International Journal of Engineering

Journal Homepage: www.ije.ir

Optimization of EDM Process Parameters Using Statistical Analysis and Simulated Annealing Algorithm

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P A P E R I N F O

Paper history:
Received 11 February 2014
Received in revised form 13 May 2014
Accepted 14 August 2014

Keywords:
Electrical Discharge Machining (EDM)
Optimization
Signal To Noise Analysis (S/N)
Modeling
Simulated Anealing Algorithm (SA)
Analysis Of Variance (ANOVA)

A B S T R A C T

Nowadays, electrical discharge machining (EDM) has become one of the most extensively used non-traditional material removal processes. 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 and aerospace components. However, EDM is a costly process and hence proper selection of its process parameters is essential to reduce production cost and improve product quality. In this study the effect of input EDM process parameters on AISI2312 hot worked steel, widely used in mold manufacturing, is modeled and optimized. The proposed approach is based on statistical analysis on the experimental data. The input parameters are peak current (I), pulse on time (Ton), pulse off time (Toff), duty factor (η) and voltage (V). Material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR) are the most important performance characteristics of the EDM process. The experimental data are gathered using Taguchi L36 design matrix. Taguchi robust design technique was applied to obtain the signal to noise ratio (S/N ratio) for the quality characteristics being investigated. In order to establish the relations between the input and the output parameters, various regression functions have been fitted on the evaluated S/Ns data based on output characteristics. The significance of the process parameters on the quality characteristics of the EDM process was also evaluated quantitatively using the analysis of variance (ANOVA) method. Then, statistical analyses and validation experiments have been carried out to select the best and most fitted models. In the last section of this research, simulated annealing (SA) algorithm has been employed for optimization of the performance characteristics. Using the proposed optimization procedure, proper levels of input parameters for any desirable group of process outputs can be identified. 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 the proposed modeling technique and simulated annealing algorithm are quite efficient in modeling and optimization of EDM process parameters.

doi: *10.5829/idosi.ije.2015.28.01a.20*

1. INTRODUCTION

AISI2312 is one of the most difficult-to-cut hotworked alloys. Formation of complex shapes (of this material) along with reasonable speed and surface finish is very difficult by traditional machining processes. Electrical discharge machining (EDM) is one of the most suitable non-conventional material removal processes to shape this alloy. EDM is a thermo-electric process in which material is removed from the workpiece by erosion effect of series of electric discharges (sparks) between tool and workpiece immersed in a dielectric liquid. Its unique feature of using thermal energy to machine electrically conductive parts has been its distinctive advantage in the manufacture of molds, dies, aerospace and surgical components. The EDM process has a very strong stochastic nature due to the complicated discharge mechanism making it difficult to optimize the process [1]. The process performance can be improved by selecting the optimal combination of process parameters. Optimization of process parameters of EDM is a multi-objective optimization task as, in practice, the performance measures (material removal rate, tool wear rate and surface roughness) are conflicting in nature. Though much work has been

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reported in literature to improve the process performance, proper selection of process parameters still remains a challenge.

2. LITERATURE REVIEW

From exhaustive literature review, it is found that there are few controllable parameters such as peak current (I), voltage (V), pulse on time (T_{on}), pulse off time (T_{off}) and duty factor (η) [2-4]. These parameters, in turn, determine the process output characteristic, among which, material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR) are the most important ones. Figure 1, illustrates the input and output parameters for EDM process [1, 5].

Review of the research work reveals that much work has been done on various aspects of EDM process. These studies have mostly emphasized on the modeling and optimization of process parameters for different materials.

Seung-Han Yanga et al. [6], proposed an optimization methodology for the selection of best process parameters in EDM using artificial neural networks (ANN) and simulated annealing (SA) algorithm. An integrated artificial neural network model is constructed based on experimental data. A reliable function generated from counter-propagation neural network, was employed to simultaneously maximize the material removal rate as well as minimize the surface roughness using simulated annealing algorithm.

Raoa and Rangajanardha et al. [7], developed a hybrid model using artificial neural networks and genetic algorithm (GA) to optimize the surface roughness in electric discharge machining.

