Multi Response Optimization of Process Parameters in Electric Discharge Machining of High Strength Low Alloy (HSLA) Steel

V.K. Saini[a]*, Zahid A. Khan[b] and Arshad Noor Siddiquee[b]
[a]*Department of Mechanical Engineering, IMS Engineering College, Ghaziabad,* Uttar Pardesh, India.
[b]*Department of Mechanical Engineering, Jamia Millia Islamia, New Delhi, India.*
*vksainig@gmail.com

Abstract

This research work has presented an investigation on the optimization and the effect of machining parameters on the electrode wear ratio, material removal rate and surface roughness in Electrical discharge Machining (EDM) operations with the use of fuzzy logic. Fuzzy reasoning of the multiple performance characteristics has been developed based on fuzzy logic. A multi-response performance index (MRPI) is used to solve the electrical discharge machining process with multiple performance characteristics. The Taguchi method, the signal-to-noise (S/N) ratio and the analysis of variance are employed to find the main effect and to determine their optimum process parameters. Experimentation was planned as per Taguchi's L9 orthogonal array. The optimum configuration of process parameters which are essential for the economic, efficient, and effective utilization of these processes were determined by experiments.

Keywords- EDM, HSLA, Machining, Surface roughness, Material removal rate, Fuzzy logic.

Introduction

Electrical discharge machining is one of the most widely used non-traditional machining processes. This technique utilises thermoelectric process to erode undesired materials from the work piece by a series of discrete electrical sparks between the workpiece and the electrode. A pulse discharge occurs in a small gap between the work piece and the electrode and removes the unwanted material from the parent metal through melting and vaporising. The electrode and the work piece must have electrical conductivity in order to generate the spark. Lin *et al*. (2000; 2001) analyse the best factor combination in combination of Taguchi method and fuzzy logic, to improve the quality properties of material removal rate (MRR) and electrode wastage, and to establish an algorithm for multiple quality properties to achieve obscure design targets. Tsai *et al*. (2001) tried to predict surface finish in EDM process using various neural networks and ANFIS, and their performances had been compared. Lin *et al*. (2002) used the grey relational analysis based on an orthogonal array and fuzzy-based Taguchi method for optimising the multi-response process is reported. Both the grey relational analysis method without using the S/N ratio and fuzzy logic analysis are used in an orthogonal array table in carrying out experiments for solving the multiple responses in the EDM process. Wang *et al*. (2003) used genetic algorithm (GA) with artificial neural network (ANN) to find out optimal process parameters for optimal performances. ANN is used to model the process, where weights are updated by GA. In the optimization phase Gen-Hunter Software is used to solve multi-objective optimization problem. Two output parameters, MRR and surface roughness considered here to be optimized as a process performance. Chang *et al*. (2006) uses data mining to effectively analyse and confirm that the factors affecting discharge for EDM. The Taguchi method is used to experiment with electrodes of the same size and different shapes, based on key factors acquired under the consideration of the interaction between factors, and analyse the experimental results respectively with average values and S/N ratio. Oguzhan *et al*. (2006) introduces a user-friendly intelligent system for the selection of EDM parameters. In this system, a compact selection method based on expert rules, which were obtained from experimental results and extracted from the knowledge of skilled operators, is presented. Expert rules are evaluated by the fuzzy set theory. The developed fuzzy model uses fuzzy-expert rules, triangular membership functions for fuzzification and centroid area method for defuzzification processes. Kanlayasiri *et al*. (2007) presents an investigation of the effects of machining variables on the surface roughness of wire-EDMed DC53 die steel. Mandal *et al*. (2007) attempt to model and optimize the complex EDM process using soft computing techniques. ANN with back propagation algorithm is used to model the process. As the output parameters are conflicting in nature so there is no single combination of cutting parameters, which provides the best machining performance. A multi-objective optimization method, non-dominating sorting genetic algorithm-II is used to optimize the process. Tzeng *et al*. (2007) describes the application of the fuzzy logic analysis coupled with Taguchi methods to optimise the precision and accuracy of the high-speed EDM process. A fuzzy logic system is used to investigate relationships between the machining precision and accuracy for determining the efficiency of each parameter design of the Taguchi dynamic experiments. Pradhan *et al*. (2008; 2009) investigated the relationship between EDM parameters and the MRR in EDM of AISI D2 tool steel. They went further and compared the above technique with the neuro-fuzzy model. Taweel *et al*. (2009) investigated the relationship of process parameters in electro-discharge of CK45 steel with novel tool electrode material such as Al–Cu–Si–TiC composite produced using powder metallurgy (P/M) technique. The central composite second-order rotatable design had been utilized to plan the experiments, and response surface methodology (RSM) was employed for developing experimental models. Analysis on machining characteristics of EDM die sinking was made based on the developed models.

