Designing fuzzy membership functions using genetic algorithm with a new encoding method

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ABSTRACT

This article presents a new method for designing fuzzy membership functions using the genetic algorithm (GA) without the use of constraints. Conventional approaches to designing these functions often involve manual tuning or optimization techniques with limitations. However, this article introduces a constraint-free approach, as the GA requires all constraints to be met for a chromosome; if even one condition is not satisfied, the chromosome is discarded, regardless of its ideal values for other variables. Consequently, a high number of constraints, especially in the studied case, increases the likelihood of chromosome rejection, leading to a time-consuming design process and suboptimal results.

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1. INTRODUCTION

Fuzzy logic controllers (FLCs) have emerged as indispensable tools for addressing complex and uncertain scenarios in various fields. Their ability to handle imprecise data and mimic human decision-making processes has significantly contributed to their widespread adoption in control systems [1]. From engineering systems to financial modeling, FLCs have demonstrated adaptability and efficacy, offering efficient control solutions for processes that challenge traditional rule-based approaches [2].

While the demand for optimal FLC performance continues to grow, various strategies have been explored to enhance their efficiency. One such approach involves leveraging the expertise of domain specialists to craft membership functions and rule sets [3]. By tapping into their deep understanding of system behavior, FLCs can be fine-tuned to achieve maximum effectiveness. Alternatively, computational intelligence methods like genetic algorithms (GAs) introduce a data-driven dimension to optimization. GAs emulates natural evolution to iteratively refine controller parameters, resulting in controllers that dynamically adapt to changing conditions. Moreover, the integration of machine learning techniques enables controllers to learn from data, enhancing adaptability to complex and evolving systems [4].

GAs have emerged as prominent optimization techniques, demonstrating their effectiveness in improving the efficiency of fuzzy controllers [5]. By mimicking the evolutionary process, GAs generate and refine potential solutions over successive iterations. In the context of FLC optimization, GAs efficiently navigate the vast parameter space, yielding controllers with enhanced performance and adaptability. Their ability to handle multi-dimensional, non-linear optimization problems has established GAs as indispensable tools in designing robust and efficient fuzzy controllers [6].

In this article, we present a novel method for designing membership functions using a GA without imposing constraints. The paper is structured into six sections. Section 1 outlines the problem addressed in this study. Section 2 provides a review of relevant literature, highlighting major contributions and findings in the field. Section 3 identifies unsolved problems and areas requiring improvement, particularly those addressed in our manuscript. Section 4 describes our new contributions, detailing the novel method for designing membership functions using GAs. Section 5 outlines how the subsequent sections demonstrate our approach and its relevance, while section 6 concludes the paper by discussing the ramifications of our findings and their implications for future research and applications.

2. GENETIC ALGORITHM

The GA is a powerful tool in artificial intelligence, drawing inspiration from Charles Darwin's theory of natural evolution [7]. It operates as a randomized search technique, exploring various parts of the solution space with different solution characteristics to find optimal answers iteratively [8]. At its core are genetic operators like crossover and mutation, mirroring the biological processes of reproduction and genetic variation. Through selection, fit individuals are chosen to produce offspring, inheriting their traits and potentially improving upon them [9]. This iterative process mimics natural selection, gradually refining the population towards optimal solutions [10]. GA's ability to inherit information across iterations sets it apart, enabling synchronous operation on multiple targets and facilitating global optimization [11]. By leveraging these evolutionary principles, GA proves to be a versatile and effective heuristic optimization technique for solving complex problems [12], [13]. The optimization process outlined consists of several key steps:

- Initialization: an initial population of individuals, representing active power generated by units and FC system levels, is randomly selected within defined limits.
- Evaluation: each individual's fitness is assessed using an objective function, which in this study measures the total daily operating cost derived from optimal power flow calculations.
- Termination: the process checks for predefined stopping conditions; if met, the iteration stops; otherwise, it proceeds.
- Selection: individuals are ranked based on fitness, and those with high scores progress to the next step for crossover.
- Crossover: a new population of offspring is generated by combining characteristics of selected individuals using genetic principles and specified crossover strategies.
- Mutation: new offspring undergo mutation to introduce diversity, exploring new search areas and preventing convergence to local minima.
- Best solution: the fittest individuals are statistically selected to replace the current population, with the best solution stored. Iteration continues until the maximum number of iterations is reached or stopping criteria are met [14], [15].

