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Multi objective optimization of PMEDM using response surface methodology coupled with fuzzy based desirability function approach

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A B S T R A C T

Powder mixed electro discharge machining (PMEDM) is a hybrid machining process where the electrically conductive powder is mixed into the dielectric fluid to enhance the machining efficiency as well as surface finish. In this investigation, PMEDM is performed for the machining of AISI 304 stainless steel when silicon carbide powder is mixed into the kerosene dielectric. Peak current, pulse on time, gap voltage, duty cycle and powder concentration are considered as process parameter while material removal rate (MRR), tool wear rate (TWR) and surface roughness (Ra) are considered as response. A face centered central composite design (FCCCD) based response surface methodology (RSM) is applied to design the experiment. A hybrid optimization technique like desirability coupled with fuzzy-logic method is performed to get the optimum level of the multiple performance characteristics. Analysis of variance (ANOVA) is performed for the statistical analysis. The result shows that peak current is the most significant parameter for MRR, TWR and Ra. The optimal setting for maximum MRR, minimum TWR and Ra have been obtained by desirability coupled with fuzzy-logic method.

1. Introduction

Among all the nonconventional machining process, electro discharge machining (EDM) is the most popular and successful one. This process is based on an electro-thermal process where electrical energy generates the spark, and thermal energy removes the molten metal from the workpiece. EDM is mainly used to cut the difficult-to-machine material, high strength and high-temperature resistance material (Snoeys et al., 1986). Conventional EDM has some advantages as well as some disadvantages. Therefore, to overcome the disadvantages, hybrid EDM is introduced and powder mixed EDM (PMEDM) is one of the finest hybrid EDM techniques used by the researchers (Rajagopal et al., 2013; Pandey & Singh, 2010). Dewangan et al. (2015) performed multi-objective optimization to determine

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the optimal parameter setting for improving the surface integrity of AISI P20 tool steel. They used grey relational analysis (GRA) in combination with fuzzy logic to determine the grey fuzzy reasoning grade (GFRG). Again, they adopted the Fuzzy TOPSIS and sensitivity analysis to optimize the surface crack density (SCD), white layer thickness (WLT), surface roughness (SR), and overcut (OC). They found an optimal parametric combination of peak current =1A, pulse on time= 10μs, tool-work time=0.2s, tool lift time= 1.5s to reduce the surface integrity as well as the dimensional accuracy (Dewangan et al., 2015). Pandey and Panda (2015) adopted the Taguchi methodology in combination with fuzzy-logic based on desirability function to optimize the bone drilling process to minimize the drilling induced damage bone. Bhaumik and Maity (2014, 2015, and 2016) studied the effect of tungsten carbide electrode on the machining performance of EDM during machining of AISI 304 and optimizing the responses viz. material removal rate (MRR), tool wear rate (TWR), surface roughness (Ra) using desirability coupled with grey relational analysis (GRA).

Singh and Yeh (2012) performed grey relational analysis to appraise the efficiency of optimizing multiple performance characteristics of abrasive powder mixed EDM (APM-EDM) of $6061Al/Al_2O_{3p}/20_p$. Tripathy and Tripathy (2016) applied Taguchi method coupled with technique for order of preference by similarity to ideal solution (TOPSIS) and GRA to evaluate the effectiveness of multiple performance characteristics viz. MRR, TWR, R_a for PMEDM during machining of H-11 die steel. Reddy et al. (2015) performed multi objective optimization for the response parameters such as MRR, TWR and surface roughness (SR) based on Taguchi methodology coupled with GRA for PH17-4 stainless steel. Shivakoti et al. (2013) reported the influence of $NaNO_3$ mixed water during machining of D3 die steel during powder mixed electro discharge machining. They applied GRA to optimize the multi-performance characteristics such as MRR, TWR and overcut (OC). Tang and Du (2014) adopted Taguchi methodology in combination with GRA during green electrical discharge machining of Ti-6Al-4V. They reported that this optimization was efficient and effective for the optimization of multi performance characteristics. Rupajati et al. (2014) adopted the Taguchi method coupled with fuzzy-logic method to optimize the multiple responses viz. recast layer thickness and surface roughness. They found that this optimization technique significantly could improve the multiple responses. The same optimization technique was applied to predict the MRR, TWR and SR in ultrasonic-assisted EDM (US-EDM) (Shabgarda et al., 2013). Another manufacturing processes also have been optimized using similar types of optimization technique (Barzani et al., 2015; Pandey & Dubey, 2012; Acilar & Arslan, 2011).

