Multi Response Optimization of Edm Process of OHNS Using Fuzzy Logic Approach

[1]V. Chengal Reddy,[1]P. Sivaiah,[1]K. Venkata Chalapathi,[1]R.K.Sangha Mitra
[1]Assistant Professor, Dept. of Mechanical Engineering, AITS- Rajampet, Andhra Pradesh, India.
Corresponding author mail: vcr.312@gmail.com

Abstract— In this paper, the application of the Taguchi method with fuzzy logic for optimizing the electrical discharge machining process with multiple performance characteristics has been reported. A multi-response performance index is used to solve the electrical discharge machining process with multiple performance characteristics. The machining parameters (discharge current (IP), pulse on time (T_{on}), pulse off time (T_{off}) and down time) are optimized with considerations of the multiple performance characteristics (electrode wear rate and material removal rate). Experimental results are presented to demonstrate the effectiveness of this approach.

Keywords- Electrical discharge machining; Taguchi method; Fuzzy logics, OHNS, Copper**.**

1. Introduction

Electrical discharge machining (EDM) is one of the most extensively used non-conventional material removal process. Its unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage in the manufacture of mould, die, automotive, aerospace and surgical component. The selection of appropriate parameters for maximum material removal rate and minimum electrode wear rate during the EDM process traditionally carried out by the operator's experience or conservative technological data provided by the EDM equipment manufacturers, which produced inconsistent machining performance. Some researchers carried out various investigations to improve the stock material removal rate and electrode wear rate in EDM process. Proper selection of machining parameters for the best process performance is still a challenging job.

The Taguchi method can optimize performance characteristics through the settings of process parameters and reduce the sensitivity of the system performance to sources of variation. As a result, the Taguchi method has become a powerful tool in the design of experiment methods. However, most published Taguchi applications to date have been concerned with the optimization of a single performance characteristic. Handling the more demanding multiple performance characteristics is still an interesting research problem. The theory of fuzzy logics, initiated by Zadeh in 1965 has proven to be useful for dealing with uncertain and vague information. In fact, the definition of performance characteristics such as lower-the-better, higher-the-better, and nominal-the-better contains a certain degree of uncertainty and vagueness. Therefore, optimization of the performance characteristics with fuzzy logic has been considered in this study. In this study, a fuzzy reasoning of the multiple performance characteristics has been developed based on fuzzy logic. As a result, optimization of complicated multiple performance characteristics can be transformed into the optimization of a single multi-response performance index (MRPI). In this paper, the optimization of the electrical discharge machining process with multiple performance characteristics has been investigated to illustrate this approach.

In the following, optimization of multiple performance characteristics with fuzzy logic is introduced briefly and the electrical discharge machining process is then described, after which the experimental details of using the Taguchi method with fuzzy logic to optimize the electrical discharge machining process to secure low electrode wear ratio (EWR) and high material removal rate (MRR) are given. Finally, the paper concludes with a summary.

2. Optimization of Multiple Performance Characteristics with Fuzzy Logic

Experimental design methods were developed originally by Fisher. However, classical experimental design methods are too complex and not easy to use. Furthermore, a large number of experiments have to be carried out as the number of the process parameters increases. To solve this important task, the Taguchi method uses a special design of orthogonal array to study the entire parameter space with only a small number of experiments. The experimental results are then transformed into a signal-to-noise (S/N) ratio. The S/N ratio can be used to measure the deviation of the performance characteristics from the desired values. Usually, there are three categories of performance characteristics in the analysis of the S/N ratio: the lower-the-better, the higher-the-better, and the nominal-the-better. Regardless of the category of the performance characteristic, a larger S/N ratio corresponds to better performance characteristic. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio.

Basically, the Taguchi method is designed to handle the optimization of a single performance characteristic. The usual recommendation for the optimization of a process with multiple performance characteristics is left to engineering judgment and verified by confirmation experiments. This is because several problems are encountered in the optimization of a process with multiple performance characteristics. For example: the category of each performance characteristic may not be same; the engineering unit for describing each performance characteristic may be different; and the importance of each performance characteristic may vary. As a result, the application of the Taguchi method in a process with multiple performance characteristics cannot be straightforward. In this paper, the use of fuzzy logic to deal with the optimization of a process with multiple performance characteristics is reported. First, several fuzzy rules are derived based on the performance requirement of the process. The loss function corresponding to each performance characteristic is fuzzified and then a single MRPI is obtained through fuzzy reasoning on the fuzzy rules. The MRPI can be used to optimize the process based on the Taguchi approach.

