E-ISSN: 2717-3453 | P-ISSN: 2783-1442

Journal of Fuzzy Extension and Applications

www.journal-fea.com

J. Fuzzy. Ext. Appl. Vol. 3, No. 2 (2022) 1518–168.

Paper Type: Research Paper

Type-2 Fuzzy Logic Controller Design Optimization Using the PSO Approach for ECG Prediction

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Citation:

Dirik, M. (2022). Type-2 fuzzy logic controller design optimization using the PSO approach for ECG prediction. *Journal of fuzzy extension and applications, 3*(2), 158-168.

Received: 12/03/2022 Reviewed: 14/04/2022 Revised: 21/05/2022 Accepted: 28/05/2022

Abstract

In this study, a hybrid model for prediction issues based on IT2FLS and Particle Swarm Optimization (PSO) is proposed. The main contribution of this work is to discover the ideal strategy for creating an optimal value vector to optimize the membership function of the fuzzy controller. It should be emphasized that the optimized fuzzy controller is a type-2 interval fuzzy controller, which is better than a type-1 fuzzy controller in handling uncertainty. The limiting membership functions of the type-2 fuzzy set domain is type-1 fuzzy sets, which explains the trace of uncertainty in this situation. The proposed optimization strategy was tested using ECG signal data. The accuracy of the proposed IT2FLS_PSO estimation technique was evaluated using a number of performance metrics (MSE, RMSE, error mean, error STD). RMSE and MSE with IT2FI were calculated as 0.1183 and 0.0535, respectively. With IT2FISPSO, these values were calculated as 0.0140 and 0.0029, respectively. The proposed PSO-optimized IT2FIS controller significantly improved its performance under various operating conditions. The simulation results show that PSO is effective in designing optimal type-2 fuzzy controllers. The experimental results show that the proposed optimization strategy significantly improves the prediction accuracy.

Keywords: Interval type-2 fuzzy set, Particle swarm optimization, Optimization fuzzy controller, Fuzzy sets, Prediction problem.

1 | Introduction

Optimization is a branch of computer science that deals with finding the optimal solution to a problem. It is used to find the best solution or a suitable alternative from a set of proposed solutions. Bio-inspired optimization methods can be used to solve problems that involve optimizing a particular objective function that may be constrained by a set of constraints. Unlike traditional optimization techniques, this algorithm generates a set of solutions at each iteration. These strategies focus on generating, selecting, assembling, and modifying a collection of solutions. They require more computation time than other metaheuristics because they maintain and modify a collection of solutions rather than searching for a single answer [1]-[5].

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http://dx.doi.org/10.22105/jfea.2022.333786.1207

