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Application of Taguchi approach and Simulated Annealing Algorithm in Surface Modification When EDM Hot Worked Steel

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Abstract
Among the various non-conventional processes, electro discharge machining (EDM) is most widely and successfully applied for the machining of various work piece materials. The material is removed by means of repetitive spark discharges that cause local melting and/or evaporation of the work piece material and the resulted surface is characterized by overlapping craters and features indicative of the intense thermal impact involved. The last decade has seen an increasing interest in the novel applications of electrical discharge machining process, with particular emphasis on the potential of this process for surface modification. This paper proposes an optimization methodology for the selection of best process parameters in electro discharge machining for surface modification of 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 the most important process output response, surface roughness *(SR)*.The relation between machining parameters and performance can be found out with the signal to noise analysis *(S/N)*. Next, analysis of variance (ANOVA) and F–test have been used to evaluate the relative significance of process variables affecting process outputs. Developed multi objective model is optimized by Simulated Annealing algorithm *(SA)* and machining optimal parameters setting is found. A confirmation test is also performed to verify the effectiveness of optimization procedure in determining the optimum levels of machining parameters. The consequences show that the combination of Taguchi technique, signal to noise analysis and simulated annealing algorithm is quite efficient in determining optimal EDM process parameters of surface finish in EDM.

Keywords: Taguchi technique, Signal to Noise analysis *(S/N)*, Electrical Discharge Machining *(EDM)*, Optimization, simulated annealing algorithm *(SA)*, Analysis of variance *(ANOVA)*.

Introduction

Electric-discharge machining (EDM) is a non-conventional, thermo-electric process in which the material from work piece is eroded by a series of discharge sparks between the work and tool electrode immersed in a liquid dielectric medium. This technique has been widely used in modern metal working industry for producing complex cavities in dies and moulds, which are otherwise difficult to create by conventional machining [1].

A schematic illustration of EDM process is given in "Figure 1".

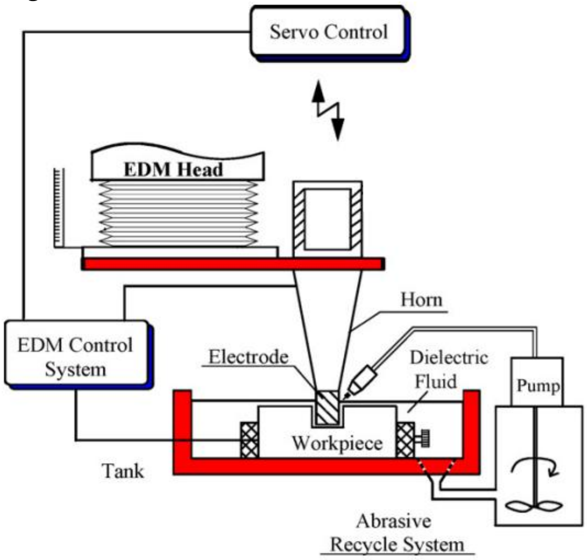

Figure 1: Schematic illustration of Electrical Discharge Machining [2]

Metal removal process in EDM is characterized by nonlinear, stochastic and time varying characteristics. In EDM, a quantitative relationship between the operating parameters and controllable input variables is often required. Many regression techniques have been used for modeling the EDM process. Neural networks and fuzzy systems form an alternative approach to generalize the experimental results and develop the system model accurately [1].

Howevere, EDM is a costly process and hence proper selection of its process parameters is essential to increase production rate and improve product quality.

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.

The superior performance of EDM than traditional machining technology has already been proved in applying toward the materials with high strength, high hardness or more complicated shapes. Since the mechanism of EDM is done by melting the unwanted parts of workpiece by high temperature spark, many defects such as porosity, cracks, improper recast layer, residual stress are easily found on the workpiece surface due to the rapid high temperature melting and cooling process during EDM. Thus, a comprehensive study to improve the surface roughness of EDMed workpiece is the crucial topics. Many studies have noticed this unavoidable effect in EDM applications and have also proposed many prescriptions to fulfill the various criteria of industrial demanding. For instance, Mohri et al. [6-8] demonstrated that by adding powder into dielectric via EDM process, a mirror-like surface could be achieved. Luo et al. [9] suggested that either the low peak current or theshort pulse duration for EDM could gain a better surface roughness in machining process.

Kiyak and Cakır [10], 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.

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 [1-5].

