Proceedings of the Third International Conference on Modeling, Simulation and Applied Optimization
Sharjah, U.A.E January 20-22 2009

A HEURISTIC ALGORITHM FOR THE OPTIMAZATION OF POWDER-MIXED EDM PARAMETERS FOR TI-CO ALLOYS

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ABSTRACT

In recent years, powder-mixed electrical discharge machining (PMEDM) has been successfully employed in manufacturing of different kinds of materials including super alloys. In this paper, mathematical models are proposed, using regression method, to model and analysis the effects of machining parameters on the machining characteristics in the PMEDM process. In this regard, the effects of four machining parameters (grain size of aluminum powder, concentration of the powder, discharge current and pulse on time) on the important process outputs, including metal removal rate and electrode wear rate, have been investigated. To model the machining process, different regression functions have been fitted to the experimental data. Then, using analysis of variance (ANOVA), the best and most fitted set of models are identified. In addition to influence of individual machining parameters, the interactions between these parameters are also investigated. Finally, a genetic algorithm procedure has been employed to optimize the process parameters for any set of desired outputs. The results show that the proposed solution procedure performs very well in solving such complicated and non-linear optimization problems.

Keywords: Electrical Discharge Machining, Modeling, Analysis of Variance, Optimization, Genetic Algorithm.

1. INTRODUCTION

In today's industry, super alloys and ceramic materials are extensively used in different industrial fields such as cutting tools, nozzles, turbine blades, internal combustion engines, and heat exchangers. However, in spite of their exceptional mechanical properties, they usually have very low machinability characteristics. Therefore, different non-traditional machining techniques are increasingly employed to form and manufacture high quality components from these materials. Among these processes, electrical discharge machining (EDM) has drawn a great deal of attention because of its broad industrial applications [1]. In this technique, material is removed by controlled erosion through a series of electric sparks between the tool (electrode) and the work piece. The rate of materials removed per unite time is known as Material Removal Rate (MRR). The thermal energy of the sparks leads to intense heat conditions on the work piece, causing melting and vaporizing of work piece material [2]. Due to the high temperature of the sparks, not only work material is melted and vaporized, but the electrode material is also melted and vaporized, which is known as electrode wear (EW).

Like other machining processes, the quality of machined parts in EDM is significantly affected by input parameters [3, 4].Due to their importance in EDM, the machining characteristics selected for this study are metal removal rate (MRR) and electrode wear (EW). These two output parameters may be calculated using the following expressions:

$$\mathrm{MRR} = \frac{\text{wear weight of workpiece}}{\text{time of machining}} \tag{1}$$

$$\mathrm{EW} = \frac{\text{wear of electorod}}{\text{wear of workpiece}} \times 100 \tag{2}$$

In the EDM, machining control variables include the work piece polarity, pulse on time, pulse off time, open discharge voltage, discharge current, dielectric fluid, grain size and concentration powder particles in the dielectric. Among these the most significant parameters include grain size of aluminum powder particles , concentration of aluminum powder particles, discharge current and pulse on time [5].
In recent years, there is an increasing trend in using ceramic materials due to their exceptional mechanical and chemical properties such as high hardness, good corrosion resistance, low specific weight, and high strength even at very high temperatures. They are extensively used in industrial fields to produce cutting tools, self-lubricating bearings, nozzles, turbine blades, internal combustion engines, heat exchangers, etc. [6,7]. However, one of the major drawbacks of these materials is the low machinability, because of their brittleness. That is why the non-contact EDM technique is one of the best manufacturing processes for these materials.
Cobalt bonded tungsten carbide is a widely used, high strength material produced by compacting techniques of powder metallurgy and high-temperature sintering. In the conventional EDM machining of this material, the machined surface would usually have a significant amount of cracks and spalling which decreases the hardness, wear and corrosion resistance of this alloy. To enhance the machined surface properties and prevent the surface defects, a technique called powder mixed electrical discharge machining (PMEDM), is used. In this method, fine powder of a specific material (usually Aluminum) is mixed into the dielectric fluid of EDM to increase the process quality.

