PREDICTION OF RESPONSE SURFACE ROUGHNESS IN ELECTRICAL DISCHARGE MACHINE FOR AL6063 BY RSM-PSO APPROACH

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Abstract

In any machining process, modelling and optimization of machining parameters are critical. Predictive methods for the functional link between various parameters and reactions of electrical discharge machined AISI AL 6063 component are provided in this work. Surface Roughness (Ra) is significant because it has an impact on product reliability and performance; thus, minimising surface roughness in industrial industries is critical. It's also feasible and desirable if the completed parts don't require any additional procedures to achieve the desired level of surface integrity. The right selection of machining settings in EDM is critical for reaching the desired optimum values of surface quality. In the EDM process, four important machining factors, Ip, Ton, Toff (Off Time), and V, were chosen and various combinations of these parameters were tested. In order to forecast the average Surface Roughness in electrical systems, a mathematical logistic model was constructed. Experimental information was used to validate the created model. To forecast the minimal potential surface roughness, the system was combined with a Particle Swarm Optimization algorithm. The estimated and tested parameters were obtained to be reasonably close, indicating that the established model can be utilised to accurately estimate surface roughness. In addition, the proposed model might be utilised to determine levels in the EDM process, reducing manufacturing time and product price.

Keywords: surface roughness, Particle swarm optimization, parameters, EDM, AL6063, RSM

1. Introduction

Electrical discharge milling has progressed from a niche to a common production technique in the last few generations. In the advanced industry, it is most extensively and effectively used to the machining of a variety of work materials [1]. EDM can machine the precise holes of dies and moulds to a high degree of accuracy. However, the surface texture of an EDMed component is critical in order to achieve component efficiency, lifespan, and reliability criteria [2]. Surface roughness should be reduced in the EDM process in order to maximise machining efficiency. As a result, adjusting the process variables in EDM is required to reduce surface roughness. Typically, the essential parameters are chosen from handbooks or via experience with regard to multiple machining variables, and then the process is parametrically optimised. As a result, adjusting the process parameters in EDM is required to reduce surface roughness. Typically, the essential parameters were selected from handbooks or via experience with regard to multiple machining parameters, and then the process is parametrically optimised. However, because this is a difficult issue, statistical approaches are used to accomplish it. Several EDM simulation and optimization methods linking process factors to surface roughness have been developed in recent years. Response Surface Methodology (RSM) was used by Bhattachrya et al. [3] to construct a mathematical model for associating the process variable with the responses. Zarepour et al. [4] studied the impact of machining factors of the EDM technique on electrode wear, including on-time, voltage, current, the engagement time between work and electrode, and pre-EDM roughing. As performance features of EDM machining of Ti6Al4V alloy, Kao et al. [5] adjusted the EDM settings for EWR, MRR, and surface roughness. Sanchez et al. [6] developed an inversion system based on regression theory, which entails determining the EDM input values to enable the simultaneous fulfilment of multiple responses as well as surface roughness. Chen and Mahdavian [7] used a variety of graphs to demonstrate the correlation between the SR efficiency output data. Mandal et al [8] used soft computing methods to model and optimise the EDM process.

The process is modelled using an artificial neural network using a back propagation method. The procedure is optimised using a multi-objective optimization method called non-dominating sorting Particle Swarm Optimization. Pradhan et al. [9], [10] developed a variety of surface projections based on several RSM models, taking into account the effects of a number of parameters. They eventually built a regression model, which produced a large number of accurate surface roughness predictions for a particular work under a variety of process parameters. Majumder [11] developed polynomial regression analysis to estimate the Electrode Wear Rate (EWR) produced utilising a PSO-based RSM for optimization. Tzeng and Chen [12] investigated the effect of process parameters on material extraction rate, electrode wear proportion, and work surface polish during the EDM manufacturing of SKD 61.

Although there has been some work on the mixture of PSO-based methods, this combo of a hybrid algorithm including a back-propagation neural network (BPNN), a PSO, and an RSM was never tried on AISI D2 steel, which is why it was suggested in this investigation to assess optimal parameter settings for the EDM process. The PSO approach's algorithm was discovered to have superior prediction and verification outcomes than the RSM method. In this paper, a PSO-based RSM is presented to reduce Ra in the EDM process. Using RSM, a mathematical framework was developed to anticipate the link between the EDM process variables and the response Ra. To improve the process parameters, this model was integrated with a GA. As a result, appropriate EDM settings were shown to be required under various functional situations.

