electrode with an outer diameter of 603 . The suction pump operates at 12 V, 1 A, capable of delivering up to 1 L/min. The microcontroller regulates the operating voltage using a power stage consisting of an LM2596 Direct Current to Direct Current (DC-DC) buck converter and a 10 kΩ digital potentiometer X9C103S. In this setup, the microcontroller digitally adjusts the resistance of the potentiometer connected to the buck converter, thereby modifying the output voltage. Finally, the electrolyte used is composed of water (H_2O) and sodium chloride (NaCl) at a concentration of 16% per liter of water, generating a conductivity of 207 mS/cm, measured with a HANNA conductivity meter, model HI5521-02.

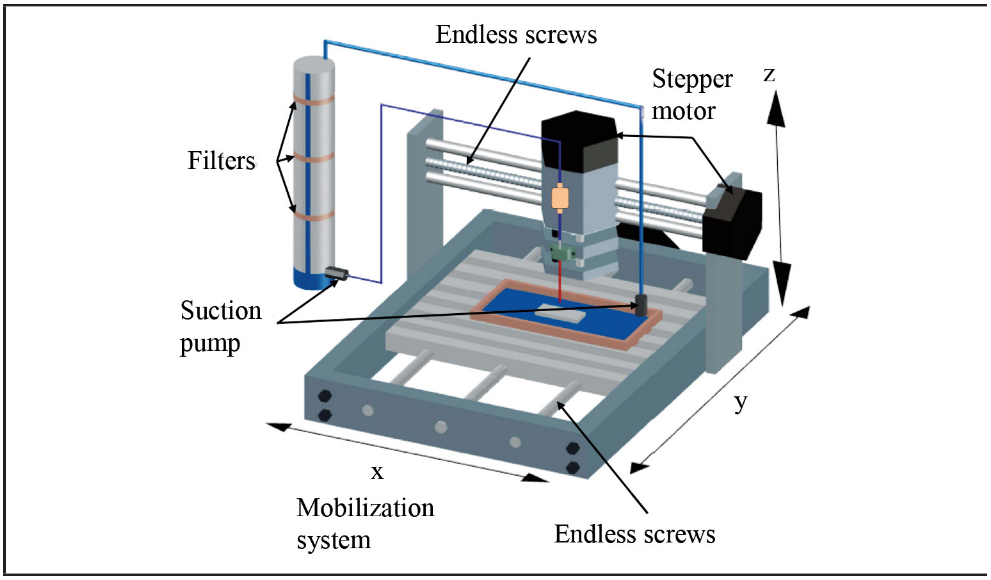

FIGURE 1
Diagram of the prototype for pulsed electrochemical machining
Source: Own elaboration.

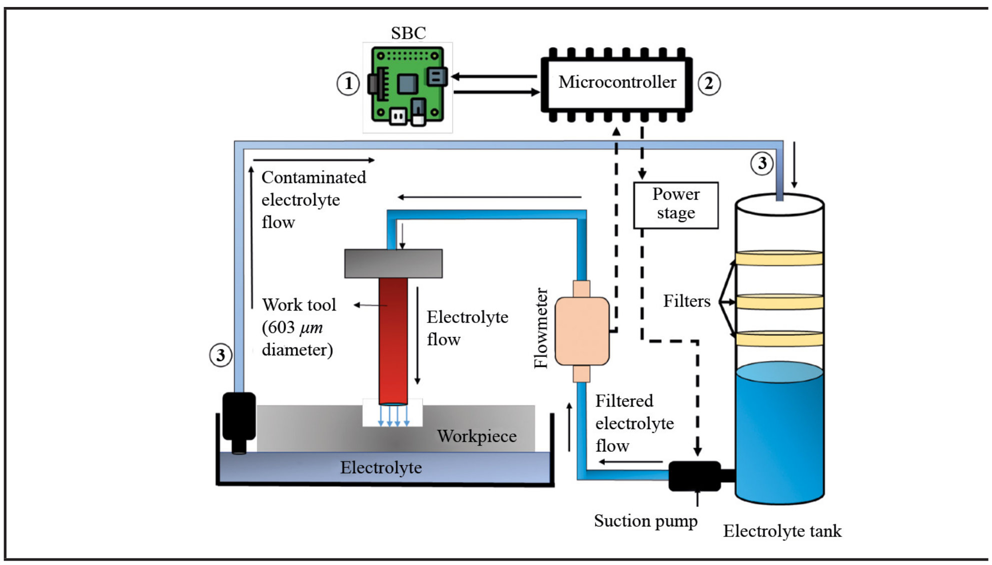

FIGURE 2
The PECM prototype
Source: Own elaboration.
Note: The PECM prototype uses control (1), monitoring (2), and an electrolyte recirculation system (3).

