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Research Article

Input Parameters optimization in EDM Process using RSM and JAYA Algorithm

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Abstract

The present work is planned to optimize the material removal rate (MRR), tool wear rate (TWR) and surface roughness (Ra) in electric discharge machining (EDM) process. Response surface methodology (RSM) is very useful for mathematical modeling to relate the input and output responses. Jaya algorithm (JA); newly developed by Rao, 2016 to optimize the complex engineering problems. In the present analysis, the effectiveness of RSM along with JA has been studied in optimization of EDM process when machining of RENE80 nickel super alloy material with aluminum as a tool electrode. Same problem had been optimized by using Taguchi method (Chandramouli et al., 2014).From the analysis, it is found that RSM and JA is very efficient to optimize EDM process.

Keywords: *Electric discharge machining, Material removal rate, Tool wear rate, Surface roughness, Jaya algorithm.*

1. Introduction

Electrical Discharge Machining (EDM) is a non-conventional machining options widely used for machining of difficult -to- machine materials with complex geometrical shapes with high precision in various manufacturing industries (Beri *et al*., 2010). It is extensively used in the aerospace, automobile, die manufacturing, plastic mould industries and surgical components (Marafona, 2009; Hoand Newman 2003). EDM process has the capacity of producing three dimensional complex shapes on any material regardless of its hardness, strength, and toughness provided its electrical resistivity is not more than 100 ohm-cm [Kunieda *et al*., 2005]. It is a thermal process, in which unwanted material is removed by erosive action of spatially discrete high frequency electrical discharges i.e. spark of high power density created by electric pulse generator at short intervals between the tool electrode and work piece electrode. During machining process, eroded particles from the gap between the electrodes are flushed with use of dielectric fluid, so surface damage can be minimized. The surface temperatures of both the tool as well as work pieces are increased to a point that is in excess of the melting points of the substances due to electric speaks generated during machining process. Cutting tool does not co-developed in the job. The material is removed in the liquid and vapor phases only thus, generated surface of debris have been melted or vaporized during machining (Kunieda *et al*., 2005). And thermal and electrical properties can play very important role in the machining performance tact with the work-piece so, no mechanical stressed. developed in the job. The material is removed in the liquid and vapor phases only thus, generated surface of debris have been melted or vaporized during machining (Kunieda *et al*., 2005). And thermal and electrical properties can play very important role in the machining performance.

The main factors influencing performance characteristics or quality characteristics of EDMed partsare: spark gap, electrical parameters (like frequency, current, and voltage), material properties of electrode, the workpiece, and the dielectric fluid i.e. melting point, thermal conductivity, and specific heat (Beri *et al*., 2010).The EDM performance is characterized by three parameters viz., material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR) etc. Several researchers carried-out various investigations for improving the process performance. Proper selection of machining parameters for the best process performance is still a challenging job. As EDM is very complex and stochastic process, it is very difficult to determine optimal parameters for best machinery performance i.e., productivity and accuracy. In the present study, MRR, TWR and Ra have been considered as responses which are conflict in nature. Higher the MRR is better whereas, lower the TWR and R_a is better. MRR reflects

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the productivity and TWR and Ra reflect the accuracy of the product.

Various research works had been reported in literature on parametric analysis, parametric modeling and optimization of EDM process to get desired responses. Some of those are discussed as follows. (Zhang*et al*. 1997) had investigated the effects of input parameters on material removal rate, surface roughness and diameter of discharge points in electro - discharge machining (EDM) of advanced ceramic materials. (Singh *et al*. 2004) had optimized the multi – responses: metal removal rate, tool wear rate, taper, radial overcut and surface roughness on electrical discharge machining of Al- 10%SiCp composites. (Yih - fong and Fu- chen 2003) had experimented and made statistical analysis on EDM process to analyze the effects of EDM parameters on response characteristics. They found from the analysis that input parameters such as pulse - on time, duty cycle, and pulse peak current have more influence on output characteristics. (Lee *et al*. 2001) had studied the influence of operating parameters of EDM of tungsten carbide on material removal rate, relative wear ratio and the surface quality of the work - piece produced.

Analysis and optimization of EDM process is difficult task, due to the various complexities in it. Systematic optimization or analysis technique is required to understand and optimize the EDM process economically. Improving the EDM process efficiency by controlling the machining operation precisely is important area of research. Recently several authors have optimized EDM process with use of statistical, evolutionary and swarm intelligence based algorithms. Some of the reported articles based on EDM optimization wth the use of various said techniques in literature, are discussed as follows.