Krishna *et al*. (2009) optimized the surface roughness of die sinking EDM by considering the simultaneous effect of various input parameters. The experiments are carried out on Ti6Al4V, HE15, 15CDV6 and M-250. Multi perceptron neural network models were developed using Neuro Solutions package. Genetic algorithm concept is used to optimize the weighting factors of the network. Maji and Pratihar (2010) presents input–output relationships of an EDM process have been established both in forward as well as reverse directions using adaptive network-based fuzzy inference system. Kao *et al*. (2010) presents the parameter optimization of the EDM process to Ti–6Al–4V alloy considering multiple performance characteristics using the Taguchi method and grey relational analysis is reported. Joshi *et al*. (2011) reports an intelligent approach for process modelling and optimization of EDM. Physics based process modeling using finite element method (FEM) has been integrated with the soft computing techniques like ANN and genetic GA to improve prediction accuracy of the model with less dependency on the experimental data. Horacio *et al*. (2011) solving an inversion model, based on the least squares theory, which involves establishing the values of the EDM input parameters to ensure the simultaneous fulfilment of material removal rate, electrode wear ratio and surface roughness.

The EDM process has a very strong complicated discharge mechanism making it too difficult to optimize the sparking process. Majority of the research work have been concerned with the improvement made to the performance such as MRR, Electrode wear rate (EWR) and surface roughness (SR). Hence, a constant drive towards appreciating the MRR, TWR and metallurgy of EDMEd surface will continue to grow with the intension of offering a more effective means of improving the performance measures.

The electrical discharge machining process

EDM is one of the earliest non-traditional machining processes. EDM process is based on thermoelectric energy between the work piece and an electrode. A pulse discharge occurs in a small gap between the work piece and the electrode and removes the unwanted material from the parent metal through melting and vaporizing. The electrode and the work piece must have electrical conductivity in order to generate the spark.

Figure 1: Electric discharge machining set up.

The experiment consists of machining the HSLA (high strength low alloy) steel work-piece using the Electric Discharge Machine (Fig. 1). Performing a single experiment involves the following steps:

i. Weighing the grinded work-piece before machining

ii. Weighing the electrode of the EDM before machining

iii. Fixing the electrode in position in the ram hold as shown in Fig. 2. Its height auto-adjusted by machine w.r.t. the workpiece to have a very small gap between its tip and the workpiece surface.

iv. Fixing the work-piece in position on the magnetic chuck of EDM's work-table (Fig. 2).

v. Flooding the volume (work tank) around work-piece by flushing with the dielectric fluid (Kerosene) upto the height where the electrode sparking region is fully immersed.

vi. Perform the machining process for a pre-decided time interval, which is 4 minutes.

vii. Intermittent Sparking is visible through the dielectric fluid. A large number of current discharges (colloquially also called sparks) happen, each contributing to the removal of material from both tool and workpiece, where small craters are formed. Erosion from the electrode is termed as wear, while that from the workpiece is the desired machining.

viii. The dielectric fluid is drained back into the dielectric tank, present below the work table. The work-piece and the electrode are taken off from the machine and their weights are taken again. The readings are carefully noted down.

Steps (i) to (viii) are repeated for all the runs experiments.

