

Optimisation of EDM Process with Fuzzy Logic Technique

C. K. Biswas and Shailesh Dewangan

Abstract: In this analysis, the optimisation of multiple responses of Electric discharge machining (EDM) using Fuzzy logic coupled with Taguchi method is attempted. The work piece material was AISI P20 tool steel and a cylindrical copper electrode was used with side impulse flushing. The influence of machining parameters, i.e., pulse current (I_p), pulse duration (T_{on}), work time (T_w), lift time (T_{up}) and Inter Electrode Gap (IEG) on the Material Removal Rate (MRR) and Surface Roughness (SR) in EDM are examined. L27 orthogonal array was used to design the experiment and the effect of the factors on the responses were studied. Experimental data has been analysed using analysis of variance (ANOVA). As the responses are conflicting in nature, a single combination of factors cannot be treated as best machining performance for all responses. Fuzzy logic is used to convert multiple responses into a single characteristic index known as Multi Performance Characteristic Index (MPCI). Finally, MPCIs were optimised by using robust Taguchi design.

Keyword- Electric Discharge Machining (EDM), Fuzzy logic, Impulse flushing, AISI P20 tool steel.

I. INTRODUCTION-

EDM is an electro-thermal non-traditional machining Process, where electrical energy is used to generate electrical spark and material removal mainly occurs due to thermal energy of the spark. EDM is mainly used to machine difficult-to-machine materials and high strength temperature resistant alloys. It is the most widely and successfully applied machining process for various work piece materials in the said advance industries [1]. With the advancement of automation technology manufacturers are more fascinated in the processing and miniaturization of components made by these costly and hard materials. Electrical discharge machining (EDM) has grown over the last few decades from a novelty to a mainstream manufacturing process. Work material to be machined by EDM has to be electrically conductive.

Quite a lot of research attempts have been made for modelling of EDM process and investigation of the process performance to recuperate MRR. Improving the MRR and surface quality are still challenging problems that restrict the expanded application of the technology [2]. A semi-empirical model of MRR for various work piece and tool electrode combinations has been presented by Wang and Tsai [3]. Luis et al. [4] have studied the influence of pulse current, pulse time, duty cycle, open-circuit voltage and dielectric flushing pressure, over the MRR and other response variable on tungsten carbide. In this paper,

optimisation of multiple performance characteristics to single optimization characteristics with help of fuzzy logic system has been attempted.

II. CONDUCT OF EXPERIMENT -

Experiments were conducted to study the effects of various machining parameters on EDM process. This study have been undertaken to investigate the effects of Discharge current (I_p), pulse on time (T_{on}) and work time (T_w), lift time (T_{up}) and Inter Electrode gap (IEG) on Material Removal Rate (MRR) and Surface Roughness (SR). The selected work piece material is AISI P20 tool steel with semi-circular shaped (100 mm diameter and 10 mm thickness). The workpiece was heated to the temperature range 843 – 898 °C in a controlled furnace and held for half an hour. Then it was oil quenched and later tempered for better toughness. A cylindrical pure copper with a diameter of 30 mm was used as a tool. The experiments were conducted on Electronica Electraplus PS 50ZNC Die Sinking Machine. Commercial grade EDM oil (specific gravity = 0.763, freezing point= 94°C) was used as dielectric fluid with impulse flushing pressure of 0.3 kgf/cm². The machining parameter and their level are presented in Table 1. The five machining parameters, each at three levels, were selected based on Orthogonal Array (OA), resulting in Twenty-seven experiments. The observations of the experiments are tabulated in Table 2. To attain more accurate results, every combination runs of experiments was machined for 60 min and then MRR was calculated by weight loss method. Central line average (R_a) value of the machined surface was measured the surface roughness, it usually expressed as R_a value in microns. Portable style type profile-meter, Talysurf (Model: Taylor Hobson, Surtronic 3+) was used for measurement with parameters cut-off length, $L_n=4\text{mm}$, sample length, $L_c=0.8\text{mm}$ and filter=2CR ISO.

III. EXPERIMENTATION-

In this experiment, lower value of SR is desired quality and higher for MRR. Therefore, SR is the lower-the-better performance characteristic and the MRR is the higher-the-better performance characteristic. MRR and SR values are converted to S/N ratio. S/N ratio x_{ij} is the i^{th} performance characteristic in the j^{th} experiment can be expressed

as given by Equation 1.

$$x_{ij} = -10\log_{10}(L_{ij}) \quad (1)$$

where L_{ij} is the loss function for i^{th} performance characteristic in the j^{th} experiment. The loss functions L_{ij} for higher-the-better and lower-the-better characteristics are expressed in Equation 2 and 3, respectively.

$$L_{ij} = \frac{1}{n} \sum_{k=1}^n \frac{1}{y_{ijk}^2} \quad (2)$$

$$L_{ij} = \frac{1}{n} \sum_{k=1}^n y_{ijk}^2 \quad (3)$$

Where n is the number of test ($n=1$), and y_{ijk} is the experimental value of the i^{th} performance characteristic in the j^{th} experiment at the k^{th} test. Table 2 shows the S/N ratio of the test runs.