2. MODEL DEVELPOMENT

In this section the mathematical models, to relate important input-output PMEDM variable, are presented. Proper selection of the process parameters has significant effects on the process outputs link MRR and EWR.

In many cases, determining the best set of process parameters is difficult and relies heavily on operators' experience or handbook values. However, this does not ensure that the selected machining parameters result in optimal machining performance for any given material and machining environment [8]. To resolve this problem, we first develop a set of mathematical models to relate the process control parameters to the machining response characteristics. The experimental results were obtained using design of experiment (DOE) technique. Then, a GA based procedure has been utilized to determine the optimal machining parameters in the PMEDM of Tungsten-Cobalt alloy. In summary, developing more accurate models and more efficient optimization procedure is the main objective of this research. The proposed approach can easily be extended to other materials and machining conditions.

The important controlling parameters in PMEDM include grain size of aluminum powder (S), concentration of the powder (C), discharge current (I) and pulse on time (T). In this study, material removal rate (MRR) and electrode wear (EW) rate have been chosen as the process response characteristics to investigate the DOE matrix shown in Table 1(Kung et. al. [9]), have been used for modeling. Some of the experimental results are also presented in this table.

Table1. *DOE matrix and results for the PMEDM performance characteristics*

No.	S	C	I	T	MRR	EW
1	2	15	2.5	100	0.2044	21.44
2	2.5	20	2	100	0.2678	19.85
3	1.5	20	2	100	0.2345	26.89
4	1.5	10	2	100	0.1338	24.57
5	2	15	2	150	0.1989	21.62
6	1.5	20	2	200	0.2454	21.02
7	1.5	10	3	200	0.1684	26.65
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
23	2.5	15	2.5	150	0.2278	22.23
24	2	10	2.5	150	0.1679	27.34
25	2.5	10	2	200	0.1798	16.77
26	1.5	15	2.5	150	0.1934	27.37
27	2	20	2.5	150	0.2679	16.61
28	2	15	2.5	150	0.2103	23.51
29	2	15	2.5	150	0.2103	23.53
30	2.5	10	3	200	0.2028	23.54

Based on DOE technique, these 30 experimental runs are sufficient to establish the relationship between machining characteristics and its controlling parameters.

Any of these output characteristics is a function of process parameters (Y = f (S, C, I, T)) which can be expressed as linear, curvilinear or logarithmic models [10]. The model adequacy checking includes a test for significance of the regression model and a test for significance on model coefficients. For this purpose, analysis of variance (ANOVA) is performed. The analysis of variance recommended that the liner model is statistically the best fit in this case.

The associated p-value for the model is lower than 0.05; i.e. α=0.05, or 95% confidence. This shows that the model is statistically significant. Based on ANOVA, the values of R^2 and adjusted R^2 are respectively 99% and 96.2% for MRR. This means that regression model provides an excellent explanation of the relationship between the independent variables and MRR response.

In the same token, the values of R^2 and adjusted R^2 are respectively 95% and 91% for EW. This also indicates a very good fit for EW response. Table 2 presented the values of "F-value"' and "Prob. > F" for linear models in terms of MRR, and EW.

Table 2. *Results of ANOVA for linear models on the performances MRR and EWR*

Source	DF.	SS	MS	f-value	Prob.>F	
For MRR						
Model	4	0.05332	0.01333	768.12	<.0001	Significant
Residual	25	0.00043	0.00002			
Total	29	0.05375				
Standard deviation = 4.16581E-3				R2=99%		
Mean= 0.215060				R2 Adjusted=96.2%		
For EW						
Model	4	88.646	22.161	768.12	<.0001	Significant
Residual	25	14.225	1.293			
Total	29	102.871				
Standard deviation = 1.13719E-2				R2=95%		
Mean=23.29188				R2 Adjusted=91%		

The liner models of response equations are as follows:

$$MRR = - 0.0784 + 0.0342\ S + 0.0100\ C + 0.0228\ I + 0.0001\ T \quad (3)$$

$$EW = 24.9 - 5.71\ S + 0.244\ C + 0.545\ I + 0.0359\ T \quad (4)$$

The above mathematical model can be used to predict the values of MRR and EW within the limits of the factors studied.