This paper presents an T2FIS-PSO hybrid model for developing IT2FIS fuzzy logic controllers and finding the best parameter values for membership functions using bio-inspired optimization techniques. The hybrid T2FIS-PSO strategy is expected to provide more accurate results than standard T2FIS approaches [6]. The type-2 fuzzy Logic System (FLS) proposed by Zadeh [7]-[9] is presented as an extension of the standard type-1 FLS, and then the associated ideas and computational techniques are developed [10]-[14]. The degrees of membership are similarly fuzzy in a type-2 fuzzy set. In this sense, a fuzzy set of type-1 is a subset of a fuzzy set of type-2 , since its secondary membership function is a one-element subset [13]. Mendel and other scientists [13] and [14] reduced the computational complexity of the type-2 FLS domain by basing it on the broad type-2 FLS. It is widely accepted by academics in a variety of fields because of its minimal computational complexity. However, the major obstacle is the difficulty in obtaining the control parameters. This increases the complexity of the FLS and complicates the computation. For this reason, several systems recommend the use of powerful fuzzy rules. There are several established methods for rule selection, including fuzzy C-means, fuzzy K-means, cluster subtraction, and singular value decomposition. Traditional parameter setting methods have a number of drawbacks, including non-spherical convergence, computational cost, and difficulty to obtain. With the advancement and refinement of intelligent algorithms, the application of intelligent algorithms to the development of FLS, such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) based on FLS, has become a focus of research [6] and [15]. PSO has been applied to a variety of optimization problems, including mathematical functions, fuzzy controllers, control parameters, and planning problems [16]-[23]. Using the hybrid IT2FIS-PSO technique, we were able to design an optimal type-2 fuzzy logic controller that determines the optimal Membership Function Parameters (MF) for controlling unstable linear systems. The results of this study were validated by predicting arrhythmia symptoms on electrocardiograms using arrhythmia signals (ECG) [3] and [24]. The human body can recognize some forms of cardiac arrhythmia caused by the electrical activity of the heart. The word electrocardiogram (ECG) refers to biological signals. Continuous recording and interpretation of the ECG is critical for detecting irregularities and consequences that may develop during the monitoring phase of heart disease. Therefore, in today's clinical practice, the processing, storage, and transmission of ECG data over digital communication networks is critical [25]. ECGs are a type of chaotic time series that serve as a bridge between chaos theory and reality. They are the most common application of chaos and thus provide an entirely new domain for predicting complicated nonlinear signals. In the real world, numerous types of complex systems have been shown to exhibit chaotic behavior. With the rapid advances in chaos theory and its application approaches, time series data obtained from an observable chaotic system has become an extremely useful tool for understanding complicated systems. This is because the observed system has a wealth of dynamical information that allows the behavior of the complex system to be studied and analyzed by examining and evaluating the potential content of the chaotic time series generated. So far, numerous techniques have been offered for prediction based on chaos theory [26]-[28].

The basic objective of this work is to develop and validate an optimization procedure based on a meta-heuristic algorithm using a type-2 fuzzy controller for monitoring ECG signals. The objective is to determine the optimal settings of the type-2 fuzzy controller in conjunction with the provided optimization techniques. In order to ensure the smallest possible error margin in the tracking of the ECG signal, the control of the behavior of a system specified by a certain metric is studied. *Fig.1* graphically represents the proposed working method PSO-FLS. Each particle represents the fuzzy rules and associated MF for the FLC inputs and outputs in this process. Each particle represents a possible solution. These parameters are needed to define the particles of the PSO algorithm and calculate the global optimal fitness.

The structure of this paper is as follows: the second section is about materials and processes. The motivation and equations for the search and optimization of the PSO and IT2FIS algorithms are discussed in detail here, as is the proposed technique for the optimization of the type-2 fuzzy controller. Section 3 summarizes the results of the experiments conducted with the proposed technique. Finally, conclusions and future work are outlined in Section 4.

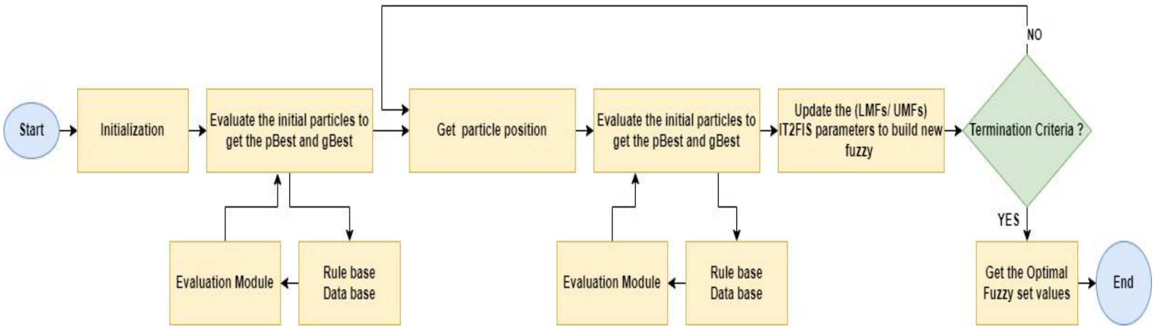

Fig. 1. Flowchart of the fuzzy membership function optimized with PSO.

2 | Material and Methods

Although previous research has focused on optimizing membership functions through PSO, none of these studies used the experimental settings used in this study to construct metrics. Since such a combination is rare in the literature, we will compare the performance of different computational techniques on these optimization problems. In this section, we provide an overview of the important ideas and concepts underlying our work.