Patel *et al* 2009 postulated empirical relations between input parameters and surface roughness, and MRR of alumina ceramic in EDM process using response surface method (RSM). (Das *et al*., 2014) applied RSM and artificial bee colony algorithm to predict MRR and surface roughness.(Rao *et al*. 2008) had optimized MRR of die sinking EDM by using multi perceptron neural network models.(Hasda 2013) had analyzed and optimized the process parameters of EDM operation using teaching learning based optimization (TLBO) algorithm. (Tzeng and Chen 2011)used hybrid optimization methodologies including a back-propagation neural network(BPNN), a genetic algorithm (GA) and response surface methodology (RSM) to predict optimal parameter settings of the EDM process.

In the present work, the experimental analysis have been carried out to investigate the factor effects on material removal rate (MRR), tool wear rate (TWR) and surface roughness (SR) in EDM process when machining of RENE80 nickel super alloy material. Experiments have been conducted by using response surface methodology. Mathematical modeling has been done to relate the input parameters and output responses.

2. Response surface methodology (RSM) and Jaya algorithm

Response surface methodology (RSM) is a collection of mathematical and statistical procedures that are useful for modeling and analysis of problem, where output response is expected by various process variables and the objective is to optimize the response. RSM is very useful to find the operating conditions that produce the best response and identify new operating conditions that produce improved part qualities over the qualities achieved. In RSM, the mathematical model is developed to develop the relationships between the process variable and response. In the RSM, the quantitative form of relationship between the desired response and independent input variables can be presented as follows;

$$Y = f(A,B,C) \tag{1}$$

where, A, B, C are input parameters and Y is the response variable,

The full quadratic model of the three factors is shown in Eq.2.

$$Y = \beta_0+\beta_1 (A) + \beta_2 (B)+\beta_3 (C)+ \beta_{11} (A^2) +\beta_{22} (B^2) + \beta_{33} (C^2) + \beta_{12} (AB)+\beta_{13} (AC)+ \beta_{23} (BC) \tag{2}$$

The betas are coefficients of linear, quadratic and interaction of input parameters A, B and C. The term $\beta 0$is the intercept term, β_1, β_2 and β_3 are the liner terms,β_{11}, β_{22} and β_{33} are the squared terms, and β_{12},$\beta_{13}$and β_{23} are the interactions between the independent / input variables. This empirical model is useful to determine the optimum parametric condition to obtain desired response variable.

Jaya algorithm: Let f(x) is the objective function to be minimized (or maximized). At any iteration i, assume that there are 'm' number of design variables (i.e. j=1,2,…,m), 'n' number of candidate solutions (i.e. population size, k=1,2,…,n). Let the best candidate best obtains the best value of f(x) (i.e. f(x)best) in the entire candidate solutions and the worst candidate worst obtains the worst value of f(x) (i.e. f(x)worst) in the entire candidate solutions. If Xj,k,iis the value of the jth variable for the kth candidate during the ith iteration, then this value is modified as per the following Eq. (1).

$$X'_{j,k,i}= X_{j,k,i}+ r_{1,j,i} (X_{j,best,i}- |X_{j,k,i}|) - r_{2,j,i} (X_{j,worst,i}- |X_{j,k,i}|) \tag{3}$$

where, Xj,best,iis the value of the variable j for the best candidate and Xj,worst,is the value of the variable j for the worst candidate. X'j,k, is the updated value of Xj,k,iand r1,j,i and r2,j,i are the two random numbers for the jth variable during the ith iteration in the range [0, 1]. The term "r1,j,i ((Xj,best,i- |Xj,k,i|)" indicates the tendency of the solution to move closer to the best solution and the term "-r2,j,i (Xj,worst,i-

│Xj,k,i│)"indicates the tendency of the solution to avoid the worst solution. X'j,k,iis accepted if it gives better function value. All the accepted function values at the end of iteration are maintained and these values become the input to the next iteration.

Fig.1 shows the flowchart of the proposed algorithm. The algorithm always tries to get closer to success (i.e. reaching the best solution) and tries to avoid failure (i.e. moving away from the worst solution.