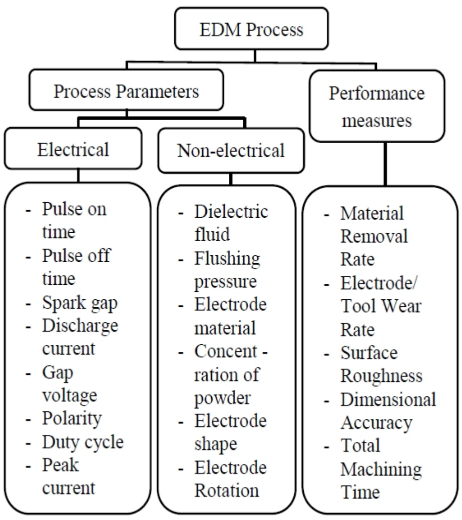

Figure 1. Important input and output parameters for EDM process [1]

Mohana et al. [8]developed a hybrid model to minimize the surface roughness in EDM using artificial neural networks and genetic algorithm.

Kansal et al. [9], studied the effect of silicon powder mixing into the dielectric fluid of EDM for machining AISI D2 dies 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 would result in optimum MRR.

To the best of our knowledge, there is no published work to statistically study and optimize the effect of machining parameters of EDM process on the most important output characteristics namely, MRR, TWR and SR for machining of AISI2312 hot worked steel parts. Therefore, the present study has two objectives 1. To establish the relationship between the input and output parameters of EDM process, and 2. To derive the optimal parameter levels for maximum MRR and minimum SR and TWR using statistical analysis of the experimental data and simulated annealing (SA) algorithm. Finally, the article concludes with the verification of the proposed approach and a summary of the major findings.

3. EXPERIMENTAL DETAILS

3. 1. Workpiece Material Hot worked alloys are among the hardest materials to shape because of their strength and chemical reactivity with tool materials. AISI2312 hot worked steel is a popular alloy used in various industries such as aerospace and plastic injection molding. Despite its unique properties, the usage of this alloy is limited due to the high processing costs, which arise because of the processing difficulties such as its poor machinability. This study applied AISI2312 hot worked steel parts since only a few researchers have done the studies regarding this material using EDM. The EDM operation is performed on AISI2312 hot worked steel parts having 10-mm thick and 40×20-mm dimension.

3. 2. Die-sinking Machine In the present study, an Azerakhsh-304H die-sinking machine has been used to perform the experiments (Cross Travel 300×250, 7kw, Iran).

3. 3. Electrode and Dielectric A total of 36 cylindrical shaped electrodes of 20-mm diameter made from commercially pure copper (99% purity and 8.98 g/cm^3 density) were used as tools. The electrodes were replaced after each experiment. The dielectric for all experiments was pure kerosene.

3. 4. EDM Parameter Setting A challenging task in EDM is the selection of optimum machining parameter combinations for obtaining higher accuracy due to process variables and complicated process mechanisms. In design of experiments (DOE), the number of required experiments (and hence the experiment cost) increases as the number of parameters and/or their corresponding levels increase. That is why it is recommended that the parameters with less likely pronounced effects on the process outputs be evaluated at fewer levels. In addition, the limitations of test equipment may also dictate a certain number of levels for some of the process parameters. The die-sinking EDM machine used for the experiments had only two settings for pulse of time - T_{off} (10 and 75 µs).

For this research, a large number of experiments were done to find the relatively appropriate machine tool settings as shown in Table 1. As shown, pulse off time is considered at two levels, while all other process variables have three levels.

According to the process variables and their corresponding levels (Table 1), two sets available using the Taguchi technique (L_8 and L_{36}). For this study, the L_{36} has been selected.

3. 5. Sample Preparation and Experimental Procedure All specimens were cleaned in an alcohol bath and then dried using a drier.

4. EVALUATION OF PERFORMANCE MEASURES

4. 1. Material Removal Rate (MRR) During the erosions, the machining time is measured and noted (45 minutes). The eroded volume is evaluated after the erosion set of the workpiece. MRR in g/hr can be calculated (Equation (1)).

$$MRR = \frac{\text{volume removed from workpiece}}{\text{time of machining}} \tag{1}$$

4. 2. Tool wear rate (TWR) The TWR, usually expressed as a percentage, and is defined by the ratio of the tool wear weight (TWW) to the workpiece removal weight (WRW) which is obtained using Equation (2). To measure the MRR and TWR, an A&D electronic balance with 0.01gr accuracy was used.