2.1 | Particle Swarm Optimization

PSO is a kind of stochastic optimization technique invented by Kennedy [29]. It is a population-based search space determined by the social behavior of a flock of birds investigating a potential search area [30]-[32]. The PSO method is often used for multivariate optimization problems because it is a population-based probability optimization strategy. When an individual or particle performs an activity, it independently analyzes the fitness value of its position relative to the other swarm members. The computation of the individual's position, the rate of progress in each dimension of the solution set, and the optimal fitness value is critical [32]. The fitness function is used to calculate the best solution for the local or global swarm based on the optimization criteria of the PSO algorithm. *Eq. (1)* and *(2)* include the PSO velocity equation. The position and velocity of each swarm particle are fixed. Each particle gradually adjusts its position depending on two factors: the p_{best} of its nearest neighbor and the g_{best} of the swarm.

$$V_i(t+1) = w * V_i(t) + c_1 * r_1 * (p_{best} - x_i(t) + c_2 * r_2 * \left(g_{best} - x_i(t)\right). \quad (1)$$

$$x_i(t+1) = x_i(t) + (1-w) * V_i(t+1). \quad (2)$$

Here c_1 and c_2 are constant factors and w is the moment of inertia. r_1 and r_2 are two random integers from the range [0, 1]. The PSO approach is used to determine optimal parameters for intuitionistic fuzzy sets of type-2. Its performance is an evaluation of IT2FIS using the recommended upper and lower membership functions (UMFs and LMFs) for the IT2FIS membership functions. The algorithm presented in *Algorithm 1* shows how IT2FIS optimizes for particle swarms.

The PSO parameters and their meanings given in *Eq. (1)*, *Eq. (2)*, and Algorithm 1 are listed in *Table 1*.

Table 1. The PSO parameters and their meanings.

Population_Size	Initial Population Size
Pbest	Best movement.
Gbest	Best position movement.
C_1, C_2	Two acceleratin constants.
W^k, w_{max}, w_{min}	Inertia, initial and final weght.
$\bar{d}$, $\underline{d}$	Spread of MFs associate with upper and lower bound.
a	Tuned parameter.
v_i	Velocity.
x_i	Position of *i* th particle.

Algorithm 1. PSO in IT2FIS.

1. Intial papulation
2. Iteration=0
3. Setting papulation size, x= $\alpha, \overline{d}, \underline{d}$
4. Setting C_1, C_2, W_{max}, W_{min}
5. While (iteration<MaxNumlt)
6. If $(x_i)<P_{best}$ then
7. $P_{best=}\ x_i$
8. end if
9. If $P_{best} < g_{best}$ then
10. $g_{best=}\ P_{best}$
11. end if
12. Calculation of Eq. (1) and (2)
13. Calculation of inertia weight (w)
14. Calculation of new position of particle ($x_i(t+1)$)
15. Iteration ++
16. End While
17. Return $\alpha, \overline{d}, \underline{d}$.

2.2 | Interval Type-2 fuzzy Inference System (IT2FIS)

Interval type-2 is a specific uniform function of a T2F MF with a single value for the second stage. An IT2FIS, denoted by $\tilde{A}$, is expressed in *Eq. (3)* or *(4)*.

$$\widetilde{A} = \left\{(x, y), \mu_{\widetilde{A}}(x, y) \mid \forall_x \epsilon\ X, \forall_u \epsilon\ J_x \subseteq [0\ 1]\right\}. \tag{3}$$

$$\widetilde{A} = \int_{x \epsilon X} \int_{u \epsilon J_x} 1/(x, u)\ J_x \subseteq [0\ 1]. \tag{4}$$

Where $\int \int$ denote the union of all acceptable x and u. An IT2FIS is defined in terms of an UMFs with $\overline{\mu}_{\tilde{A}}(x)$ and a LMFs with $\underline{\mu}_{\tilde{A}}(x)$. J_x is just the interval of $[\overline{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{A}}(x)]$. The UMF and LMF are determined using two T1F MFs representing the boundaries of the Footprint of Uncertainties (FOU). Consequently, $\mu_{\tilde{A}}(x, u) = 1$ and $\forall_u \epsilon\ J_x \subseteq [0\ 1]$ are considered as IT2FIS membership functions. The form of MFs in IT2FIS is three-dimensional; the value of the third dimension is always 1. It has been shown to outperform T1FS in noisy and well-defined systems in real-time applications, corresponding to a case where $\mu_{\tilde{A}}(x, u) = 1$ and the integral form is shown in *Fig. 2*.