1. 2. Electrolyte flow characterization

Due to the electrode dimensions, the electrolyte flow supplied by the suction pump decreases considerably. As a result, the amount of solution used during the electrochemical machining process implementation is unknown. It is related to the optimum working conditions identified in experimental tests with an operating voltage of 6 V, but there is no certainty that this flow remains constant throughout the process. For this reason, an open-loop characterization was performed using a flowmeter to quantify the electrolyte (Y) flow. The flowmeter describes this quantity as a function of two variables. One of them is an output signal from the device that produces an electrical pulse frequency denoted as (fr), which is generated by the passage of the solution through an internal mechanism of the instrument. This frequency varies depending on the magnitude of the flow. The second variable is a conversion factor (ki), determined by the amount of liquid volume delivered per unit of time. This relationship between the oscillation frequency (fr) and the conversion factor (ki) describes the flow through the flowmeter, as shown in equation (1).

$$Y = \frac{fr}{ki} \tag{1}$$

This characterization was performed for 60 minutes, generating a total of 1.182 liters of electrolyte. Therefore, clearing the parameter (ki) from equation (1), a conversion factor equivalent to 0.964 Hz·min/ml is obtained, and a total of 19.7 ml/min of electrolyte during the manufacturing process is estimated. Subsequently, the system identification module of MATLAB was used to characterize the behavior of the solution considering the quantified flow and the detected operating voltage of the suction pumps, obtaining a third-order transfer function in terms of Laplace described in equation (2), which facilitates computer-based modeling for its implementation with the proposed stochastic search.

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

1. 3. Fuzzy controller

The proposed evolutionary tuning is focused on a fuzzy controller that evaluates the electrolyte flow error (the difference between measured error and a reference value) and its change rate (described by the error derivative) as inputs through three distinctive stages in fuzzy logic: fuzzification, inference, and defuzzification. The first stage evaluates the numerical input data with real coding and transforms them into degrees of membership of the fuzzy functions. Consequently, in the second stage, an inference is performed based on a series of IF-THEN syntactical propositions or rules and the assigned sets for the output variables. Finally, in the defuzzification stage, the fuzzy conclusion is decoded into a floating-point numerical value that is interpreted by the non-conventional manufacturing system called "the plant" (according to control terminology) to regulate the behavior of the electrolyte flow to the nominal reference through continuous closed-loop feedback, as described in figure 3.

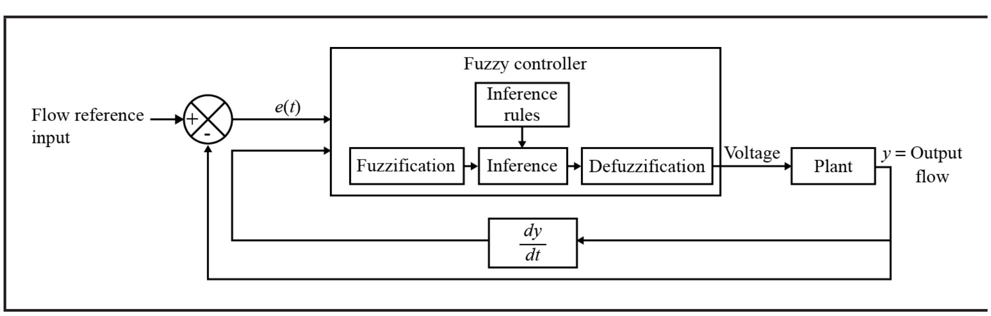

FIGURE 3
Fuzzy control diagram for regulating the electrolyte flow in PECM
Source: Own elaboration.

1. 4. Delimitation and optimization of membership functions

The error in the electrolyte flow is evaluated using the linguistic variables "Negative", "Stable", and "Positive". At the same time, "Small", "Moderate", and "Excessive" represent the terms assigned to determine the membership of the flow change. Moreover, the magnitude of the voltage required to modify the flow rate of the solution in the plant is estimated, based on the labels "Low", "Regular", and "High", using Z-type, S-type, and Gaussian functions for all cases. Additionally, table 1 presents the fuzzy associative memory that describes a general knowledge system through the relationships between input and output variables, which will later be adapted by adjusting the limits of the sets using a genetic algorithm.

TABLE 1
Fuzzy associative memory used in PECM to control electrolyte flow

Fuzzy input sets	Small	Moderate	Excessive
Negative	Low	Low	Low/Regular
Stable	Regular	Regular	Regular
Positive	High/Regular	High/Regular	High

Source: Own elaboration.

Two fundamental parameters generate each membership function described above. The transition point from 1 to the intersection with 0 is established for Z-type functions, while for S-type functions, the transition point from 0 to the intersection with 1 is settled. Gaussian functions, on the other hand, are defined by their standard deviation and center. In this sense, table 2 describes the fuzzy set labels for input variables and table 3 for output variables, with their respective symbolic representation of the parameters to be obtained through stochastic search.

TABLE 2
Input linguistic variables and symbolic representation of the parameters required for each function

Variable	Fuzzy sets		Membership function parameters
er (Error)	NE	Negative	μ-z (er; $\boldsymbol{e_1}$, $\boldsymbol{e_2}$)
	ST	Stable	μ-g (er; $\boldsymbol{e_3}$, $\boldsymbol{e_4}$)
	PO	Positive	μ-s (er; $\boldsymbol{e_5}$, $\boldsymbol{e_6}$)
dy (flow change)	SM	Small	μ-z (dy; $\boldsymbol{e_7}$, $\boldsymbol{e_8}$)
	MO	Moderate	μ-g (dy; $\boldsymbol{e_9}$, $\boldsymbol{e_{10}}$)
	EX	Excessive	μ-s (dy; $\boldsymbol{e_{11}}$, $\boldsymbol{e_{12}}$)

Source: Own elaboration.