From the above literature review, it is evident that hybrid optimization technique has mostly been adopted in EDM processes. In this study, hybrid optimization technique (Response surface methodology and desirability coupled with fuzzy-logic method) is discussed for determining the optimum level of machining parameter for improving the MRR and lower down the TWR and R_a simultaneously.

2. Material and Methods

In this investigation, powder mixed electro discharge machining (PMEDM) is carried out considering AISI 304 stainless steel and tungsten carbide (φ10mm) as workpiece and tool material, respectively. In this study, SiC powder (~30 μm) is mixed into the kerosene oil (dielectric constant=2, electrical conductivity=1.6×10^{-14} S/m). Experiments are carried out in Electronica-Electraplus PS 50 ZNC machine. The chemical composition of AISI 304 stainless steel is given in Table 1.

The machining parameters considered in this study are i) peak current(I_p), ii) pulse on time(T_{on}), iii) gap voltage(V_g), iv) duty cycle(r), v) powder concentration(P_C) while (i) material removal rate (MRR) (mm^3min^{-1}), (ii) tool wear rate (TWR) (mm^3min^{-1}) and (iii) surface roughness (R_a) (μm) are considered as response. The machining parameters and their levels are tabulated in Table 2. A face-centered central composite design (FCCCD) based response surface methodology (RSM) has been adopted to design the PMEDM process. RSM is a group of mathematical and statistical techniques which are used for modeling and analysis of problems where the response is controlled by the input variables, and the objective is to develop a relationship amongst them (Montgomery, 2001). A total of 33 experiments were performed for this study. The experimental layout, result and their respective Desirability fuzzy reasoning grade (DFRG) values are tabulated in Table 3.

Table 1
Chemical Composition of AISI 304

Element	C	Mn	Si	P	S	Cr	Ni	Fe
%	0.06	0.72	1.26	0.05	0.11	16.36	6.95	Balance

Table 2
Level values of machining parameter

Sl. No.	Factors	Levels	
		Low(-1)	High(+1)
1	I_P(A)	4	8
2	T_{on} (μs)	50	150
3	V_g (V)	45	65
4	r (%)	55	65
5	P_C (g/l)	0	10
6	Polarity	+ve	
7	Machining Time (min)	10	
8	Dielectric Fluid	Kerosene Oil	

2.1 Experimental Procedure

Experiments are performed according to design matrix. During machining, material removal from the workpiece and electrode are measured using the weight loss method and then converted to volumetric material loss. The average surface roughness is measured by Talysurf (Model: Taylor Hobson, Surtronic 3+). The output responses such as MRR and TWR are calculated from the experimental data.

$$Material\ Removal\ Rate(MRR) = \frac{Volumetric\ material\ loss\ from\ workpiece(mm^3)}{Machining\ Time(\min)} \tag{1}$$

$$Tool\ Wear\ Rate(TWR) = \frac{Volumetric\ material\ loss\ from\ electrode(mm^3)}{Machining\ Time(\min)} \tag{2}$$

3. Result and discussion

3.1 Optimization using desirability with the fuzzy-logic method

Multi response optimization converts all the output responses to a scale-free single response and then optimizes the single response. In this study, a hybrid technique such as desirability coupled with the fuzzy-logic method is used to optimize the responses.