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

4. 3. Surface Roughness (SR) The SR value of the machined product is also one of the most important quality characteristics. The parameter Ra is used in this study. The average roughness (Ra) is the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation. Therefore, the Ra is specified by Equation (3) [1, 10]:

In this equation, Ra is the arithmetic average deviation from the mean line, L the sampling length, and Y the ordinate of the profile curve [1]. After machining, the surface finish of each sample was measured with an automatic digital Surtronic (3+) SR tester.

$$Ra = \frac{1}{L}\int_0^L |Y(x)|\ dx \tag{3}$$

5. SIGNAL TO NOISE RATIO ANALYSIS

To help determine the best process design, signal-to-noise (S/N) ratio is used in Taguchi methods as an index of robustness. In the Taguchi method, the term 'signal' represents the desirable value (mean) for the output characteristic and the term 'noise' represents the undesirable value for the output characteristic (Figure 2).

Noise factors cause variability and deterioration of performance from the ideal function and lead to variability in the quality characteristic. Generally, there are a number of noise factors existing in the EDM process, such as, machining time, electrode consumption, electrode shape and size, and aging working oil, etc. Very clearly, they have close mutual interaction, leading to somewhat uncertain control over the gap conditions. For the simplification of experimentation, every experimental trial uses the totally new electrode with the same sizes [10-12].

TABLE 1. Process variables and their corresponding levels

No	Symbol	Factor	Unit	Range	L1	L2	L3
1	A	T_{OFF}	µs	10 – 75	10	75	-
2	B	T_{ON}	µs	25-200	25	100	200
3	C	I	A	2.5-7.5	2.5	5	7.5
4	D	V	V	50-60	50	55	60
5	E	η	s	0.4-1.6	0.4	1	1.6

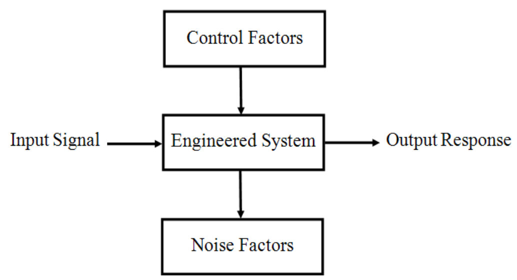

Figure 2. Schematic of an engineered system

TABLE 2. The process characteristics and their corresponding signal to noise ratio (S/N)

No	TWR	SR	MRR	S/N for TWR	S/N for SR	S/N for MRR
1	11.4	3.9	0.0078	-21.159	-11.821	-42.158
2	2.6	7.1	0.0676	-8.404	-17.025	-23.401
3	0.6	13.5	0.1487	4.467	-22.606	-16.554
4	9.0	3.2	0.0073	-19.172	-10.103	-42.734
5	3.3	6.9	0.0462	-10.541	-16.777	-26.707
6	0. 4	12.7	0.1520	7.158	-22.076	-16.363
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
31	42.0	4.9	0.0349	-32.473	-13.803	-29.143
32	2.3	6.3	0.0098	-7.131	-15.986	-40.175
33	0.7	8.8	0.0947	3.046	-18.889	-20.473
34	47.0	4.9	0.0189	-33.453	-13.803	-34.471
35	1.6	5.5	0.0142	-3.876	-14.807	-36.954
36	0.2	9.8	0.1140	14.202	-19.824	-18.862

Based on the process under consideration, the S/N ratio calculation may be decided as "the Lower the Better, (LB)" for output characteristics which the lower values are desired such as TWR and SR and "the Higher the Better, (HB)" for output characteristics which the higher values are desired such as MRR, are given in the following Equations [12].

$$\textbf{LB}: \; S/N(\eta) = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{4}$$

$$\textbf{HB}: \; S/N(\phi) = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \tag{5}$$

where nis the number of iteration in a trial, in this case, n=1 and y_j the j^{th} measured value in a run.
The results of S/N ratios for the process parameters are shown in Table 2.