3. FUZZY CONTROLLER

Dr. L. A. Zadeh, a Professor at the University of California at Berkeley, introduced the concept of fuzzy set theory and fuzzy control during the 1960s [16]. His innovative approach involved extending Boolean logic to a continuous form, allowing for a smooth transition between 0 and 1, thus enabling the definition of soft boundaries. These soft boundaries paved the way for the creation of FLCs, which have found increasing applications in systems with nonlinearity and uncertainty. FLCs are designed based on the human operator's familiarity and understanding [17].

Fuzzy control utilizes fundamental principles of fuzzy logic to govern a plant or system using linguistic variables instead of strict mathematical equations [18]. This approach involves representing, manipulating, and applying the experiential knowledge of humans to achieve effective control over the system. FLCs are comprised of four primary components:

- Fuzzifier: the fuzzifier takes real-valued input data and transforms it into fuzzy sets. This mathematical process, known as fuzzification, converts an element in the universe of discourse into the corresponding membership value of the fuzzy set [19].
- Knowledge base: fuzzy logic utilizes a straightforward rule format, such as "IF x is a AND y is b THEN z is c," to address control problems without the need for complex mathematical modelling. The Knowledgebase comprises two essential elements: a database defining the membership functions, and a rule base containing fuzzy rules constructed to guide the control actions [20].
- Inference engine: the inference engine establishes a connection between the premises of fuzzy sets and their corresponding consequences. It determines which control rule to activate and how the logic

connection should be established between the premise components. Depending on the method used to determine the output, the inference system can be classified as either Mamdani-type or Sugeno-type [21].

– Defuzzifier: the defuzzifier converts the output fuzzy sets into a precise, crisp value. This transformation process, known as defuzzification, involves converting fuzzy sets into crisp sets. Several defuzzification methods exist, including centroid, bisector, mean of maxima, smallest of maxima, and largest of maxima [22].

Figure 1 illustrates the structure of a fuzzy controller, which involves defining two input variables: the error denoted as 'e' and the change of error represented as 'de.' The output variable is labeled 'u.' On the other hand, Figure 2 displays the input and output variables of a Fuzzy system [23], [24]. The error and change of error inputs are categorized into seven membership functions each, namely: big negative (BN), medium negative (MN), small negative (SN), zero (ZE), small positive (SP), medium positive (MP) and big positive (BP). Similarly, the output variable 'u' is also divided into the same seven membership functions.

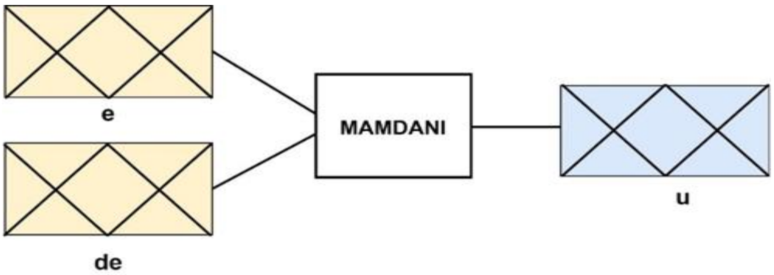

Figure1. Input and output variables

4. ENCODINGOF MEMBERSHIP FUNCTIONS

4.1. Conventional method

Encoding in genetic representation involves structuring parameters into chromosomes or strings to represent solutions. These chromosomes typically contain organized sequences of parameters. In a specific system utilizing triangle-type membership functions, the parameters determining the shape of each triangle are crucial, including the horizontal coordinate of the vertex (x2), left base point (x1), and right base point (x3), as depicted in Figure 2.

