An Application of Fuzzy *c*-Means Clustering to FLC Design for Electric Ceramics Kiln

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ABSTRACT - This paper presents an application of fuzzy *c*-means clustering to designing the fuzzy logic controller for the temperature control in electric ceramics kiln. This research aims to controlling the temperature in firing step of burning the ceramic products which were coated with black, intensely red and green chemical substances. The experimental results show that the fuzzy *c*-means clustering designed FLC gives better temperature characteristics when compared to the conventional FLC and the hard *c*-means clustering designed FLC.

KEYWORDS - Fuzzy logic controller, fuzzy *c*-means clustering, controller design, electric kiln

1. Introduction

In the ceramics producing process, both the temperature and the timing control is very critical to the quality of products. The product qualities includes the color, the smoothness, clear surfaces and endurance of the ceramics produced. In [4],[5] and [10] the controllers used are the fuzzy logic controllers where in the design of the fuzzification part of the controllers, all the fuzzy sets are approximated i.e. the shape of the membership functions, the starting points and ranges for each fuzzy set, the slopes for all the set and the overlapping areas. The designs were carried on using the designer's experiences without any acceptable reasons. In this paper, we are proposing to overcome the stated problem by using the Fuzzy-*c*-means clustering method to find appropriate fuzzy sets for each working parameter of the ceramics kiln. In this research, the control system consists of a fuzzy FCM controller, thermocouple, SCR power control unit, A/D-D/A converter and an electric kiln as shown in Fig. 1.

2. Conventional FLC Design

The three main parts of a Fuzzy Logic Controller are the fuzzification part, fuzzy inference part and the defuzzification part as shown in Fig..2

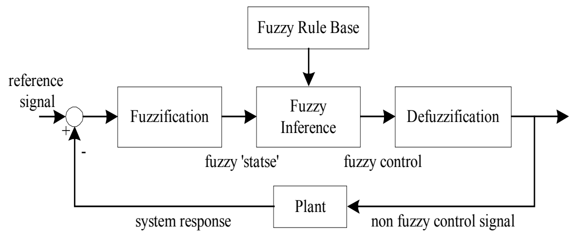


Figure 1. The Structure of Kiln Control System

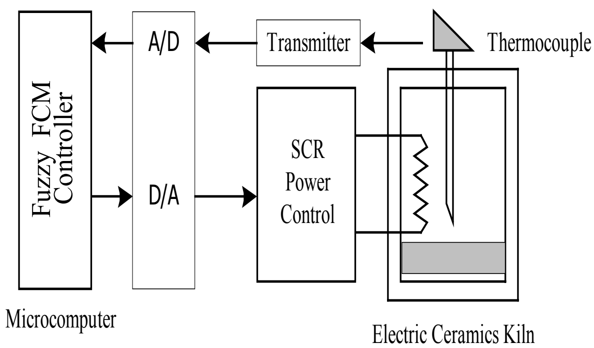


Figure 2. The Structure of Fuzzy Logic Controller

Generally, in the design process of the fuzzy inference part [11] , fuzzy rules are created from the closed loop control system as shown in Fig. 3. The input variables of the fuzzy logic controller are the error (E) and the error rate (ER). The output of the controller is the control voltage (CV). Let the step response of the feedback system be as illustrated in Fig. 4. The phase plane can be constructed with the two inputs, E and ER as illustrated in Fig. 4. Let us design a set of fuzzy control rules to reduce the overshoot and the rise time. Referring to the phase plane of the system step response shown in Fig. 4., the fuzzy control rule can be formulated as table 1.

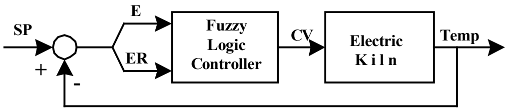


Figure 3. The Closed Loop Control System

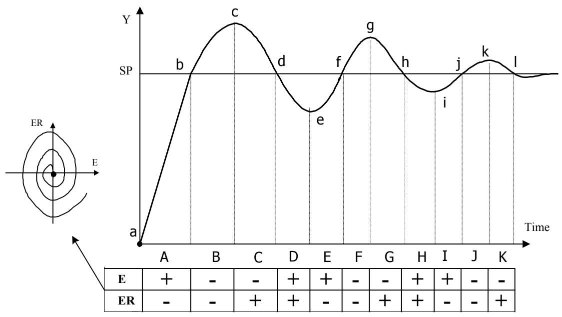


Figure 4. Time-Response of Controlled System

Table 1. Shows Fuzzy Rules Generated

Fuzzy Rule		ER						
		NB	NM	NS	AZ	PS	PM	PB
E	NB				NB	NM		
	NM				NM			
	NS	NS			NS	AZ		PM
	AZ	NB	NM	NS	AZ	PS	PM	PB
	PS	NM		AZ	PS	AZ		
	PM				PM			
	PB			PM	PB			

For the defuzzification part, a method of defuzzification is to be selected from the popular ones, center of gravity (COA), mean of maximum (MOM) etc.