TABLE 3
Output linguistic variables and symbolic representation of the parameters required for each function

Variable	Fuzzy sets		Membership function parameters
Vo (Voltage)	*LO*	Low	μ-z (vo; $\boldsymbol{e_{13}}$, $\boldsymbol{e_{14}}$)
	RE	Regular	μ-g (vo; $\boldsymbol{e_{15}}$, $\boldsymbol{e_{16}}$)
	HI	High	μ-s (vo; $\boldsymbol{e_{17}}$, $\boldsymbol{e_{18}}$)

Source: Own elaboration.

Based on the symbolic representation described in table 2 and table 3, the structure of each chromosome in the population for the genetic algorithm was established. This structure comprises 18 genes, which represent the parameters of the membership functions, while maintaining the form described by equation (3).

$$Chromosome = [e_1, e_2, e_3 \ldots e_{18}] \tag{3}$$

According to the syntax of equation (3), an initial population of 100 chromosomes was randomly generated, with an interval of the universe of discourse for the error genes from −25 to 25 ml/min. On the other hand, the respective genes for the flow rate change as a function of time were established under the same criteria in an interval from −30 to 30 ml/min^2. Finally, the output variable genes were generated from 0 to 12 V. It is crucial to emphasize that the initial population intervals exhibit a magnitude comparable to that observed during the open-loop characterization. However, these intervals serve merely as a starting reference for the algorithm and do not guarantee an optimal solution. These bounds can be extended or reduced during the optimization process, depending on the offspring at each iteration and the score of the fitness function that produces a better response. Once the initial population was generated, the objective function observed in equation (4) was defined, which considers the mean squared error of the flow as an evaluation criterion for evaluating the plant performance. This is possible because it provides the difference between actual values and predicted values (Ye *et al.*, 2020), using the output generated by the fuzzy control algorithm and the membership functions of each chromosome.

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

Based on the fitness of each chromosome obtained with equation (4), the population is selected using an elitism operator and a BLX-α crossover method to generate offspring. This crossover operator generates a random offspring based on the combination of genes from two parent chromosomes and a random alpha value for each iteration with a uniform distribution between 0 and 1, as shown in equation (5).

$$D_n = rand[(Gn_{min} - D * \alpha), (Gn_{max} + D * \alpha)] \tag{5}$$

Where Dn is the chromosome generated as offspring, Gn_{min} is the minimum gene value of the parents [$G1$, $G2$], Gn_{max} is the maximum gene value of the parents [$G1$, $G2$], D is the difference of $Gn_{max} - Gn_{min}$ and α a random value between [0-1]. In addition, a 6% is proposed to perform a uniform mutation, randomly selecting the affected population for two study cases: 60 and 80% of population crossover. These criteria are analyzed by their distribution under the Kolmogorov-Smirnov test. If normality is satisfied by applying the T-student and Chi-square test, the significance of each treatment is shown. The results are compared with a classical PID controller tuned using the Ziegler-Nichols method (Ellis, 2012), whose operating values are set to $Kp = 0.618951$, $Ki = 0.602411$, and $Kd = -0.00367841$.

2. Results and discussion

In this section, a discussion is presented regarding the performance achieved with the genetic algorithm in the search for optimal parameters for the membership functions of the fuzzy controller. In this sense, the convergence for the crossover with 60 and 80% of the population is described in the graph of figure 4, visualizing a behavior with greater efficiency by the approach with a higher crossover rate, reaching a convergence of 0.0734 in the 60th generation. This is attributed to the chosen elitist selection and the Alpha factor in the BLX-α crossover operator, which is randomly and uniformly modified in each iteration. This adjustment increased search space when the α value was higher, while the offspring maintained closer values to the parent genes when α was close to zero. Therefore, the genetic diversity of the offspring derived from this operator is ensured, in addition to obtaining a faster algorithm convergence without falling into local optima (Takahashi & Kita, 2001; Sato & Oyama, 2021).

It should be noted that the root-mean-square error is an average measurement based on a set of outputs. Consequently, although the convergence error is similar, the evaluation with an 80% crossover suggests that the system is more stable, as the deviations from the desired behavior are less significant. Similarly, a smaller error can lead to more precise adjustments, which is crucial in precision manufacturing applications.