6. MATHEMATICAL MODELING

Regression models can be used to predict the behavior of input variables (independent variables) and S/N values associated with each test response results [13]. The last three columns of Table 2 are the S/N ratio outputs for each test setting. These data can be used to develop mathematical models. Any of the above S/N ratios is a function of process parameters, which are expressed by linear, curvilinear or logarithmic functions; as stated in Equations (6) to (8), respectively.

$$Y_1 = b_0 + b_1S + b_2V + b_3F + b_4D + b_5A \tag{6}$$

$$\begin{aligned} Y_2 = {} & b_0 + b_1S + b_2V + b_3F + b_4D + b_5A + b_{11}SS + b_{22}VV \\ & + b_{33}FF + b_{44}DD + b_{55}AA + b_{12}SV + b_{13}SF + b_{14}SD \\ & + b_{15}SA + b_{23}VF + b_{24}VD + b_{25}VA + b_{34}FD + b_{35}FA \\ & + b_{45}DA \end{aligned} \tag{7}$$

$$Y_3 = b_0\, S^{b1}\; V^{b2}\; F^{b3}\; D^{b4} A^{b5} \tag{8}$$

In the above formula, b_0, b_1, …b_5 are the regression coefficients to be estimated. In this study, based on the S/N data given in Table 2, the regression model is developed using MINITAB software.

The choice of the model depends on the nature of initial data and the required accuracy. Using regression technique, in MINITAB Software, three types of mathematical functions (linear, curvilinear and logarithmic) have been fitted to the experimental data [14-16]. Models representing the relationship between process parameters and output characteristics can be stated in Equations (9) to (17). Stepwise elimination process was used to modify the initial proposed models. For instance, as can be seen in Equation (13), independent variable A was eliminated because of its insignificant effect on SR in the curvilinear model.

Adequacy of models were checked by analysis of variance (ANOVA) technique within the confidence limit of 95% [17, 18]. Results are shown in Table 3. Given the required confidence limit (Pr), the correlation factor (R^2) and the adjusted correlation factor (R^2-adj) for these models, it is evidence that curvilinear model is superior to the other two; thus, these models are considered as the best representative of the authentic EDM process throughout this paper.

6. 1. Linear Model

$$S/N\,(MRR) = -84.0 - 0.0386\,A + 0.0482\,B + 2.86\,C + 0.633\,D + 0.870\,E \tag{9}$$

$$S/N\,(SR) = -8.98 + 0.00879\,A - 0.0358\,B - 0.844\,C + 0.0086\,D - 0.113\,E \tag{10}$$

$$TWR = -38.3 - 0.0402\,A + 0.172\,B - 1.48\,C + 0.297\,D + 0.372\,E \tag{11}$$

6. 2. Curvilinear Model

$$S/N\,(MRR) = -389.336 - 0.0240008\,A + 0.0765327\,B + 8.40539\,C + 11.5007\,D - 2.06607\,E - 0.000273424\,BB - 0.628644\,CC - 0.0988255\,DD + 0.00684932\,BC \tag{12}$$

$$S/N\,(SR) = -6.7214 - 0.046117\,B - 1.79636\,C + 0.000149017\,BB + 0.146804\,CC - 0.00476137BC \quad (13)$$

$$S/N\,(TWR) = -12.5099 + 0.150794\,B - 4.32222\,C - 0.000479414\,BB + 0.0262243BC \quad (14)$$

6. 3. Logarithmic Model

$$S/N\,(MRR) = e^{-10.300} A^{-0.143} B^{0.477} C^{1.541} D^{4.040} E^{0.216} \quad (15)$$

$$S/N\,(SR) = e^{0.023} A^{-0.033} B^{0.348} C^{0.449} D^{-0.068} E^{0.035} \quad (16)$$

$$TWR = e^{6.240} A^{0.149} B^{-1.640} C^{0.751} D^{-1.850} E^{-0.117} \quad (17)$$

In the next step the proposed models were validated using new set of experiments (Table 4). Table 5 illustrates the mean error of the new six experiments for the output characteristics. According to the results, the curvilinear model is the best model among the proposed models for the three process characteristics.