Table 1 Parameter and their level

Control Parameter					
Parameter	Symbol	Level			Unit
		1	2	3	
Discharge current	I_p	2	5	8	A
Pulse-on Time	T_{on}	100	300	500	μs
Lift Time	T_{up}	0.0	0.7	1.4	S
Work time	T_w	0.2	0.6	1.0	S
Inter electrode gap	IEG	90	170	250	μm
Fixed Parameter					
Duty Cycle	ζ	90			%
Voltage	V	45			V
Flushing Pr	Fp	0.3			Kgf/cm ²
Sensitivity	SEN	6			

IV. OPTIMISATION OF MULTIPLE QUALITY CHARACTERISTICS WITH FUZZY LOGIC –

Taguchi method is a powerful Design of Experiment (DOE), which can optimise single performance characteristics of EDM effectively [6, 7]. In this study, MRR and SR are two quality characteristics, which are to be optimised using fuzzy logic method. Signal to noise (S/N) ratio are calculated for the experimental results that can be used to measure the deviation of the show 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 [5]. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio. Furthermore, a statistical analysis of variance (ANOVA) is performed to identify the process parameters that are statistically significant. The optimal combination of the process parameters can then be predicted based on the above analysis.

V. FUZZY LOGIC SYSTEM –

Fuzzy logic is a mathematical theory of inexact reasoning that allows modelling of the reasoning process of human in linguistic terms. The fuzzy logic

control allows the existence of uncertainty in handling parameter values [8]. Fuzzy logic system (Mamdani system) comprises of a fuzzifier, membership functions, a fuzzy rule base, an inference engine, and defuzzifier [9]. The fuzzifier uses membership functions to fuzzify S/N ratios of each performance characteristic are shown in Fig. 1. Next, the inference engine (Mamdani fuzzy inference system) performs fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts fuzzy predicted value into a Multi Performance Characteristics Index (MPCI) response that can be used to find the better accuracy of output of the MPCI in EDM using Taguchi L_{27} processed based.

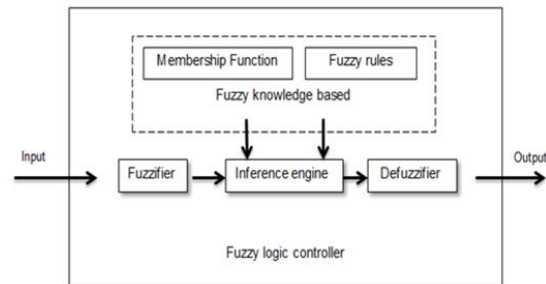


Fig. 1 Fuzzy Logic system

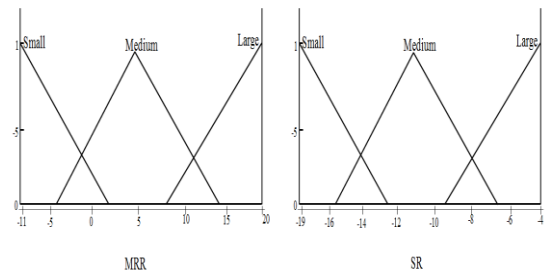


Fig. 2 Membership Function of MRR and SR

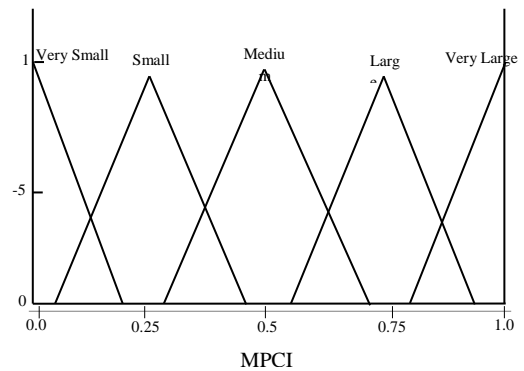


Fig. 3 Membership function of MPCI

VI. RESULT AND DISCUSSION-

The effect of the machining parameter (I_p , T_{on} , T_{up} , T_w , and IEG) on the responses of MRR and SR have been analysed. Fig. 2 is showing the graphical representation of three fuzzy subsets (Small, Medium, Large) assigned to inputs, i. e., S/N ratios for MRR (x_1) and SR (x_2). Fig. 3 is showing the

output membership functions in which the five fuzzy subsets (Very Small, Small, Medium, Large, Very Large) are assigned to an output, i. e., MPCI (Y). Various degrees of membership of the fuzzy sets are calculated based on the values of x1, x2 and Y.