3. THE OPTIMIZATION PROCDURE

Models (3) and (4) establish the relationships between process parameters and PMEDM machining characteristics. They can be used in two ways:

1) Predicting EDM machining response characteristics for a given set of input parameters.

2) Predicting process parameters for a desired EDM characteristic specification.

The later seems to be more practical since in real life situations, it is desired to have some specific machining responses; i.e. MRR and EW. For this purpose, a set of non-linear equations must be solved simultaneously for all the process parameters.

Since finding the optimal (desired) MRR and EW is the problem of combinatorial explosion, evolutionary algorithms can be employed as the optimizing procedure. These techniques would make the combination converge to solutions that are globally optimal or nearly so. Evolutionary algorithms are powerful optimization techniques widely used for solving combinatorial problems. As a promising approach, one of these algorithms, called Genetic Algorithm (GA), is implemented for prediction purposes in this research.

Genetic Algorithm, first proposed by John Holland in 1975, has been adapted for large number of applications in different areas. Genetic algorithm can be applied to solve a variety of optimization problems including problems in which the objective function is discontinuous, non differentiable, stochastic, or highly nonlinear. It belongs to a general category of stochastic search methods and has its philosophical basis in Darwin's theory of survival of the best and most fitted individuals. The main characteristic of GA is that it operates simultaneously with a large set of search space points. Besides, the applicability of GA is not limited by the need of computing gradients and the existence of discontinuities in the objective function. This is so because the GA works only with function values, evaluated for each population individual. Moreover, GA employs multiple starting points speeding up the search process. Genetic algorithm repeatedly modifies a population of individual solutions.

At each iteration, the solutions (chromosomes) in the current population are evaluated and sorted according to a "fitness criterion". The individuals with better fitness values have higher chance to participate in the next generation as the parents of new children. Over successive generations, the population "evolves" toward an optimal solution.

There are three main operators in GA: selection, crossover and mutation. Selection means that two individuals from the whole population of individuals are selected as “parents”. Crossover serves to exchange the segments of selected parents between each other according to a certain probability. In other words, it combines two parents to form children for the next generation. The mutation operation randomly alters the value of each element in a given chromosome according to a given mutation probability. Mutation forms new children at random so as to avoid premature convergence. The procedure may be stopped after the terminated condition has been reached. A complete description of this algorithm and some of its applications can be found in [11] and [12].

For optimization process, we first define the prediction function as follow:

$$EF = \alpha_1\left(\frac{MRR - MRR_d}{MRR}\right)^2 + \alpha_2\left(\frac{EW - EW_d}{EW}\right)^2 \qquad (5)$$

This mean square error function is used as the fitness function in the optimization process. In the above function, MRR and EWR are material removal rate and electrode wear rate given by (1) and (2) respectively. In the same manner, MRR_d and EW_d are the target (desired) output values for the machining operation.

The objective is to set the process parameters at such levels that these values are achieved. The coefficients α_1 and α_2 represent weighing importance of different output parameters in the prediction function. In the optimization process, the purpose is to minimize this objective function. By doing so, the process parameters are calculated in such way that the PMEDM parameters approach their desired values. For this purpose, a GA method is employed to find the best machining variables with respect to process specifications.

4. AN ILLUSTRATIVE EXAMPLE

In this section a numerical example is presented to illustrate the performance of proposed procedure and solution technique.