Work piece material

The material chosen for work piece was High Strength Low Alloy (HSLA) steel. HSLA steel is a type of steel alloy that provides many benefits over regular steel alloys. In general, HSLA alloys are much stronger and tougher than ordinary plain carbon steels. They are used in cars, trucks, cranes, bridges and other structures that are designed to handle a lot of stress, often at very low temperatures. HSLA steels are so called because they only contain a very small percentage of carbon. Typical HSLA steel contains 0.15% carbon, 1.65% manganese and low levels (under 0.035%) of phosphorous and sulphur. HSLA work piece was originally an L-shaped sheet having the largest dimensions of 85 cm X 45 cm and thickness of 1.3 cm. This was cut down into 12cm X 4cm size pieces by using the Shearing machine. The surface to be machined needs to be smooth and free from any sort of corrosion or scaling. Fig. 3 shows the work piece, which is achieved by first filing the pieces and then grinding the surface using a CNC Grinder.

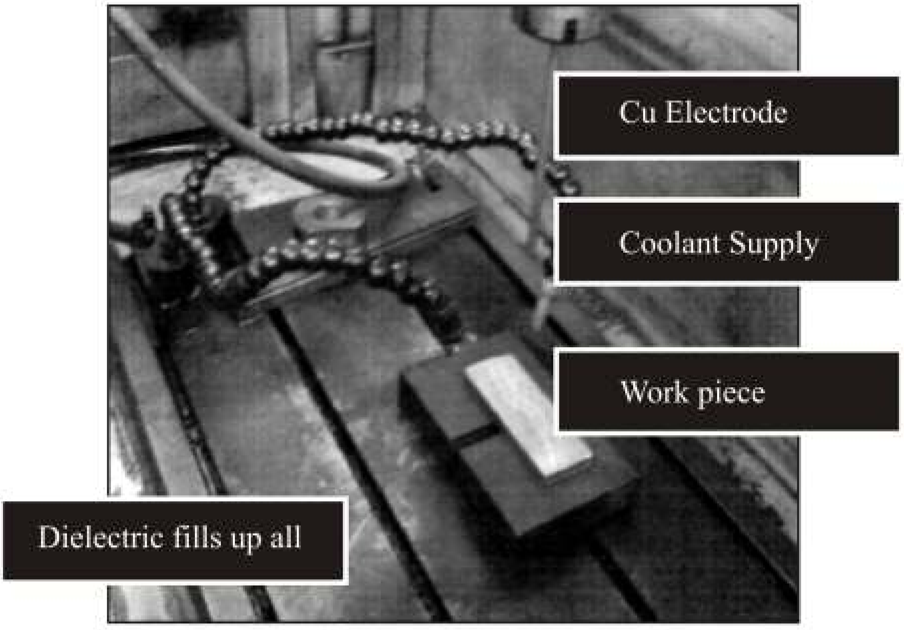

Figure 2: Machining of work material.

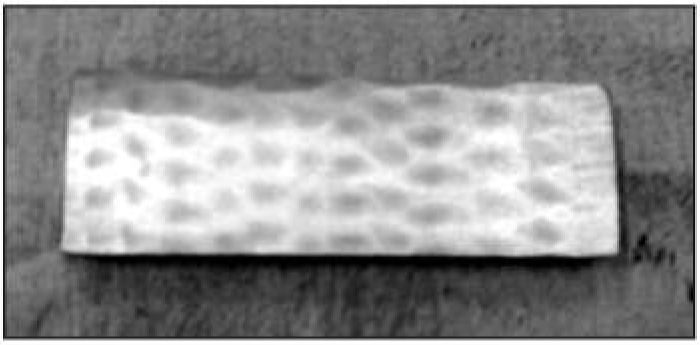

Figure 3: HSLA work-piece after grinding.

Taguchi Method

Taguchi method, developed by Dr. Genichi Taguchi, is a set of methodologies for optimization of a process or product. The parameter design is the key step in the Taguchi method to achieving high quality without increasing cost. In the Taguchi method, the experimental values are transformed into a signal-to-noise ratio η. The term "signal" represents the desirable value (mean) for output characteristic and the term "noise" represents the undesirable value for the output characteristic. Usually there are three categories of the performance characteristic in the analysis of the S/N ratio, that is, the lower-the-better, nominal-the-better and the higher-the-better.