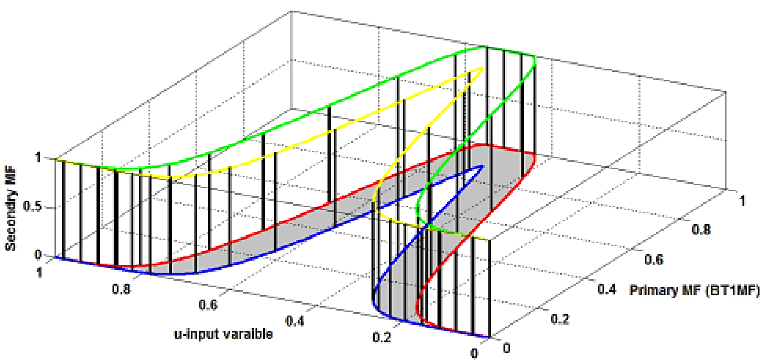

Fig. 2. 3D representation of the interval type-2 membership function [33].

A T2F is defined by IF-THEN rules, with T2F as antecedent and consecutive sets. To create a T2F controller, it is necessary to understand the block structure used in T1F, since the basic blocks are identical. A T2F, as shown in *Fig. 3*, consists of a fuzzifier, a rule base, a fuzzy inference engine, and an output processor. A Type Reducer (TR) and a defuzzifier are included in the output processor. TR is the main difference between T1F and T2F systems. The TR of T2F is used to generate a T1F output set of unique integers. Type reduction is included as it relates to the type of membership degrees of the elements [30].

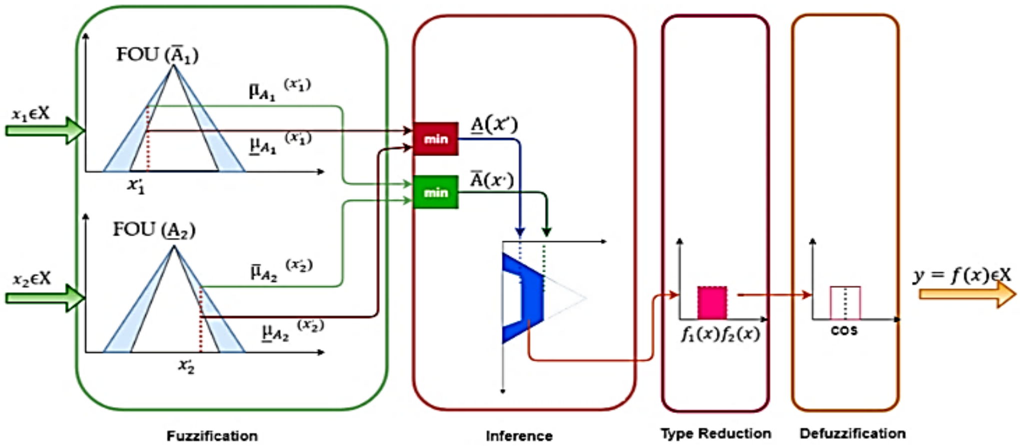

Fig. 3. Structure of a type-2 fuzzy logic system.