3.1.1 Steps for desirability-fuzzy logic method

1. Calculate the desirability index (d_i) for each output response.
2. Apply fuzzy-logic system. The fuzzifier uses the membership function to fuzzify the desirability of each performance characteristics.
3. Generate the fuzzy rules. Then deffuzzifier converts the predicted fuzzy value into desirability-fuzzy reasoning grade (DFRG).
4. Perform the statistical analysis of variance (ANOVA).

5. Evaluate the optimal parameter settings for the machining parameter.
6. Perform the confirmation test

3.1.2 Calculation of Desirability function

To calculate the desirability index (d_i) for each output response, higher the better is chosen for material removal rate and lower the better is chosen for tool wear rate and surface roughness. The desirability index value of material removal rate, tool wear rate and surface roughness are calculated by Eq. (4) and Eq. (7) respectively.

Desirability for "Higher-the-better" (HB) (Ramanujam et al., 2014)

$$\text{If } \hat{y} \le y_{\min}, d_i = 0 \tag{3}$$
$$\text{If, } y_{\min} \le \hat{y} \le y_{\max}, d_i = \left(\frac{\hat{y}-y_{\min}}{y_{\max}-y_{\min}}\right)^r \tag{4}$$
$$\text{If } \hat{y} \ge y_{\max}, d_i = 1 \tag{5}$$

Desirability for "Lower-the-better" (LB)

$$\text{If, } \hat{y} \le y_{\min}, d_i = 1 \tag{6}$$
$$\text{If } y_{\min} \le \hat{y} \le y_{\max}, d_i = \left(\frac{\hat{y}-y_{\max}}{y_{\min}-y_{\max}}\right)^r \tag{7}$$
$$\text{If, } \hat{y} \ge y_{\max}, d_i = 0 \tag{8}$$

where, y_{min} is a lower tolerance limit of ŷ, y_{max} is a higher tolerance limit of ŷ, d_i is desirability value, r represents the desirability function index. In this study, it is considered as 1.

3.1.3 Desirability fuzzy–logic method

In desirability method, each response is categorized by higher the better, lower the better and nominal is the best quality characteristics. A complicated multi-objective optimization problem can be solved by integrating the desirability analysis and fuzzy-logic method.

Now a day's fuzzy rule based modeling is widely used because it can easily represent the uncertain and imprecise relationships which is very difficult to describe with the precise mathematical modeling (Latha & Senthilkumar, 2009, 2010; Singh et al., 2013). A fuzzy logic system consists of a fuzzifier, membership functions, a fuzzy rule base, an interference engine and a defuzzifier. Different types of membership functions are used for fuzzy analysis such as triangular, trapezoidal, sigmoid and Gaussian, etc. The most popular fuzzy interferences are Mamdani and Sugeno. Mamdani model has been widely used to solve the complicated problems because of its easiness (Latha & Senthilkumar, 2009, 2010; Singh et al., 2013). For this study, a triangular shaped membership function is used for fuzzification of input and output function.

For fuzzifying, the input variable, the linguistic membership function such as small, medium and large are used. The output is fuzzified by using the membership function such as very small, small, medium, large and very large. 33 fuzzy rules are used for fuzzy interface engine based on 33 experiments run. The crisp value of DFRG is obtained using the center of gravity defuzzification method. MATLAB fuzzy logic toolbox is used to implementing the fuzzy logic. The relationships between the input and the output are presented in the form of 'if-then' rule which are presented below:

Rule 1: if MRR is large and TWR is large, and R_a is large then DFRG is very large
Rule 2: if MRR is medium and TWR is medium, and R_a is medium then DFRG is large
…………
…………

Rule n: if MRR is small and TWR is small, and R_a is small then DFRG is very small

Fuzzy rules are directly derived based on the larger the better characteristics. The membership functions of three input and output parameters are shown in Fig.1 and Fig. 2. Fuzzy logic rule viewer is shown in Fig.3. In this figure the row represents the fuzzy rules, the first three columns represent the input desirability of MRR, TWR and R_a respectively. The last column represents the defuzzified multi characteristics perform index i.e. DFRG. The desirability and DFRG values are tabulated in Table 3.