Smaller-is-better:
$$\eta_{ij} = -10\log\left(\frac{1}{n}\sum_{j=1}^{n} y_{ij}^2\right) \quad \text{... (1)}$$

Nominal-is-better:
$$\eta_{ij} = -10\log\left(\frac{1}{ns}\sum_{j=1}^{n} y_{ij}^2\right) \quad \text{... (2)}$$

Larger Nominal-is-best:
$$\eta_{ij} = -10\log\left(\frac{1}{n}\sum_{j=1}^{n} \frac{1}{y_{ij}^2}\right) \quad \text{... (3)}$$

Where, y_{ij} is the i^{th} experiment at the j^{th} test, n is the total test and s is the standard deviation. Factor levels that have maximum S/N ratio are considered as optimal. The aim of this research was to produce minimum surface roughness (Ra) and EWR, maximum MRR in an EDM machining operation. Smaller-the-better quality characteristic is used for surface roughness as smaller Ra values represent better or improved surface finish also smaller-the-better quality characteristic is used for the EWR. Larger nominal-is-best quality characteristic is used for MRR.

Machining parameter selection

Machining experiments for determining the optimal machining parameters were carried out by setting: for each experiment the combinations of the 3 input parameters viz. pulse on-time (A) in the range of 10 μs to 300 μs, duty factor (B) in the range of 4 to 10, discharge current (C) in the range of 1.5A to 6A, all having 3 levels (Table 1), is changed according to the experimental plan in L9 orthogonal array.

Table 1: Factors and levels used in the experiment.

Symbol	Machining parameter	Unit	Level 1	Level 2	Level 3
A	Pulse on-time	μs	10	150	300
B	Duty Factor		4	7	10
C	Discharge Current	A	1.5	4	6

Machining performance evaluation

The machining performance is evaluated by the EWR and the MRR. The EWR is defined as the ratio of the electrode wear weight (EWW) in gram, under a period of machining time in minute (T), i.e.

EWR (gram/min) = EWW/T

R is defined as the ratio of work piece removal weight (WRW) under a period of machining time in minutes (T), i.e.

MRR (gram/min) = WRW/T

In the experiments, the machining time for each work piece is 4 min. basically, the lower is the EWR in the EDM process, and 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

Orthogonal Array experiment

In order to select an appropriate orthogonal array for 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 three-level process parameter counts for two degrees of freedom. Therefore, there are two degrees of freedom for each process parameters (Pulse on-time, Duty Factor and Discharge Current). Once the degrees of freedom are evaluated, the appropriate orthogonal array is selected to serve the specific purpose. Basically, 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. The experimental layout for all the cutting is shown in Table 2.

Table 2: Experimental layout using an L9 orthogonal array.

Run	LEVEL OF CONTROL PARAMETERS		
	(A)	(B)	(C)
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Experimental results and discussion

The measured response refers to the average values of the performance characteristics for each parameter at different levels. The average values of EWR, MRR and Surface roughness were obtained and reported in Table 3.

Analysis of the signal-to-noise (S/N) ratio

The S/N equation depends on the criterion for the quality characteristic to be optimized. There are three categories of performance characteristics, i.e., the lower-the-better, nominal-the-better and the higher-the-better. In this study, the lower-the-better performance characteristic is selected to obtain minimum surface roughness and electrode wear rate. Higher the better performance characteristic is selected for the material removal rate. The S/N values calculated for all the 9 observations using equation (1) and (3) are shown in Table 4. Now S/N ratios suitably divided three categories: low (L), medium (M) and high (H) according the range of S/N values. Now S/N ratios suitably divided three categories: low (L), medium (M) and high (H) according the range of S/N values as shown in the Table 4.

Table 3: L_9 machining orthogonal array with the values of response variables.