TABLE 3. ANOVA results for S/N ratio models

Model	Variable	R^2	R^2 (adj)	F value	Pr>F
Linear	MRR	88.0%	86.0%	44.10	<0.0001
	SR	87.2%	85.0%	40.81	<0.0001
	TWR	85.7%	83.4%	36.82	<0.0001
Curvilinear	MRR	97.2%	**96.3%**	101.1	<0.0001
	SR	95.2%	**94.0%**	79.46	<0.0001
	TWR	93.9%	**92.8%**	91.80	<0.0001
Logarithmic	MRR	93.5%	92.4%	86.44	<0.0001
	SR	90.9%	89.3%	59.68	<0.0001
	TWR	85.6%	83.2%	35.56	<0.0001

TABLE 4. New process variables for model validation

NO	T_{off} (μm)	T_{on} (μm)	I (A)	η (s.)	V (V)
1	75	150	12	1.3	55
2	75	50	18	1	55
3	75	100	24	0.7	55
4	75	150	24	1	55
5	75	150	18	0.7	55
6	75	50	12	0.7	55

Figure 3, demonstrates the interaction effect of peak current and pulse on time on TWR (three out of the five parameters remained constant). As illustrated, within the range of 25-to-200 μs, by increasing the pulse on time the TWR decreases. Similarly by increasing the peak current, within the range of 2.5-to-7.5A, the TWR increases. Figure 4 demonstrates the interaction effect of peak current and pulse on time on SR. As illustrated, by increasing the peak current and pulse on time the SR increases. Figure 5 demonstrates the interaction effect of peak current and pulse on time on MRR. As illustrated, by increasing the peak current and pulse on time the MRR increases.

TABLE 5. Results of validation experiments

Machining parameters	Error (%)		
	Linear	Logarithmic	Curvilinear
MRR	9.96	8.66	**6.34**
SR	5.82	4.97	**3.54**
TWR	6.38	5.62	**4.25**

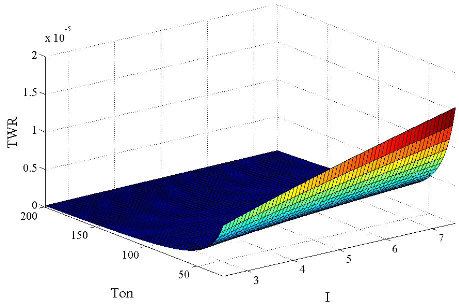

Figure 3. Interaction plot for TWR

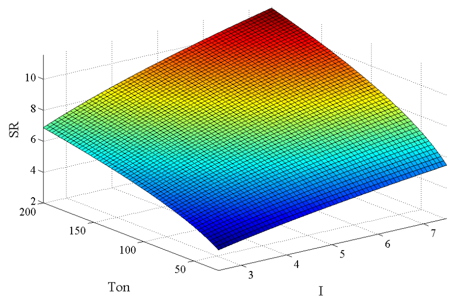

Figure 4. Interaction plot for SR

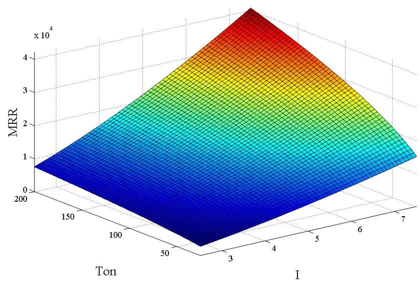

Figure 5. Interaction plot for MRR

7. ANALYSIS OF VARIANCE (ANOVA)

The ANOVA is used to find the most influential parameters to the process factor-level response. In this investigation, the experimental data are analyzed using the F-test and the contribution rate [13, 16]. ANOVA has been performed on the above model to assess their adequacy, within the confidence limit of 95%. ANOVA results indicate that the model is adequate within the specified confidence limit. The calculated determination coefficient (R^2) for this model is 95.2%. Result of ANOVA is shown in Table 3.

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 are illustrated in Table 6, 7 and 8 [14-19].

ANOVA results may provide the percent contributions of each parameter [20].

$$P_i\,(\%) = \frac{SS_i - (DOF_i \times MS_{error})}{Total\ Sum\ of\ Squre} \tag{18}$$

In the above formula, according to the ANOVA results (Table 5), P_i is contribution percentage, SS_i sum of square, DOF_i degree of freedom of i th factor, and MS_{error} mean sum of square of error [20].

The percent contributions of the EDM parameters on MRR, SR and TWR are shown in Figures 6, 7 and 8 respectively.

According to Figure 6, peak current is the major factor affecting the MRR with 54% contribution. It is followed by pulse on time and voltage with 18.8 and 10.5% respectively. The remaining (4%) effects are due to noise factors or uncontrollable parameters.

Moreover, pulse on time is the major factor affecting the SR (Figure 7) with 59.25% contribution, followed by peak current with 26.65% 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 (Figure 8).

