# An Input-weighted, Multi-Objective Evolutionary Fuzzy Classifier, for Alcohol Classification

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*Abstract: The success of the evolutionary computational methods in scanning at problem's solution space and the ability to produce robust solutions, are important advantages for fuzzy systems, especially in terms of "interpretability" and "accuracy". Many techniques have been introduced for multi-objective evolutionary fuzzy classifiers by considering this advantage. However, these techniques are mostly fuzzy rule-based methods. In this study, instead of designing an optimal rule table or determining optimal rule weights, the inputs are weighted, and no rules are used. The average of the degrees of membership obtained with their Membership Function (MF) is calculated as the "input membership degree (μInp)" for each input. The μInps are then weighted, and a single coefficient is generated to be used for the output. With the output, results are obtained for different objective functions. The weights of the inputs and the MFs parameters of all variables (inputs and outputs) are optimized with NSGA-II. The performance of the method has been tested for alcohol classification. As a result, it has been proven that the method can generate designs that can classify at shallow error levels with different sensors at different gas concentrations. In addition, it has been observed that the proposed method produces more successful solutions for alcohol classification problems when compared to other MOEFC techniques.*

*Keywords: Multi-Objective Fuzzy Classifier; Multi-Objective Optimization; Input-Weighted Multi-Objective Fuzzy Classifier*

# 1 Introduction

One of the main issues to be considered in Fuzzy Systems design is optimizing the balance of "interpretability" and "accuracy" which generally conflict with each other. Evolutionary computational methods have been proposed in many studies for this delicate balance. The success of Evolutionary Algorithms (EAs) for designing the architectures of single-output fuzzy systems has also inspired Multi-Objective Evolutionary Fuzzy Classifiers (MOEFCs). In this context, MOEFC has a hybrid structure that combines the approximate reasoning capability of fuzzy logic with the robust adaptation performance of EAs, for complex classification problems. Within the scope of MOEFCs, EAs are applied to Fuzzy Rule-Based Systems (FRBSs) for rule tuning, mining, selection, weighting and are applied to Fuzzy Inference Systems (FISs) for parameter tuning. EAs can also easily incorporate prior knowledge into the system [1]. During the evolutionary design process, models are widely used to approach classification problems as they are characterized by a good balance between their accuracy and their level of interpretability [2].

The two main components that determine the performance of a Fuzzy Classifier (FC) are the adequate structure and the determination of the parameters. While constructing the structure of an FC, choosing the adequate variables, assigning enough Membership Functions (MFs) for each variable, and designing a practical fuzzy rule table are essential for the model's performance. In addition to these tasks, setting the MFs' parameters will become highly complex due to its vast search space, especially when considering high-dimensional problems. This challenge in the FC design is examined in detail in [3]. To overcome this problem, although different heuristic techniques are suggested today, the Genetic Algorithm (GA) was primarily preferred in the first examples [4]-[5]. EA-based FCs are generally rule-based systems. Ishibuchi et al. [4] used a method to minimize the number of fuzzy rules on the one hand and increase accuracy on the other. Gorzalczany and Rudzinski [6] applied their proposed multi-objective GA method in the technical field of glass identification in forensic science as decision support. In [7], fuzzy sets are not tuned, but prior knowledge of the distribution of fuzzy sets is required. Ducange et al. [8] tested their proposed MOEFC method on two Internet traffic datasets obtained from real-world networks. They applied cross-validation and cross-testing on the datasets. In both cases, they achieved successful low complexity and high interpretability results. Pietari et al. [9] proposed a different approach for FRBS design. True positive and false positive rates were determined instead of the commonly used misclassification rate as accuracy measures. The model also has interpretability, which is then allowed to be adjusted. The method used the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [10] method to balance objectives.

The convergence performance of the model is low in approaches that randomly generate the initial population [11]. Also, some methods use aggregate fitness functions [12] [13]. Vaishali et al. [14] aimed to improve the accuracy of existing diagnostic procedures in predicting Type 2 Diabetes. In the initialization phase, they selected the essential features with GA from the dataset they used and applied MOEFC on the features. In the method, they achieved the maximum rate of the classifier with the minimum number of rules.

When literature studies are examined, it is seen that MOEFC methods are mainly based on FRBSs. In most studies, the number of fuzzy rules and the resulting error were considered objectives for balancing accuracy and interoperability. Unlike the classical FRBSs, this study uses the weighted-input approach, thus eliminating the need for effective rule design or optimal rule weighting. Another advantage of the method is that it can provide information about the relative importance of the inputs for all objectives in the problem. The average of the membership degrees obtained with its MFs is calculated as "the input membership degree ($\mu Inp$)" for each input. Then, $\mu Inp$s are weighted, and a single coefficient is produced to be used for the output. With the output, results are obtained for different objective functions. The weights of the inputs and the MFs parameters of all variables (inputs and outputs) are optimized with NSGA-II. The performance of the proposed method has been tested on the alcohol classification problem. Using five Quartz Crystal Microbalance (QCM) sensors with different structures, measurements have been obtained in environments with different gas concentrations. The objective is to design a fuzzy classifier that can classify five different types of alcohol by evaluating the measurements of a QCM sensor. In this context, the main idea of the study is to design a MOEFC that can make the best classification for all sensors. Experimental results have proven that the method can successfully classify five different types of alcohol with a single solution vector. In [15], a coding scheme using accuracy and diversity and an entropy-based diversity criterion are proposed in evolutionary multi-objective optimization algorithms for MOEFC.