The main objectives of the present study are: 1) to establish the relationship between EDM process parameters and the process output characteristic, and 2) to determine the optimal parameter levels for minimum surface roughness by application of simulated annealing algorithm. 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.

Experimental procedure and Design of Experiments

In the present 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. A total of 4 tests were performed on each samples, two tests on each side.

The 36 sets of data needed for modeling, are obtained using L_{36} Taguchi matrix. The experimental set up and conditions are shown in "table 1".

Table 1: Experimental set up and conditions

Equipment	Specification
Machine tool	EDM (Azarakhsh 304H), Cross Travel 300×250, 7kw, Iran
Work specimen material	2312 (40CrMnMoS86) hot worked steel with dimensions of 40×20×10 mm
Electrode	Copper (99.8% purity and 8.98 g/cm3 density) with dimensions of Φ16×60 mm
Roughness tester	Surtronic 3+ with 0.1 accuracy, R_a, German
Weighing machine	A&D, with 0.01 accuracy, Japan
Dielectric	pure kerosene

Figure 2: Die-sinking EDM machine used for experiments

"Table 2" lists the machining parameters range of changes. As show, pulse off time is considered at two levels, while all other process variables have three levels. The *SR* is considered as the performance characteristic to evaluate the machining quality.

Table 2: Design scheme of experimental parameters and levels

Symbol	Factor	Unit	Range of changes	levels		
				l.1	l.2	l.3
A	T_{off}	µS	10 – 75	10	75	-
B	T_{on}	µS	25 –200	25	100	200
C	I	A	2.5 – 7.5	2.5	5	7.5
D	η	S	0.4 – 1.6	0.4	1	1.6
E	V	V	50 – 60	50	55	60

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

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

Figure 3: Digital surface roughness tester

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 [11]. 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 [10]:

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

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

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 *SR* is the measure of performance in EDM process, the *SB* criterion is selected for *SR*.

The matrix of experimental tests (L_{36}), result of *SR* and its corresponding *S/N* ratio are shown in "Table 3".

Table 3: Experimental lay out (L_{36}), results of *SR* and *S/N* ratio

No.	T_{off}	T_{on}	I	η	V	SR (μm)	S/N of SR
1	1	1	1	1	1	3.9	-11.821
2	1	2	2	2	2	7.1	-17.025
3	1	3	3	3	3	13.5	-22.606
4	1	1	1	1	1	3.2	-10.103
5	1	2	2	2	2	6.9	-16.777
6	1	3	3	3	3	12.7	-22.076
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
31	2	1	3	3	3	4.9	-13.803
32	2	2	1	1	1	6.3	-15.986
33	2	3	2	2	2	8.8	-18.889
34	2	1	3	1	2	4.9	-13.803
35	2	2	1	2	3	5.5	-14.807
36	2	3	2	3	1	9.8	-19.824

- Regression modeling

Many problems in engineering and science involve exploring the relationships between two or more variables.

Regression analysis is a statistical technique that is very useful for these types of problems [12]. In this paper, the output response is *S/N*'s associated with experimental tests. In this study, various regression functions have been fitted on the data given in "Table 3". Among these models, quadratic regression model was found to be the most appropriate in terms of estimating the real process. Eq. (3) shows the adjusted second order regression model for EDM process:

$$S/N = -9.11 + 0.0517\,T_{on} - 4.92\,\eta + 0.000149\,T_{on}^2 + 0.00527\,I^2 - 0.00101\,T_{on}\times I - 0.000460\,I\times V + 0.0901\,\eta\times V \qquad (3)$$

- Analysis of variance (ANOVA)

Analysis of variance (ANOVA) is a mathematical way to determine precision of modeling for a group of observations, which shows how the proposed model fits with experimental results [10]. ANOVA has been performed within the confidence limit of 95%.

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 [12].

Table 4: Result of ANOVA for signal to noise ratio (S/N)

Machining parameters	Degree of freedom	Adjusted (SS_j)	F-Value
A	1	2.937	2.62
B	2	246.909	110*
C	2	113.621	50.62*
D	2	2.021	0.90
E	2	4.104	1.83
Error	26	29.181	-
Total	35	-	-

*Significant Parameters

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

According to Figure 4, pulse on time is the major factor affecting the S/N with 62% contribution. Whereas peak current, pulse off time, duty factor and voltage have smaller effects on S/N with 29%, 1%, 0.5% and 0.5% contributions, respectively. The remaining (7%) effects are due to noise factors or uncontrollable parameters.