Table 3

Experimental layout and DFRG value of PMEDM performance characteristics

Exp.	Process parameter					Observed value			desirability			
No.	I_p	T_{on}	V_g	r	P_C	MRR	TWR	R_a	d_i(MRR)	d_i(TWR)	$d_i(R_a)$	DFRG
1	4	50	45	55	10	1.6458	0.02132	5.640	0.156322	0.833307	1	0.594
2	8	50	45	55	0	4.1650	0.05632	8.390	0.541235	0.5	0	0.395
3	4	150	45	55	0	2.5791	0.02132	6.730	0.156737	1	0.7575	0.536
4	8	150	45	55	10	6.6295	0.07096	7.980	0.725261	0.749922	0.0675	0.441
5	4	50	65	55	0	1.2083	0.02132	6.450	0.085122	0.916693	0.85	0.451
6	8	50	65	55	10	6.1375	0.03399	7.780	0.812682	0.5	0.565	0.279
7	4	150	65	55	10	2.3041	0.01066	5.810	0.096015	0.916693	0.825	0.464
8	8	150	65	55	0	6.3583	0.09396	8.672	0.846191	0.333307	0.0475	0.485
9	4	50	45	65	0	2.1366	0.03398	6.380	0.024299	0.5	0.9675	0.080
10	8	50	45	65	10	5.5041	0.05131	7.340	0.812167	0.416693	0.2	0.561
11	4	150	45	65	10	2.1458	0.02132	6.210	0.3652	0.916693	0.975	0.619
12	8	150	45	65	0	5.7860	0.09396	8.340	0.888594	0	0.0925	0.250
13	4	50	65	65	10	2.2250	0.02132	5.800	0	1	0.8575	0.665
14	8	50	65	65	0	5.1291	0.08123	8.370	0.848289	0.5	0.1175	0.493
15	4	150	65	65	0	1.4668	0.03632	6.910	0.042617	0.833307	0.7175	0.863
16	8	150	65	65	10	8.0125	0.09686	7.240	1	0.083307	0.4325	0.472
17	6	100	55	60	5	3.6664	0.04265	7.110	0.412001	0.75	0.485	0.547
18	6	100	55	60	5	3.4683	0.04265	7.020	0.411687	0.75	0.4425	0.5
19	6	100	55	60	5	3.6666	0.03865	7.130	0.415343	0.612066	0.4325	0.485
20	6	100	55	60	5	3.5208	0.04265	7.020	0.424377	0.662316	0.4675	0.5
21	6	100	55	60	5	3.5591	0.03998	7.070	0.409539	0.612066	0.4187	0.5
22	6	100	55	60	5	3.5015	0.03965	7.110	0.394361	0.68748	0.4425	0.493
23	4	100	55	60	5	2.3708	0.03198	6.330	0.123228	0.68748	0.9325	0.537
24	8	100	55	60	5	6.1910	0.07397	8.150	0.796462	0.166693	0.2425	0.433
25	6	50	55	60	5	2.8900	0.03632	6.260	0.402779	0.778603	0.5225	0.426
26	6	150	55	60	5	3.6875	0.05631	6.630	0.555018	0.61191	0.3925	0.5
27	6	100	45	60	5	3.2667	0.03398	6.940	0.425093	0.662316	0.4	0.445
28	6	100	65	60	5	3.6830	0.03631	7.060	0.407491	0.662316	0.4625	0.5
29	6	100	55	55	5	3.2583	0.03198	7.220	0.377023	0.833307	0.3925	0.475
30	6	100	55	65	5	3.5166	0.04065	7.270	0.457232	0.662316	0.3825	0.5
31	6	100	55	60	0	2.8910	0.05331	7.740	0.292115	0.611988	0.3	0.44
32	6	100	55	60	10	3.9583	0.03298	6.970	0.387074	0.833307	0.6175	0.550
33	6	100	55	60	5	3.6333	0.04365	7.060	0.383418	0.612066	0.4175	0.514

