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Modeling and Optimization of Process Parameters in PMEDM by Genetic Algorithm

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***Abstract*—** This paper addresses modeling and optimization of process parameters in powder mixed electrical discharge machining (PMEDM). The process output characteristics include metal removal rate (MRR) and electrode wear rate (EWR). Grain size of Aluminum powder (S), concentration of the powder (C), discharge current (I) pulse on time (T) are chosen as control variables to study the process performance. The experimental results are used to develop the regression models based on second order polynomial equations for the different process characteristics. Then, a genetic algorithm (GA) has been employed to determine optimal process parameters for any desired output values of machining characteristics.

***Keywords*—** Regression modeling, PMEDM, Genetic Algorithm, Optimization.

I. INTRODUCTION

DIFFERENT non-traditional machining techniques are increasingly employed to manufacture different high quality industrial components. Among the non-traditional methods of machining processes, electrical discharge machining (EDM) has drawn a great deal of attention because of its broad industrial applications including different dies and tools [1]. In this process material is removed by controlled erosion through a series of electric sparks between the tool (electrode) and the work piece. 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 and electrode wear rate. These two output parameters may be calculated using the following expressions:

$$MRR = \frac{\text{wear weight of workpiece}}{\text{time of machining}} \quad (1)$$

$$EWR = \frac{\text{wear of electorod}}{\text{wear of workpiece}} \times 100 \quad (2)$$

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 are the followings [5]:

1. Grain size of aluminum powder particles (SAl, µm)
2. Concentration of aluminum powder particles (CAl, g/l)
3. The discharge current (IP, A)
4. The pulse on time (TP, µs).

In recent years, there is a 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.

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To enhance the machined surface properties and prevent the surface defects, a technique called powder mixed electrical discharge machining (PMEDM), is now being 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.

II. MODEL DEVELOPMENT

Selection of the appropriate machining parameters has significant effects on the process quality such as MRR and EWR. In many cases, determining the best set of process parameters is difficult and relies heavily on operators' experience or handbook values [8]. However, this does not ensure that the selected machining parameters result in optimal machining performance for any given material and machining environment.

To resolve this problem, experimental data and regression analysis, 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 are the main objectives of this research. The proposed approach can easily be extended to any 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 influence of the above parameters. For illustrative purposes, the data presented by Kung et. al. [9] is used here. The complete experimental scheme is shown in Table I.

Based on DOE technique, these 30 experimental runs are sufficient to establish the relationship between PMEDM 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, shown in their general forms as follows:

$$Y=a_0 + a_1S +a_2C + a_3I + a_4T \quad (3)$$

$$Y=a_0 + a_1S +a_2C + a_3I + a_4T + a_{11}S^2 + a_{22} C^2 + a_{33}I^2 + a_{44} T^2 + a_{12}SC + a_{13} SI + a_{14} ST + a_{23} CI + a_{24} CT + a_{34} IT \quad (4)$$

$$Y = a_0\ S^{a1}\ C^{a2}\ I^{a3}\ T^{a4} \quad (5)$$

The model adequacy checking includes test for significance of the regression model, test for significance on model coefficients and test for lack-of-fit [10]. For this purpose, analysis of variance (ANOVA) is performed. The analysis of variance recommended that the quadratic 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 over 99% for MRR. This means that regression model provides an excellent explanation of the relationship between the independent variables and MRR response. By the same token, the values of R^2 and adjusted R^2 are respectively 97% and 87.3% for EWR. This indicates a very good fit for EWR response. For linear and logarithmic models, the lack-of-fit test indicates that these models are insignificant, and therefore need not to be evaluated any further.

TABLE I
DOE MATRIX AND RESULTS FOR THE PMEDM PERFORMANCE CHARACTERISTICS

No.	S	C	I	T	MRR	EWR
1	2	15	2.5	150	0.2103	23.12
2	2.5	10	3	100	0.1908	17.29
3	1.5	20	3	200	0.2684	19.44
4	2	15	2.5	150	0.2104	17.26
5	1.5	10	3	100	0.1564	25.14
6	2.5	20	3	100	0.2908	20.77
7	2	15	2.5	100	0.2044	21.44
8	2.5	20	2	100	0.2678	19.85
9	1.5	20	2	100	0.2345	26.89
10	1.5	10	2	100	0.1338	24.57
11	2	15	2	150	0.1989	21.62
12	1.5	20	2	200	0.2454	21.02
13	1.5	10	2	200	0.1454	22.99
14	2.5	20	3	200	0.3028	24.68
15	2.5	10	2	100	0.1678	23.94
16	2	15	2.5	150	0.2104	21.65
17	2	15	2.5	200	0.2164	15.98
18	1.5	10	3	200	0.1684	26.65
19	2.5	15	2.5	150	0.2278	22.23
20	2	10	2.5	150	0.1679	27.34
21	2.5	10	2	200	0.1798	16.77
22	1.5	15	2.5	150	0.1934	27.37
23	2	20	2.5	150	0.2679	16.61
24	2	15	2.5	150	0.2104	27.37
25	1.5	20	3	100	0.2564	23.55
26	2	15	2.5	150	0.2103	23.51
27	2	15	2.5	150	0.2103	23.53
28	2.5	10	3	200	0.2028	23.54
29	2.5	20	2	200	0.2798	23.53
30	2	15	3	150	0.2219	23.52

Table II shows the values of "F-value"' and "Prob. > F" for each term on the performances of MRR, and EWR. In the case of MRR the S, C, I, T, S^2, C^2, S.I, S.T and I.T can be regarded as significant term due to their "Prob. > F" values being less than 0.05. Similarly, the S, C, S^2, C^2, S.C, S.I, S.T and C.T for EWR are the significant terms.