3. THE ELECTRICAL DISCHARGE MACHINING PROCESS

The electrical discharge machining removes work-piece by an electrical spark erosion process. The variations in the machining parameters, such as the pulse-on time, discharge current, pulse-off time and downtime, greatly affect the measures of the machining performance, for example, the EWR and the MRR. Therefore, proper selection of the machining parameters can result in better machining performance in the electrical discharge machining process.

*3.1. **Machining parameter selection***

In this study, an EDM machine (KT-200) was used as the experimental machine. Cylindrical pure copper with a diameter of 6 mm was used for an electrode to erode a work-piece with a diameter of 6 mm. The schematic diagram of the experimental set-up is shown in Fig. 1. The workpiece and electrode were separated by a moving dielectric fluid such as kerosene. Machining experiments for determining the optimal machining parameters carried out by setting: discharge current is in the range of 5 to 15 amps pulse on time in the range of 29 to 63 microsec pulse off time is in the range of 5 to 9microsec down time is in the range of 1 to 3 sec. To perform the experimental design, three levels of the machining parameters (discharge current, pulse on time, pulse off time, down time) were selected as shown in table1. The initial machining parameters were selected as follows: discharge current 5amps, pulse on time 29 microsec, pulse off time 5 microsec, down time 1 sec.

Table 1: Machining parameters and their levels

Symbol	Machining Parameter	Unit	Level1	Level2	Level3
A	**Discharge Current**	**A**	**5**	**10**	**15**
B	**Pulse on Time**	**μsec**	**29**	**43**	**63**
C	**Pulse Off Time**	**μsec**	**5**	**7**	**9**
D	**Down Time**	**sec**	**1**	**2**	**3**

Fig.1. EDM Machine

*3.2. **Machining performance evaluation***

Evaluation of MRR:

The material MRR is expressed as the ratio of the difference of weight of the work-piece before and after machining to the machining time and density of the material.

MRR (gm/min) = Work-piece Removal rate/ Time

Evaluation of electrode wear rate:

EWR is expressed as the ratio of the difference of weight of the tool wear weight to the machining time. That can be explain this equations

EWR (gm/min) = Electrode wear rate/ Time

In the experiments, the machining time for each work-piece is 30 min. Basically, the lower is the EWR in the EDM process, the better is the machining performance. However, the higher is the MRR in the EDM process, the better is the machining performance. Therefore, the EWR is the lower the-better performance characteristic and the MRR is the higher -the-better performance characteristic

4. DETERMINATION OF THE OPTIMAL MACHINING PARAMETERS

In this section, the use of the Taguchi method with fuzzy logic to determine the machining parameters with optimal machining performance in the EDM process is illustrated.

4.1. Orthogonal array experiment

To select an appropriate orthogonal array for the experiments, the total degrees of freedom need to be computed. The degrees of freedom are defined as the number of comparisons between process parameters that need to be made to determine which level is better and specifically how much better it is.

For example, a two-level process parameter counts for one degree of freedom. The degree of freedom associated with interaction between two process parameters are given by the product of the degrees of freedom for the two process parameters. In the present study, the interaction between the machining parameters is neglected. Therefore, there are 11 degrees of freedom owing to one two-level machining parameter and five three-level machining parameters in the EDM process. Once the degrees of freedom are known, the next step is select an appropriate orthogonal array to fit the specific task.

The degrees of freedom for the orthogonal array should be greater than or at least equal to those for the process parameters. In this study, an L9 orthogonal array was used because it has 17 degrees of freedom more than the 11degrees of freedom in the machining parameters. This array has 4 columns and 9 rows and it can handle one two-level process parameter and seven three-level process parameters, at most. Each machining parameter is assigned to a column and 9 machining parameter combinations are required. Therefore, only 9 experiments are needed to study the entire machining parameter space using the L9 orthogonal array.