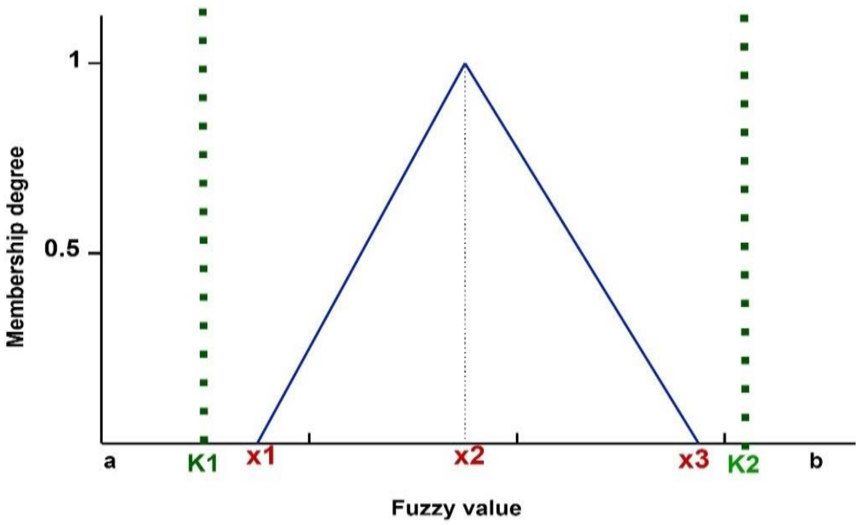

Figure 2. Representation of triangular membership function

As depicted in Figure 2, the membership function is defined using the three variables, x1, x2, and x3, within the interval [a, b], and it can be defined as follows (1) [25].

$$\begin{cases} \frac{x-x_1}{x_2-x_1} & x_1 \le x < x_2 \\ \frac{x_3-x}{x_3-x_2} & x_2 \le x \le x_3 \\ 0 & \end{cases} \tag{1}$$

Furthermore, ensuring the triangular shape's integrity, membership functions must adhere to constraints such as (2).

$$\begin{cases} x_1 < x_2 \\ x_2 < x_3 \\ x_1 > K1 \\ x_3 < K2 \end{cases} \tag{2}$$

However, genetic operators may occasionally produce chromosomes that violate these constraints, leading to the rejection of genes associated with illegal chromosomes. For a system with 21 membership functions, 84 constraints are needed. If any of these constraints are not satisfied, the chromosome will be rejected, even if it contains optimal values for other functions. This can prolong optimization time and yield uncertain results.

Each function is determined by 3 parameters: x1, x2, and x3. Therefore, previous research has sought to optimize these parameters to enhance the membership functions. However, in our solution, we did not attempt to optimize these parameters.

4.2. Proposed method

In our solution, we avoided relying on the points x1, x2, x3, unlike previous method that utilize the constraints. Indeed, the use of constraints can diminish the performance of the GA. To mitigate the impact of constraints on the GA, it has been suggested not to employ them. This allows for greater flexibility.

As shown in Figure 3 we assigned each x point a range of length 'm' For example, for the point x1, it varies between p1 and p1+m; for x2, the range is [p2, p2+m], and for x3, the range is [p3, p3+m]. From the Figure 3, it can be observed that:

$$\begin{cases} x_1 = P1 + R1 \\ x_2 = P2 + R2 \\ x_3 = P3 + R3 \end{cases} \tag{3}$$

where points P1, P2, and P3 are constants. The decision to choose 0.31 for the range 'M' depends on the number of bits in binary encoding. With 5 bits, we can represent 32 values from 0 to 31, and by dividing the value by 100. The parameters r1, r2, and r3 vary between 0 and 0.31. In this case, the representation of a membership function within a chromosome is achieved using the parameters R1, R2, and R3, rather than x1, x2, and x3, as illustrated in Figure 4.

