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NSGA Optimization of Performance of Powder Mixed EDM

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***Abstract*—Powder mixed electrical discharge machining is one of the techniques used in EDM to improve the machining performance. In this paper, an attempt has been made to study the effect of aluminium powder when mixed in kerosene dielectric fluid. The work and tool electrode materials used are W300 die-steel and electrolytic copper respectively. Pulse peak current, pulse on-time and concentration of aluminium powder are taken as the process parameters. The output responses considered are material removal rate (MRR) and surface roughness (R_a). The experiments are planned using face centered central composite design procedure. Empirical models are developed for MRR and R_a using response surface methodology (RSM) to study the effect of process parameters. The results show that Al powder mixed kerosene produces high MRR of 415 mg/min and low surface roughness value of 4.38 µm. Further, using nondominated sorting genetic algorithms (NSGA-II) the optimal process parameters for achieving maximum MRR and minimum R_a is obtained and presented here.**

***Index Terms*—PMEDM, Kerosene, MRR, R_a, CCD, RSM, NSGA-II.**

I. INTRODUCTION

Electrical discharge machining (EDM) has been an important manufacturing process for the tool, mould, and dies industries for several decades. The process is finding an increasing industrial use owing to its ability to machine geometrically complex in hard materials that are extremely difficult using conventional machining1. New trends in EDM have improved its process performance to a greater extent. These techniques include rotation of the tools or workpiece, electrode design and shape, addition of powder to the dielectric fluid, alternate dielelctric fluids and even dry EDM [1].

To improve the performance of EDM, dielectric fluid suspended with different powders were attempted by several investigators. Powder mixed electric discharge machining (PMEDM) improves material removal rate (MRR), quality of the electric discharge machined surface and also reduces the surface defects.

Initial studies show that, impurities like copper, aluminium, iron and carbon in dielectric fluid causes improvement in the material removal rate (MRR)[2]. Addition of electrically conductive powder to the dielectric fluid reduces the insulating strength of the dielectric and increases the spark gap between the tool and workpiece. As a result, the process becomes more stable thereby improving MRR and surface finish. The improvement in the MRR and surface finish depends on the thermo-physical properties of the powder, particle size and concentration [3]. Powder addition modifies wave form of the pulse current and causes multiple discharges, which create smaller crater and smaller debris that will easily flush the gap and accelerate the MRR [4, 5].

Due to the wide use of highly automated machine tools in the industry, manufacturing requires reliable models and methods for the prediction of the responses of the machining processes.16 Several artificial intelligence and knowledge based soft computing approaches including neural network, genetic algorithm, fuzzy logic and their hybrids have recently been used for the optimization of different machining processes for a variety of materials.

Goldberg's notion of nondominated sorting in GAs along with a niche and speciation method to find multiple Pareto-optimal points simultaneously, and suggested that this method can be extended to higher dimensional and more difficult multi-objective problems[6]. In another study predictions of surface finish for various work materials with the change of electrode polarity based upon six different neural-networks models and a neuro-fuzzy network model have been illustrated[7]. RSM with GA has been used for optimization of surface roughness for machining of mild steel[8]. Some authors proposed multi-objective optimization method based on a Non-Dominated Sorting Genetic Algorithm (NSGA) to optimize Cutting velocity and surface finish in Wire-electrical discharge machining [9]. Comparative studies of statistical models and artificial neural networks for predicting the tool wear in machining steel were also reported[10]. However, NN based studies have not been applied yet for predictive modeling of multiple parameters during electrical discharge machining of ceramics. This may be due to the simultaneous modeling of multiple output parameters of varying nature and magnitudes in case of ceramics, through a single NN model/architecture. Whereas micro-genetic algorithm implemented simultaneously to optimize two conflicting responses such as tool life and operation time in turning process in terms of cutting depth, feed and speed[10].

