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Grey-based Taguchi Technique for Solving the Multi-objective Problem When EDM Hard Worked Steel

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Abstract

In this paper Taguchi method has been employed to optimize Electrical Discharge Machining (EDM) process for 40CrMnMoS86 hot worked steel parts. The experimental data are gathered based on Taguchi L_{36} design matrix. The tests are conducted under varying peak current *(I)*, voltage *(V)*, pulse on time *(T_{on})*, pulse off time *(T_{off})* and duty factor *(η)*. The effects of these input parameters are then determined on three important process output responses, namely; Surface Roughness *(SR)*, Tool Wear Rate *(TWR)* and Material Removal Rate *(MRR)*. Using these data and signal-to-noise *(S/N)* ratio analysis, the process parameters can be set to achieve desired surface roughness, tool wear and material removal rates. Next, analysis of variance (ANOVA) and F–test have been used to evaluate the relative significance of process variables affecting process outputs. A set of verification tests is also performed to verify the accuracy of optimization procedure in determining the optimal levels of machining parameters. The results indicate that Taguchi technique is quite efficient in determining optimal process parameters.

Keywords: Taguchi technique, Electrical Discharge Machining, Optimization, Analysis of variance, signal to noise.

1. Introduction

Electrical Discharge Machining (EDM) has become one of the most extensively used non-traditional material removal process. Its unique feature of using thermal energy to machine hard to machine electrically conductive materials is its distinctive advantage in the manufacturing of moulds, dies, aerospace and surgical components [1,2]. A schematic illustration of EDM process is given in Figure 1.

EDM technique is specially useful when the workpiece is hard, birttle and requires high surface finish. Therefore, the merits of the EDM technique become most apparent when machining such material as 40CrMnMoS86 hot worked steel parts which have very high hardness in reinforcement. In addition, mechanical and physical properties of hot worked steel such as hardness, toughness and high wear resistance, has made it an important material for engineering components particularly in making moulds and dies.

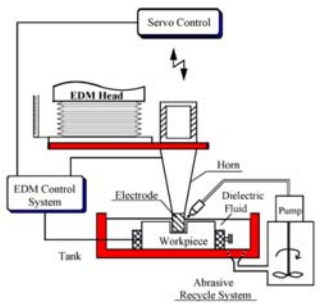

Fig 1 : Schematic illustration of Electrical Discharge Machining [2].

Like any other machining processes, the performance of EDM is significantly affected by its process parameter settings. Important process parameters in EDM are peak current *(I)*, voltage *(V)*, pulse on time *(T_{on})*, pulse off time *(T_{off})* and duty factor *(η)* [3-5]. These parameters, in turn, determine the process output characteristics, among which Surface

Roughness *(SR)*, Tool Wear Rate *(TWR)* and Material Removal Rate *(MRR)* are the most important ones.

In recent years, statistical analysis and Design of Experiments (DOE) technique have increasingly been employed to establish the relationships between various process parameters and the process outputs in variety of manufacturing industries.

It is well known that modeling the relationships between the input and output variables for non-linear, multi-variable systems are very difficult via traditional modeling methods [6]. In recent years, various approaches such as Artificial Neural Networks (ANNs) and fuzzy logic (FL) are employed to predict performance characteristics of EDM processes under different parameters setting. Specifically, Taguchi method and Artificial Neural Networks (ANNs) have demonstrated great potential in the modeling of the input–output relationships of complicated systems [6, 8]. For instance, Mohana et al [7] and Krishna and Hanumantha [9] developed ANN models based on experimental data for EDM. The proposed ANN models were then combined with Genetic Algorithm (GA) to minimize roughness.