The relationship between three inputs, x1, x2 and the output Y were represented in the form of if-then control rules that is:

Rule 1: if x1 is Small and x2 is Small then Y is Very Small else

Rule 2: if x1 is Small and x2 is Medium then Y is Small else

.....
 Rule N: if x1 is Large and x2 Large then Y is Very Large.

For each rule, the two inputs are assigned in the fuzzy subsets of Small, Medium and Large and the corresponding membership functions, $\mu(x1)$ and $\mu(x2)$, respectively. The output is assigned to any of the five fuzzy subset membership functions $\mu(Y)$. The number of rules yielded from the present study is 27 and the membership function of the fuzzy set is indicated in Fig. 4. Fuzzy rules are directly derived based on the fact that larger-the-better characteristic. By tacking maximum-minimum compositional operation, the fuzzy reasoning of these rules yields a fuzzy output. Finally, the center of gravity method defuzzification is adopted to transform the fuzzy inference output μY into a non-fuzzy value Y_0 [7], which is known as the crisp output, is calculated with the help of Equation 4.

$$Y_0 = \frac{\sum \sum_{N=1}^{27} Y \mu Y}{\sum \mu Y} \quad (4)$$

The crisp value Y_0 is called as MPCI. Based on the above discussion, larger the MPCI smaller is the variance of the performance characteristics around the desired value. Table 2 shows the MPCI for each run. The mean of MPCI for each level of the machining parameters is summarised in MPCI table (Table 3). In addition, the means of the MPCI for the twenty-seven experiments are also calculated and listed in Table 3. Fig. 5 shows the main plot for MPCI. However, the relative importance amongst the machining parameters for the multiple performance characteristics still needs to be known so that the optimal combinations of the machining parameter levels can be determined more accurately.

The following factor settings have been identified as to yield the best combination of process variables: Factor Ip= 2A, Ton= 500 μ s, Tup= 1.4s, Tw= 1s and IEG= 90 μ m.

VII. ANALYSIS OF VARIANCES-

The Analysis of Variance (ANOVA) is presented in Table 4, which indicates the process parameters

significantly effect the performance characteristics. This is accomplished by separating the total variability of the MPCI, which is measured by the sum of the squared deviations from the total mean of the MPCI, into contributions by each of the process parameter and the error. The p-value is the probability of obtaining a test statistic that is at least as extreme as the actual calculated value, if the null hypothesis is true. A commonly used cut-off value for the p-value is 0.05. In addition, the F-test determines which process parameters have a significant effect on the performance characteristic. Usually, the change of the process parameter has a significant effect on the performance characteristic when the F value is large.

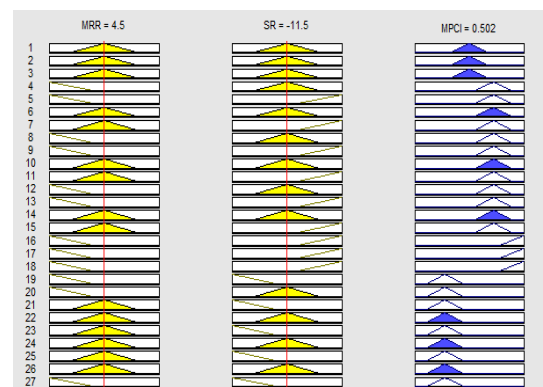


Fig. 4 Fuzzy logic reasoning procedure

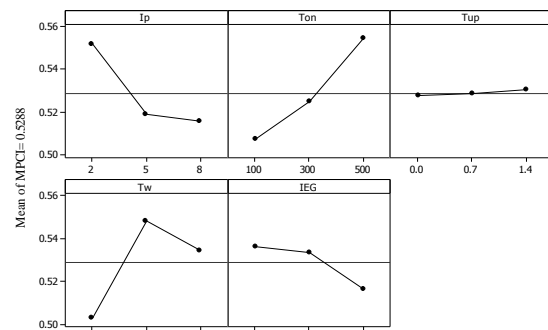


Fig. 5 Main effect plot for MPCI

VIII. CONCLUSION-

This paper 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: Factor Ip= 2A, Ton= 500 μ s, Tup= 1.4s, Tw= 1s and IEG= 90 μ m. The performance characteristics such as MRR and SR can be improved through this approach.