Similar to EDM, modeling and optimization of process parameters in PMEDM are also carried out by various researchers [11]. Various responses such as metal removal rate (MRR), electrode wear rate (EWR), grain size of powder (S), concentration of the powder (C), discharge current (I), pulse on time (T_{on}) are chosen as control variables to study the performance. Then genetic algorithm (GA) has been employed to determine optimal process parameters for any desired output values of machining characteristics [11]. In a similar study non-dominated sorting genetic algorithm (NSGA-II) has been used to optimize MRR and R_a during machining of tungsten carbide and cobalt composites. The process parameters studied were I, T_{on} , electrode rotation and flushing pressure [12].

Elaborate scrutiny of the literature reveals that material removal mechanism of PMEDM process is very complex and theoretical modeling of the process is very difficult. Regarding empirical results, much research work is required with more work-tool-powder-parametric combinations to make the process commercially applicable.

The present experimental design is based on central composite design matrix. From the experimental data, multiple regression models for the MRR and R_a are obtained. NSGA has been used to obtain an optimal combination of parameters and a non-dominated set is obtained and reported in this paper.

II. EXPERIMENTATION

The experiments were conducted on a die sinking EDM machine, model C-425 manufactured by the Electronica Industries, India. To conduct experiments with aluminium suspended kerosene as dielectric fluid, a separate dielectric re-circulating system has been fabricated and attached to the machine.

The work material chosen for the present study is W300 die-steel (0.32% C, 0.8 % Si, 4.5 % Cr, 1% Mn, 0.3% V and remaining Fe). It is extensively used in fabrication of tools and dies. The required sizes of workpieces were wire-cut from a blank. Electrolytic copper of diameter 9.5 mm was chosen as a tool electrode material. The experiments were conducted with powder mixed kerosene as dielectric fluids. External jet flushing with a pressure of 0.75 kPa was used for all the experiments. The metal powder selected was aluminium with average particle size of 27 µm. In this study face cantered central composite design (FCCCD) was selected. FCCCD designs comprise a set of two-level factorial points, axial points and center runs. The factorial points contribute to the estimation of linear terms and two-factor interactions. The axial points contribute to the estimation of quadratic terms.

The controllable variables chosen for the experimentation were peak current (I), pulse on-time (T_{on}), concentration of the powder (C). Other factors such as gap voltage (35 V), machine servo sensitivity, lift time and flushing pressure were kept constant. The range of input parameters were fixed from the pilot experiments and the literature. The experimental conditions are shown in the Table 1. Metal removal rate (MRR) and average surface roughness (R_a) are the response parameters measured for all the experiments. MRR was measured by weight loss method and the R_a values were measured by using stylus type roughness tester. For the selected three input process parameters the design consists of each 20 experiments using Al powder mixed with kerosene as dielectric fluid.

Table 1 Experimental Conditions

Workpiece	W300 Die-steel
Workpiece size	20 mm×40 mm×6 mm
Electrode	Copper Ø9.5 mm
Voltage (V)	35
Dielectric fluid	Al powder + kerosene
Polarity	positive, Negative
Peak current(A)	6, 12, 18
Pulse-on time (µs)	120, 220, 320
Powder concentration of powder (g/L)	0, 2, 4
Duty factor (%)	75

III. EMPIRICAL MODELLING

The Response Surface Methodology (RSM) was used to develop the quadratic regression equations for the output responses. RSM is a method which uses quantitative data from the experiments to determine and simultaneously solve multi variant equations. Values of correlation coefficients, R-Sq for MRR for kerosene over 0.95 and for R_a it is over 0.85. The fit summary recommended that the quadratic model is statistically significant for analysis of MRR and R_a. The associated p-value for the models are lower than 0.05 (i.e. $\alpha = 0.05$, or 95% confidence) indicates that the developed empirical models (Eqs. 1-2) are statistically significant.