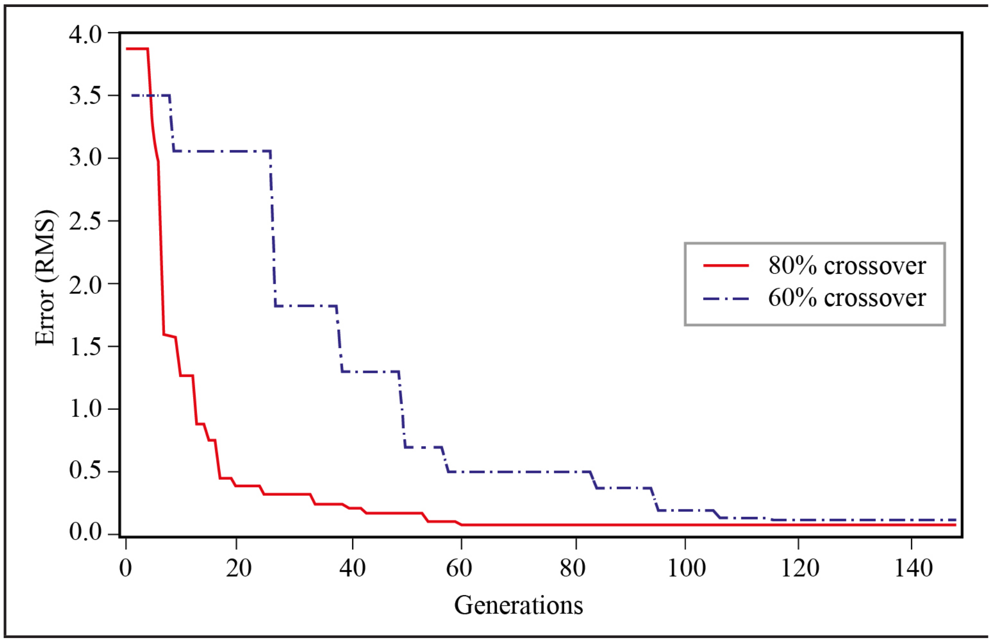

FIGURE 4
Achieved convergence in each treatment of the genetic algorithm
Source: Own elaboration.

In addition to the above, the average error, deviation, and distribution behavior for each experiment class determined by the Kolmogorov-Smirnov test are shown in table 4. It is observed that the p parameter of the Kolmogorov-Smirnov (K-S) test maintains a value higher than the significance threshold of 0.05, thus indicating that the statistical distribution presents normality (*i. e.*, the population distribution follows a Gauss-like function). Based on these results, T-Student and Chi-square tests were applied to determine the statistical significance between the two crossover criteria in the genetic algorithm population. As a result, p-significance values of 0.0103 and 0.0089, were obtained respectively, allowing to reject the null hypothesis and demonstrate the existence of significant differences in the efficiency of the algorithm when using crossover rates of 60 and 80% for this problem.

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

Technique	% crossover	Average error	Standard deviation	K-S test (p-value)	T-Student (p-value)	Chi-square (p-value)
GA	**60**	0.0925	0.008235	0.09127	0.0103	0.0089
	80	0.0738	0.010572	0.32913		

Source: Own elaboration.

Once the analysis described above was completed, the chromosomes with the best fitness from the previous experiments were extracted to be evaluated in the pulsed electrochemical machining plant, in order to analyze the control response of the electrolyte flow. Furthermore, these results were compared with the response provided by a PID control tuned with the Ziegler-Nichols method, observing through figure 5 the flow behavior under each control criterion to reach the ideal flow reference established at 19.7 ml/min.

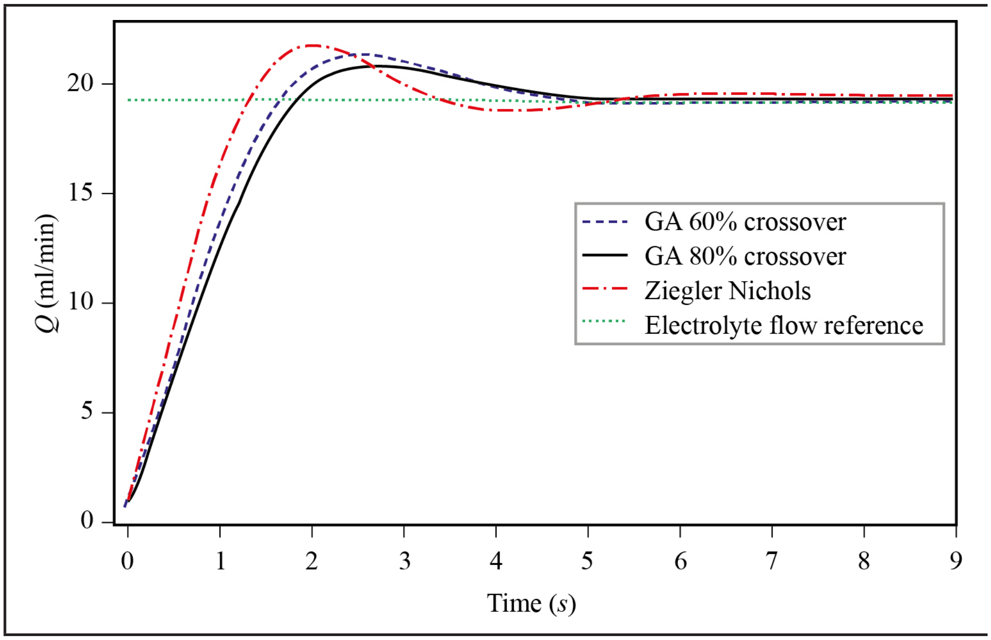

FIGURE 5
Electrolyte flow response*
Source: Own elaboration.