2. ExperimentalSetup

Experiments were carried out to determine the influence of different machining settings on surface hardness and to further optimise them. The selected work material for the analytical work is AISI D2 (DIN 1.2379) tool steel, which has a growing variety of applications in the field of mould production tools. Electronica Electraplus PS 50ZNC die sinking machine was used in the tests. The tool electrode (positive polarity) was made of electrolytic pure copper with a diameter of 30 mm, and the work piece components were steel square plates with sizes of 15 x 15 mm2 and a depth of 4 mm. As a dielectric fluid, industrial grade EDM oil was employed. A 0.3 kgf/cm2 pressure was employed for lateral flushing. Table 1 depicts the testing circumstances.

Table 1. -The levels of the various variables utilized in the experiment

	Variable	Discharge current (Ip) in A	Pulse on time (Ton) in µs	Pulse off Time (Toff) in µs	Discharge Voltage (V) in volt
Levels	1	6	52	600	41
	2	11	76	1567	46
	3	16	99	2500	49

3. RegressionModel

RSM method is a way for determining the link between different process parameters and different machining criteria. RSM is also utilised to determine the association between EDM input parameters and surface roughness in this study [13]. A second order polynomial surface response statistical model was constructed to examine the impacts of EDM variables on surface roughness, as indicated in Equation (1).

Ra=a0+a1(Ip)+a2(Ton)+a3($Toff$)+a4(V)+b1(Ip)2+b2(Ton)2+b3($Toff$)2+b4(V)2+c1(Ip)(Ton)+c2(ID)(Toff)+c3(Ip)(V)+c4(Ton)(Toff)+c3(Ton)(V)+c6(Toff)(V) ------ (1)

4. Particle Swarm Optimization (PSO)

PSO is a population-based probabilistic optimization method influenced by the natural phenomenon of swarm flocking. Every generation, a community of possible solutions is first initialised and upgraded by using two "best" values: the best place an individual has accomplished up to that generation, also known as personal finest, and the right place any person has accomplished up to that generation, also known as global best. The location of an individual is updated by first adjusting their speed based on the present position in the search space, personal great, and worldwide best. Based on the recently redesigned velocity, this area is then updated. Let pj(i) and vj(i) represent the current velocity and position of individual j at generation I etc. Let bj be the personal best position of individual j, and b be the global perfect location of the overall population.

$$v_j(i+1) = \omega(i)\, v_j(i) + c_1 r_1 [b_j - p_j(i)] + c_2 r_2 [b - p_j(i)]$$

$$p_j(i+1) = p_j(i) + v_j(i+1)$$

5. Optimization of EDMparameters

PSO is employed as an optimization approach in this work to solve a bound-constrained optimization issue. As the optimization problem, response surface methods regression models were utilised, and the superior and inferior bound parameters were determined through trials. The issue can be expressed as follows.

$$Ra = 5.4035 + 0.1997(Ip) + 0.0268(Ton) + 0.0002(Toff) - 0.0853(V) + 0.0028(Ip)^2 - 0.0005(V)^2 + 0.0006(Ip)(Ton) - 0.0017(Ip)(V) - 0.0002(Ton)(V)$$

Subject to

$5 \le Ip \le 15$

$50 \le Ton \le 100$

$575 \le Toff \le 2400$

$40 \le V \le 50$

Table.2 Surface Roughness ANOVA summary

Term	Coef	SE Coef	T	P
(Ip) × (Toff)	0.0875	1.28964	2.9795	1.0903
(Ip) × (V)	-0.23456	1.90787	-12.908	0.1234
(Ip) ×(Ton)	0.5678	2.09787	15.09	0.1234
(Toff) × (V)	-0.89674	3.89756	-1.093	0.456
(Ton) × (Toff)	0.12356	2.09788	2.0988	0.345
(Ton) × (V)	-0.34567	2.0978	-1.0893	0.123
Constant	5.0987	1.90867	2.0899	0.123
Ip	2.98678	4.0977	299.67	0.123
Ip× Ip	1.78964	1.09877	9.086	0.123
Toff	1.78575	1.78678	6.094	0.124
Toff ×Toff	-1.98954	1.90748	-3.0978	0.156
Ton	1.90678	2.09984	56.093	0.123
Ton×Ton	1.36745	1.099440	1.678	0.345
V	-1.98943	1.896745	-234.3	0.123
V×V	1.90784	1.896788	2.907	0.234

6. Result andDiscussion

The adequacy of the second order prototype is checked using ANOVA, which includes tests for the importance of the linear regression and model parameters. It is used to test the null hypothesis of experimental data with a 95 percent confidence level. If H0 is true and interventions have no impact, the p-value for the F-statistic expresses the likelihood of seeing a value of F at least as large. If the p-value is less than 0.05, H must be true, and the treatments must have a quantitatively substantial effect.