$$\text{MRR (mg/min)} = 244.36+164.48\,I-6.88T_{on}-3.82C-22.03I\times I-16.28T_{on}\times T_{on}+18.37C\times C+7.77I\times T_{on}+13.55C\times I-4.424T_{on}\times C \quad (1)$$

$$R_a\,(\mu m) = 7.86+1.26\,I+0.03\,T_{on}-0.15\,C-1.25\,I\times I+0.43\,T_{on}\times T_{on}-1.30C\times C+0.16\,I\times T_{on}+0.31\,C\times I+0.40\,T_{on}\times C \quad (2)$$

IV. RESULTS AND DISCUSSION

Effective of process parameters on MRR

As can be seen from this Fig. 1, the MRR tends to increase, considerably with increase in peak current for any value of pulse on-time. Hence, maximum MRR is obtained at high peak current of 18 A and high pulse on-time 220 µs. This is due to their dominant control over the input energy.

Effect of pulse on-time

From the Fig. 2, it is evident that, affect of T_{on} is not significant on MRR. MRR decreases with increase in T_{on}. A decrease in MRR with the increase in pulse on-time is due to the widening of plasma channel, which reduces the intensity of energy required to melt and evaporate the material during the EDM process. This might have also coupled with the effect of frequent short-circuiting at higher pulse on-time during PMEDM. In order to obtain higher MRR middle level of pulse-on time 220 μs at higher concentrations of powder to be selected.

Effect of powder concentration

The effect of concentration and peak current on MRR is shown in Fig. 3. This reveals that, addition of powder to the dielectric fluid enhances the MRR particularly with higher peak currents of 18 A. With increase in concentration of the powder, the MRR tends to increase. This is because powder causes bridging effect between both the electrodes, facilitates the dispersion of discharge into several increments and hence increases the MRR. The maximum MRR is obtained at highest level of concentration of added Al powder (4 g/L) and peak current (18 A). Further improvement in the MRR is expected at higher concentrations of powder.

Effective of process parameters on R_a

Effect of peak current

As can be seen from this Fig. 4, the R_a tends to increase, considerably up to the 12 A peak current. Beyond 12 A peak current, There is no significant change in the R_a with further increase in the peak current beyond 12 A. The R_a also increases with increase in pulse on-time. This is due to their dominant control over the input energy. It is clear from this figure, that the best surface finish is obtainable at the lower level of peak current (6 A) and pulse on-time (120 μs).

Effect of pulse on-time

The effect of concentration and pulse on-time on R_a is shown in Fig. 5. This figure displays that the value of R_a increases with increase in pulse on-time after reaching some level (220 μs). At the same time R_a is smaller for the medium and higher concentration of the powder. In this way, in order to obtain a good surface finish, low values of pulse on-time (120 μs).

Effect of powder concentration

The effect of concentration and peak current on R_a is shown in Fig. 6. This figure displays that the value of R_a tends to decrease for high value of concentration of the added powder when peak currents are low. Addition of powders are not effective with higher pulse on-time which produces multiple layers of white layers on the workpiece surface increasing R_a. In order to obtain a good surface finish, low values of peak current (6 A) and high level of concentration of added powder (4 g/L) should be used. However, more improvement in the surface roughness is still expected at higher concentrations of aluminium powder at lower currents.

V. NSGA OPTIMIZAITON

The objective of the empirical modeling is to achieve higher MRR with a desired surface roughness. In this study, the responses such as MRR and R_a obtained from the regression analysis (Equ. 1-4) were selected to find the optimal combination of the process parameters. This multi-objective optimization problem is optimized using nondominated sorting genetic algorithm (NSGA-II). The problem can be formulated as given below.

Maximize $MRR = f(I, T_{on}, C)$
and minimize $R_a = f(I, T_{on}, C)$
subject to,

$$6 \leqslant I \leqslant 18$$

$$120 \leqslant T_{on} \leqslant 320$$

$$0 \leqslant C \leqslant 4$$

$$MRR > 0$$

It starts with a random initial generation. First, the parents and off-spring are combined to form a string. When the objective functions of all strings in a generation are calculated, the solutions are classified into various non dominated fronts. The crowded tournament selection operator is also used to compare two solutions and returns the winner of the tournament according to two attributes: (1) a non-dominated front in the population and (2) a local large crowding distance.