Note: * = using the best-fit chromosomes found with the genetic algorithm with 60 and 80% crossover, and the response generated by the PID controller was tuned using the Ziegler Nichols method.

The responses described in figure 5 are evaluated using the control criteria expressed by the percentage of overshoot, steady-state error, and establishment time for each proposed control method, as described in table 5. According to these results, the response obtained with the tuning using the genetic algorithm with a crossover rate of 80% presents the best operating conditions in the electrolyte regulation system, generating the lowest overshoot and steady-state error, with a faster settling time of the flow than the other evaluation criteria. It should be noted that all controllers achieved a steady-state error below 5%, which is a beneficial outcome in terms of control effectiveness (Golpîra *et al*., 2021). However, the overshoot and the speed at which settling is achieved modify the efficiency of each controller, justifying the selection of the optimized fuzzy algorithm with 80%.

TABLE 5
Performance of the controller tuned with the genetic algorithm and Ziegler Nichols

Test	Technique	% Crossover	% Overshoot	Establishment time (s)	Stable state error
1	**GA**	60	9.87	6.3	0.1378
2	**GA**	80	7.95	4.8	0.1151
3	**PID**	-	12.87	7.2	0.4254

Source: Own elaboration.

As previously mentioned, the fuzzy controller tuned to the genetic algorithm with a crossover rate of 80% consistently demonstrates superior performance. This efficiency is achieved through the correct establishment of membership functions within the universe of discourse. Details of the parameters used to generate these functions for each input and output variable are given in table 6, emphasizing that these same values refer to the chromosome with the best fitness in the optimization.

TABLE 6
Parameters of the membership functions established with the best chromosome in genetic optimization

Variable	Z-Function		Gaussian Function		S-Function	
Error	21.01992	−5.6668102	−3.76895	5.690491	−3.73185	20.49572
Flow change	24.12211	−3.2505198	0.184454	9.644604	10.71312	19.74284
Voltage	2.839203	6.42387185	5.860775	1.704887	7.732722	8.689607

Source: Own elaboration.

Furthermore, as shown in figure 6 and figure 7, the membership functions of the input variables associated with the error and the change in flow over time are depicted, considering the parameters outlined in table 3. The sets are used in the first stage of the fuzzy approach, where the input data are transformed into corresponding degrees of membership according to the sets estimated by the genetic algorithm.

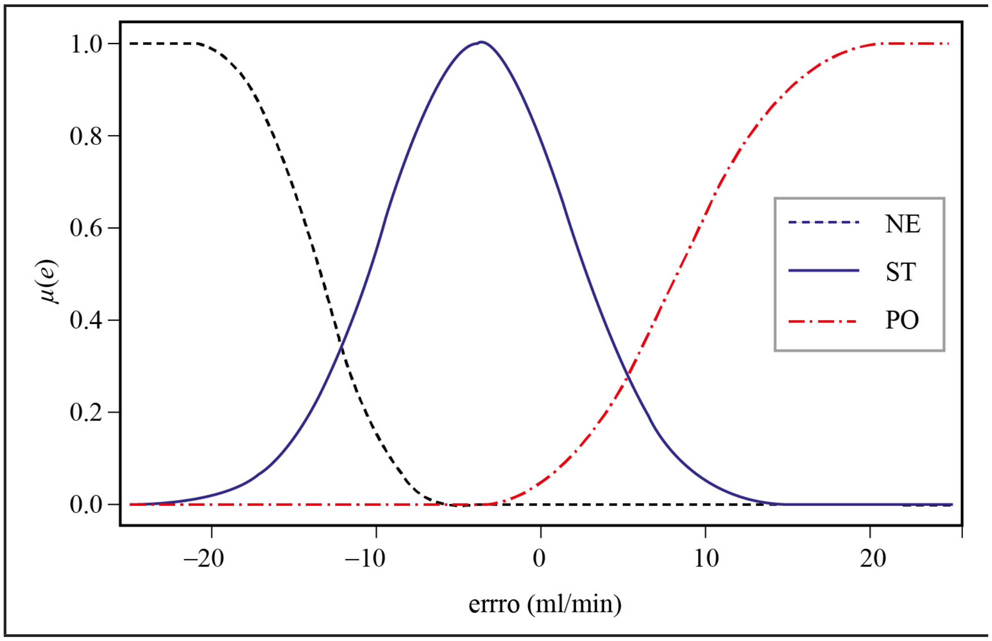

FIGURE 6
Membership functions for the error evaluation obtained with the fittest chromosome in the evolutionary tuning
Source: Own elaboration.

Therefore, based on the estimated coverage for each linguistic input variable, a correct transformation of all possible significant states of the input variables is ensured. However, if there is data outside of them, the asymptotic characteristics of the proposed functions always ensure a grade of membership to maintain an affiliation with the fuzzy labels and to achieve a relationship with the output variables. On the other hand, the membership functions for the output variable are shown in figure 8, allowing an estimate of the voltage value through the fuzzy associative memory from table 1.