The experimental combinations of the machining parameters using the L9 orthogonal array is presented in table 2.

Table 2: L_9 Orthogonal array

Sl No.	**Design of Experiment (L_9 Orthogonal Array)**			
	A	**B**	**C**	**D**
1	**1**	**1**	**1**	**1**
2	**1**	**2**	**2**	**2**
3	**1**	**3**	**3**	**3**
4	**2**	**1**	**2**	**3**
5	**2**	**2**	**3**	**1**
6	**2**	**3**	**1**	**2**
7	**3**	**1**	**3**	**2**
8	**3**	**2**	**1**	**3**
9	**3**	**3**	**2**	**1**

4.2. Signal-to-noise ratio

In the Taguchi method, a loss function is defined to calculate the deviation between the experimental value and the desired value. Usually, there are three categories of the performance characteristics in the analysis of the signal to-noise ratio, i.e., the lower-the-better, the higher-the-better, and the nominal-the-better. To obtain optimal machining performance, the minimum EWR and the maximum MRR are desired. Therefore, the lower-the-better EWR and the higher-the-better MRR should be selected.

The loss function L_{ij} of the lower-the-better performance characteristic can be expressed as

$$\frac{S}{N} = -10 \log \frac{1}{n}\left(\sum y^2\right)$$

where L_{ij} is the loss function of the ith performance characteristic in the jth experiment, n the number of tests, and y_{ijk} is the experimental value of the ith performance characteristic in the jth experiment at the kth test.

The loss function of the higher-the-better performance characteristic can be expressed as

$$\frac{S}{N} = -10 \log \frac{1}{n}\left(\sum \frac{1}{y^2}\right)$$

The loss function is further transformed into an S/N ratio. In the Taguchi method, the S/N ratio is used to determine the deviation of the performance characteristic from the desired value. The S/N ratio Z_{ij} for the ith performance characteristic in the jth experiment can be expressed as

$$\frac{S}{N} = 10 \log \frac{y}{S_y^2}$$

Table 3 shows the experimental results for the EWR and its S/N ratio and MRR and its S/N ratio based on the experimental parameter combinations (Table 2). As shown in Table 3, the engineering units for describing the EWR and the MRR are different. To consider the two different performance characteristics in the Taguchi method, the S/N ratios corresponding to the EWR and MRR are processed by the fuzzy logic unit.

Table 3: Experimental results for MRR, EWR and its S/N ratio

S.No	MRR (gm/min) (Y1)	S/N Ratio of MRR	EWR (gm/min) (Y2)	S/N Ratio of EWR
	HIGHER – THE – BETTER		LOWER – THE- BETTER	
1	0.0289	-30.78204	0.00031	70.17277
2	0.0421	-27.51436	0.00036	68.87395
3	0.0201	-33.93608	0.00026	71.70053
4	0.1334	-17.49688	0.00224	72.39578
5	0.0926	-20.66778	0.00136	57.32922
6	0.0846	-21.45259	0.00036	68.87395
7	0.1308	-17.66785	0.00224	52.99504
8	0.1275	-17.88979	0.00280	51.05684
9	0.0882	-21.09063	0.00078	62.15811

4.3 Fuzzy Expert System :

A fuzzy rule based system consists of four parts:

- ✓ Knowledge base
- ✓ Fuzzifier
- ✓ Inferenceengine
- ✓ Defuzzifier.

A block diagram representing these four functions is given in this continuation.

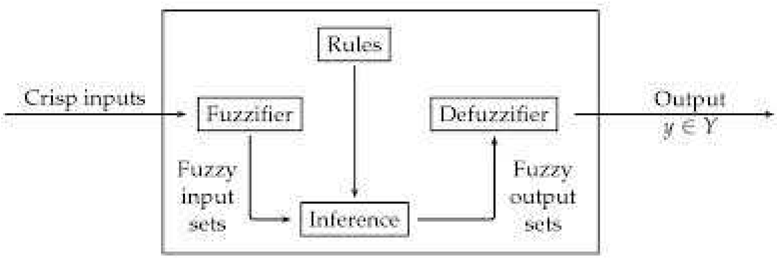

Fig.2. A block diagram of Fuzzy Logic System

✓ *Fuzzifier:*

The real world input to the fuzzy system is applied to the fuzzifier. In fuzzy literature, this input is called crisp input since it contains precise information about the specific information about the parameter. The fuzzifier convert this precise quantity to the form of imprecise quantity like 'large', 'medium', 'high' etc. with a degree of belongingness to it. Typically the value ranges from 0 to 1.