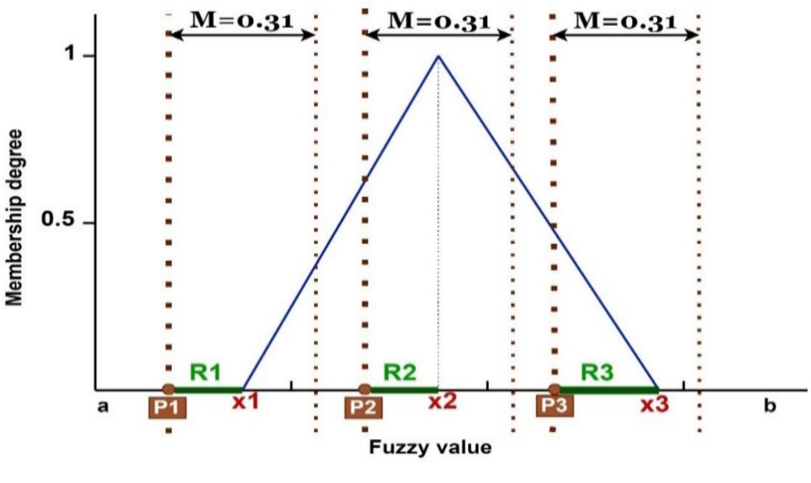

Figure 3. Proposed presentation for membership function

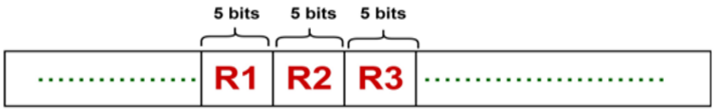

Figure 4. Chromosome structure

From Figure 5, it is evident that the utilized membership functions are symmetric. Each membership function has its own parameters, such as r1, r2, and r3, which define its shape and position relative to the axis. The values of these parameters can vary from one membership function to another. For example, the second point X_{Sp2} of the 'small positive' membership function is presented as follows:

$$X_{Sp2} = P2 + R_{Sp2} \tag{4}$$

due to the symmetry of the functions, it can also be stated that:

$$X_{sn2} = X_{sp2} \tag{5}$$

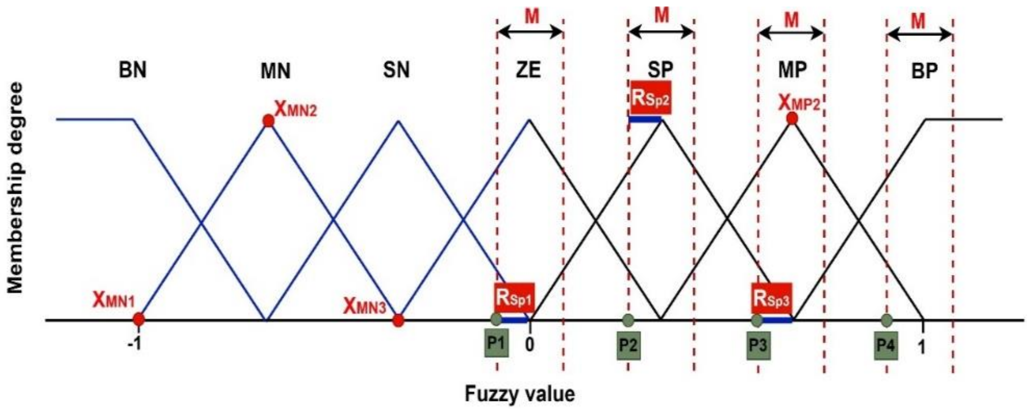

Figure 5. Representation of symmetric membership functions

Negative membership functions are not considered in the optimization process, and their parameters are not included in the chromosome. After optimization, these functions are reconstructed from the positive functions. Table 1 contains the genetic parameters' values utilized in this study.

Table 1. Parameters of GA

Parameter	Value
Population size	20
Number of generations	400
Mutation	0.1
Crossover	0.8

The fitness function employed in this context is the integral square of the error, as defined by the following:

$$ISE = \int e^2 \tag{6}$$

this fitness function measures the cumulative squared discrepancy between the actual and expected outputs, providing a comprehensive evaluation of the system's performance across various conditions or datasets. Figure 6 provides a visual representation of the fuzzy membership, which has been refined and optimized through the iterative process of a GA over a span of 200 generations.