Ling Wu et al. [10] added aluminum and surfactant in the dielectric in order to improve the surface finish of SKD steel parts. It is observed the best distribution effect is found when the concentrations of the Al powder and surfactant in the dielectric are 0.1 and 0.25 g/L, respectively. Han Yang and Srinivas et al [11] proposes an optimization methodology for the selection of best process parameters in electro discharge machining. They employed Simulated Annealing (SA) algorithm to maximize the *MRR* as well as minimize the *SR* on steel work pieces. A constrained multi-objective optimization methodology for EDM process has been presented using simulated annealing approach. A reliable function generated from counter-propagation neural network was employed to evaluate the non-dimensional multiple objective values. H.K. Kansal et al [12] studied the effect of silicon powder mixing into the dielectric fluid of EDM on machining characteristics of AISI D2 (a variant of high carbon high chrome) die steel. The confirmation runs showed that the setting of peak current at a high level, pulse-on time at a medium level, pulse-off time at a low level, powder concentration at a high level, and gain at a low level produced optimum *MRR* from AISI D2 surfaces when machined by silicon powder mixed EDM.

Kiyak and Cakır [13], have studied the effects of EDM parameter levels on surface roughness for machining of 40CrMnNiMo864 tool steel (AISI P20) which is widely used in the production of plastic mold and die. It is observed that Surface roughness increases with increasing pulsed current and pulse time. Low current and pulse time produces minimum surface roughness that means good surface finish quality. The selection of these machining parameters is not useful because machining process generally becomes very slow. Material removal rate will be low and thus machining cost increases. This combination should be used in finish machining step of EDM process.

In this study the effects of EDM parameter levels on 40CrMnMoS86 hot worked steel have been investigated. As mentioned earlier, *SR*, *TWR* and *MR*R are the most important performances characteristic in EDM. In turn, these output characteristics are determined by the process parameter settings, such as peak current *(I)*, voltage *(V)*, pulse on time *(T_{on})*, pulse off time *(T_{off})* and duty factor *(η)*.

The main objectives of the present study are: 1) to establish the relationship between EDM process parameters and process output characteristics, and 2) to determine the optimal parameter levels for maximum material removal rate, minimum tool wear rate and surface roughness. The proposed procedure is based on statistical analysis of the experimental data. The article concludes with the verification of the proposed approach and a summary of the major findings.

2. Experimental Equipment and Design of Experiment (DOE)

In this study, an Azerakhsh-304H die-sinking machine has been used to perform the experiments (Figure 2). The test specimens were of 40CrMnMoS86 hot worked steel with dimensions of 60mm×20mm×10mm. A total of 4 tests were performed on each samples, two tests on each side.

The electrodes were made of 16mm cylindrical shape copper (99.8% purity and 8.98 g/cm^3 density). The pure kerosene was used as the dielectric fluid in all experiments. The 36 sets of data needed for modeling, are obtained using L_{36} Taguchi matrix. Table 1 lists the ranges of machining parameters. As show, pulse off time is considered at two levels, while all other process variables have three levels.

The *MRR*, *SR* and *TWR* are considered as the performance characteristics to evaluate the machining quality.

The machining time for each test was 45 minutes. Furthermore, the experiments have been done in random order to increase accuracy.

Material removal rate *(MRR)* is expressed as the work piece removal weight *(WRW)* under a period of machining time in minute *(T)*, that is:

$$MRR\,(gr/\min) = \frac{WRW}{T} \qquad (1)$$

Fig 2: Die-sinking EDM machine used for experiments

Fig 3 : Digital surface roughness tester and electronic balance

Tool wear ratio *(TWR)*, usually expressed as a percentage, is defined by the ratio of the tool wear weight *(TWW)* to the work piece removal weight *(WRW)*, that is:

$$TWR\,(\%) = \frac{TWW}{WRW} \times 100 \qquad (2)$$

Table 1: Process parameters and their design levels

No.	Symbols	Factors	Units	Level		
				1	**2**	**3**
1	A	Pulse off time (T_{off})	μS	10	75	-
2	B	Pulse on time (T_{on})	μS	25	100	200
3	C	Peak current (I)	A	2.5	5	7.5
4	D	Duty factor (η)	S	0.4	1	1.6
5	E	Voltage (V)	V	50	55	60

After machining, the surface finish of each specimen was measured with an automatic digital Surtronic (3+) *SR* tester (Figure 3).