TABLE 6. Result of ANOVA for Material Removal Rate

Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (MS_j)	F-Value	Contribution Percentage (%)
A	1	56.76	16.810	6.895*	2.34
B	1	428.92	35.195	14.435*	18.80
C	1	1227.77	203.516	83.471*	54.00
D	1	240.79	52.439	21.508*	10.50
E	1	35.83	36.870	15.122*	1.45
BB	1	33.42	33.415	13.705*	1.36
CC	1	123.50	123.498	50.652*	5.33
DD	1	35.15	46.875	19.225*	1.44
BC	1	26.88	26.880	11.025*	1.81
Error	26	63.39	2.438	-	-
Total	35	2272.39	-	-	-

*Significant Parameters, $F_{0.05,1,26} = 4.23$

TABLE 7. Result of ANOVA for Tool Wear Rate

Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (MS_j)	F-Value	Contribution Percentage (%)
B	1	5479.63	146.49	9.537*	80.00
C	1	329.12	853.36	55.557*	4.54
BB	1	102.73	102.73	6.688*	1.27
BC	1	530.11	530.11	34.512*	7.45
Error	27	476.16	15.36	-	-
Total	35	6917.75	-	-	-

*Significant Parameters, $F_{0.05,1,26} = 4.23$

TABLE 8. Result of ANOVA for Surface Roughness

Machining parameters	Degree of freedom (Dof)	Sum of square (SS_j)	Adjusted (MS_j)	F-Value	Contribution Percentage (%)
B	1	236.984	12.3943	17.3869*	59.25
C	1	106.886	9.1071	12.7756*	26.65
BB	1	9.925	9.9252	13.9232*	2.32
CC	1	6.735	6.7348	9.4477*	2.50
BC	1	14.633	14.6330	20.5274*	3.50
Error	26	38.242	1.4708	-	-
Total	35	398.771	-	-	-