This approach avoids overshoot effects and maintains a faster speed to reach a steady state with lower error than that obtained with a PID method, as previously observed in table 5. Additionally, figure 9 shows the control space of the fuzzy controller that describes the set of possible values that the control variable can adopt to achieve the desired performance in the regulation of electrolyte flow. This behavior is adopted in consideration of the fuzzy associative memory from table 1, emphasizing a tendency to maintain a value of 10 V when the error in flow estimates a higher degree of membership in the "Positive" set and the membership of the flow change over time is established in the "Small" label, ensuring an effective correction to reach the reference without causing an overshoot due to a higher voltage. These control actions help to prevent damage to electronic devices caused by voltage spikes, usually generated in control systems by abrupt changes in the evaluation variables. In classical systems such as PID, these overshoots are usually caused by a wrong setting of the proportional gain *Kp* and the derivative gain *Kd*, in addition to insufficient damping (Ortega *et al*., 2021). On the other hand, the optimized fuzzy control system provides a broader range of interpretation of the input variables by weighting them through sets and assigning memberships according to their state and not a specific value, as is done in the classical PID control (Dumitrescu *et al*., 2021).

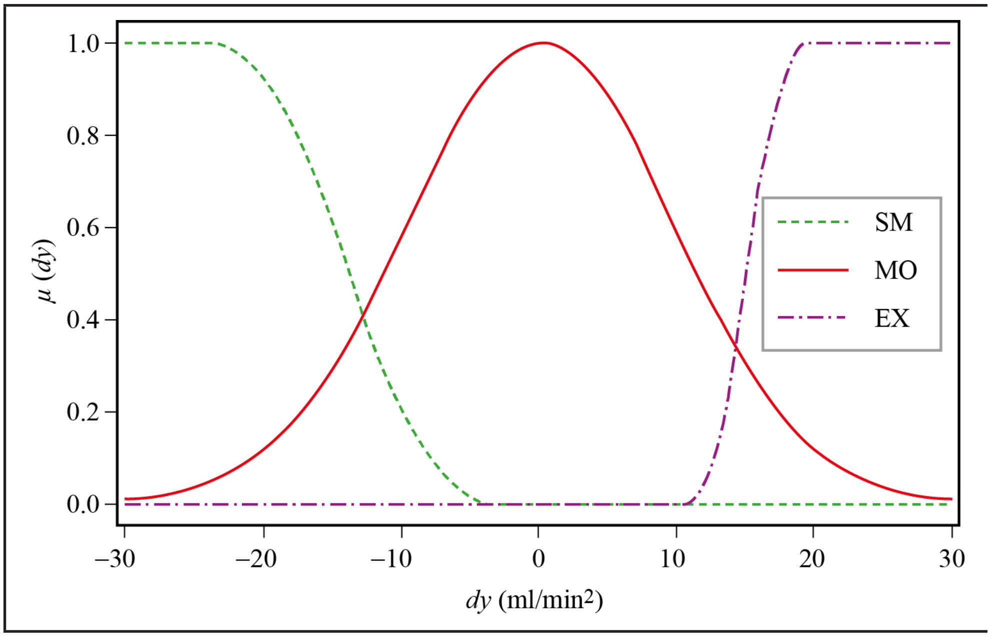

FIGURE 7
Membership functions for the evaluation of flow change over time obtained with the fittest chromosome in the evolutionary tuning
Source: Own elaboration.

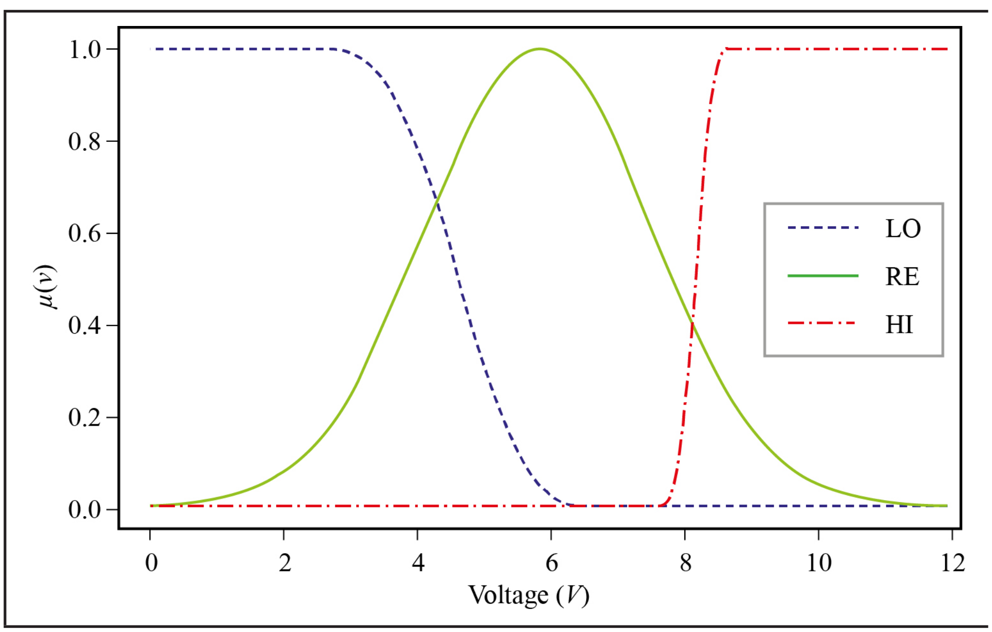

FIGURE 8
Membership functions for voltage estimation obtained with the fittest chromosome in the evolutionary tuning
Source: Own elaboration.