The stream RT of Karnik and Mendel [34] and [35] combines the output sets into a single output using one of their approaches, as shown in *Fig. 3*. The equation illustrates the mathematical expression for this *Procedure (5)*.

$$Y_{cos}(x) = [y_l, y_r] = \int_{y^1 \in [y_l^1, y_r^1]} \cdots \int_{y^1 \in [y_l^M, y_r^M]} \int_{f^1 \in [\underline{f}^1, \bar{f}^1]} \cdots \int_{f^M \in [\underline{f}^M, \bar{f}^M]} \Big/ \frac{\sum_{i=1}^{M} f^i y^i}{\sum_{i=1}^{M} f^i}. \tag{5}$$

The left and right ends of this middle of the sets define it completely. The following set of the IT2FIS defines these two endpoints (y_l, y_r). Here, $\underline{f}^{\,i}$ and $\bar{f}^{\,i}$ are the lower and upper firing levels of the i-th rule, and M is the number of rules fired. These points are given in *Eq. (6)* and *(7)*. The outputs of the interval type-2 fuzzy system are represented by y_l and y_r.

$$y_l = \frac{\sum_{i=1}^{M} f_l^{\,i} y_l^{\,i}}{\sum_{i=1}^{M} f_l^{\,i}}. \tag{6}$$

$$y_r = \frac{\sum_{i=1}^{M} f_r^{\,i} y_r^{\,i}}{\sum_{i=1}^{M} f_r^{\,i}}. \tag{7}$$

3 | Simulation Results

The proposed optimization technique is used to determine the optimal settings for the type-2 fuzzy controller required to anticipate the behavior of the ECG signal in this study. The simulations were performed in MatLab®R2021 on an Intel®CoreTMi7-6700 CPU with 16GB RAM and a 3.40 GHz clock speed running Windows®10 (64 Bit). The goal of the fuzzy controller is to track a given signal with the lowest possible errors given by the controller's performance criteria. The main difference between dynamic and fixed parameter tuning in metaheuristic algorithms is that in dynamic tuning the selected parameters are changed during the iterations, leading to better solutions. The aim is to optimize the settings of the MFs of the type-2 fuzzy controller for signal tracking using the PSO algorithm to optimize the fuzzy controller using original techniques and their modifications. In this part, the results of fuzzy controller optimization for ECG signal behavior prediction are presented. The approach uses a metaheuristic algorithm to generate a vector containing the parameters required for the MFs of the optimized IT2FIS controller. Metaheuristic techniques in this case are versions of the PSO algorithm since they dynamically change the parameters using interval type-2 fuzzy systems. *Table 2* contains the parameters used in the proposed model.

Table 2. Parameters of the PSO and IT2FIS.

Parameer	PSO	Parameter	IT2FIS
Function Tolerance	1.0000e-06	And Method	"prod"
Inertia Range	[0.1000, 1.1000]	Or Method	"probor"
Initial Swarm Span	2000	Implication Method	"prod"
Max Iteration	15	Aggregation Method	"sum"
Max Stal Iterations	20	Defuzzification Method	"wtaver"
Min Neighbors Fraction	0.2500	Inputs	1x4 fisvar
Objective Limit	0	Outputs	1x1fisvar
Seif-Adjustment Weight	1.4900	Rules	1x70 fisrule
Social Adjustment Weight	1.4900	Type Reduction Method	
Swarm Size	'min (100, 10*number of variables)'	"Karnikmendel"	
Distance Metric	"rmse"		

Mean Square Error (MSE), Root Mean Square Error (RMSE), root mean square error (EM), and standard deviation of error (Std) are all metrics used to measure algorithm performance during optimization.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2. \qquad \text{[36] and [37]} \quad (8)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2}. \qquad \text{[38]} \quad (9)$$

$$\text{Error Mean} = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i). \qquad \text{[37]} \quad (10)$$

$$\text{Error St. D} = \sqrt{\sum_{i=1}^{N}\frac{(x_i - \bar{x}_i)^2}{N-1}}. \qquad \text{[39] and [40]} \quad (11)$$

Where N is the number of data, $\bar{x}$ and $\bar{y}$ are the average of the predicted and actual, x_i and y_i are the predicted and actual values, respectively. Since the FIS has no predefined fuzzy rules, it is optimized using PSO, a global optimization technique for learning the rules. The maximum number of rules is limited by the number of possible MF combinations for the inputs. This limit can be exceeded because redundant rules are deleted during the adaptation process. The maximum iterations are set to 15. Training errors can be reduced by increasing the number of iterations. Increasing the number of iterations, on the other hand, prolongs the fitting process and may cause the rule parameters to be overfitted to the training data. The behavior of the FIS has changed with the training data and parameters shown in *Table 3*. Result of tuning the FIS using the given training data and options.