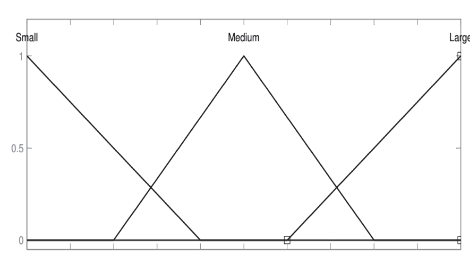

Fig. 1. Membership functions for MRR, TWR and R_a

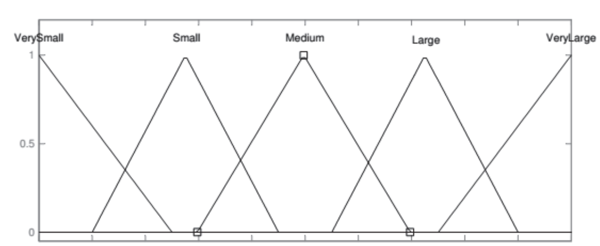

Fig. 2. Membership functions for desirability-fuzzy reasoning grade

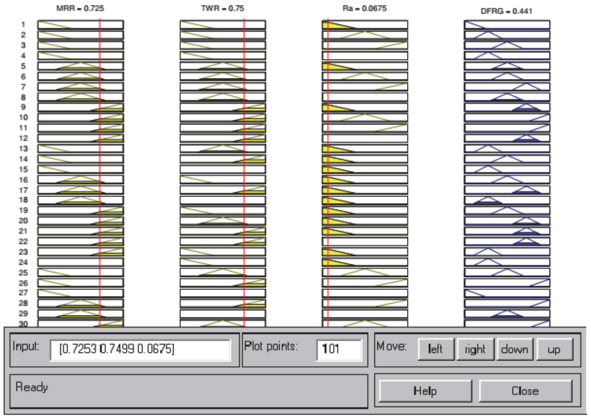

Fig. 3. Fuzzy logic reasoning procedure

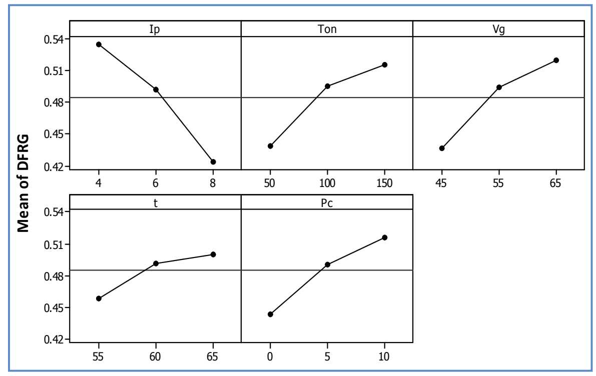

Fig. 4. Main effect plot for DFRG

Table 4
ANOVA table for DFRG

Source	DF	Seq SS	Adj MS	F	P	% of contribution
Regression	11	0.490514	0.044592	50.29	0.000	96.34
Linear	5	0.144760	0.052045	58.69	0.000	28.43
I_P	1	0.055411	0.022707	25.61	0.000	10.88
T_{on}	1	0.026106	0.080378	90.64	0.000	5.12
V_g	1	0.031375	0.054308	61.24	0.000	6.16
r	1	0.008171	0.105219	118.65	0.000	1.60
Pc	1	0.023697	0.000417	0.47	0.500*	4.65
Interaction	6	0.345754	0.057626	64.98	0.000	67.90
$I_P \times T_{on}$	1	0.037201	0.037201	41.95	0.000	7.30
$I_P \times V_g$	1	0.017589	0.017589	19.84	0.000	3.45
$T_{on} \times$ Pc	1	0.041851	0.041851	47.19	0.000	8.22
$V_g \times$r	1	0.100600	0.100600	113.45	0.000	19.75
$V_g \times$Pc	1	0.116230	0.116230	131.07	0.000	22.82
r×Pc	1	0.032283	0.032283	36.41	0.000	6.34
Residual Error	21	0.018622	0.000887			3.65
Lack-of-Fit	15	0.016146	0.001076	2.61	0.122*	3.17
Pure Error	6	0.002476	0.000413			0.48
Total	32	0.509136				100