The remainder of the paper is designed as follows: In Section 2, a background of the study is explained. First, the concept of Multi-Objective Optimization (MOO) is emphasized. Then, the NSGA-II method, which can be successfully applied to Multi-Objective Optimization Problems (MOOP), is explained with its main steps and basic procedures. Finally, the proposed method is introduced in the section. In Section 3, first, the experiments for alcohol classification and the data set designed according to the results of the experiments are described. Then, the implementation of the method to the problem is explained and finally, the results are shared and interpreted in detail. Section 4 concludes this work.

# 2 The Background of the Proposed Method

From the MOEFC perspective, the basic approach of MOO methods is to search for a set of non-dominated fuzzy systems with different trade-offs between accuracy and complexity. For an effective MOEFC design, accuracy maximization is as crucial as complexity minimization. Within the scope of the study, the MOEFC method, which aims for optimal classification by the same solution vectors, has been proposed for these conflicting objectives. The NSGA-II algorithm is preferred for parameter tuning of MFs, and optimal input weights in the proposed method. Therefore, this section examines the concept of MOO, and the NSGA-II algorithm is explained. Finally, the proposed method is introduced in detail.

## 2.1 Multi-Objective Optimization

The MOOP can be formally expressed as in [16]: finding an n-dimensional possible solution vector $x = (x_1, x_2, x_3, \ldots, x_n)^T$ of decision variables that will satisfy many constraints and optimizes the vector function $f(x)=[f_1(x), f_2(x), f_3(x), \ldots, f_r(x)]$ and $D \subseteq R^n$ is an $n$-dimensional bounded decision space. $R$ represents the objectives. The constraints define the objective space $\mathcal{F}$, containing all the admissible solutions. Since it is challenging to optimize conflicting objectives simultaneously, a set of Pareto optimal solutions is generated instead of a single optimal solution. Pareto optimal solutions present objective function values of a multi-objective optimization model. None of the objective functions can be increased in value without decreasing some of the other objective values in this set of solutions [17].

Without loss of generality, this study adopts the following basic concepts of MOO:

- ***Pareto dominance:*** Feasible solutions $x \prec y$ if and only if $f_i(x) \prec f_i(y)$ $(\forall i=1, 2, 3, \ldots, m)$ and $f_j(x) \leq f_j(y)$ $(\exists j \in \{1, 2, 3, \ldots, m\})$
- ***The Pareto optimal set (or non-dominated set)*** is defined as PS = {x ∈ D| x is Pareto optimal} and *the Pareto optimal front* is defined as $PF^* = \{f(x) | x \in PS\}$
- ***External archive:*** A solution matrix saves the non-dominated solution vectors achieved so far

Although many GA-based techniques have been developed for MOOP, NSGA-II is more advantageous than its counterparts in terms of computation time [18]. Deb et al. [10] showed that NSGA-II could produce more successful solutions than many other MOO techniques in finding an alternative set of solutions and converging to the actual Pareto-optimal set. Moreover, in their comprehensive survey on the controller tuning problem in intelligent control systems, Rodríguez-Molina et al. [19], emphasized that NSGA-II is the popular choice compared to other meta-heuristic methods. Therefore, in this study, the NSGA-II method was preferred.

## 2.2 Non-dominated Sorting Genetic Algorithm II (NSGA-II)

The first EA-based methods proposed for MOOP were generally developed based on GA [1]. NSGA [20] initially developed for real parameter optimization in multi-objective constrained optimization problems, is one of the first famous examples of these methods [2]. However, NSGA has been criticized for its high computational complexity, lack of elitism, and the necessity of determining the sharing parameter, and its improved versions are presented [21]. In this context, the NSGA-II [10] is a significantly revised version of NSGA. The NSGA-II includes three basic procedures: fast non-dominated sorting (for the entire population [14]), crowding distance assignment, and the main loop.

Formally, the NSGA-II can be briefly summarized as following steps [22].

***Initialize solutions:*** Generating initial solutions considering the lower and upper bounds.

***Non-dominated sorting:*** Sorting the initial solutions according to the criteria of non-domination.

***Crowding distance:*** Once the sorting is complete, the crowding distance value is assigned to the front. Solutions are selected according to rank and crowding distance.

***Selection:*** The selection of solutions is carried out using a binary tournament selection with the crowded-comparison operator ($\prec_n$).

***Genetic operators:*** New solutions are produced by crossover and mutation operations.

***Recombination and selection:*** Old and new solutions are combined, and the solutions to be used in the next cycle are determined by selection. Solution selection continues for each objective until the number of populations exceeds the number of solutions available.

## 2.3 Proposed Method: An Input-weighted Multi-Objective Evolutionary Fuzzy Classifier

MOEFCs are the techniques in which fuzzy approach and multi-objective EAs are hybridized. Therefore, in this section, the proposed method is introduced from the side of both main components.

### 2.3.1 Fuzzy Logic Side

The proposed MOEFC technique differs from the classical fuzzy logic system. In the method, all MFs of the input and output variables are of type *"Gaussian combination membership function (gauss2mf)"* [23]. Compared to other MFs, in many studies, better solutions have been obtained with the gauss2mf [24] [25].

gauss2mf calculates the membership degrees using a combination of two Gaussian MFs given in (1).