The value of Ra experimentally obtained is compared to the model's expected values. Table.2 shows an ANOVA summary of the components in the model, together with their related coefficients, standard errors, t-statistics, and p-values, to aid in deciding whether to discard or not to exclude a null hypothesis.

The p-values of 10 terms are all below 0.05, indicating that they are significant in the model. R2 and R2adj have values of 100 percent and 100 percent, respectively. Where R2 = 100% implies that the predictors or components in the prototype account for 100% of the overall variation in the answer, and R2 adj is 100%, which adjusts for the number of model parameters, indicates the significance of the association.

Table.3 shows the degrees of freedom (DF), the sequential sums of squares (Seq. SS), the adjusted sums of squares (Adj SS), the adjusted mean squares (Adj MS), the F-statistics from the adjusted mean squares, and the p-value for the ANOVA analysis of the results. The sequential sum of squares is the sum of squares multiplied by the number of prior terms in the model, which is determined by the estimations.

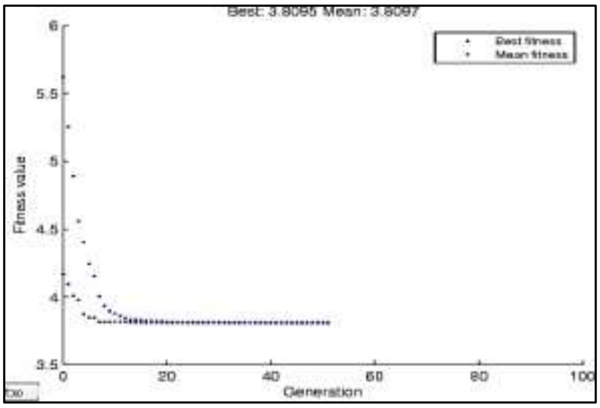
Table.3 Variance analysis of the surface roughness fitted model

Source	Regression	Linear	Square	Interaction	Residual Error	Total
DF	15	3	3	7	9	34
Seq SS	24.908	43.098	1.9073	2.904	1.6889	23.999
Adj SS	45.909	32.905	1.9899	2.8984	1.894	
Adj MS	3.09784	7.90784	1.09788	1.89678	1.79789	
F	1978.9	197.09	56.09	568.97		
P	0.123	0.123	0.123	0.123		

The modified sums of squares are the sums of squares when all other terms in the model are present and the model order is not important. As can be seen in this table, the regression model's p-value is less than 0.05, implying that the Ra fitting the prediction model with linear and square terms is important at the 96 percent level. The 0.05 does not include the phrases Ton2, V2, (Ip)(Toff), (Ton) (Toff), and (Toff) (V). The following formula depicts the modified truncated model in this manner.

Figure1. Plot of fitness value with number of generations.

Ra=&5.4035+0.1997(Ip)+0.0268(Ton)+0.0002($Toff$)−0.0853(V)+0.0028(Ip)2&−0.0005(V)2+0.0006(Ip)(Ton)−0.0017(Ip)(V)−0.0002(Ton)(V)



The optimization is done in MATLAB's PSO system. To achieve the different optimal parameters, the PSO variables were modified, and the optimum GA variables used for parameter design are as follows:

Size of the population: 100; generations: 200; population kind: double matrix; Number of stalls produced: 50; Rank scaling is a fitness function; the roulette wheel is a choice function. Modification function: adaptive viable; Crossover function: 2 points; Crossover fraction: 0.8; Forward movement, migration fraction: 0.8. Figure 1 shows a plot of fitness value vs the number of iterations.

Table.4 shows the best (optimal) material clearance condition that results in the lowest surface roughness. An experiment was done using the optimal parameter values for surface roughness in order to acquire the desired response attribute values. Table.4 shows the PSO-predicted surface roughness value and the experimental data with the PSO-predicted parametric optimal setting. Because the percentage of error of the anticipated value with regard to the experimentally obtained values for surface roughness is not great, the forecasts are in consistent with the experimental data.

Table 4. The process parameters' optimal value

Optimized value of input parameters	Response	Surface Roughness (Ra)
	Ip	6
	Ton	49
	Toff	580
	V	49
	Predicted Value	4.98
	Exp value	5.093
	% Error	4.09

7.Conclusion

The process variables of the EDM process were optimised using a hybrid PSO based RSM method in this article. The geometry between surface quality and input process variables was developed using an RSM model. To discover the best conditions leading to the lowest surface roughness level, the produced regression analysis was combined with a developed PSO. The PSO proved to be effective in optimising the response variable. To get the optimum values of independent factors, the RSM-based surface roughness prototype can be optimised using PSO. An observation was used to confirm the expected optimum material removal rate. Because the greatest % absolute error of the expected values with regard to the experimentally measured data for surface roughness was not high, this outcome verifies the predictive performance of PSO.

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