Exp. run	LEVEL OF CONTROL PARAMETERS			Measured response parameters		
	A	B	C	EWR (gram/min)	MRR (gram/min)	SR (µm)
1	10	4	1.5	0.0038	0.0090	1.7819
2	10	7	4.0	0.0021	0.0035	1.7841
3	10	10	6.0	0.0023	0.0042	1.4583
4	150	4	4.0	0.0015	0.0020	1.6523
5	150	7	6.0	0.0022	0.0025	1.5396
6	150	10	1.5	0.0035	0.0045	1.7417
7	300	4	6.0	0.0025	0.0012	1.6171
8	300	7	1.5	0.0030	0.0035	1.6043
9	300	10	4.0	0.0020	0.0022	1.6180

Table 4: Signal to Noise ratios.

Exp. No.	S/N (EWR)	S/N (MRR)	S/N (SR)	Classifying S/N ratios		
				S/N (EWR)	S/N (MRR)	S/N (SR)
1	48.4043	40.9151	-5.0177	L	H	L
2	53.3801	48.9432	-5.0284	M	M	L
3	52.7654	47.5350	-3.2769	M	M	H
4	56.4782	53.9794	-4.3618	H	L	M
5	52.9563	52.0412	-3.7482	M	M	H
6	49.1186	46.9357	-4.8195	L	H	M
7	52.0412	58.0618	-4.1747	M	L	M
8	50.4576	49.1186	-4.1057	L	M	M
9	53.9794	52.9563	-4.1796	H	M	M

Calculation of MRPIs

In this paper, the use of fuzzy logic to deal with the optimization of a process with multiple performance characteristics is used. Using a procedure originated by Ebrahim Mamdani in the late 70s, three steps are taken:

1) Fuzzification (Using membership functions to graphically describe a situation)

2) Rule evaluation (Application of fuzzy rules)

3) Defuzzification (Obtaining the actual results)

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. MRPIs were calculated by using MATLAB (Fuzzy logic toolbox)) for calculating the single-value MRPI (Multi Response Performance Index). The first step is to define the membership functions for EWR, MRR and Surface roughness. Trapezoidal function has been selected as it is the most commonly used function in engineering calculations. Low, medium and high values were defined for the functions according to the range calculated in the previous step. These membership functions are shown Figure (3a, 3b, and 3c):

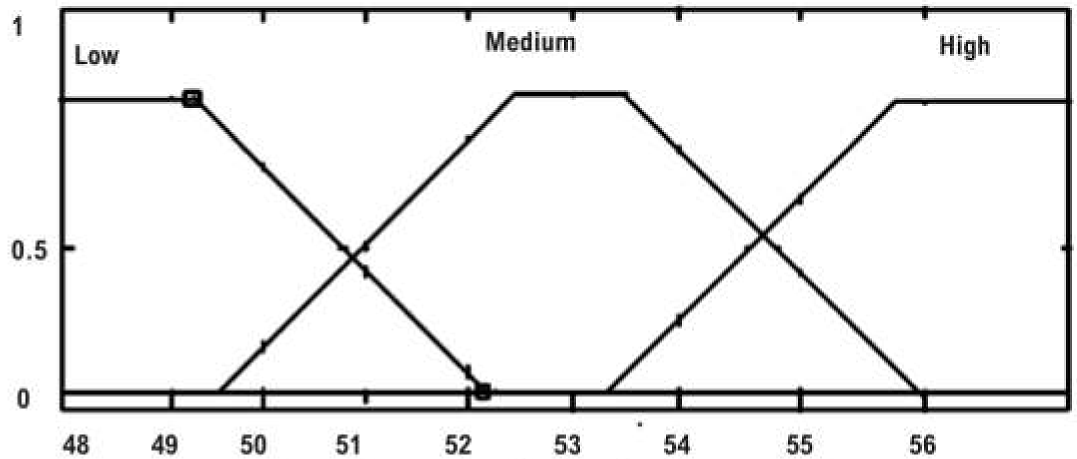

Figure 3a: Membership function for EWR (S/N).