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{1}$$

where $\sigma$ represents the standard deviation, and $c$ represents the mean for the Gaussian function. Membership value is computed for $x$.

gauss2mf can be used on the MATLAB platform, as given in (2) [26].

$$\mathrm{y} = \mathrm{gauss2mf}(\mathrm{x}, [\sigma_1\ \mathrm{c}_1\ \sigma_2\ \mathrm{c}_2]) \tag{2}$$

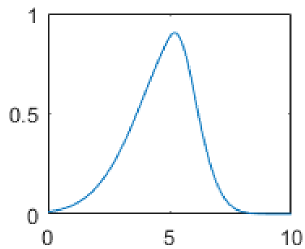


Figure 1
gauss2mf with the parameters $\sigma_1$=2, $c_1$=6, $\sigma_2$=1, $c_2$=5

Figure 1 shows the gauss2mf plotted with parameters $\sigma_1=2$, $c_1=6$, $\sigma_2=1$, $c_2=5$. Each Gaussian function defines the shape of one side of the MF. The left curve is drawn using the parameters $\sigma_1$ and $c_1$ for (1). The parameters $\sigma_2$ and $c_2$ are used for (3), and the right curve is drawn.

$$f(x;\sigma,c) = 1 - e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{3}$$

In addition, *"the input membership degree (μInp)"* is determined for each input. The membership value of *μInp1* with *n* MFs for *x* is computed by (4).

$$\mu Inp1(x) = \left(\sum_{i=1}^{n} \mu Inp1.MF_i(x)\right) / n \tag{4}$$

Then, all the inputs are weighted. Using these weighted inputs, the coefficient $z$ is calculated with (5).

$$z = (\sum_{i=1} (\mu Inp_i * w_i)) / (\sum_{i=1} w_i) \tag{5}$$

In (5), $w_i$ is the randomly assigned weight for $\mu Inp_i$. The output is the average of the membership values calculated with the MFs of the output variable for the coefficient $z$. For output with $n$ MFs, the $\mu Out$ is calculated by (6).

$$\mu Out(z) = (\sum_{i=1}^{n} \mu Out.MF_i(z)) / n \tag{6}$$

In the fuzzy system design described, the NSGA-II method is used to optimize the parameters of the MFs of all variables, the weights of the inputs, and the output that determines the system results for different objectives.

### 2.3.2 NSGA-II Side

In the proposed method, the number of weights to be optimized is equal to the number of inputs. MFs in both input and output variables are of the gauss2mf type. As shown in (2), gauss2mf is a function that has 4 parameters. Accordingly, the number of parameters to be optimized for MFs will be 4 times the total number of MFs. Thus, the number of dimensions ($D$) in each solution vector is calculated with (7).

$$D = count(Input) + 4 * count(MFs\ of\ \text{var}iables) \tag{7}$$

The output takes values in the range [0, 1]. In this context, lower bound and upper bound points are determined in the range of [0, 1] for each class. In the proposed method, the aim is to bring the outputs closer to the center of the targeted class. Therefore, for each class, the center point must be calculated. Table 1 shows the classes' lower bound, upper bound, and center points for a classification problem with $c$ classes.

Table 1

The lower bounds, upper bounds, and center points calculated for $c$ classes

| | **Class 1** | **Class 2** | **…** | **Class m** |
|---|---|---|---|---|
| Lover bound | 0 | 1/m | | m-1/m |
| Upper bound | 1/m | 2/m | | 1 |
| Center | 1/(2*m) | 3/(2*m) | | (2*m-1)/(2*m) |

The absolute value of the difference between the output produced by the system and the center point of the targeted class is measured as the error ($e$), as given in (8).

$$e = |Out - center| \tag{8}$$

The errors are calculated for all patterns in the data set, and the total error ($E$) is determined by (9).

$$E = \sum_{i=1} e_i \tag{9}$$

The objective function of the proposed method, given in (10), is to minimize the classification error obtained for each objective with the same solution vector.

$$f(E) = \min(f_1(E), f_2(E), f_3(E), ..., f_r(E)) \tag{10}$$

# 3 Experimental Study

The performance of the proposed method is tested on a dataset used in [27] and shared in the UCI database, designed with data from five different sensors for the alcohol classification problem and can be found at

https://archive.ics.uci.edu/ml/datasets/Alcohol+QCM+Sensor+Dataset

The method was coded in the MATLAB R2017b platform and run on a computer having the Intel(R) Core (TM) i7-4710MQ 2.50 GHz processor with 8 GB RAM and Windows 8 operating system.

This section introduces the selected MOOP, and the experiments for the dataset used are explained. Then, the proposed MOEFC method implementation to the problem is presented, and the obtained results are discussed in detail.

## 3.1 Selected MOOP and Dataset

Within the scope of the study, the alcohol classification problem is selected as an example of MOOP. The problem is one of the popular classification problems, which has been studied for years and offers solutions with different techniques.

### 3.1.1 Alcohol Classification Problem

Recognition and classification of chemical compounds play an essential role in determining the compound's usage areas and harmful effects. In this regard, alcohols are many chemical compounds in the cosmetic and hygiene industry [27]. One of the sensors that can detect types of alcohol is a Quartz Crystal Microbalance (QCM) [28]. The QCM is essentially an electromechanical oscillator and has the characteristics of a sensitive piezoelectric effect [29]. It is widely used as a gas sensor in cases where chemicals in gases have different densities according to their types. However, precise detection in a sensor cannot be classified all at once [30]. Therefore, using these sensors with artificial intelligence techniques is less costly. Thus, an informed decision about many chemical products can be made automatically.

