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مسعود آزادی مقدم، فرهاد کلاهان

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گواهی ارائه مقاله

بدین وسیله گواهی می‌شود مقاله زیر در

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عنوان مقاله :

Reduction of Tool Wear in EDM Process Using Statistical Analysis and Simulated Annealing Algorithm

نویسندگان :

مسعود آزادی مقدم، فرهاد کلاهان

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Reduction of Tool Wear in EDM Process Using Statistical Analysis and Simulated Annealing Algorithm

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Abstract— 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, pulse on time and pulse off time, duty factor and voltage. Tool wear rate is one of the most important performance characteristic of the EDM process. Taguchi robust design technique was applied to obtain the signal to noise 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 data, based on output characteristic. The significance of the process parameters on the quality characteristic of the EDM process was also evaluated quantitatively using the analysis of variance method. Then, statistical analyses and validation experiments have been carried out to select the best and most fitted model. In the last section of this research, simulated annealing algorithm has been employed for optimizations of process parameters. The results indicate that the proposed modeling technique and simulated annealing algorithm are quite efficient in modeling and optimization of EDM process parameters.

Index Terms— Electrical discharge machining (EDM), Optimization, Signal to noise analysis (S/N), Modeling, Simulated annealing (SA) algorithm, Analysis of variance (ANOVA).

I. Introduction

AISI2312 is one of the most difficult-to-cut hot worked alloys. Formation of complex shapes (of this material) along with reasonable speed is very difficult by traditional machining. Electric 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 work piece by erosion effect of series of electric discharges (sparks) between tool and work piece 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 moulds, dies; aerospace and surgical components. The EDM process has a very strong stochastic nature due to the complicated discharge mechanisms making it difficult to optimize the process [1-5]. The process performance can be improved by selecting the optimal combination of process parameters.

However, experimental optimization of any machining process is costly and time consuming due to the complex, coupled and non-linear nature of the input–output variables of machining processes. Hence, many researchers have concentrated on improvement and optimization of performance measures of EDM process by using different modifications and optimization methods like Taguchi technique, response surface methodology, artificial neural network, genetic algorithm (GA), grey relational analysis (GRA), fuzzy logic, factorial design, simulated annealing (SA) algorithm etc. with variation of different electrical and non-electrical process parameters [6-9].

II. Experimental Details

A. Experimental details

a) Work piece 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 poor machine ability. 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 10mm thick and 40×20mm dimension.

b) 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). Die-sinking machine used is shown in figure 2.

Fig. 1. Die-sinking EDM machine used

c) Electrode and Dielectric

A total of 36 cylindrical shape electrodes of 20-mm diameter made from 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.

d) 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).

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

TABLE I. 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

e) Sample Preparation and Experimental Procedure

All the specimens were cleaned in an alcohol bath and then dried using a drier.

III. Evaluation of Performance Measures

The TWR, usually expressed as a percentage, and is defined by the ratio of the tool wear weight (TWW) to the work piece removal weight (WRW) which is obtained using equation (1). To measure the TWR an A&D electronic balance with 0.01gr accuracy was used.

$$TWR\ (\%) = \frac{TWW}{WRW} \times 100 \qquad (1)$$

IV. Signal To Noise 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 very new electrode with the same sizes. [10]. 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 "the Higher the

Better, (HB)" for output characteristics which the higher values are desired such as material removal rate, are given in the following equations [11, 12].

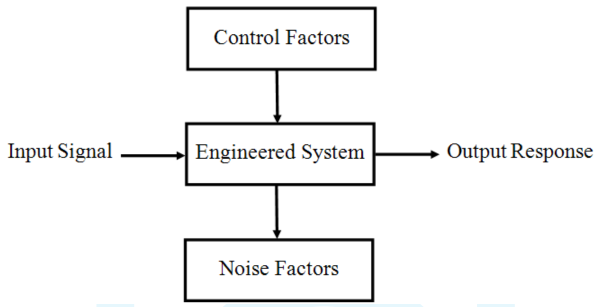

Fig. 2. Schematic of an engineered system

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

$$\textbf{HB}: \; S/N(\phi) = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^{2}}\right) \tag{3}$$

Where n is number of iteration in a trial, in this case, n =1 and y_j is the j[th] measured value in a run.