And then for the fuzzification part, fuzzy sets are created approximately as shown in Fig. 5

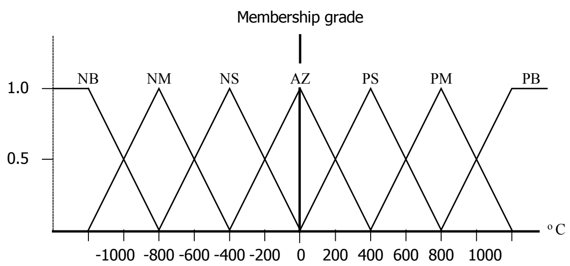


Figure 5. Typical Fuzzy Sets in Conventional Designed Fuzzy Logic Controller

As seen in Fig. 5. conventional design of the fuzzy sets follows the following rules : Generally used membership function is the triangular-shaped function, the ranges for each set are equally divided from the universe of discourse of the parameter, the peak points are at the mid-range points and adjacent sets overlap to the mid-range points etc.

It can easily be seen that these rules have very little relationships to the behavior of the controlled system and the designers cannot explain clearly why to follow these rules.

3. Fuzzy *c*-Means Fuzzification Design

3.1 Fuzzy Set Determination by FCM Method

Firstly, controlled system or plant is to be controlled by any available controller to operate over its whole range of operation and then the input and output variables of the plant are recorded. The operating data of the controlled system is analyzed by the fuzzy *c*-means clustering method to separate into groups or clusters of data and each cluster of data is then interpreted into a fuzzy set of the variable.

3.2 Hard *c*-Means Clustering Method

The hard *c*-means algorithm [3, 8] partitions a collection of n vector x_j , j= 1,….n, into c groups G_i ,I=1,…,c, and finds a cluster center in each group such that an objective function of distance measure is minimized. When the Euclidean distance is chosen as the distance measure between a vector x_k in group j and the corresponding cluster center c_i, the objective function can be defined by

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \left(\sum_{k, x_k \in G_i} \left\| x_k - c_i \right\|^2 \right) \quad (1)$$

The partitioned groups are defined by an c × n binary membership matrix **U**, where the element u_{ij} is 1 if the jth data point x_j belongs to group i, and 0 otherwise. Once the cluster centers c_i are fixed, the minimizing u_{ij} can be derived as follows:

$$u_{ij} = \begin{cases} 1 \text{ if } \left\| x_j - c_i \right\|^2 \subseteq \left\| x_j - c_k \right\|^2, \text{ for each } k \neq i, \\ 0 \quad \text{otherwise.} \end{cases} \quad (2)$$

Since a given data point can only be in a group, the membership matrix has the following properties:

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1,2,3,..., n \quad (3)$$

and

$$\sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij} = n \quad (4)$$

If u is fixed, then the optimal center c that minimize equation(1) is the mean of all vectors in group i:

$$c_i = \frac{1}{|G_i|} \sum_{k, x_k \in G_i} x_k \quad (5)$$

where

$$|G_i| = \sum_{j=1}^{n} u_{ij} \quad (6)$$

3.3 Fuzzy *c*-Means Clustering Method

The Hard *c*-Mean could be improved with use of fuzzy set method. To develop these method in classification, we classify the various data points as a fuzzy *c*-partition [3, 8] on a universe of data points and assign membership value to it that determine from the data of each point and the data of a cluster center in each group. Hence, a single point can have partial membership in more than one class and the membership value that the *k*th data point has in the *i*th class with the following notation:

$$\mu_{ik} = \mu_{A_i}(x_k) \in [0,1] \quad (7)$$

In the determination of the fuzzy *c*-partition matrix **U** for grouping a collection of *n* data sets into *c* classes, we define an objective function J_m for a fuzzy *c*-partition,

$$\mathbf{J}_m(\mathbf{U}, \mathbf{v}) = \sum_{k=1}^{n} \sum_{i-1}^{c} (\mu_{ik})^{m'} (d_{ik})^2 \quad (8)$$

where

$$d_{ik} = d(\mathbf{x}_k - \mathbf{v}_i) = [\sum_{j=1}^{m} (x_{kj} - v_{ij})^2]^{1/2} \quad (9)$$

and where μ_{ik} is the membership of the *k*th data point in the *i*th class, d_{ik} is distance measure or Euclidean distance between the *i*th cluster center and the *k*th data point in m-space, m′ is a weighting parameter which has a range $m' \in [1,\infty)$ and $\mathbf{v}_i$ is *i*th cluster center, which is described by m coordinates and can be arranged in vector form, $\mathbf{v}_i = \{v_{i1}, v_{i2}, \ldots, v_{im}\}$.