### 3.1.2 Data Background

In this study, 5 different types of alcohol are classified as 1-octanol, 1-propanol, 2-butanol, 2-propanol, and 1-isobutanol, with 5 different QCM sensors, as in [27]. Each of the QCM sensors has two different channels: the channel including "molecularly imprinted polymers (MIP)" and the channel including "nanoparticles (NP)". The MIP and NP ratios used in the sensors are: 1-1, 1-0, 1-0.5, 1-2, and 0-1, respectively. The gas sample is passed through each sensor at five different air-gas concentrations, and the measurements obtained are saved in the data set. The ratio of air and gas concentrations in ml is presented in Table 2.

Table 2

Air-gas concentrations in experiments

| | Air ratio | Gas ratio |
|---|---|---|
| 1 | 0.799 | 0.201 |
| 2 | 0.700 | 0.300 |
| 3 | 0.600 | 0.400 |
| 4 | 0.501 | 0.499 |
| 5 | 0.400 | 0.600 |

### 3.1.3 Dataset Design

25 experiments were performed with each QCM sensor at the specified MIP and NP channel ratios and in the environments presented in Table 2, that is, for a total of 50 different scenarios. Therefore, there are 1250 samples in the data set.

The data set values obtained for each scenario are normalized in the range to [0 1] with (11). $x_i$ represents the number to be normalized, $x_{min}$ and $x_{max}$ represent the minimum and maximum values in the respective scenario, respectively.

$$x_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{11}$$

60% of the samples (15 samples) in each scenario were used for training and 40% (10 samples) for testing. These training and testing samples are selected randomly in each scenario.

## 3.2 Implementation of the Proposed Method to the Problem

In the main structure of the system, measurements in different gas concentrations are included as inputs to the system, and the obtained output membership degree

($\mu Out$) is used for classification with each sensor. In the study, equal numbers of MFs are used in the variables (1 to 4). Figure 2 illustrates a design for training the proposed method with 2 MFs in each variable.

When equations (3), (4), and (5) are used with the design parameters given in Figure 2, the $\mu Out$ of the system can be calculated. The produced $\mu Out$ value is evaluated separately for each sensor. The system's training aims to get the $\mu Out$ values closer to the class centers. Thus, the main objective is to design a model that obtains minimum error for all sensors [31].

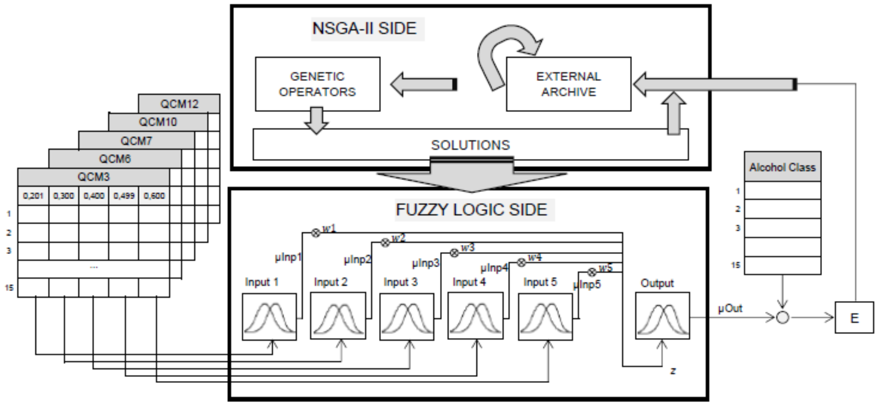


Figure 2
Proposed MOEFC model that has 2 MFs in its variables

Since the system will produce $\mu Out$ value in the range of [0, 1], the lower and upper bounds and center points are assigned in the range of [0, 1] for alcohol classes. Accordingly, the determined values are shown in Table 3.

Table 3
The lower bounds, upper bounds, and center points assigned for the alcohol classification

| | **1-octanol** | **1-propanol** | **2-butanol** | **2-propanol** | **1-isobutanol** |
|---|---|---|---|---|---|
| Lover bound | 0 | 0.2 | 0.4 | 0.6 | 0.8 |
| Upper bound | 0.2 | 0.4 | 0.6 | 0.8 | 1 |
| Center | 0.1 | 0.3 | 0.5 | 0.7 | 0.9 |

The performance of the system is determined by reference to the values in Table 3. Accordingly, the error (E) on *n* samples is calculated by (12) for each sensor.

$$E = \sum_{i=1}^{n} | \mu Out_i - Center_i | \qquad (12)$$

In terms of genetic operators, the length of each artificial chromosome is determined by selected variable numbers. The weights to be assigned are equal to the number of inputs, and considering Eq. (2), 4 parameters are required for each MF. Accordingly, for the 1, 2, 3, and 4 MFs numbers used in the experiments, solution vectors with 29, 53, 77, and 101 items are required, respectively. The artificial chromosome structure designed for the system shown in Figure 2 is presented in Figure 3.

As seen in Figure 3, the first 5 items in the solution vector are the weights assigned to the inputs randomly. The following 4 items are the parameters set to the gauss2mf ($\sigma_1$, $c_1$, $\sigma_2$, $c_2$) type MF of Inp1. Since each variable has 2 MFs, 8 parameters are required for all variables.