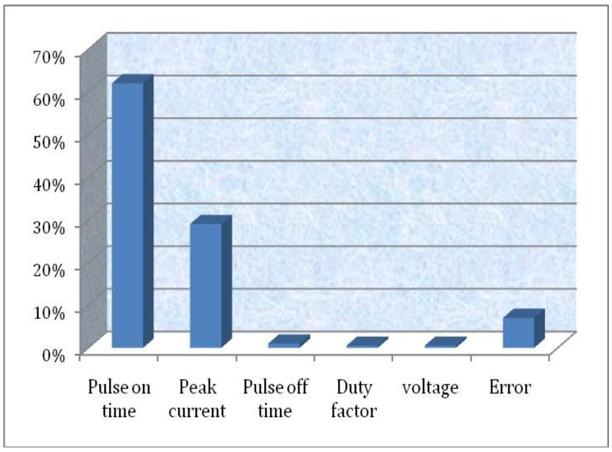

Figure 4: The effect of machining parameters S/N

Simulated annealing algorithm

Once the process model is ready, the optimum process parameters have to be determined. Unlike other non-conventional optimization schemes, Simulated Annealing (SA) process uses single point search method. This algorithm begins with an initial reasonable solution in solution field. Then a new solution in neighborhood of initial solution is formed. If the objective functions value of this new condition be better than initial value or the probability function implemented in *SA* has a higher value than a randomly generated number between zero and one, *SA* accepts this solution. The probability function implemented in *SA* given as follows [10].

$$P = \exp\,(\frac{\Delta F}{T_i}) \qquad (4)$$

ΔF is absolute difference between the objective function of the current solution and the new solution in each step and T_i is system's temperature. In *SA*, T_i is updating corresponding to annealing coefficient *(λ)* and according to relationship:

$$T_i + 1 = \lambda T_i \,, i = 0,1\ldots n \text{ and } 0.8 < \lambda < 1 \quad (5)$$

Small amount of λ accelerates algorithm convergence, but larger amounts increases fortune of non healing solutions acceptance. In optimization of developed multi objective model, every solution is a combination of peak current *(I)*, voltage *(V)*, pulse on time (T_{on}), pulse off time (T_{off}) and duty factor (η). Figure 5 shows Simulated Annealing algorithm's performance in optimal solution finding.

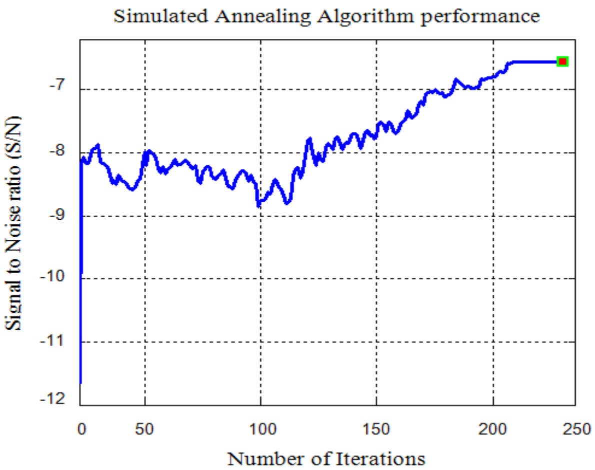

Figure 5: SA Algorithm performance

Confirmation experiments

To evaluate the adequacy of the proposed approach and statistical analysis, a verification test has been carried out based on the predicted value. The optimal levels of the process parameters are predicted based on *S/N* ratios given in "Table 3". These settings should result in *S/N* ratios of -6.4. "Table 5" shows the comparison between the predicted and experimental results using optimal process parameters.

Table 5: Results of confirmation experiments

	Prediction	Experiment	Difference	Error (%)
S/N	-6.4	-6.8	0.4	6.2
Parameter setting of optimal condition (T_{off} = 20µs, T_{on} = 45 µs, I = 2.5 A, η = 0.4S, V =60V)				

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 surface roughness for machining of 40CrMnMoS86 hot worked steel parts.

Taguchi experimental design can effectively reduce the experimental sample size and determine significant factors Statistical analysis reveals that the proposed regression model can accurately represent the actual process. Then a SA technique was employed to find optimal set of process parameters (T_{off} = 20µs, T_{on} = 45 µs, I = 2.5 A, η = 0.4S, V = 60V). The experimental result for the optimal setting shows that there is considerable improvement in the surface roughness therefore the proposed approach is quite capable in predicting EDM process output.

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