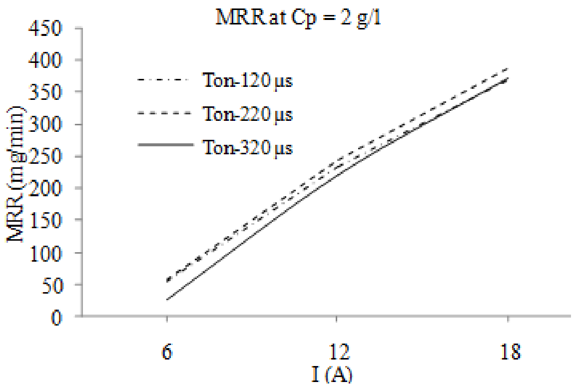

Figure 1 Effect of peak current on MRR

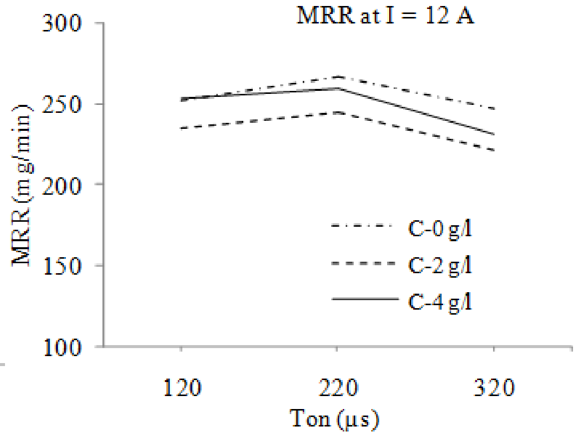

Figure 2 Effect of pulse on-time on MRR

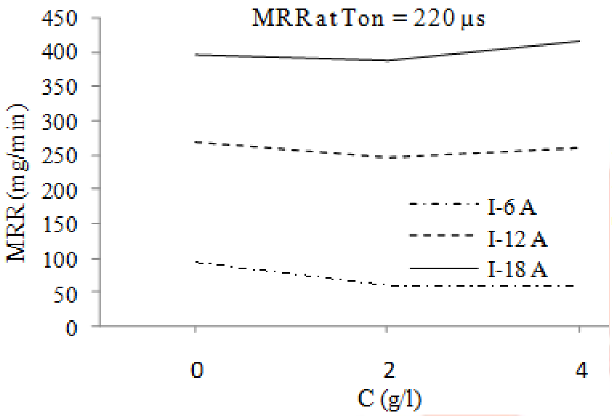

Figure 3 Effect of concentration of powder on MRR

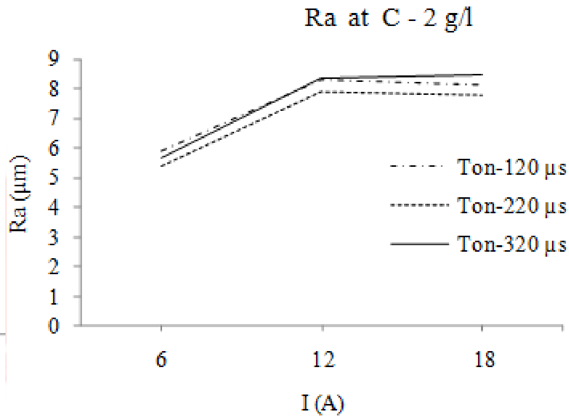

Figure 4 Effect of peak current on R_a

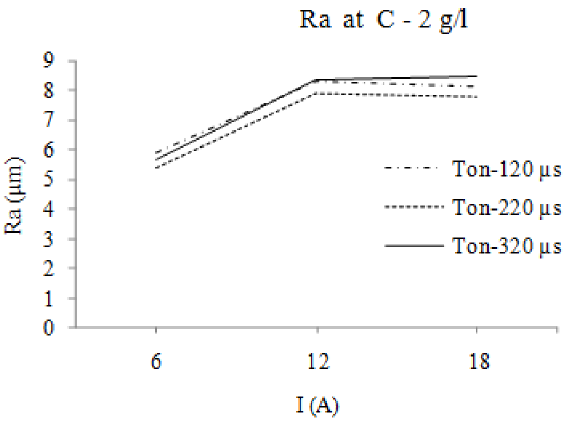

Figure 5 Effect of pulse on-time on R_a

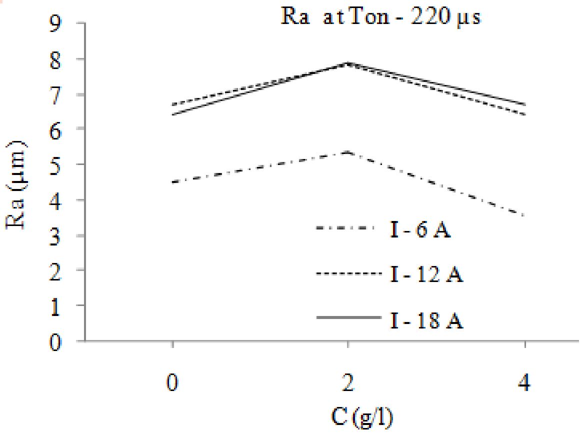

Figure 6 Effect of concentration of powder on R_a

The first condition makes sure that the chosen solution lies on a better non-dominated front, and the second condition ensures a better spread among the solutions. The simulated binary crossover (SBX) is used here to create two offspring from two-parent solutions. The random simplest mutation operator is applied randomly to create a solution from the entire search space.

The control parameters of NSGA-II must be adjusted to give the best performance [13]. The parameters are: probability of crossover pc = 0.5 with distribution index ηc=10, mutation probability pm = 0.05 and population size pz=100. It was found that the NSGA-II with those control parameters produces better convergence and distribution of optimal solutions located along the Pareto optimal solutions. The 1,000 generations are quite enough to find the true optimal solutions.

A set of non-dominated solutions has been obtained using NSGA-II and the best solution has been considered for validation by performing the experiments. The results were tabulated along with the percentage error in the Table 2.