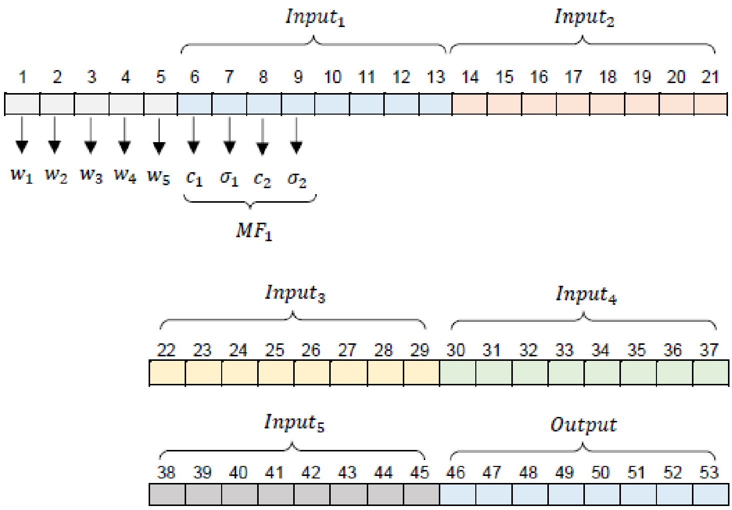


Figure 3
Detail of a solution vector for the model that has 2 MFs in its variables

The parameter settings for the NSGA-II are shown in Table 4. The maximum cycle number (MCN) is set to 10000 in each trial. The algorithm has been run 3 times independently for each scenario.

Table 4
Parameter setting for the NSGA-II

| Parameter | Value |
|---|---|
| Population size | 50 |
| Crossover fraction | 0.8 |
| Mutation fraction | 0.1 |
| Pareto front population | 50 |

## 3.3 Results and Discussion

The results obtained with the proposed MOEFC method are shared and discussed in detail in this section. The results are evaluated in 4 categories based on the MF numbers used.

The results obtained in the experiments are presented in Figures 4-7, with graphs drawn for different goals. Graphs "a" in the figures: error values calculated based on sensors at the end of the training process, graphs "b": number of misclassifications for training data, based on sensors, graphs "c": weights assigned to inputs, and graphs "d": number of misclassifications obtained for test samples, based on sensors.

### 3.3.1 Scenarios That Have 1 MF in Each Variable

The proposed method's results by using only one MF in each variable are examined. This experiment is essential to analyze the interpretative ability of the technique.

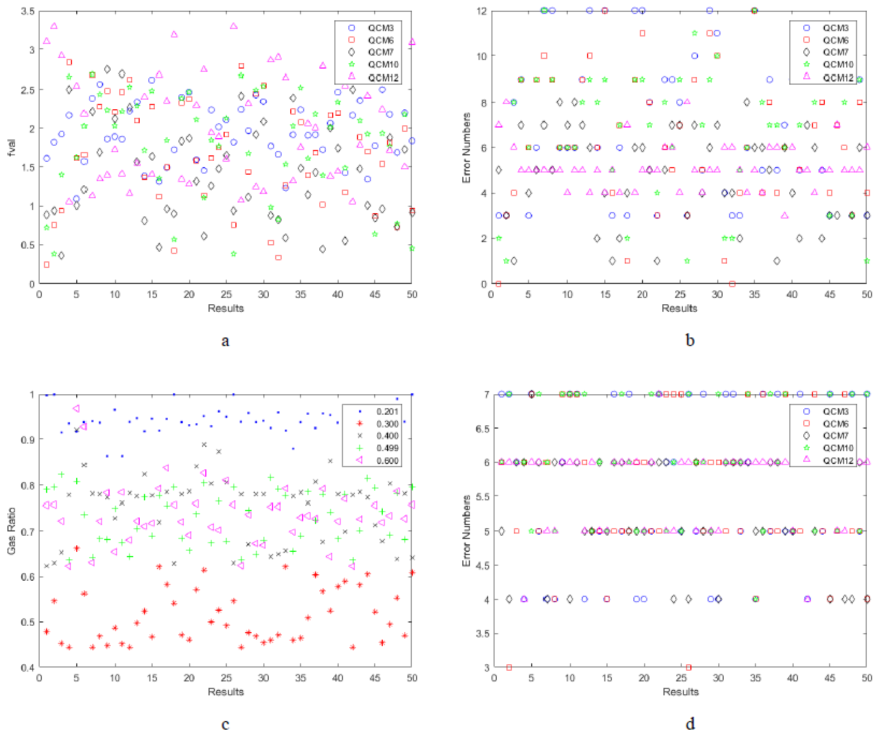


Figure 4
The results obtained for the scenario where each variable of the proposed method has 1 MF

Looking at graph “a” in Figure 4, it is seen that QCM6 and QCM7 can make more successful classification than with other sensors for the MOEFCs designed with the obtained solutions. Graph “b” shows that with 2 solutions in the set of Pareto optimal solutions, correct classification can be made with QCM6 in the model to be designed at all gas concentrations. The “c” graph shows that the environment with a gas concentration of 0.201 is more effective on the solutions because the weights assigned for measurements made in this environment are at a higher level. The “d” graph shows that QCM6 can also produce successful solutions for test samples, and with the proposed method, error-free classification can be made in 2 design samples.

### 3.3.2 Scenarios That Have 2 MFs in Each Variable

Figure 5 shows the results obtained at the end of training and testing for MOEFC with 2 MFs in each variable.