ACKNOWLEDGEMENTS

The authors are thankful to Prof. K P Maity, Professor and HOD, ME of NIT Rourkela, India for his continuing help and support for this work. Part of the work is maintained by Ph. D. Research scholar

Table 2 Machining parameters and MPCl

Run	I _p	T _{on}	T _{up}	T _w	IEG	S/N Ratio		MPCl
						MRR	SR	
1	2	100	0	0.2	90	5.53	-11.75	0.502
2	2	100	0	0.2	170	5.86	-11.53	0.503
3	2	100	0	0.2	250	5.50	-9.71	0.505
4	2	300	0.7	0.6	90	-4.46	-8.69	0.524
5	2	300	0.7	0.6	170	-3.55	-7.64	0.571
6	2	300	0.7	0.6	250	-3.86	-7.16	0.607
7	2	500	1.4	1	90	-9.82	-4.61	0.626
8	2	500	1.4	1	170	-10.92	-5.58	0.625
9	2	500	1.4	1	250	-9.49	-5.93	0.503
10	5	100	0.7	1	90	0.00	-13.39	0.503
11	5	100	0.7	1	170	5.16	-14.57	0.503
12	5	100	0.7	1	250	3.63	-14.17	0.503
13	5	300	1.4	0.2	90	-3.94	-13.55	0.503
14	5	300	1.4	0.2	170	-5.57	-13.73	0.502
15	5	300	1.4	0.2	250	-9.94	-15.33	0.468
16	5	500	0	0.6	90	9.39	-5.44	0.623
17	5	500	0	0.6	170	9.96	-7.96	0.550
18	5	500	0	0.6	250	8.30	-8.88	0.516
19	8	100	1.4	0.6	90	13.04	-17.09	0.515
20	8	100	1.4	0.6	170	11.40	-16.95	0.516
21	8	100	1.4	0.6	250	11.52	-17.68	0.516
22	8	300	0	1	90	19.79	-18.73	0.516
23	8	300	0	1	170	19.65	-18.28	0.516
24	8	300	0	1	250	19.98	-17.90	0.516
25	8	500	0.7	0.2	90	16.25	-17.59	0.516
26	8	500	0.7	0.2	170	14.89	-18.03	0.515
27	8	500	0.7	0.2	250	13.64	-18.44	0.515

Table 3 Average MPCl by factor level

EDM Parameter	Average MPCl by factor level			Max-Min
	Level 1	Level 2	Level 3	
I _p	0.5518	0.5190	0.5157	0.0361
T _{on}	0.5073	0.5248	0.5543	0.0470
T _{up}	0.5274	0.5286	0.5304	0.0030
T _w	0.5032	0.5487	0.5346	0.0454
IEG	0.5364	0.5334	0.5166	0.0199
Mean value of MPCl= 0.5288				

Table 4 Analysis of Variance for MPCl

Source	DF	Seq SS	Adj MS	F	P	% contribution
I _p	2	0.00716	0.00358	3.15	0.070	15.13
T _{on}	2	0.01016	0.00508	4.47	0.029	21.46
T _{up}	2	0.00004	0.00002	0.02	0.982	00.00
T _w	2	0.00973	0.00486	4.29	0.032	20.56
IEG	2	0.00206	0.00103	0.91	0.422	04.36
Residual Error	16	0.01817	0.00113			38.38
Total	26	0.04735				

REFERENCE-

- [1] Snoeys, R., Staelens, F., and Dekeyser, W.; Current trends in nonconventional material removal processes, *Ann. CIRP*, 1986, 35(2):467-480.
- [2] Wang K., Hirpa L. Gelgele, Yi Wang, Qingfeng Yuan, Minglung Fang.; A hybrid intelligent method for modeling the EDM process, *International Journal of Machine Tools & Manufacture*, 2003, 43, pp.995-999.
- [3] Wang P.J.; Tsai K.M.; Semi-empirical model on work removal and tool wear in Electrical Discharge Machining, *Journal of Materials Processing Technology*, 2001, Volume-114, Issue 1, pp. 1- 17.
- [4] Luis C.J., Puertas I., Villa G.; Material Removal Rate and electrode wear study on the EDM of silicon carbide, *Journal of Materials Processing Technology*, 2005, 164-165, pp.889-896.
- [5] Puri and Deshpande., Simultaneous optimization of multiple quality characteristics of WEDM based on fuzzy logic and Taguchi technique, *Proceedings of the Fifth Asia Pacific Industrial Engineering and Management Systems Conference*, 2004.
- [6] Ross P J., *Taguchi Techniques For Quality Engineering*, McGraw-Hill, New York, 1988.
- [7] Lin J.L. and Lin C.L.; The use of grey-fuzzy logic for the optimization of the manufacturing process, *Journal of Materials Processing Technology*, 2005, 160 pp. 9-14.
- [8] Kao C.C., Albert J. Shih and Miller S.F., Fuzzy Logic Control of Micro-hole Electrical Discharge Machining, *Journal of Manufacturing Science and Engineering*, December 2008, Vol. 130/ 064502-1.
- [9] Tzeng and Chen, Multi-objective optimization of high-speed Electrical Discharge Machining process using a Taguchi fuzzy-based approach, *Journal of Materials and Design*, 28 (2007) 1159-1168, 2007.