Table 3. Result of tuning the FIS using the given training data and options.

Interation	f-count	Best f (x)	Mean f (x)	Stall Iterations
0	100	0.1714	0.3262	0
1	200	0.1608	0.448	0
2	300	0.1397	0.3931	0
3	400	0.1345	0.3727	0
4	500	0.1345	0.3539	1
5	600	0.1345	0.3828	2
6	700	0.1345	.3788	3
7	800	0.1311	0.3629	0
8	900	0.1189	0.3407	0
9	1000	0.1189	0.3722	1
10	1100	0.1127	0.3787	0
11	1200	0.1127	0.3442	1
12	1300	0.1127	0.3702	2
13	1400	0.1127	0.3556	3
14	1500	0.1127	0.3716	4
15	1600	0.1127	0.3526	5

The graphical representation of the FIS created using the test data can be found in *Fig. 4*.

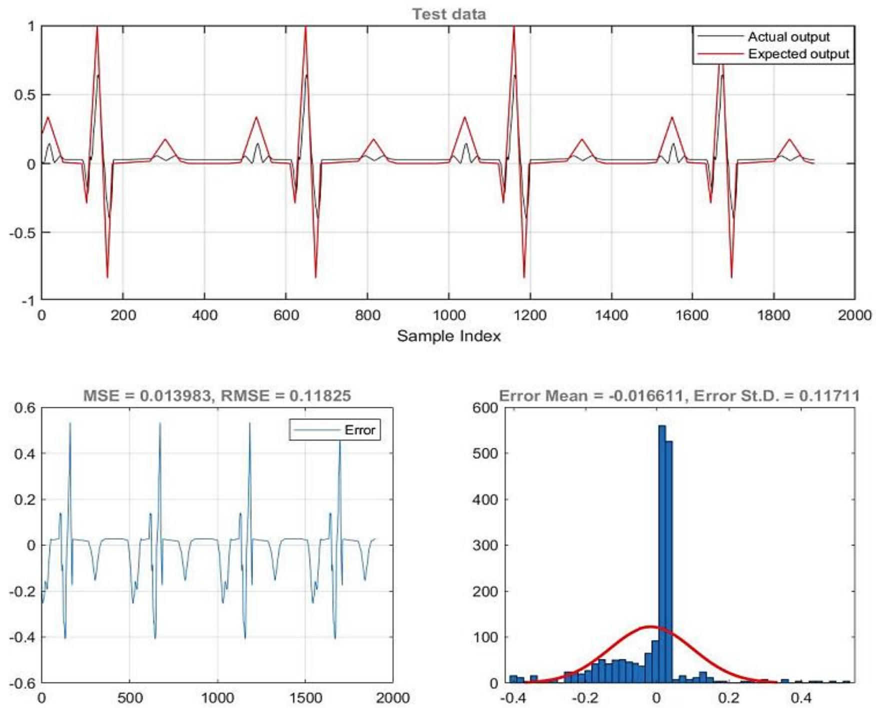

Fig. 4. The actual generated output with the expected validation output.

Fuzzy type-2 consists of both upper and lower membership functions. *Table 1* and *Fig. 5* show the results obtained when optimizing the upper membership functions.

Table 4. Results obtained using optimized upper MFs of FIS.