To measure the *MRR* and *TWR* an A&D electronic balance with 0.01gr accuracy has been used. (Figure 3).

3- Analysis and discussion of the experimental results

- **Signal to noise analysis**

Taguchi method uses design of experiments to study the entire parameters space with small number of experiments [6]. It also makes use of signal–to–noise (*S/N*) ratios as performance measures to optimize the output quality characteristic against such variations in noise factors. In this method, a loss function is defined to calculate the deviation between the experimental value and the desired value. This loss function is further transformed into *S/N* ratio. Based on the process under consideration, the *S/N* ratio calculation may be decided as "the Larger the Better, (LB)" or "the Smaller the Better, (SB)" as are given in the following equations [13]:

$$LB : S/N = -10Log\left(\frac{1}{m}\sum_{i=1}^{m}\frac{1}{y_i^2}\right) \qquad (3)$$

$$SB : S/N = -10Log\left(\frac{1}{m}\sum_{i=1}^{m}y_i^2\right) \qquad (4)$$

In the above, *S/N* is the ratio calculated from the observed values, y_i represents the experimentally observed value of the i^{th} experiment, and m is the repeated number of each experiment. Since the *MRR*, *TWR* and *SR* are the measure of performance in EDM process, the LB criterion is selected for *MRR* and the SB is used for *TWR* and *SR*.

The corresponding *S/N* ratios for 36 tests are shown in Table 2.

The optimum level of these significant parameters has been found by examining the level averages of the factors. For each process output response, the *S/N* ratio determined from the experimentally observed values has been statistically evaluated by ANOVA technique (Figures 4-6). Generally, a greater *S/N* corresponds to a better performance and hence the optimal level of each machining parameter is the level with the greatest *S/N* value.

As illustrated in plots of 4, 5 and 6, the optimal machining parameters, given by analysis of signal to noise, can be determined. For example, Fig. 4 demonstrates that the optimal combination of parameters settings for maximizing *MRR* is 1-3-3-3-1 which correspond to T_{off} =10 μs; T_{on}=200 μs; I=7.5 A; η=1.6s and V=50 V. Similarly, from Fig 5 and 6, the optimal parameter settings can be determined to minimize *SR* and *TWR*.

Table 2 : Results of signal to noise ratio (S/N)

No.	S/N MRR	S/N SR	S/N TWR
1	-42.158	-11.821	-21.159
2	-23.401	-17.025	-8.404
3	-16.554	-22.606	4.467
4	-42.734	-10.103	-19.172
5	-26.707	-16.777	-10.541
6	-16.363	-22.076	7.158
.	.	.	.
.	.	.	.
.	.	.	.
16	-30.934	-13.255	-31.111
17	-26.055	-20.000	-16.517
18	-31.937	-15.268	1.138
19	-37.924	-13.803	-30.903
20	-23.557	-16.902	-20.857
21	-34.471	-16.258	-1.412
26	-35.340	-15.268	-2.270
.	.	.	.
.	.	.	.
.	.	.	.
30	-27.453	-21.289	5.621
31	-29.143	-13.803	-32.473
32	-40.175	-15.986	-7.131
33	-20.473	-18.889	3.046
34	-34.471	-13.803	-33.453
35	-36.954	-14.807	-3.876
36	-18.862	-19.824	14.202

- **Analysis of Variance (ANOVA)**

Analysis of variance (ANOVA) has been performed on the above experimental data to assess their adequacies and to determine significant parameters affecting each process outputs. Results of ANOVA are presented in Tables 6 to 8.