The optimal value for the machining parameter is shown in Fig.4. From the main effect plot of DFRG, the optimal parametric combination of higher MRR, lower TWR and R_a has been found at I_P=4A, T_{on}=150µs, V_g=65V, r=65% and Pc=10g/l. Statistical analysis of variance (ANOVA) is performed for each machining parameter shown in Table 4. In this table, the insignificant terms are eliminated, and the remaining terms are provided. The regression equation for this model is

$$\mathrm{DFRG} = 4.41842+0.11166\times I_P + 0.00468\times T_{on} - 0.07251\times V_g - 0.09195\times r + 0.01366\times Pc - 0.00048\, I_P\times T_{on} - 0.00166\, I_P\times V_g - 0.00020 T_{on}\times Pc + 0.00159\, V_g\times r - 0.00170\, V_g\times Pc + 0.00180\, r\times Pc \quad (9)$$

4. Confirmation test

The confirmation experiment is the ultimate step to establish and confirm the progress of the quality characteristics using the optimum level of the design parameter. The confirmation experiment is conducted by setting the machining parameter at the optimum level. The predicted DFRG ($\hat{\gamma}$) at its optimum level of the machining parameter can be found out by

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q}(\overline{\gamma_i} - \gamma_m) \quad (10)$$

where, γ_m is mean of DFRGs all experiments run, $\overline{\gamma_i}$ mean of DFRG at the optimum level of its parameter, and q is the number of machining parameter that significantly affect DFRG. For the quality improvement, the initial machining parameter is considered to be I_P=4A, Ton=100µs, Vg=55V, r=60%

and Pc=5g/l. Table 5 shows the confirmatory experiment at this optimum level. The optimum parameter for this experiment is obtained from the main effect plot. DFRG value for initial machining condition is 0.537, and it enhances up to 0.582 for optimal design. So the improvement of DFRG is 0.045. From this investigation, it is clearly seen that quality characteristics are greatly improved.

Table 5

Results of machining performance using initial and optimal machining parameters

	Initial machining parameters	Optimum machining parameter	
		Prediction	Experiment
Setting level	$I_{P1}T_{on2}V_{g2}\ r_2Pc_2$	$I_{P1}T_{on3}V_{g3}\ r_3Pc_3$	$I_{P1}T_{on3}V_{g3}\ r_3Pc_3$
MRR	2.3708		2.4591
TWR	0.03198		0.01066
R_a	6.330		5.124
DFRG	0.537	0.776	0.582
Improvement in DFRG	8.37%		

5. Conclusions

In this research work, a hybrid optimization technique (desirability coupled with the fuzzy-logic method) has been performed to optimize the PMEDM responses viz. material removal rate, tool wear rate and surface roughness during machining of AISI 304 stainless steel. Based on the experiment the following conclusions are drawn:

- The optimum parametric combination of peak current=4A, pulse on time =150µs, gap voltage=65V, duty cycle=65% and powder concentration=10g/l has been determined.
- ANOVA results show that peak current is the most significant parameter for all the responses.
- A hybrid technique of desirability-fuzzy logic method in combination with RSM-based experimental design has a good potential to do away with the difficult task of multi response optimization by converting the data into a single DFRG. Thus it can be effectively used for optimizating the machining parameter in PMEDM to enhance the material removal rate and surface finish with lower tool wear rate.

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