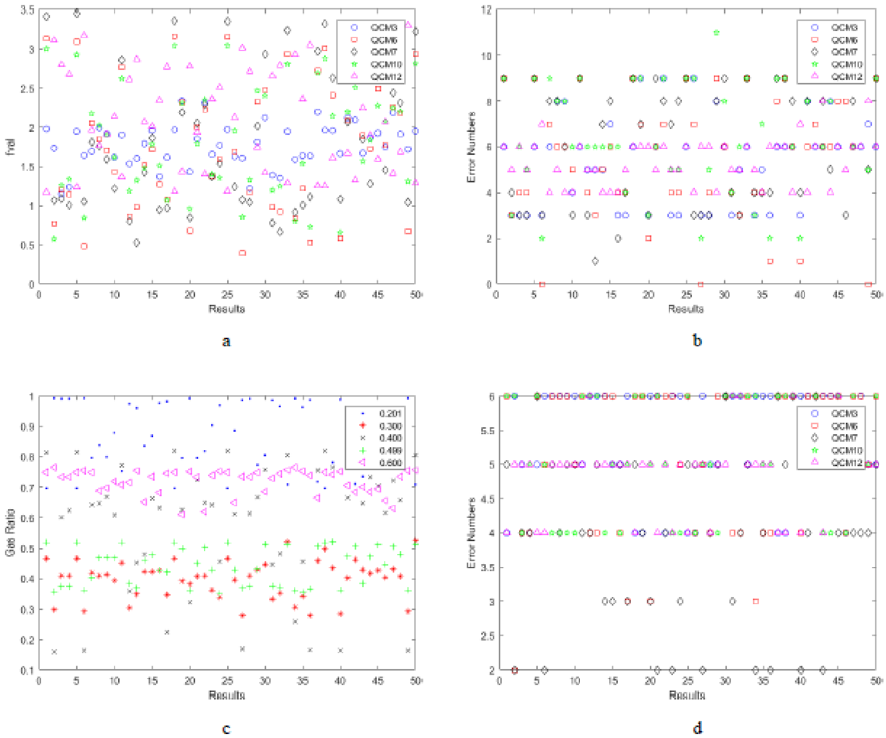


Figure 5

The results obtained for the scenario where each variable of the proposed method has 2 MFs

Figure 5 graphs show that the optimal solutions in the Pareto set are generally successful in favor of QCM6 and QCM7. The error levels obtained for these sensors and the classification errors are lower than other sensors' results. For the training dataset, error-free classification can be made by QCM6 in 3 different designs. In addition, by QCM6 and QCM7, 1 classification error can be obtained in 1 and 2 different MOEFC designs, respectively. Regarding the test dataset, by QCM6 and QCM7, 1 classification error can be obtained in 1 and 9 different designs, respectively. When the weights are examined, the weights determined for the 0.201 and 0.600 gas concentration inputs are increased significantly compared to the results obtained with 1 MF in many examples. In contrast, the weights determined for the 0.300 and 0.499 gas concentration inputs are decreased.

### 3.3.3 Scenarios That Have 3 MFs in Each Variable

Figure 6 presents the experimental results obtained for the MOEFC model with 3 MFs in each variable.

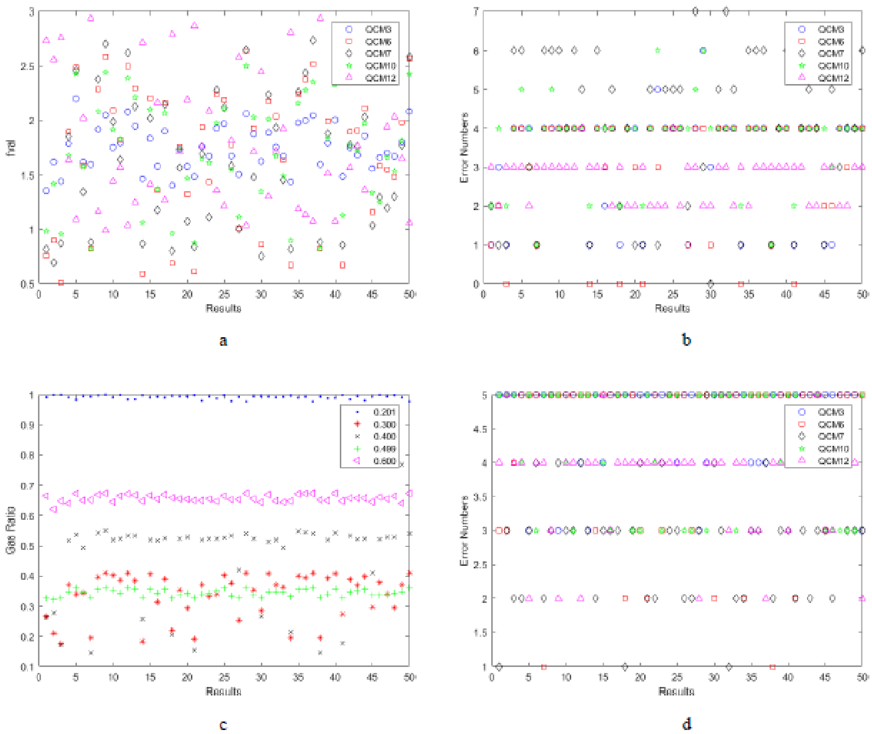


Figure 6

The results obtained for the scenario where each variable of the proposed method has 3 MFs

Figure 6 graphs show that the error rates obtained for the sensors are reduced to the 0.5-3.0 range compared to the results with 1 and 2 MF. In optimal, multi-objective solutions, better results are obtained in favor of the QCM6 sensor. Note that QCM12 errors are significantly higher, while the errors obtained with other sensors are low. On the other hand, in classifications made with other sensors, misclassifications are higher than QCM12. This contrast can be interpreted as the $\mu Out$ values obtained with the QCM12 do not approach the cluster centers. In 6 different MOEFC designs, all the training data can be classified correctly by the QCM6. Also, all samples can be classified correctly by QCM7 in 1 design. However, in test samples, QCM7 is more successful. Error-free classification can be made in 3 different designs by QCM7 and 2 by QCM6. When the weights are examined, it is seen that the weights of 0.201 gas concentration are superior to the others. An interesting result is that the weights cluster at specific intervals.