The backward elimination process removes the rest of insignificant terms to adjust the fitted quadratic models. Through the backward elimination, the final curvilinear models of response equations are as follows:

$$MRR= -0.00751 +0.02925. S + 0.00107. C + 0.02100. I +0.0001. T + 0.00094. S^2 + 0.00030. C^2 + 0.00038. S. I + 0.000004. S. T + 0.000004. I. T \quad (6)$$

$$EWR= 98.51523 - 61.85566. S - 0.40935. C + 11.27579. S^2 - 0.00024. C^2 + 0.3935. S. C + 0.7200. S. I + 0.0418. S. T - 0.1800. C. I - 0.00035. C. T \quad (7)$$

For illustrative purposes, the distributions of real data around regression lines for these models are illustrated in Figures 1 and 2. These figures demonstrate a good conformability of the developed models to the real process.

TABLE II.
RESULTS OF ANOVA FOR EACH TERM ON THE PERFORMANCES MRR AND EWR

Symbol	Degree of freedom	MRR		EWR	
		F-Value	Pr > F	F-Value	Pr > F
S	1	354.97	<.0001*	14.56	0.0189*
C	1	76.60	<.0001*	17.31	0.0141*
I	1	124.33	<.0001*	0.22	0.6633
T	1	66.66	<.0001*	0.94	0.3865
S*S	1	6.47	0.0224*	2.70	0.1760
C*C	1	1.40	0.2559	9.90	0.0346*
I*I	1	6.41	0.0231*	0.15	0.7207
T*T	1	6.41	0.0231*	20.06	0.0110*
S*C	1	6699.45	<.0001*	29.92	0.0054*
S*I	1	1.40	0.2559	9.18	0.0388*
S*T	1	1.40	0.2559	57.99	0.0016*
C*I	1	0.14	0.7153	11.78	0.0265*
C*T	1	6.41	0.0231*	47.05	0.0024*
I*T	1	0.14	0.7153	0.74	0.4370
Residual	15				
Total	29				

*significant terms

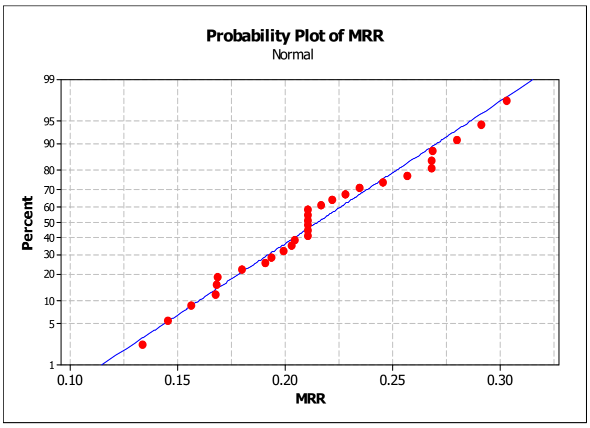

Fig. 1 predicted MRR vs. actual values

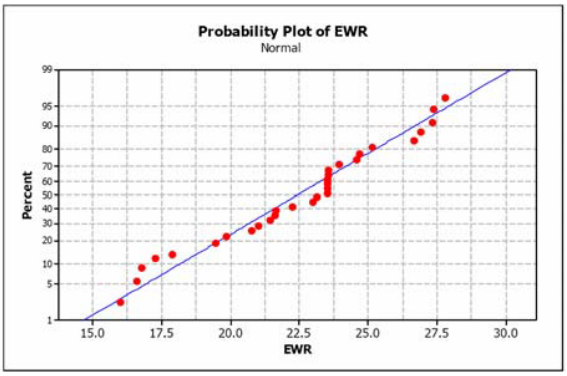

Fig. 2 predicted EWR vs. actual values

III. THE OPTIMIZATION PROCEDURE

The mathematical models furnished above provide one to one relationships between process parameters and EDM 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 EWR. 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 EWR is the problem of combination 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 new and 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 "faintness 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 alternates the value of each element in a given chromosome according to the 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:

$$EF = \alpha_1 \frac{(MRR - MRR_d)}{MRR} + \alpha_2 \frac{(EWR - EWR_d)}{EWR} \quad (8)$$

This 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 EWR_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.

IV. 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 user according to relative importance given to each response specification. Without loss of generality, in this example the values of all components of PMEDM (*S,C,I,T*) are considered to have the same importance and therefore, constants $\alpha_1$and α_2 are set to unity.