Each of the cluster coordinates for each class can be calculated as

$$v_{ij} = \frac{\sum_{k=1}^{n} \mu_{ik}^{m'} \cdot x_{kj}}{\sum_{k=1}^{n} \mu_{ik}^{m'}} \quad (10)$$

where j is a variable on the coordinate space , i.e., j = 1, 2, …,m.

The optimum fuzzy c-partition will be the smallest of the partitions described in Equation (8) ;

$$\mathbf{J}_m^*(\mathbf{U}^*, \mathbf{v}^*) = \min_{M_{fc}} \mathbf{J}(\mathbf{u}, \mathbf{v}) \quad (11)$$

The effective algorithm for fuzzy classification is called iterative optimization as follows

1. Fix *c* ($2 \le c < n$) and select a value for parameter m′. Initialize the partition matrix, $\mathbf{U}^{(0)}$. Each step in this algorithm will be labeled r = 0, 1, 2, . . .
2. Calculate the *c* centers $\{\mathbf{v}_i^{(r)}\}$ for each step.
3. Update the partition matrix for the *r*th step, $\mathbf{U}^{(r)}$ as follows:

$$\mu_{ik}^{(r+1)} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}^{(r)}}{d_{jk}^{(r)}} \right)^{2/(m'-1)} \right]^{-1} \quad \text{for } \mathbf{I}_k = \phi \quad (12)$$

or

$$\mu_{ik}^{(r+1)} = 0 \ \text{ for all classes i where } i \in \tilde{\mathbf{I}}_k \quad (13)$$

where

$$I_k = \{i \mid 2 \le c < n; d_{ik}^{(r)} = 0\} \quad (14)$$

and

$$\tilde{\mathbf{I}}_k = \{1, 2, \ldots, c\} - \mathbf{I}_k \quad (15)$$

and

$$\sum_{i \in \mathbf{I}_k} \mu_{ik}^{(r+1)} = 1 \quad (16)$$

4. If $\| \mathbf{U}^{(r+1)} - \mathbf{U}^{(r)} \| \le \varepsilon_L$, stop; otherwise set r = r+1 and return to step 2.

4. Research Methodologies

In the design process of the FLC, fuzzy rules are defined for two input variables, the error (E) and the error rate (ER), and single output variable, the control voltage (CV) which are used as the input and output variables of the plant respectively. The design were carried on using the plant of electric ceramics kiln with the procedures:

4.1) With the auto-tuning PID controller operate the plant in steps over its full range of operation and at each step, record the values of the input and output variables of the plant which can be shown in Fig. 6., 7. and 8. for setpoint at 1225 °C.

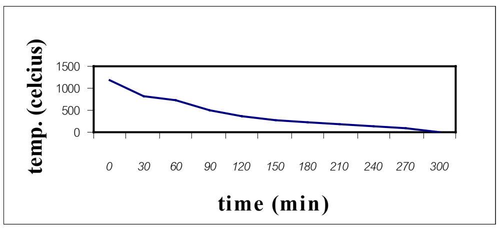


Figure. 6. The Recorded Values of E

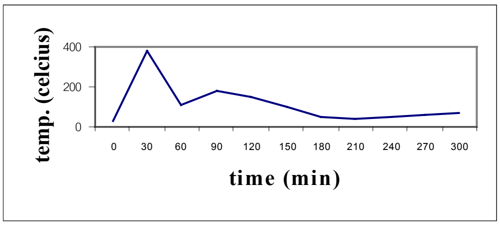


Figure. 7. The Recorded Values of ER

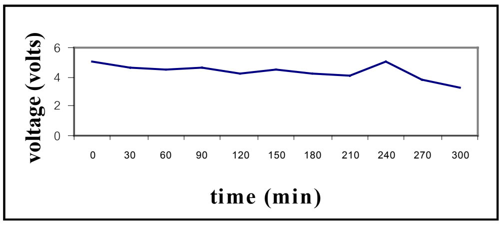


Figure. 8. The Recorded Values of CV

4.2) The fuzzy *c*-partition from 4.1 are then analyzed by fuzzy *c*-means clustering algorithms for 7 clusters of data for the input variables and the output variable as shown in Fig. 9. The obtained clusters were then normalized to get the fuzzy sets as shown in Fig. 10.