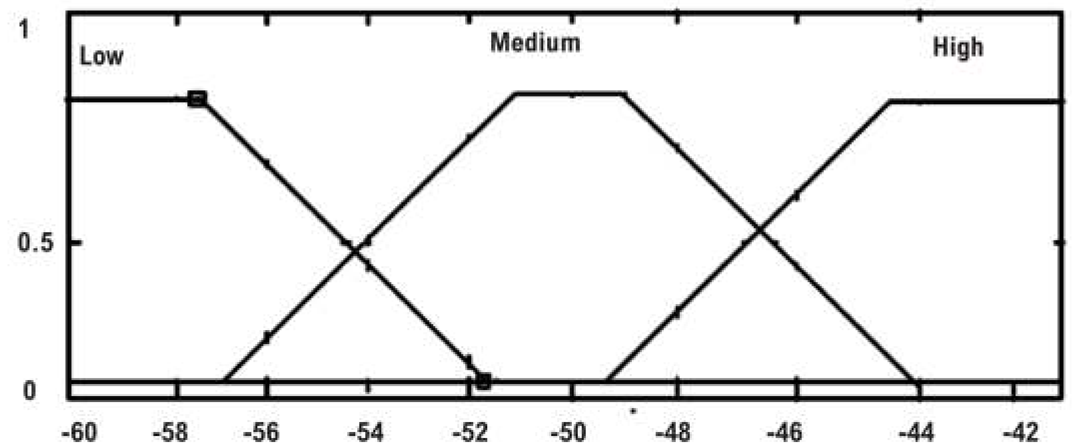

Figure 3b: Membership function for MRR (S/N).

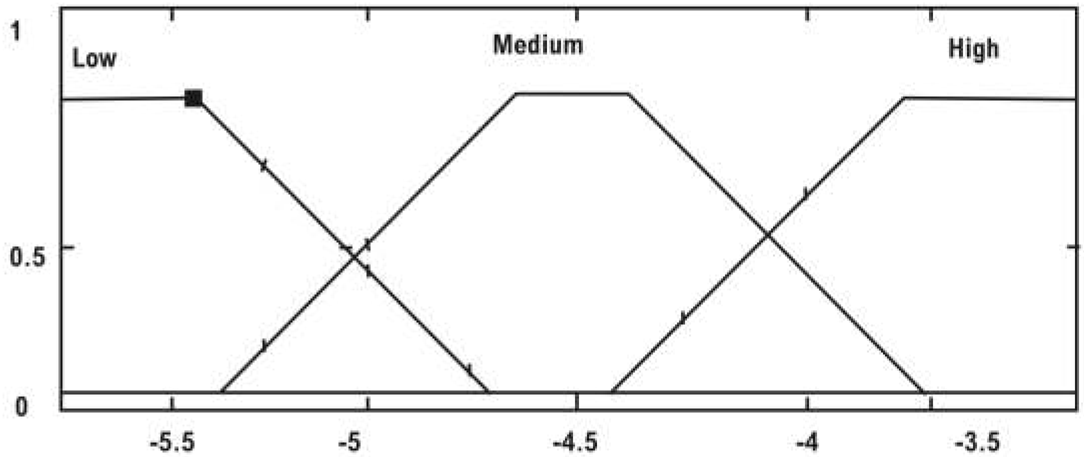

Figure 3c: Membership function for Surface Roughness (S/N).

Output membership function for the output, i.e. MRPI was defined. According to the input S/N values, it was decided on having seven levels for the output function: very small, small, low medium, medium, high medium, large and very large as shown in Figure 4.