Table 2 Comparison between predicted and experimental values of R_a

Response	**For I=12A, T_{on} = 18o µs, C = 2.3 g/L**		
	Predicted	***Obtained***	***Error (%)***
MRR (mg/min)	260.83	277.47	6.37
R_a (μm)	6.299	6.58	4.46

VI. CONCLUSION

Based on the experimental results, conclusions can be drawn as follows: This research has proved that the PMEDM using Al powder and copper electrode is possible in improving the MRR and surface integrity of the W300 steel.

Two stage efforts of formulation of empirical models for MRR and R_a by surface response methodology and multi-objective optimization of this models using NSGA-II resulted in simultaneously maximize MRR and to improve maximum possible surface quality. These findings can assist other researchers and industrialist in the EDM machining of W300 die-steels. Other conclusions drawn on electrical discharge machining of W300 die-steel with and without Al powder in kerosene dielectric fluid under various machining conditions are as follows:

- Maximum MRR of 415 mg/min is obtained at a high peak current of 18 A, low T_{on} of 120 µs, and a high concentration of 4 g/L of Al powder.
- To produce low surface roughness values, a low peak current of 6 A, a low value T_{on} of 120 µs, and a higher concentration of powder of 4 g/L should be selected for kerosene dielectric fluids.
- The optimal parameters obtained from NSGA-II algorithm for machining with Al powder mixed kerosene: I - 12A, T_{on} - 180 µs and C - 4g/L.

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