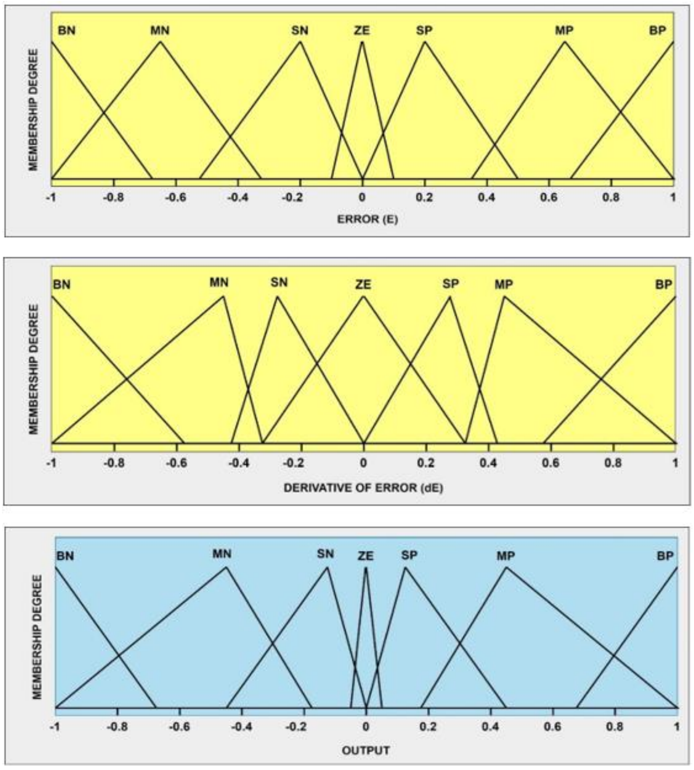

Figure 6. Optimized membership functions: error membership, derivative of error membership and output membership

5. RESULT AND DISCUSSION

After employing a GA to refine the membership functions of the fuzzy controller without constraints, we proceeded to assess the efficacy of our approach by integrating the controller into the speed regulation of an asynchronous machine. With a reference speed of 300 rad/s and a 10n load applied between 2s and 3s, Figure 7 illustrates the comparison between the responses of the asynchronous machine's rotational speed generated by the conventional method and our method.

Figure 7, it is evident that our method outperforms the conventional method both in terms of initial response and load resistance. As shown in the figure, the speed response is quickly achieved after the load application, unlike the second case with the conventional method. Results depicted in Figure 7 unmistakably demonstrate the promising outcomes yielded by the implementation of the fuzzy controller. Moreover, our approach significantly reduces the time required for the optimization process compared to conventional methods. This efficiency stems from our GA methodology, which incorporates all generated chromosomes.

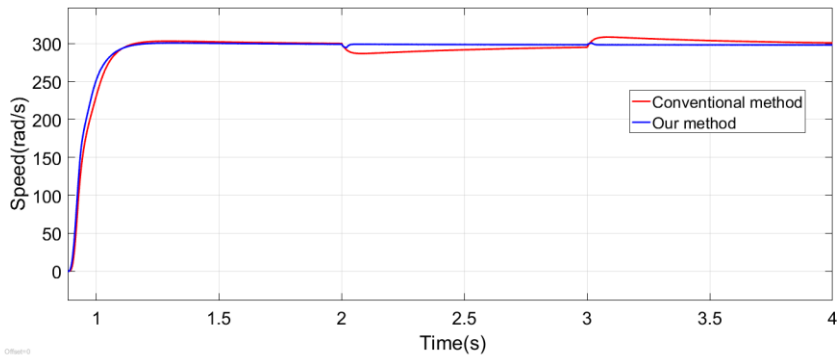

Figure 7. Speed response for induction motor using fuzzy controller

6. CONCLUSION

In summary, this article introduces an innovative approach to optimize fuzzy controller membership functions using the GA, sidestepping the drawbacks of constraints. The conventional use of constraints often leads to the rejection of chromosomes, causing time-intensive optimization and suboptimal outcomes. By eliminating constraints, the proposed method enables a more comprehensive exploration of solutions, resulting in improved optimization efficiency and better results. This constraint-free GA not only accelerates the optimization process but also enhances adaptability for intricate challenges, showing promise for advancing optimization techniques in complex systems.

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