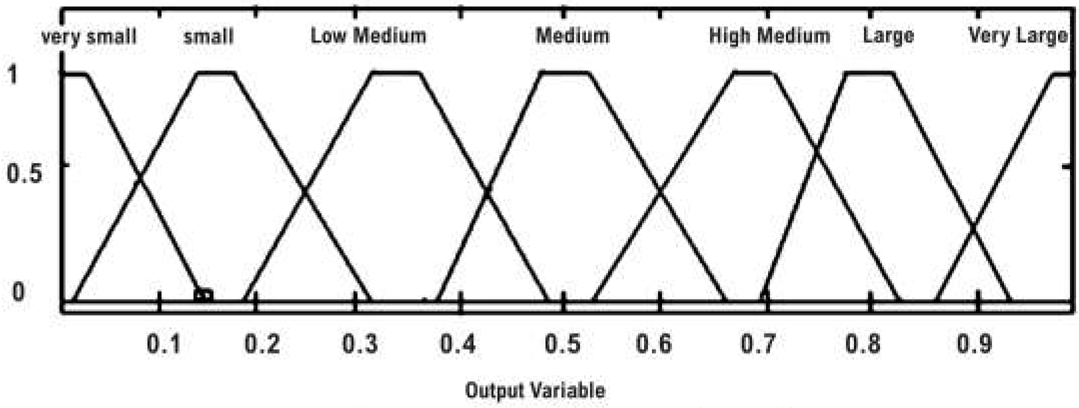

Figure 4: Output membership function.

The next step was to define a rule base for calculating MRPI from the input values of S/N. As mentioned before, there are three levels of input variables and seven levels of the output variable i.e. MRPI. How the Rule-base was decided is captured in the Table 5.

Table 5: Linguistic variables for the rule base.

S.NO.	S/N (EWR)	S/N (MRR)	S/N (SR)	MRPI
1	LOW	LOW	LOW	VERY SMALL
2	LOW	MEDIUM	MEDIUM	LOW MEDIUM
3	LOW	HIGH	HIGH	HIGH MEDIUM
4	MEDIUM	LOW	MEDIUM	LOW MEDIUM
5	MEDIUM	MEDIUM	HIGH	HIGH MEDIUM
6	MEDIUM	HIGH	LOW	MEDIUM
7	HIGH	LOW	HIGH	HIGH MEDIUM
8	HIGH	MEDIUM	LOW	MEDIUM
9	HIGH	HIGH	MEDIUM	LARGE

After defining the rule base, as above, values of MRPI were obtain the by inserting the S/N values for the three input parameter. The values of MRPI, after inserting the values of S/N are given in the Table 6. The MRPI values that we have obtained above depend on the rule base and also the range of the three levels for each of the input variable. Thus, these values are subjective and may vary according to the rule base selected and also the range decided for the different levels of each input variable. To determine the optimal machining conditions, it is required to find the greatest MRPI values among all possible combinations of the process parameters.

Table 6: MRPI values corresponding to all control & response parameters.

EXP. RUN	LEVEL OF CONTROL FACTORS			MEASURED RESPONSE PA RAMETERS			MRPI
	A	B	C	S/N(EWR)	S/N(MRR)	S/N(SR)	
1	1	1	1	48.4043	-40.9151	-5.0177	0.470
2	1	2	2	53.3801	-48.9432	-5.0284	0.446
3	1	3	3	52.7654	-47.5350	-3.2769	0.333
4	2	1	2	56.4782	-53.9794	-4.3618	0.650
5	2	2	3	52.9563	-52.0412	-3.7482	0.661
6	2	3	1	49.1186	-46.9357	-4.8195	0.151
7	3	1	3	52.0412	-58.0618	-4.1747	0.333
8	3	2	1	50.4576	-49.1186	-4.1057	0.463
9	3	3	2	53.9794	-52.9563	-4.1796	0.538

Table 7: Avg. MRPI values for a factor at particular level.

FACTOR	A	B	C
Level 1	0.4653	0.4843	0.4280
Level 2	0.5873	0.5900	0.6113
Level 3	0.4780	0.4563	0.4913
Range (Max-Min)	0.1220	0.1337	0.1833
Rank	3	2	1