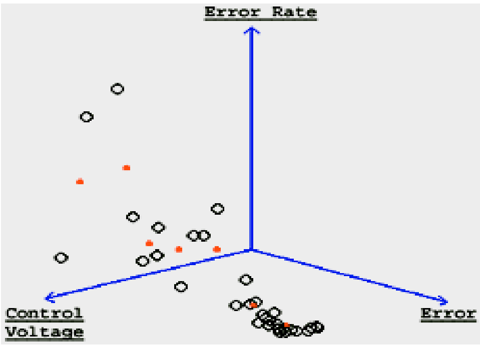
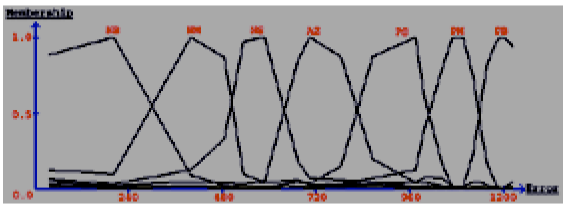
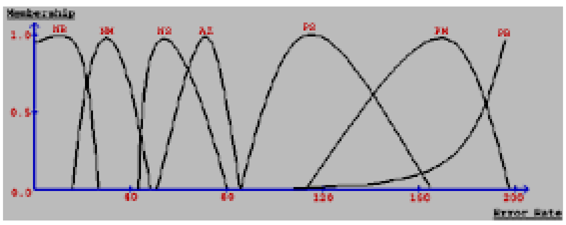


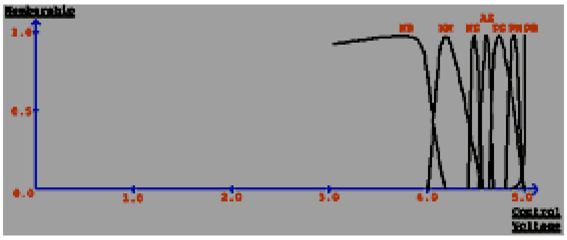
Figure 9. The Converged Fuzzy Partition for Temperature in Electric Ceramics Kiln



(a) The Fuzzy Set of E



(b) The Fuzzy Set of ER



(c) The Fuzzy Set of CV

Figure 10. The Fuzzy Sets from FCM Method

4.3) Implement the fuzzy logic controller with fuzzy sets obtained in 4.2 and operate the controller.

5. Experimental Results

The fuzzy *c*-means clustering designed FLC was tested on the setpoint of 1225 °C for the electric kiln of 45 cm. in high, 35 cm. in internal diameter, 45 cm. in external diameter. The results were compared to the results by conventional designed FLC and hard *c*-means clustering designed FLC on the same setpoint, the proposed controller were able to give the output response as following :

5.1) Operating characteristics temperature (°C) vs time (min.) of the ceramics kiln control by conventional designed fuzzy logic controller is shown in Fig. 11.

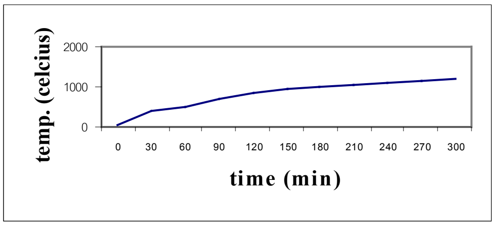


Figure 11. Temperature Characteristics of The Conventional FLC

5.2) Operating characteristics temperature (°C) vs time (min.) of the ceramics kiln control by hard *c*-means clustering designed fuzzy logic controller is shown in Fig. 12.

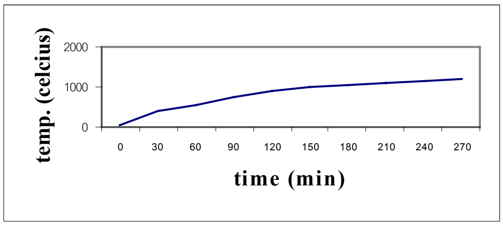


Figure 12. Temperature Characteristics of The Hard c-Means Designed FLC

5.3) Operating characteristics temperature (°C) vs time (min.) of the ceramics kiln control by fuzzy *c*-means clustering designed fuzzy logic controller is shown in Fig. 13.

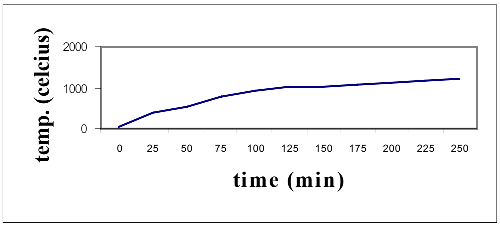


Figure 13. Temperature Characteristics of The Fuzzy c-Means Designed FLC

6. Conclusion

This paper has investigated the application of fuzzy *c*-means clustering algorithms in the design of the fuzzy sets for the fuzzy logic controller of the electric ceramics kiln temperature control. This method of the design is expected to solve the problem of the classical or conventional design method. The results from the experiments show that the fuzzy *c*-means clustering designed FLC gives better output response when compared to the conventional FLC and the hard *c*-means clustering designed FLC. Moreover it gives products with a high quality of color, very close to the standard ceramics products.

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