✓ Knowledge base:

The main part of the fuzzy system is the knowledge base in which both rule base and database are jointly referred. The database defines the membership functions of the fuzzy sets used in the fuzzy rules whereas the rule base contains a number of fuzzy IF THEN rules.

✓ *Inference engine:*

The inference system or the decision making input perform the inference operations on the rules. It handles the way in which the rules are combined.

✓ *Defuzzifier:*

The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works opposite to the input block .In general, two most popular fuzzy inference systems are available: Mamdani fuzzy model and Sugeno fuzzy model. The selection depends on the fuzzy reasoning and formulation of fuzzy IF-THEN rules. Mamdani fuzzy model [Mamdani, 1975] is based on the collection of IF-THEN rules with both fuzzy antecedent and consequent predicts. The benefit of this model is that the rule base is generally provided by an expert and hence to a certain degree it is translucent to explanation and study. Because of easiness; Mamdani model is still most commonly used technique for solving many real world problems. The first step in system modeling was the identification of input and output variables called the system variables. In the selection procedure, the inputs and the outputs are taken in the form of linguistic format. A linguistic variable is a variable whose values are words or sentences in natural or man-made languages. Linguistic values are expressed in the form of fuzzy sets. A fuzzy set is usually defined by its membership functions. In general, triangular or trapezoidal membership functions are used to the crisp inputs because of their simplicity and high computational efficiency [Yager and Filev (1999)]. The triangular membership function as described below can be used in the model.

In the following, the concept of fuzzy reasoning is described briefly based on the two- input± one-output fuzzy logic unit. The fuzzy rule base consists of a group of if± then control rules with the two inputs, x1 and x2, and one output y, i.e.

_ Rule 1: if x1 is A1 and x2 is B1 then y is C1 else

_ Rule 2: if x1 is A2 and x2 is B2 then y is C2 else

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_ Rule n: if x1 is An and x2 is B_n then y is C_n.

A_i, B_i, and C_i are fuzzy subsets defined by the corresponding membership functions, i.e., m_{Ai} , m_{Bi} and m_{Ci} . In this paper, three fuzzy subsets are assigned in the two inputs Seven fuzzy subsets are assigned in the output Various degree of membership to the fuzzy sets is calculated based on the values of x_1, x_2, and y. Nine fuzzy rules (table 4) are derived directly based on the fact that larger is the S/N ratio, the better is the performance characteristic. By taking the max± min compositional operation, the fuzzy reasoning of these rules yields a fuzzy output. Supposing that x1 and x2 are the two input values of the fuzzy logic unit, the membership function of the output of fuzzy reasoning can be expressed as

$\mu C0(y) = [\mu_{A1}(x1) \wedge \mu_{B1}(x2) \wedge \mu_{C1}(y)] \vee \ldots [\mu_{An}(xn) \wedge \mu_{Bn}(xn) \wedge \mu_{Cn}(y)]$

Here ^ is the minimum operation and v is the maximum operation.

Finally, a defuzzification method, called the center-of-gravity method, is adapted here to transform the fuzzy interface output µC0 into a non-fuzzy value yo, i.e.

$$Y_0 = \frac{\Sigma\, y.\mu co\,(y)}{\Sigma\, \mu co\,(y)}$$

In this paper, the non-fuzzy value y0 is called an MRPI. Based on the above discussion, the larger is the MRPI, the better is the performance characteristic. Table 5 shows the experimental results for the MRPI using the experimental combinations of Table 2.