In addition to the description of fuzzy control space, when the dominant set of the error is equivalent to “Negative,” and the change is “Small,” the output voltage is situated in the “Low” function. This action indicates that the electrolyte delivery system can achieve a change in flow with a voltage below 3 V. Given that the solution passes through a tool of reduced dimensions, it is more efficient for the flow to be decreased by maintaining the power voltage at a level close to the operational limits of the suction pumps. However, if the membership of the flow variable remains in the “Stable” set, then the dominant output maintains an electrical voltage value within the range of the “Regular” function, consolidating an electrical voltage magnitude sufficient to retain the flow reference and the best conditions for the manufacturing process. Maintaining a constant flow has excellent benefits for electrochemical machining. According to Catarino (2024), it helps maintain an adequate material removal rate without excessively increasing the lateral over-cutting of the manufactured parts. Conversely, the overcut is substantially extended when the flow rate increases, and the material removal rate is poor when the flow rate decreases below the expected rate.

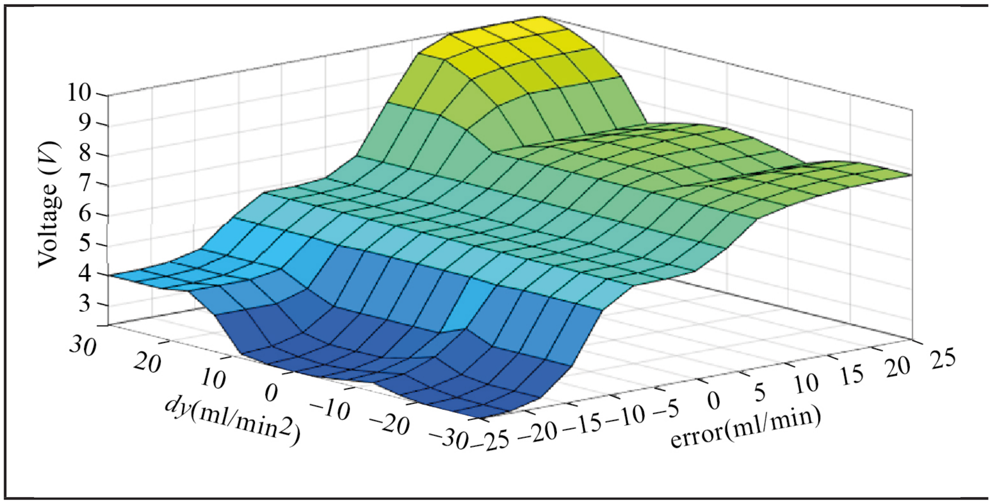

FIGURE 9

Control space after the evolutionary tuning for the pulsed electrochemical machining system

Source: Own elaboration.

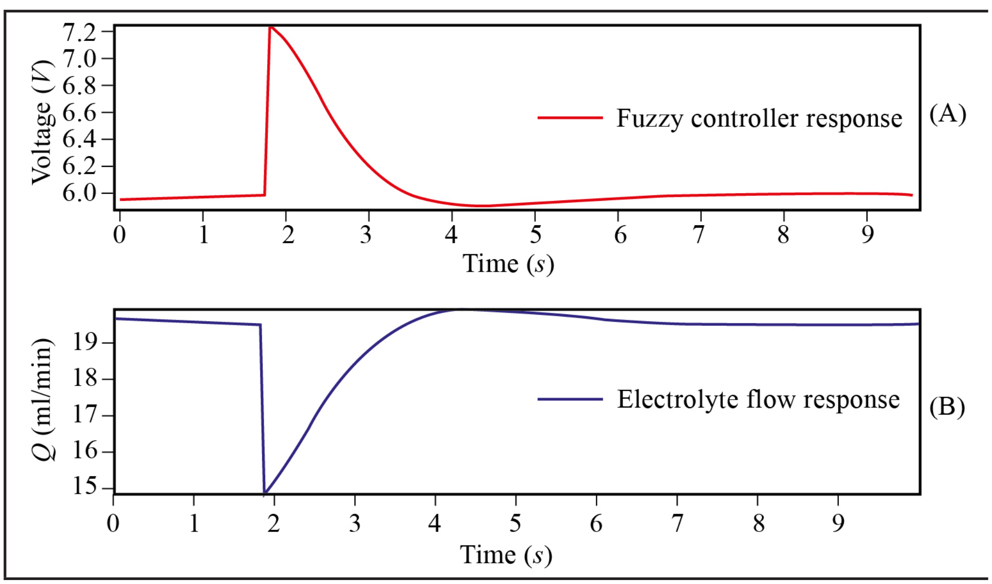

FIGURE 10

Test of the fuzzy control

Source: Own elaboration.