*Significant Parameters, $F_{0.05,1,26} = 4.23$

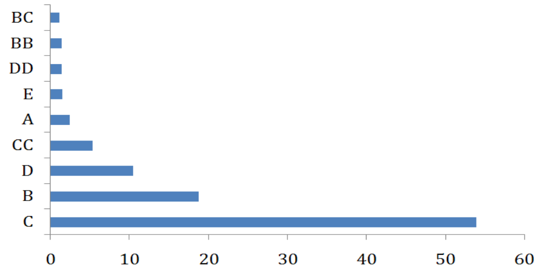

Figure 6. The effect of machining parameters on the MRR

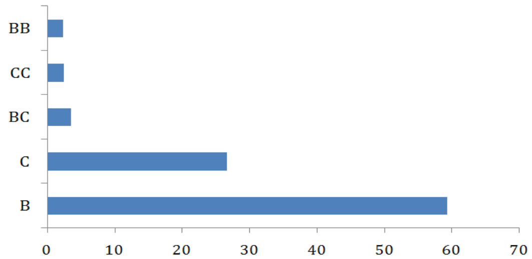

Figure 7. The effect of machining parameters on the SR

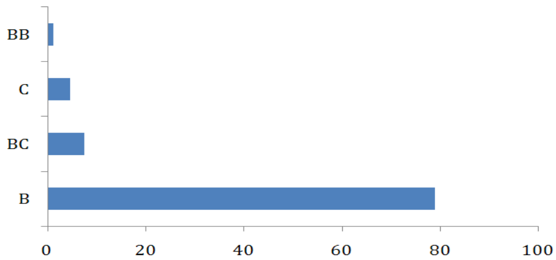

Figure 8. The effect of machining parameters on the TWR

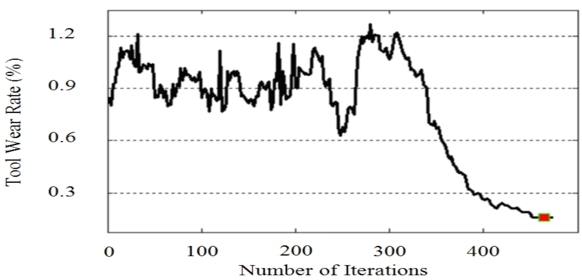

Figure 9. Simulated annealing algorithm convergence curve for TWR

8. SIMULATED ANNEALING ALGORITHM

For real and large size optimization problems, the traditional optimization methods are often inefficient and time consuming. With the advent of computer technology and computational capabilities in the last few decades, the applications of heuristic algorithms are widespread. These techniques are usually based on the physical or natural phenomena. In 1953, Metropolis proposed a procedure used to simulate the cooling of a solid for reaching a new energy state. The annealing process, used in metal working, involves heating the metal to a high temperature and then letting it gradually cools down to reach a minimum stable energy state. If the metal is cooled too fast, it won't reach the minimum energy state. Later Kirkpatrick and his colleagues used this concept to develop a search algorithm called simulated annealing (SA) [21]. Among different heuristic algorithms, SA is one of the most powerful optimization methods that simulates the cooling process of a molten metal. The general stages of the SA algorithm for the job scheduling on parallel machines are as follows:

1. Begin: Initialize the temperature parameter T_0 and the cooling schedule; r (0 < r < 1) and the termination criterion (e.g. number of iterations k = 1… K). Generate and evaluate an initial candidate solution (perhaps at random); call this the current solution, c.
2. Generate a new neighboring solution, m, by making a small change in the current permutation of jobs and evaluate this new solution
3. Accept this new solution as the current solution if:

3-a) The objective value of new solution, f (m), is better than of the current solution, f (c).

3-b) The value of acceptance probability function given by (exp (f (m) – f (c)) / T_k) is greater than a uniformly generated random number "rand"; where 0 < rand < 1.

4. Check the termination criterion and update the temperature parameter (i.e., $T_k = r \times T_{k-1}$) and return to Step 2.

The main advantages of SA are its flexibility, its fewer tuning parameters, and its ability to escape local optima and to approach global optimality [20]. The algorithm is quite versatile since it does not rely on any restrictive properties of the mathematical formulation of the problem and hence can be adapted to a wide range of problems. In addition, for any heuristic optimization procedure, the algorithm parameters should be tuned to enhance its performance. Therefore, the ease of tuning a given algorithm is an important feature in selecting a proper solution technique. In SA, there are only two major tuning parameters -the initial temperature and cooling schedule. As a result, SA can easily be "tuned" with minimum trial runs [21].Simulated annealing can avoid local optima by occasionally taking downward steps. That is, a non-improving neighbor may be accepted as the new current solution. To do so, the initial temperature, T, starts out large and is gradually reduced as search progresses (see Step 4). The result is that early in the search, the current solution "bounces around" the search landscape with little inhibition against moving to the solutions of lower fitness. As the number of iterations increases, the bounces become lower in amplitude and worse neighbors are accepted with lower probabilities and only when they are not much worse than the current solution. Thus, at the start of SA most worsening moves are accepted, but at the end only improving ones are likely to be accepted. This, to a large extent, helps the algorithm jump out of local optima. The details of this technique and its various applications are well documented in related literature [21]. Final optimization results are summarized in Table 7. Figure 9 shows the simulated annealing algorithm convergence for minimization of TWR.

9. RUNNING CONFIRMATION EXPERIMENTS

To evaluate the adequacy of the proposed approach and statistical analysis, a set of verification test has been carried out based on the predicted values.

TABLE 9. Optimization results of the proposed SA algorithm and confirmation experiments

Optimal condition				
	Prediction	**Experiment**	**Difference**	**Error (%)**
MRR	0.82	0.78	0.04	4.8
TWR	0.18	0.17	0.1	5.5
SR	2.5	2.6	0.1	4
Parameter setting for MRR (T_{off} = 10 μs, T_{on}=195 μs, I = 7.49 A, η =0.4 S, V = 50.01V)				
Parameter setting for TWR (T_{off} = 10.01μs, T_{on}=113.93 μs, I =2.6 A, η =1.01 S, V =60 V)				
Parameter setting for SR (T_{off} =10.04 μs, T_{on}=25.01 μs, I =2.5 A, η =0.4 S, V =55.08 V)				

The optimal levels of the process parameters are predicted based on S/N value given in Table 2. Table 9 shows the comparison between the predicted and experimental results using optimal process parameters. As indicated, the differences between predicted and actual process outputs are less than 6%. 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 values.

10. CONCLUDING REMARKS

This study is focused on modeling, and optimization of EDM process on AISI 2312 hotworked steel parts. The following can be concluded from the present study.