According to ANOVA procedure, large *F*–value indicates that the variation of the process parameter makes a big change on the performance characteristics. In this study, a confidence level of 95% is selected to evaluate parameters significances. Therefore, *F*–values of machining parameters are compared with the appropriate values from confidence table, $F_{\alpha,v1,v2}$; where α is risk, v_1 and v_2 are degrees of freedom associated with numerator and

denominator which illustrated in Table 3, 4 and 5 [14]. Within 95% confidence limit, ANOVA results indicate that all 5 process parameters are significant for *MRR*. On the contrary, only pulse on time and peak current have meaningful effects on *SR* and *TWR*.

Percent contribution indicates the relative significance of a factor on the process output characteristic. The percent contributions of the EDM parameters on *MRR*, *SR* and *TWR* are shown in Figures 7, 8 and 9 respectively. According to Figure 7, peak current is the major factor affecting the *MRR* with 59% contribution. Whereas pulse on time, duty factor, pulse off time and voltage have smaller effects on *MRR* with 20%, 12%, 3% and 2% contributions, respectively. The remaining (4%) effects are due to noise factors or uncontrollable parameters.

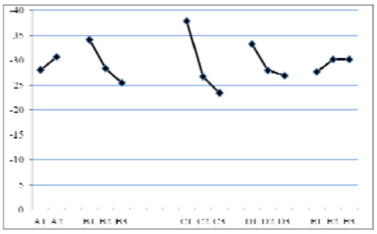

Fig 4 : Plot of main effects for signal to nose ratio of MRR

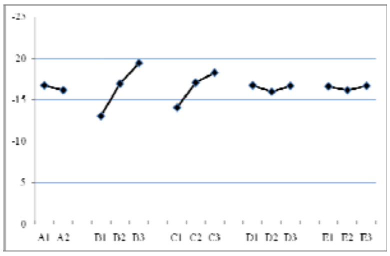

Fig 5: Plot of main effects for signal to nose ratio of SR

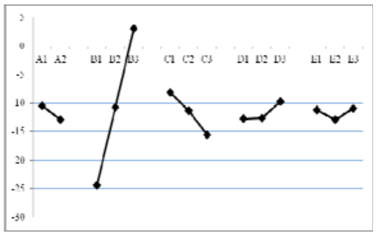

Fig 6 : Plot of main effects for signal to nose ratio of TWR

Moreover, pulse on time is the major factor affecting the *SR* with 61% contribution, followed by peak current with 28% effect. The remaining parameters have little effects on this output. The main process parameter affecting tool wear rate is pulse on time with 80% contribution. For *TWR*, peak current, duty factor, pulse off time and voltage have no significant effects. The remaining (14%) effects are due to noise factors or uncontrollable parameters.

Table 3 : Result of ANOVA for Material Removal Rate

Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (SS_j)	F-Value
A	1	56.75	56.75	18.79*
B	2	462.32	231.16	76.53*
C	2	1351.26	675.63	223.67*
D	2	275.94	137.97	45.68*
E	2	47.54	23.77	7.87*
Error	26	78.54	3.02	-
Total	35	2272.35	-	-

*significant
$F_{0.05,1,26} = 4.23$ & $F_{0.05,2,26} = 3.37$

Table 4 : Result of ANOVA for Surface Roughness

Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (SS_j)	F-Value
A	1	2.937	2.937	2.62
B	2	246.909	123.454	110.00*
C	2	113.621	56.810	50.62*
D	2	4.104	2.052	1.83
E	2	2.021	1.011	0.90
Error	26	29.181	1.122	-
Total	35	398.773	-	-

*significant
$F_{0.05,1,26} = 4.23$ & $F_{0.05,2,26} = 3.37$

Table 5 : Result of ANOVA for Tool Wear Rate

Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (SS_j)	F-Value
A	1	54.51	54.51	1.65
B	2	5554.28	2777.14	83.89*
C	2	329.38	164.69	4.98*
D	2	67.95	33.97	1.03
E	2	25.91	12.96	0.39
Error	26	860.68	33.10	-
Total	35	6892.71	-	-