Note: *a*) Voltage response generated by the fuzzy controller when applying a disturbance, *b*) electrolyte flow behavior with applied control voltage

As a complement, a test of the fuzzy control is presented by applying a disturbance to the electrolyte flow. The graph in figure 10 *a*) describes the voltage response to correct the flow to the identified disturbance, and figure 10 *b*) shows the response of the solution flow until the stability of the nominal flow of 19.7 ml/min is regained.

Furthermore, a delay of approximately 153 ms is observable between the generation of a response by the fuzzy controller and the beginning of electrolyte regulation. Nevertheless, this behavior is usually expected in electronic devices and does not indicate any problems due to the small magnitude of the delay. Finally, figure 11 shows photographs of linear machining made with the PECM prototype using the test electrode. In addition, some measurements are presented showing the application of PECM for developing structures on the micrometer scale.

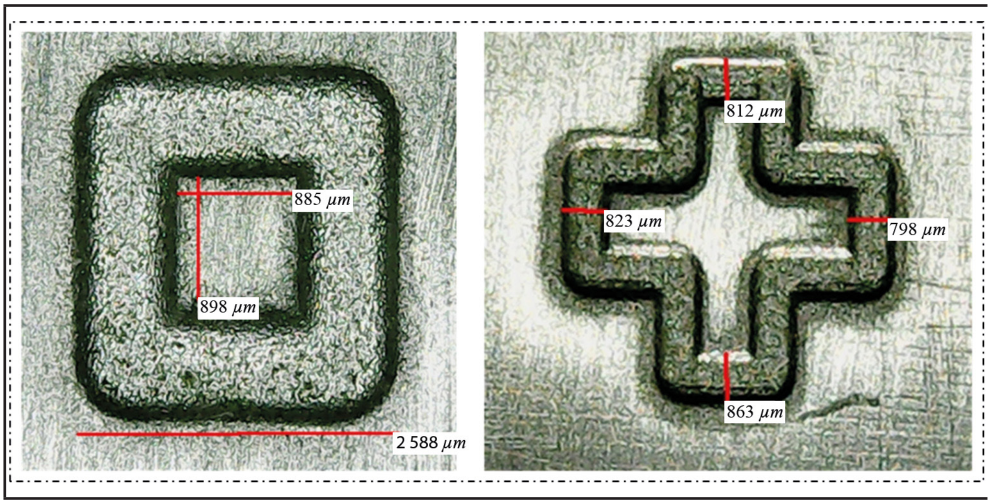

FIGURE 11
Linear machining developed with the PECM prototype
Source: Own elaboration.

Prospective

The constant technological development, the trend of miniaturization of parts for the development of conductive components, and the increase of demand in the metal-mechanical manufacturing sector have caused enormous challenges to produce components (of metallic origin) with reduced dimensions (in micrometer scale) and high complex specifications. Due to these circumstances, significant research has been carried out to perfect manufacturing methods capable of producing metal tools of this nature efficiently during their production.

Pulse electrochemical machining (PECM) is a modern manufacturing method with excellent capabilities for developing small-scale tools with complex morphologies using chemical and electrical principles during its application. However, due to the nature of the process, difficulties have arisen during its implementation, establishing the optimization of control as an opportunity to ensure efficient operation and better results. For this reason, part of the objective of this research is to use computational strategies derived from artificial intelligence, such as Fuzzy Logic and Genetic Algorithms, to address the problems identified in the metal-mechanical industrial sector. In this way, we aim to generate a solution using these intelligent strategies to optimize the operation of manufacturing components in this industry.

Conclusions and future work

A genetic algorithm was developed to optimize the membership function parameters used in a fuzzy logic controller to regulate electrolyte flow in a pulsed electrochemical machining system. The performance of the evolutionary algorithm was analyzed by studying the population crossover percentage at 60 and 80%, with elitist selection and BLX-α crossover operator, obtaining better performance and faster convergence in the criterion with a higher crossover rate. Furthermore, a Kolmogorov-Smirnov normality test was applied to each treatment, demonstrating a normal distribution with significant differences according to the T-student and Chi-square tests. This demonstrates that both treatments have remarkably different performances. Thus, the best response by the electrolyte flow regulation system was obtained with the criterion chromosome with 80% crossover, presenting a settling time 1.5 s faster than the time generated by 60% crossover and a difference of 2.4 s in the time required by the PID to achieve stability. Finally, the fuzzy controller tuned with the genetic algorithm generates a lower steady-state error, and overshoot than the PID controller tuned with the Ziegler-Nichols method by a magnitude of 0.3103 and 4.92%, respectively. Therefore, it is demonstrated that the stochastic derived from bio-inspired algorithms effectively optimizes control parameters in fuzzy systems.

Future research aims to evaluate the benefits of electrolyte regulation in manufacturing microchannels and specific perforations using the non-conventional PECM manufacturing process.

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