Interation	f-count	Best f (x)	Mean f (x)	Stall iterations
0	100	0.1127	0.3257	0
1	200	0.1127	0.3928	0
2	300	0.1103	0.2925	0
3	400	0.1014	0.2882	0
4	500	0.09827	0.2707	0
5	600	0.06759	0.2902	0
6	700	0.06759	0.2783	1
7	800	0.06759	0.277	2
8	900	0.06759	0.2746	3
9	1000	0.06285	0.2611	0
10	1100	0.06285	0.2656	1
11	1200	0.06285	0.2653	2
12	1300	0.06285	0.2454	3
13	1400	0.06285	0.2252	4
14	1500	0.06285	0.2135	5
15	1600	0.05985	0.1703	0

When comparing the predicted validation result of the modified FIS with the actual generated result using validation data and the actual produced result, it was found that changing the UMF parameters increased the performance of the FIS. The results obtained by adjusting the UMFs in the FIS structure are not reasonable. It is obvious that in this case, the functions of LMFs must be changed as well. The results of the functions and the graphical representations derived using the optimized FIS structure for both membership functions (LMFs and UMFs) can be found in *Table 5* and *Fig. 6*, respectively.

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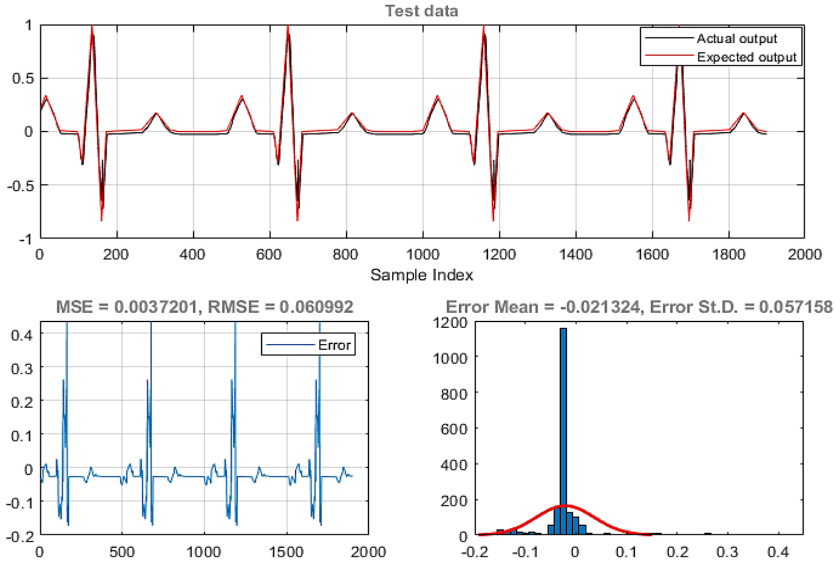

Fig. 5. The result of the actual, expected, error, and error histogram obtained with optimized upper MFs of FIS.

Table 5. Results obtained using optimized lower and upper MFs of FIS.

Iteration	f-count	Best f (x)	Mean f (x)	Stall Iterations
0	100	0.05985	0.1493	0
1	200	0.05985	0.1368	0
2	300	0.05491	0.1066	0
3	400	0.05421	0.09809	0
4	500	0.05421	0.1038	1
5	600	0.05421	0.1179	2
6	700	0.05421	0.09997	3
7	800	0.05421	0.07972	4
8	900	0.05421	0.07945	5
9	1000	0.05345	0.0911	0
10	1100	0.05345	0.08205	1
11	1200	0.05212	0.07336	0
12	1300	0.05212	0.0732	1
13	1400	0.05212	0.07687	2
14	1500	0.05209	0.0708	0
15	1600	0.05206	0.06181	0