### 3.3.4 Scenarios That Have 4 MFs in Each Variable

Final experiments within the scope of the study are for MOEFCs with 4 MFs in each variable. In these experiments, it is expected that the accuracy is increases compared to the previous ones, but the interpretation ability of the model is expected to decrease. The obtained results are presented in Figure 7.

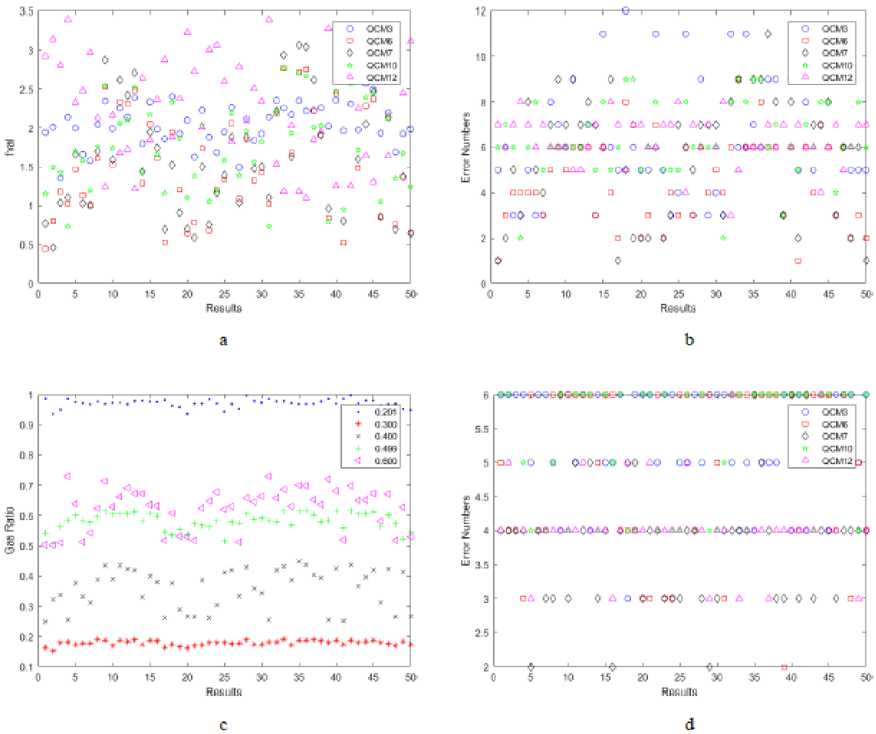


Figure 7
The results obtained for the scenario where each variable of the proposed method has 4 MFs

From Figure 7, it is seen that optimal, multi-objective solutions focus on the QCM6 and QCM7 sensors, like previous experiments. Most solutions that achieve low error levels achieve minimal error rates by these two sensors. The results are not different in terms of classification errors. However, although in many experiments, lower error rates are obtained by QCM3 compared to QCM12, the number of classification errors obtained with QCM3 is higher. In the classification made for the test dataset, the best success is achieved with 4 different designs that make 2 misclassifications. In 3 of these, the best classification can be made by

QCM7 and in one by QCM6. Weights are similarly in favor of 0.201 gas concentration. At a gas concentration of 0.300, the minimum weight coefficients are obtained.

## 3.4 Comparisons

In this section, the classification results of the proposed method for different sensors are evaluated. The classification results of the method with different parameter sets are examined, and its performance is compared with other MOEFC methods in the literature. Selected comparison algorithms are the Multi-Objective Differential Evolution Algorithm-based Fuzzy Clustering (MODEFC) [32], the NSGA-II-based Fuzzy Clustering (MOGAFC) [33], and Multi-Objective Modified Differential Evolution based Fuzzy Clustering (MOMoDEFC) [34] methods.

For each scenario, the solutions with the smallest total error ($E_{SUM}$) obtained for the objectives among the 50 optimal solutions in the Pareto solution set are given in Table 5 ($E_{SUM} = E_{QCM3} + E_{QCM6} + E_{QCM7} + E_{QCM10} + E_{QCM12}$).

Table 5

Solutions with the smallest total error obtained for each scenario

| | | E1 | E2 | E3 | 0.201 | 0.300 | 0.400 | 0.499 | 0.600 |
|---|---|---|---|---|---|---|---|---|---|
| **1 MF** | QCM3 | 1.6652 | 3 | 5 | 0.9598 | 0.4710 | 0.6490 | 0.7905 | 0.7537 |
| | QCM6 | 0.3350 | 0 | 5 | | | | | |
| | QCM7 | 0.8267 | 4 | 6 | | | | | |
| | QCM10 | 0.8272 | 2 | 6 | | | | | |
| | QCM12 | 2.8977 | 6 | 6 | | | | | |
| **2 MFs** | QCM3 | 1.4323 | 3 | 6 | 0.9918 | 0.3812 | 0.3207 | 0.3612 | 0.7520 |
| | QCM6 | 0.6795 | 0 | 2 | | | | | |
| | QCM7 | 0.8464 | 3 | 2 | | | | | |
| | QCM10 | 0.9572 | 2 | 6 | | | | | |
| | QCM12 | 2.7784 | 6 | 5 | | | | | |
| **3 MFs** | QCM3 | 1.4411 | 1 | 2 | 0.9993 | 0.1759 | 0.1710 | 0.3274 | 0.6475 |
| | QCM6 | 0.5080 | 0 | 1 | | | | | |
| | QCM7 | 0.8708 | 1 | 2 | | | | | |
| | QCM10 | 0.9562 | 2 | 2 | | | | | |
| | QCM12 | 2.7622 | 3 | 3 | | | | | |
| **4 MFs** | QCM3 | 1.6263 | 2 | 2 | 0.9701 | 0.1694 | 0.2657 | 0.5740 | 0.5175 |
| | QCM6 | 0.7825 | 3 | 3 | | | | | |
| | QCM7 | 0.5850 | 2 | 2 | | | | | |
| | QCM10 | 1.3804 | 3 | 4 | | | | | |
| | QCM12 | 2.7257 | 5 | 3 | | | | | |