In the proposed models, the weighting factors α_1 and α_2 can be set by the user according to the relative importance given to each response specification. In this example, all machining variables of Powder-Mixed EDM (*S,C,I,T)* are considered to have the same importance, and therefore constants α_1 and α_2 are set to unity. The evaluation of the effects of different values for α_1 and α_2 on the optimal machining parameters, can be a subject for future studies. In this case, the problem turns to a multiple objective optimization problem which can still be solved by GA.

As the inputs in the optimization process, the desired (target) values for the EW and MRR are adopted from the experimental results presented in Table 1. The error function given in (5), along with PMEDM models (3) and (4), are embedded into genetic algorithm. The best set of tuning parameters for the algorithm, found by several trial runs, is given by Table 3.

Table 3. *Genetic Algorithm parameters settings*

No. of Generations	Population size	Selection	Crossover rate	Crossover	Mutation rate
200	27	Tournament	85%	OX	1%

The objective is to determine the values of control parameters (S, C, I, T) in such a way that the process output responses (MRR and EW) converge towards their desired values. This is done through minimization of the error function. The process variables found by the algorithm for the five sample values of desired machining characteristics (MRR_d and EW_d), are presented in Table 4. A comparison between predicted and desired values of process outputs is also shown in Table 4.

Table 4. *Comparison between desired and predicted values*

No	Process variables (predicted by GA)				Process outputs (desired)		Process outputs (predicted by GA)		Error (%)	
	S	C	I	T	MRR	EW	MRR_d	EW_d	MRR	EW
1	1.75	16	2.4	160	0.2103	23.12	0.2115	23.1680	-0.5674	-0.2072
2	1.75	10	2.4	150	0.1564	25.14	0.1560	24.8204	0.2564	1.2877
3	2.25	12	2.8	190	0.2044	21.44	0.2033	21.5393	0.5411	-0.4610
4	2	14	2.3	170	0.1989	21.62	0.1987	21.5773	0.1007	0.1979
5	2	18	2.7	120	0.2454	21.02	0.2447	20.8949	0.2861	0.5987
6	1.75	18	2.1	170	0.2278	22.23	0.2285	22.2607	-0.3063	-0.1379
7	2.5	14	2.5	170	0.2219	23.52	0.2207	23.4298	0.5437	0.3850

The errors between predicted and desired (actual) values of process responses are calculated, using the following formula:

$$\text{Error} = \frac{\text{Desired} - \text{Predicted}}{\text{Predicted}} \times 100 \qquad (6)$$

As shown, the largest error is around 1.3% while most parameters deviate from their desired values by less than 0.5%. These results illustrate that the proposed procedure can effectively be used to determine optimal process parameters for any desired output values of PMEDM operation.

5. CONCLUSION

Cost optimization has become an important aspect of manufacturing industries. One of key factors in improving productivity and reducing production cost is to employ special purpose manufacturing techniques. Powder mixed electro discharge machining (PMEDM) is an important non-traditional machining process widely used for machining of difficult-to-machine materials such as tungsten-cobalt ceramics. Optimization of PMEDM process parameters is essential to improve machining performance. On the other hand, there is no single optimal combination of machining parameters, as their influences on the machining performance characteristics, such as material removal rate and electrode wear rate, are quite complicated and involve many mutual interactions. In the present work, a set of linear regression models is developed to represent the relationship between input process parameters and output machining characteristics. The adequacy of the proposed models has been investigated using ANOVA technique. With the confidence levels between 92%-99%, the proposed models have very good conformability to the real process. Then an optimization method, based on Genetic Algorithm, has been employed to determine the proper process parameters values for any given set of desired machining characteristics. Computational results show that the proposed GA method can accurately determine machining parameters for any desired process output specification. The choice of one solution over the other depends on the requirement of the process engineer. If the requirement is a lower electrode wear rate or higher material removal rate, a suitable combination of process variables can be selected. In any case, optimization can help to increase production rate considerably by reducing machining time and electrode wear. The evaluation of other algorithms, in terms of solution quality and computational speed, may be a future research area. In addition, modeling and optimizing of other manufacturing process may be good extension of the present work.

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