*significant
$F_{0.05,1,26} = 4.23$ & $F_{0.05,2,26} = 3.37$

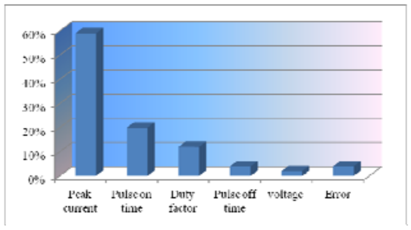

Fig 7 : The effect of machining parameters on the MRR

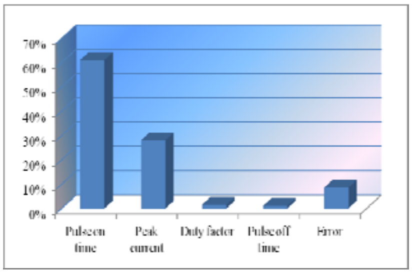

Fig 8 : The effect of machining parameters on the SR

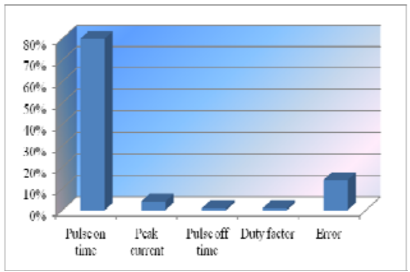

Fig 9 : The effect of machining parameters on the TWR

4. Confirmation experiments

To evaluate the adequacy of the proposed approach and statistical analysis, a set of verification tests has been carried out based on the predicted values. The optimal levels of the process parameters are predicted based on *S/N* ratios given in Tables 3 to 5. These settings should result in *S/N* ratios of -12.18 for *MRR*, -10.03 for *SR* and 55.8 for *TWR*. Table 6 shows the comparison between the predicted and experimental results using optimal process parameters. As indicated, the differences between predicted and actual process outputs are only 4.1% for *MRR*, 8.4% for *SR* and 7.6% for *TWR*. Given the nature of EDM process and its many variables, these results are quite acceptable and prove that the experimental results are correlated with the estimated value.

Table 6 : Results of confirmation experiments

	Optimal condition			
	Prediction	Experiment	Difference	Error (%)
Setting level	$A_1 B_3 C_3 D_3 E_1$	$A_1 B_3 C_3 D_3 E_1$		
S/N ratio for MRR	-12.18	-12.69	0.51	4.1
Setting level	$A_1 B_3 C_1 D_3 E_3$	$A_1 B_3 C_1 D_3 E_3$		
S/N ratio for SR	-10.03	-10.95	0.92	8.4
Setting level	$A_2 B_3 C_2 D_3 E_1$	$A_2 B_3 C_2 D_3 E_1$		
S/N ratio for TWR	18.87	17.43	1.75	7.6

5. Conclusion

Optimizing the process parameters is a significant step to achieve high quality product with desired output characteristics. In this study a Taguchi based procedure has been employed to optimize EDM process parameters for machining of 40CrMnMoS86 hot worked steel parts. Taguchi experimental design can effectively reduce the experimental sample size and determine significant factors. The experimental data were gathered using Taguchi L_{36} design matrix. Based on signal to noise analysis, the best set of process parameter values has been determined so that *MRR* is maximized and *SR* and *TWR* are minimized. This procedure may also be used to optimally determine the process parameters settings for any desired output values. Then, based on the ANOVA results with 95% confidence interval, significant parameters for each process output characteristic were determined. These analyses may also show the percent contribution of process parameters on the output characteristics. It is shown that peak current and pulse on time are the most important process parameters affecting *MRR*, *SR* and *TWR*. Finally, a set of confirmation tests was performed based on optimal parameter values predicted by *S/N* analysis. The results of confirmation tests reveal that the proposed approach is quite capable in predicting EDM process outputs.

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