The results of S/N ratios for the process promoters are shown in Table II.

TABLE II. THE PROCESS CHARACTERISTICS AND THEIR CORRESPONDING SIGNAL TO NOISE RATIO (S/N)

No	Tool Wear Rate	S/N for Tool Wear Rate
1	11.4	-21.159
2	2.6	-8.404
3	0.6	4.467
4	9.0	-19.172
.	.	.
.	.	.
.	.	.
33	0.7	3.046
34	47.0	-33.453
35	1.6	-3.876
36	0.2	14.202

V. 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 II 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 4 to 6 respectively.

$$Y_1 = b_0 + b_1S + b_2V + b_3F + b_4D + b_5A \tag{4}$$

$$\begin{aligned} Y_2 = {} & b_0 + b_1S + b_2V + b_3F + b_4D + b_5A \\ & + b_{11}SS + b_{22}VV + b_{33}FF + b_{44}DD + b_{55}AA \\ & + b_{12}SV + b_{13}SF + b_{14}SD + b_{15}SA + b_{23}VF \\ & + b_{24}VD + b_{25}VA + b_{34}FD + b_{35}FA + b_{45}DA \end{aligned} \tag{5}$$

$$Y_3 = b_0\, S^{b1}\; V^{b2}\; F^{b3}\; D^{b4}\; A^{b5} \tag{6}$$

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 II, 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 7 to9.

Stepwise elimination process was used to modify the initial proposed models. For instance, as can be seen in Equation 9, independent variable A was eliminated because of its improper effect on TWR in the curvilinear model.

a) Linear Model

$$S/N\,(TWR) = -38.3 - 0.0402\,A + 0.172\,B - 1.48\,C + 0.297\,D + 0.372\,E \tag{7}$$

b) Curvilinear Model

$$S/N\,(TWR) = -12.5099 + 0.150794\,B - 4.32222\,C - 0.000479414\,BB + 0.0262243BC \tag{8}$$

c) Logarithmic Model

$$S/N\,(TWR) = e^{6.240} A^{0.149} B^{-1.640} C^{0.751} D^{-1.850} E^{-0.117} \tag{9}$$

Adequacies of models were checked by analysis of variance (ANOVA) technique within the confidence limit of 95% [17, 18]. Results are shown in Table III. 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 other two, thus, this model is considered as the best representative of the authentic EDM process throughout in this paper.

In the next step the proposed models validation using new set of experiments (Table IV). Table V illustrates the mean error of the new six experiments for the output characteristic. According to the result, the curvilinear model is the best model among the proposed models for the process characteristic.

TABLE III. ANOVA RESULTS FOR S/N RATIO MODELS

Model	R^2	R^2 (adj)	F value	Pr>F
Linear	85.7%	83.4%	36.82	<0.0001
Curvilinear	**93.9%**	**92.8%**	**91.80**	**<0.0001**
Logarithmic	85.6%	83.2%	35.56	<0.0001

TABLE IV. NEW PROCESS VARIABLES FOR MODEL VALIDATION

NO	T_{off} (µm)	T_{on}(µm)	I(A)	η(Sec.)	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

TABLE V. RESULTS OF VALIDATION EXPERIMENTS

Machining parameters	Error (%)		
	Linear	Logarithmic	Curvilinear
TWR	6.38	5.62	**4.25**

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.

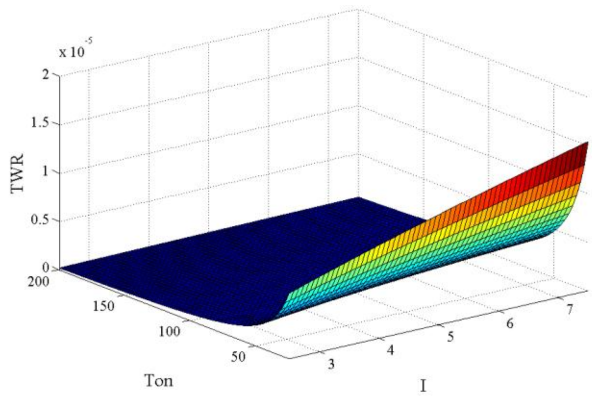

Fig. 3. interaction plot for TWR

VI. Analysis Of Variance (Anova)

The ANOVA is used to investigate 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 VI.