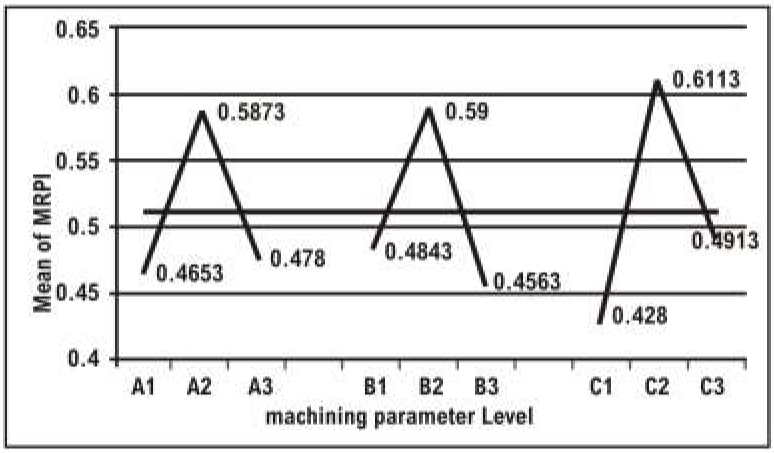

Figure 5: Main effect response graph.

The optimum machine setting is, therefore, A- level 2, B- level 2, C- level 2 i.e. A2B2C2 In the above Table 7, The italized number in each column of factors is the highest MRPI for each factor, which also indicates the best level for each factor. Control factors with large range of MRPI values among their levels have more significant influences in the EDM process. Ranks are allotted on this basis. It is clear that control parameter C (discharge current or pulse current) has the strongest effect on the dimensional quality of machined products, followed by parameters B (duty factor) and A (pulse on-time). They are regarded as the most important process factors due to their combination directly affecting the thermal input rate. The relative effect among the control factors for the MRPIs can be verified by using the ANOVA so that the optimal combinations of the control factors can be accurately determined.

Analysis of Variance

The larger is the MRPI, the smaller is the variance of the performance characteristics around the desired value. However, the relative importance amongst the machining parameters for the multiple performance characteristics still need to be known so that the optimal combinations of the machining parameter levels can be determined more accurately.

Table 8: Summary of ANOVA result.

Source Model	Parameter	Sum of Squares	DF	Mean Square	F Value	Prob > F	% Contribution	
		0.1088	6	0.0181	37.67	0.0261		Significant
A	Pulse on-time	0.0269	2	0.0135	28.03	0.0344	24.59	
B	Duty factor	0.0298	2	0.0149	30.96	0.0313	27.16	
C	Discharge current	0.0520	2	0.0260	54.02	0.0182	47.38	
Error		0.00096	2	0.00048			0.88	

ANOVA is performed to identify the process parameters of EDM that significantly affect the MPRI. An ANOVA consists of sums of squares, corresponding degrees of freedom, the F-ratios corresponding to the ratios of two mean squares, and the contribution proportions from each of the control factors as shown in Table 8. Parameter C i.e. Discharge current with a contribution of 47.38% has the greatest effect on the machining output characteristics. Parameter B i.e. machine's Duty factor with a 27.16% share is the next most significant influence on the output parameters, followed by Parameter A i.e., Pulse on-time (TON) (24.59%).

Conclusion

This research work has presented an investigation on the optimization and the effect of machining parameters on the EWR, MRR and SR in EDM operations. The input parameters chosen were Pulse on-time (Ton), Duty factor and Discharge current (or pulse current). The L_9 orthogonal array was chosen to be able to study the effect of control (input) parameters on the output parameters. S/N ratios for all experiments were calculated corresponding each of the output parameter. A single value – MRPI is obtained through fuzzy reasoning (creating rule base) on these S/N ratios. The MRPI can be used to optimize the process based on the Taguchi approach. Optimization of MRPI in the process has been achieved through the proper system model simulation that it can meet targeted quality characteristic levels.

The following factor-level settings have been identified to yield the best combination:

Input parameter A – Level 2

Input parameter B – Level 2

Input parameter C – Level 2

The level of importance of the machining parameters on the EWR, MRR and surface roughness is determined by using ANOVA. Parameter C i.e. Discharge current with a contribution of 47.38% has the greatest effect on the machining output characteristics. Parameter B i.e. machine's Duty factor with a 27.16% share is the next most significant influence on the output parameters, followed by Parameter A i.e., Pulse on-time (T_{ON}) (24.59%).

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