Table 4: Fuzzy rule table

MPCI		S/N Ratio of MRR		
		Low	**Medium**	**High**
S/N Ratio of TWR	**Low**	Low	Medium	High
	Medium	Low	Medium	Medium
	High	Medium	Low	Medium

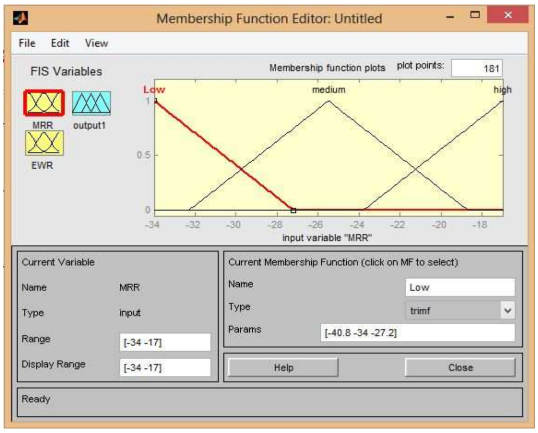

Fig.3.Membership Function for MRR

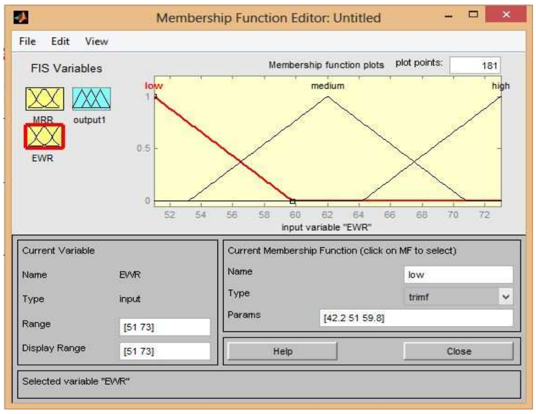

Fig.4.Membership Function for EWR

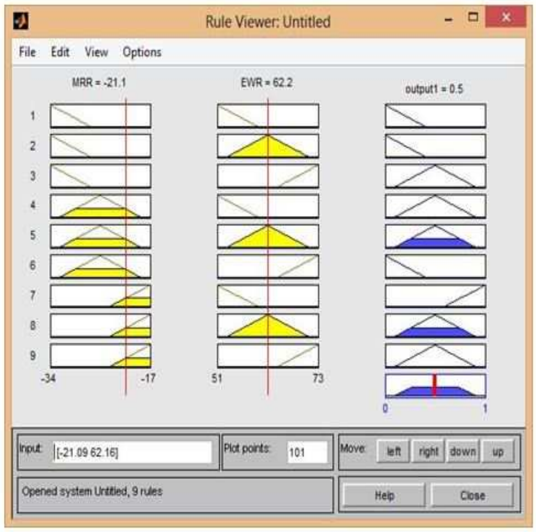

Fig.5.Multi Performance Characteristic Index

Table 5: Results for MRPI

S/N Ratio of MRR	**S/N Ratio of EWR**	**MPCI**
-30.78204	70.17277	0.458
-27.51436	68.87395	0.337
-33.93608	71.70053	0.500
-17.49688	72.39578	0.500
-20.66778	57.32922	0.558
-21.45259	68.87395	0.399
-17.66785	52.99504	0.864
-17.88979	51.05684	0.868
-21.09063	62.15811	0.500

Confirmation test

Optimized values:

MRR (gm/min) = $\frac{\text{Workpiece Removal Weight}}{\text{Time}}$

EWR(gm/min)= $\frac{\text{Electrode Wear Weight}}{\text{Time}}$

Table 6: Confirmation experiment results

Initial Machining Parameters		Optimized Machining Parameters
Setting Level	$A_1B_1C_1D_1$	$A_3B_2C_3D_3$
EWR (gm/min)	0.000310	0.000189
MRR (gm/min)	0.0289	0.1481

5. CONCLUSION

The work has presented the use of fuzzy logic for optimization of the EDM process with multiple performance characteristics. The following factor settings have been identified as to yield the best combination of process variables: Discharge Current = 15A, Pulse-on-Time=29µs, Pulse-off-Time = 9µs, and Down Time = 3 sec. The performance characteristics such as MRR and EWR can be improved through this approach.

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