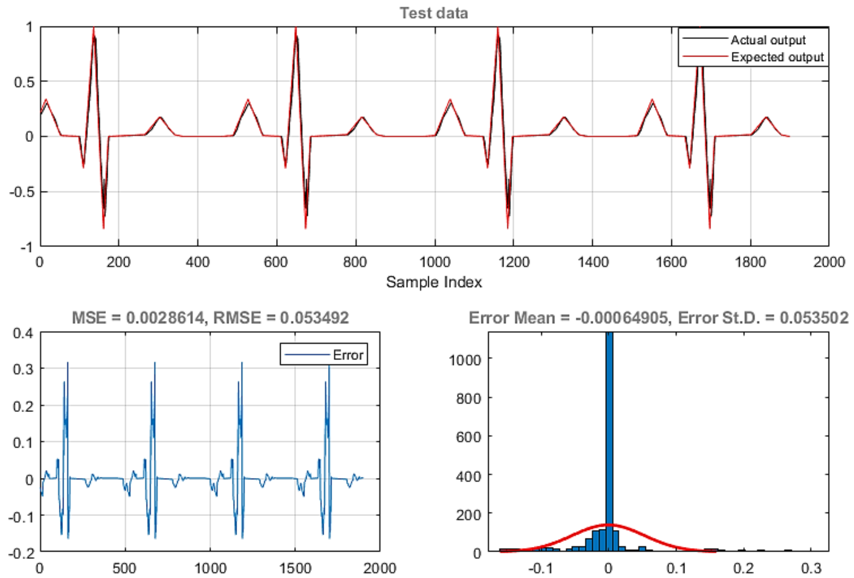

Fig. 6. The result of the actual, expected, error, and error histogram obtained with optimized upper and lower MFs of FIS.

When both modified upper and lower parameter values are included in the tuned and trained FIS with validation data, performance appears to increase. Compared to type-1 MFs, type-2 MFs have additional tunable properties. Thus, if the training data are suitable, a tuned type-2 FIS may fit better than a tuned Type-1 FIS. Changing any of the FIS attributes or tuning decisions, such as the number of inputs, the number of MFs, the type of MFs, the optimization technique, or the number of tuning iterations, can yield different tuning results. *Table 7* shows a statistical comparison of the performance of the metaheuristic algorithms used to test the proposed optimization method. The improvement in the values of MSE, RMSE, error-mean and error-Std shows the applicability of the proposed structure. After this modification, metaheuristic algorithms for type-2 fuzzy controllers were found to give satisfactory results on optimization problems. As can be seen in *Fig. 6*, we can say that there is enough statistical evidence that the PSO algorithm performs better in solving this problem, since it provides a small difference in the error in estimating the desired signal. Finally, in *Table 6*, we show a summary of all the above methods and can see that the best fuzzy controller was found by IT2FIS_PSO (UMFs and LMFs) with an average error of -6.4905e-04. This is important for the design of an optimal fuzzy controller because the goal is to find the best possible controller.

Table 6. An overview of the results of the proposed method.

	MSE	RMSE	ErrorMean	ErrorSTD
IT2FIS	0.0140	0.1183	-0.0166	0.1171
IT2FIS_ PSO (UMFs)	0.0037	0.0610	-0.0213	0.0572
IT2FIS_ PSO (UMFs and LMFs)	0.0029	0.0535	-6.4905e-04	0.0535

4 | Conclusions

Fuzzy controllers are widely used nowadays because they are able to solve problems that were once considered almost unsolvable. The results of parameter optimization of membership functions of type-2 fuzzy controllers for ECG signal estimation have been presented in this article as quite excellent. Moreover, it was found that the generated controller values were remarkably close to the desired signal trajectory. However, we used the PSO metaheuristic, which was found to be beneficial for optimizing the MF. The experiment used the original PSO metaheuristic in conjunction with dynamic parameter fitting by interval fuzzy systems of type-2. The collected results are presented in both tabular and graphical forms. From the results in *Table 6*, we can infer that parameter adjustment in the PSO algorithm using fuzzy logic is a viable choice for fuzzy control as these techniques provide competitive results. This is also evident in the simulation results, where we obtained fewer steady state errors and higher stability compared to the FLCs created using PSO. Therefore, we expect the hybrid method to perform better on increasingly difficult problems. The results show that the hybrid method performs better than the controls. Therefore, we can conclude that by integrating this bio-inspired method with others, we can improve the development of fuzzy logic controllers. In this regard, we intend to continue research in this area and investigate other types of problems that depend on the behavior of the algorithm and the use of type-1 and type-2 fuzzy logic. Various forms of fuzzy systems for dynamic parameter tuning in metaheuristic algorithms will be explored in future research and applied to a variety of control problems. In addition, it is intended to investigate multi-objective optimization techniques for dynamic parameter tuning using extended type-2 fuzzy systems to extend the controller to generalized type-2 fuzzy controllers and obtain better results for more complicated problems.

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