As the inputs in the optimization process, the desired (target) values for the EWR and MRR are adopted from the experimental results presented in Table 1. The error function given in (8), along with PMEDM models (6) and (7), are embedded into genetic algorithm. 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 EWR) converge towards their target values. This is done through minimization of the error function. The best tuning parameters found for the algorithm are presented in Table3.

TABLE III.
THE BEST TUNING PARAMETERS FOR THE GA PROCEDURE

No. of Generations	Population size	Crossover rate	Crossover mechanism	Mutation rate
800	30	80%	Scatter	1%

A comparison between predicted and desired values of process responses is shown in Table 4, for any set of the test runs. The errors between predicted and target (actual) values process responses are calculated as follows:

$$Error = \frac{Traget - \Pr edicted}{\Pr edicted} \times 100 \quad (9)$$

As shown, the largest error is around 5.5% while most parameters deviate from their desired values by less than 1%. These results illustrate that the proposed procedure can be efficiently used to determine optimal process parameters for any desired output values of PMEDM operations.

TABLE IV.
COMPARISON BETWEEN TARGET AND CALCULATED VALUES

NO	Target		Prediction		Error (%)	
	MRR_d	EWR_d	MRR	EWR	MRR	EWR
1	0.2103	23.12	0.2122	23.1407	0.8954	0.0895
2	0.1564	25.14	0.1611	25.1345	2.9174	0.0219
3	0.2044	21.44	0.2121	21.4463	3.6304	0.0294
4	0.2454	21.02	0.2484	20.9887	1.2077	0.1491
5	0.2278	22.23	0.2411	22.2068	5.5164	0.1045
6	0.1798	16.77	0.1822	16.7450	1.3172	0.1493
7	0.1989	21.62	0.2005	21.5305	0.7980	0.4157
8	0.2028	23.54	0.2025	23.5609	0.1481	0.0887
9	0.2219	23.52	0.2289	23.4805	3.0581	0.1682

V. Conclusion

Powder mixed electro discharge machining (PMEDM) is an important non-traditional machining processes widely used for machining of difficult-to-machine materials such as cobalt-tungsten ceramics. Optimization of PMEDM process parameters is very 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 involves many mutual interactions. In the present work, a set of second order curvilinear regression models is developed to represent relationship between input process parameters and output machining characteristics. The adequacy of the proposed models has been investigated using ANOVA technique. The results of ANOVA indicate that the proposed models have very good conformability to the real process. Then an optimization method, based on Genetic Algorithm, have 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 efficiently and 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. Optimization will help to increase production rate considerably by reducing machining time and electrode wear. In future, this study can be extended to different work materials and hybrid optimization techniques.

REFERENCES

[1] H. Zarepour, A.F. Tehrani, D. Karimi, and S. Amini, "Statistical analysis on electrode wear in EDM of tool steel DIN 1.2714 used in forging dies," *J. Mater Process Tech.*, vol. 188, pp. 711–714, 2007.

[2] A.Ghosh, A.K. Mallik, *Manufacturing Science*, Affiliated East-West Press, New Delhi, 1991.

[3] B.H. Yan, H.C. Tsai, F.Y. "Huang, The effect of EDM of a dielectric of a urea solution in water on modifying the surface of titanium". *Int. J. Mach. Manuf.*, vol. 45, no. 2, pp. 194–200, 2005.

[4] K.H. Ho, S.T. Newman, "State of art electrical discharge machining (EDM)", *Int. J. Mach. Manuf.* Vol. 43, no 13,pp 1287–1300, 2003.

[5] Puertas, C.J. Luis, "A study on the machining parameters optimization of electrical discharge machining", *J. Mater. Process Tech* , vol. 144, pp. 521–526, 2003.

[6] M.M. Schwartz, *Engineering applications of ceramic materials*, American Society for Metals, Metals Park, Ohio. 1995.

[7] F.K. locke, "Modern approaches for the production of ceramic components", *J. Eur. Ceram. Soc.*, vol. 17, pp. 457–465, 1997.

[8] J.T. Huang and Y.S. Liao, "Optimization of machining parameters of wire-EDM based on grey relational and statistical analysis", *Int. J. Prodn. Res*. vol. 41, no. 8, pp. 1707–1720, 2003.

[9] K.Y. Kung, J.T. Horng, and K.T. Chiang, "Material removal rate and electrode wear ratio study on the powder mixed electrical discharge machining of cobalt-bonded tungsten carbide", *Int. J. Adv Manuf. Technol.*, to be published.

[10] D.C. Montgomery, E.A. Peck, G.G. *Vining, Introduction to Linear Regression Analysis*, Third ed., Wiley, New York, 2003.

[11] G.R. Cheng, *Genetic algorithm and engineering design*, New York: John Wiley & Sons, 1997.

[12] J.C. Su , J.Y. Kao, and Y.S. Tarng, "Optimization of the electrical discharge machining process using a GA-based neural network". *Int. J. Adv. Manuf. Tech*., vol. 24, pp 81–90, 2004.

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