The S/N model for MRR, SR and TWR were developed from the experimental data. Then, statistical analyses have been carried out to select the best and most fitted models. Next, simulated annealing (SA) algorithm has been employed for optimizations of process parameters. The predicted and measured values are fairly close, which indicates that the developed model can be effectively used to predict the MRR, SR and TWR for EDM process.

Validation of the models via new set of experiments illustrated that the curvilinear model is the best and most fitted among the proposed models.

Peak current followed by pulse on time are the most significant factors affecting the MRR with 54% and 18% percent contribution, respectively.

Pulse on time followed by peak current are the most significant factors affecting the SR with 59.25% and 26.65% percent contribution, respectively.

pulse on time is the most significant factor affecting the TWR with 80% percent contribution.

The study can be extended using other methods like response surface methodology, hybrid approaches composed of ANN and heuristic algorithms to undertake the modeling and optimization for EDM of AISI2312 hot worked steel parts and etc.

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Optimization of EDM Process Parameters Using Statistical Analysis and Simulated Annealing Algorithm

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PAPER INFO

Paper history:
Received 11 February 2014
Received in revised form 13 May 2014
Accepted 14 August 2014

Keywords:
Electrical Discharge Machining (EDM)
Optimization
Signal to Noise Analysis (S/N)
Modeling
Simulated Anealing Algorithm (SA)
Analysis Of Variance (ANOVA)

چکیده

امروزه ماشین‌کاری تخلیه الکتریکی به یکی از پرکاربردترین فرآیندهای پیشرفته ماشین‌کاری تبدیل شده است. در این فرآیند به دلیل استفاده از انرژی گرمایی برای براده‌برداری، سختی ماده، عامل باز دارنده نبوده و می‌توان مواد سختی که برای ساخت قالب‌های تزریق پلاستیک و قطعات مربوط به صنعت هوا-فضا به کار می روند را به آسانی ماشین‌کاری کرد. از آنجا که این فرآیند هزینه‌بر می‌باشد، لذا انتخاب صحیح پارامترهای ماشین‌کاری در قیمت تمام شده و کیفیت قطعات تولیدی مؤثر می‌باشد. در این تحقیق، تاثیر پارامترهای تنظیمی در ماشین‌کاری تخلیه الکتریکی فولاد گرم‌کار ۲۳۱۲ مورد استفاده در صنعت قالب‌سازی، مدل سازی و بهینه سازی شده است. مدل سازی فرآیند توسط روش های آماری و با استناد بر داده های تجربی انجام یافته است. پارامترهای ورودی شامل جریان الکتریسیته، زمان‌های روشنی و خاموشی پالس، فاکتور کار و ولتاژ کاری می‌باشند. همچنین نرخ براده‌برداری، نرخ خوردگی الکترود و زبری سطح به عنوان مشخصه‌های خروجی فرآیند درنظر گرفته شده اند. به منظورگردآوری داده های مورد نیاز در انجام این تحقیق، آزمایشات تجربی با استفاده از طرح تاگوچی L36 انجام شده است. پس از اخذ داده های مورد نظر، از روش تاگوچی مقدار سیگنال به نویز مربوط به هر مشخصه خروجی محاسبه شده و سپس جهت ایجاد ارتباط بین پارامترهای ورودی و مشخصه‌های خروجی با بکارگیری توابع رگرسیونی، مدل‌های ریاضی طراحی گردید. سپس توسط تحلیل‌های آماری ، مدل رگرسیونی اصلح مربوط به هر مشخصه خروجی فرآیند انتخاب شد. در بخش آخر این تحقیق، با به کارگیری الگوریتم تبرید تدریجی سطوح مختلف پارامترهای ورودی برای نیل به خروجی بهینه‌ی مد نظر، تعیین شدند. بر اساس روش بهینه سازی پیشنهادی می توان بهترین مجموعه از پارامترهای تنظیمی فرآیند را به منظور کسب خروجی مورد نظر تعیین نمود. نتایج بهینه سازی نیز توسط آزمایشات تجربی صحه گذاری گردید. نتایج حاصل از بهینه‌سازی و آزمایشات تجربی نشان داد که به کارگیری هم‌زمان روش مدل‌سازی مطرح شده والگوریتم تبرید تدریجی می‌تواند به ابزاری کار آمد برای مدل سازی و بهینه‌سازی پارامترهای فرآیند تخلیه الکتریکی تبدیل شود.

doi: *10.5829/idosi.ije.2014.28.01a.20*