The columns in Table 5 contain the following information:

**E1:** The error levels of the sensors, at the best classification, obtained by Eq. (11) for 50 samples

**E2:** Misclassification numbers of sensors for the training dataset for 50 samples, at the best classification

**E3:** Misclassification numbers of sensors for test dataset for 50 samples, at best classification

Columns 0.201, 0.300, 0.400, 0.499 and 0.600 show the error levels of the sensors obtained by Eq. (11) at these gas ratios.

When the results given in Table 5 are examined, it is seen that the classification success of the design with 3 MFs in each variable is higher than the other designs. Therefore, the algorithms model MOEFC with 3 MF in each variable in the comparison. For a fair comparison, the parameter settings for all algorithms have been assigned as in Table 4. The MCN is 10000 in each trial, and the algorithm has been run three times independently.

Table 6

Air-gas concentrations in experiments

| | | **E1** | **E2** | **E3** | **0.201** | **0.300** | **0.400** | **0.499** | **0.600** |
|---|---|---|---|---|---|---|---|---|---|
| MODEFC | QCM3 | 16.582 | 1 | 4 | 0.9375 | 0.3001 | 0.2788 | 0.3912 | 0.6963 |
| | QCM6 | 0.531 | 1 | 4 | | | | | |
| | QCM7 | 0.898 | 2 | 4 | | | | | |
| | QCM10 | 0.817 | 3 | 5 | | | | | |
| | QCM12 | 26.421 | 3 | 6 | | | | | |
| MOGAFC | QCM3 | 14.715 | 2 | 2 | 0.9807 | 0.2189 | 0.2091 | 0.3964 | 0.7007 |
| | QCM6 | 0.662 | 0 | 1 | | | | | |
| | QCM7 | 0.883 | 2 | 3 | | | | | |
| | QCM10 | 0.871 | 3 | 3 | | | | | |
| | QCM12 | 25.458 | 3 | 3 | | | | | |
| MOMoDEFC | QCM3 | 15.090 | 1 | 2 | 0.9468 | 0.2013 | 0.199 | 0.3117 | 0.6817 |
| | QCM6 | 0.554 | 1 | 1 | | | | | |
| | QCM7 | 0.937 | 2 | 3 | | | | | |
| | QCM10 | 0.859 | 1 | 2 | | | | | |
| | QCM12 | 28.796 | 4 | 5 | | | | | |
| iwMOEFC | QCM3 | 14.411 | 1 | 2 | 0.9993 | 0.1759 | 0.171 | 0.3274 | 0.6475 |
| | QCM6 | 0.508 | 0 | 1 | | | | | |
| | QCM7 | 0.871 | 1 | 2 | | | | | |
| | QCM10 | 0.956 | 2 | 2 | | | | | |
| | QCM12 | 27.622 | 3 | 3 | | | | | |

The best results of the proposed method and other MOEFC methods are compared in Table 6. In Table 6, the proposed method is shortly named "*iwMOEFC*". While MODEFC and MOGAFC make a total of 10 misclassifications for the samples in the training dataset, MOMoDEFC makes 9, and iwMOEFC makes 7. However, the misclassification numbers of the algorithms for the test set are as follows: MODEFC=23, MOGAFC=12, MOMoDEFC=13 and iwMOEFC=10. It can also be seen from column E1 that iwMOEFC can classify values closer to the classification centers. In the E1 column, the distances of the classification values to the class centers are given. Accordingly, iwMOEFC has the minimum classification errors for the QCM3, QCM6 and QCM7 sensors. Moreover, iwMOEFC has produced minor error levels than other MOEFC methods at different gas ratios.

It has been observed that the solutions in the Pareto optimal set are generally successful in favor of the QCM6 sensor. In terms of weights, it is seen that more successful classifications can be made in an environment with a gas concentration of 0.201, and this environment is more effective in the general classification. However, measurements in an environment with a gas concentration of 0.300 have the lowest effect on classification.

## Conclusions

The balance of accuracy and interpretability, one of the fundamental criteria in fuzzy system design, is particularly influential in system design and performance. EAs can successfully scan the problem's solution space by focusing on efficient solution regions in numerical optimization problems. These algorithms also provide adaptive training in many multi-objective fuzzy classifier methods, as they are not trapped in local optimal solutions. In this study, multi-objective EA is used for MOEFC design, but instead of a rule table, the weighted-input approach is applied for input-output interaction on the fuzzy logic side of the system. In this way, it can obtain information about the relative importance of the inputs for each objective in the problem.

The proposed method was used for alcohol classification. Alcohols were classified by evaluating the results obtained with different gas sensors in environments with different gas-air densities.

When the classification results are examined, it is proven that the proposed method can make successful classifications for many sensors simultaneously, with negligible error levels, even in environments with different gas-air densities. In addition, compared to other MOEFC methods, the performance of the method is more effective and provides superior solutions.

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