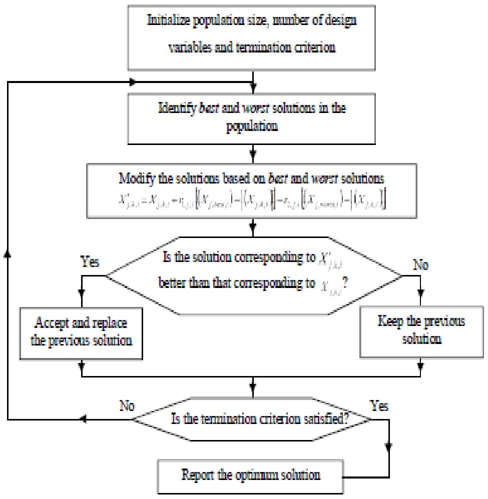

Fig. 1. Flowchart of the Jaya algorithm

3. Case study

The experimental data is taken from Chandramouli *et al*., 2014, to test the effectiveness of the proposed hybrid technique (i.e. RSM and jaya algorithm). The experimental data is shown in Table 1.RSM technique is applied on experimental data as given in Table 1 to postulate the mathematical relationships between input parameters and output responses: MRR, TWR and Ra. Intended from of second order mathematical equation is given in Eq.2. The developed mathematical models for MRR are given in Eq.4, TWR in Eq.5 and Ra in Eq.6.

$$Y_{MRR} = 80.971+9.944*A-3.0252*B-11.515*C-0.234*A*B+0.366*A*C+0.310*B*C \quad (4)$$

$$Y_{TWR} = 7.677+2.813*A-0.149*B-1.914*C-0.081*A*B+0.058A*C+0.0517*B*C \quad (5)$$

$$Y_{Ra} = 0.679+0.038*A+0.183*B+0.159*C+0.001*A*B-0.002*A*C-0.007*B*C \quad (6)$$

The model equations of MRR (Eq.4), TWR (Eq.5) and surface roughness (Eq.6) have been solved by jaya algorithm for process optimization. Details of jaya algorithm are explained in section 2. In each of the jaya algorithm runs, optimal parametric condition and the corresponding output response value are produced. In the present case, optimal parametric setting has been obtained in first run itself. Maximum MRR value i.e. MRR = 388 mm³/min for EDM machining of RENE80 nickel super alloy is obtained at current (A) = 24 A, pulse on time (B) = 30µs and pulse off time (C)= 50µs and lower tool wear rate (TWR = -33 mg/min) is obtained at current (A) = 6 A, pulse on time (B) = 10 µs and pulse off time (C)= 50µs, and Minimum surface roughness (i.e. Ra =3.57 micron) is obtained at current (A) = 24 A, pulse on time (B) = 30 µs and pulse off time (C)= 50µs; these are also listed in Table 2. Thus single objective optimization is carried out for material removal rate (MRR), tool wear rate (TWR) and surface roughness (R_a) separately.

Table1 Experimental results

S.No.	Input parameters			Output parameters		
	Current (A)	Pulse on time (B)	Pulse off time (C)	MRR	TWR	Ra
1	6	10	10	18.8	4.83	3.67
2	6	20	20	8.5	5.2	5.25
3	6	30	50	9.5	3.4	3.94
4	15	10	20	128.3	26.3	4.18
5	15	20	50	87.5	14.71	5.15
6	15	30	10	52.8	9.7	6.46
7	24	10	50	253.6	48.3	5.99
8	24	20	10	165	35.5	5.94
9	24	30	20	212.3	33.8	6.21

Table 2 Optimum output responses obtained by JAYA algorithm

Output response	Input parameters		
	Current (A)	Pulse on time (B)	Pulse off time (C)
MRR = 388 mm³/min	24 A	30µs	50µs
TWR = -33 mg/min	6 A	10µs	50µs
Ra = 3.57 micron	24 A	30µs	50µs

Conclusions

1. Electrical discharge machining (EDM) is versatile machining process very useful for machining of hard materials.
2. Process parameters have great effect on output responses.
3. Optimum parametric selection is very important for achieving desired quality levels.
4. Mathematical modeling has done by RSM technique for material removal rate (MRR), tool wear rate (TWR) and surface roughness (R_a).
5. Optimal parametric settings has obtained by JAYA algorithm are as follows: for maximization of MRR it is: current (A) = 24 A, pulse on time (B) = 30µs and pulse off time (C)= 50µs; for lower tool wear rate it is: current (A) = 6 A, pulse on time (B) = 10 µs and pulse off time (C)= 50µs, and minimum Ra value it is: current (A) = 24 A, pulse on time (B) = 30 µs and pulse off time (C)= 50µs.
6. RSM and JAYA algorithm is found to be very effective to model and optimize the EDM process

when machining of RENE80nickel super alloy material.

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