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 VI [14-19].

TABLE VI. RESULT OF ANOVA FOR TOOL WEAR RATE

parameters	Degree of freedom (Dof)	Sum of square (SSj)	Adjusted (MSj)	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,	$F_{0.05,1,26} = 4.23$				

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

$$P_i\,(\%) = \frac{SS_i - (DOF_i \times MS_{error})}{Total\ Sum\ of\ Squre} \tag{10}$$

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

The percent contribution of the EDM parameters on TWR is shown in Figures 4. According to Figure 4, the main process parameter affecting tool wear rate is pulse on time with 80% contribution.

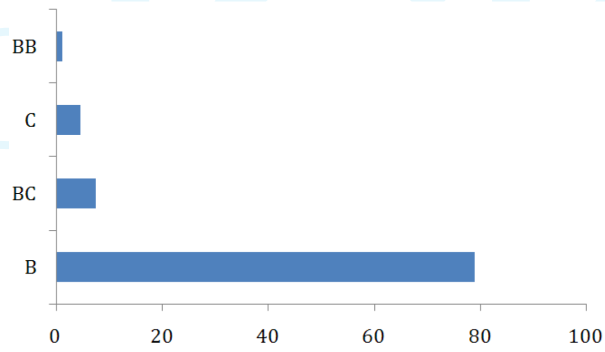

Fig. 4. The effect of machining parameters on the TWR

VII. 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 metalworking, 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 will not reach the minimum energy state. Later Kirkpatrick and his colleagues used this concept to develop a search algorithm called Simulated Annealing (SA) [14]. 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 [14].

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 [14].

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 extend, helps the algorithm jump out of local optima. The details of this technique and its various applications are well documented in relate literature [14].

The final optimization result is summarized in Table VII. Figure 5, shows the simulated annealing algorithm convergence for minimization of TWR.

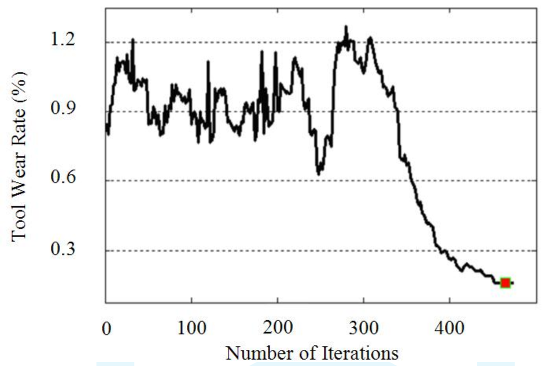

Fig. 5. Simulated annealing algorithm convergence curve for TWR

VIII. 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.

The optimal levels of the process parameters are predicted based on S/N value given in Table 2. Table VII, shows the comparison between the predicted and experimental results using optimal process parameters. As indicated, the differences between predicted and actual process output is less than 6%. Given the nature of EDM process and its many variables, these results are quite acceptable and prove that the experimental result is correlated with the estimated values.

TABLE VII. OPTIMIZATION RESULTS OF THE PROPOSED SA ALGORITHM AND CONFIRMATION EXPERIMENTS

TWR	Optimal condition			
	Prediction	Experiment	Difference	Error (%)
	0.18	0.17	0.1	5.5
Parameter setting (Toff = 10.01µs, Ton =113.93 µs, I =2.6 A, η =1.01 S, V =60 V)				

IX. Concluding

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

1. The S/N model for TWR was 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 TWR for EDM process.
2. Validation of the models via new set of experiments illustrated that the curvilinear model is the best and most fitted among the proposed models.
3. Pulse on time is the most significant factor affecting the TWR with 80% percent contribution.
4. The study can be extended using other methods like response surface methodology, hybrid approaches composed of ANN and heuristic algorithms.

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