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Full Length Article

Multi-attribute optimization of machining process parameters in powder mixed electro-discharge machining using TOPSIS and grey relational analysis

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ABSTRACT

Powder Mixed Electro-Discharge Machining (PMEDM) is a hybrid machining process where a conductive powder is mixed to the dielectric fluid to facilitate effective machining of advanced material. In the present work application of Taguchi method in combination with Technique for order of preference by similarity to ideal solution (TOPSIS) and Grey Relational Analysis (GRA) have been adopted to evaluate the effectiveness of optimizing multiple performance characteristics for PMEDM of H-11 die steel using copper electrode. The effect of process variables such as powder concentration (C_p), peak current (I_p), pulse on time (T_{on}), duty cycle (DC) and gap voltage (V_g) on response parameters such as Material Removal Rate (MRR), Tool Wear Rate (TWR), Electrode Wear Ratio (EWR) and Surface Roughness (SR) have been investigated using chromium powder mixed to the dielectric fluid. Analysis of variance (ANOVA) and F-test were performed to determine the significant parameters at a 95% confidence interval. Predicted results have been verified by confirmatory tests which show an improvement of 0.161689 and 0.2593 in the preference values using TOPSIS and GRA respectively. The recommended settings of process parameters is found to be $C_p = 6$ g/l, $I_p = 6$Amp, $T_{on} = 100$ µs, DC = 90% and $V_g = 50$ V from TOPSIS and $C_p = 6$ g/l, $I_p = 3$Amp, $T_{on} = 150$ µs, DC = 70% and $V_g = 30$ V from GRA. The microstructure analysis has been done for the optimal sample using Scanning Electron Microscope (SEM).

1. Introduction

Electrical Discharge Machining (EDM) is a thermoelectric process where erosion of workpiece material occurs by high frequency controlled pulses generated in the dielectric medium between the tool and workpiece electrodes separated by a small gap. The limitations of the process include low surface quality and poor material removal rate. A plasma channel is created due to the continuous bombardment of ions and electrons generating temperature in the range of 8000 °C–12000 °C in the discharge gap which causes vaporization and erosion of the material. Powder mixed electro-discharge machining (PMEDM) is a promising technique which overcomes the limitations and improves the machining capabilities of EDM. Addition of a fine conductive powder to the dielectric fluid decreases its insulating strength and consequently increases the inter-electrode space causing an easy removal of the debris. On application of a voltage of 80–315 V, an electric field in the range of 10^5–10^7 V/m is formed, giving rise to positive and negative charges on the powdered particles. The powdered particles start moving in a zig-zag path on getting energized, thus forming clusters in the sparking area. The bridging effect takes place underneath the sparking area causing multiple discharges in a single pulse leading to quicker sparking and erosion from the workpiece surface. This easy short circuit enhances the machining rate of the process. The plasma channel gets widened and enlarged, producing steady and consistent sparks forming shallow craters on the workpiece surface with superior surface quality. Material removal occurs from both the electrode surfaces and under suitable machining conditions, the removed material combined with the powder particles get deposited on the surface of the workpiece, modifying and improving the properties resulting in breakdown of the dielectric fluid. As the sparking trend changes in the presence of abrasive powders, lot of alteration in the surface properties occurs.

The process variables of PMEDM play a considerable role in material removal mechanism. Performance of the PMEDM process depends upon characteristics like powder type, concentration, particle size, electrode area and workpiece constituents. The roughness and properties of the machined surface of AISI H13 was found to be affected by the electrode area in presence of silicon powder within the dielectric as suggested by Pecas and Henriques. Furthermore,

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material transfer from Cu, Cu-Cr and Cu-W electrodes to AISI H13 in presence of tungsten powder in the dielectric has been reported in References 1–3. The effect of mixing different powders and additives to the dielectric has been reported in Reference 4 whereas the investigation on surface modification has been carried out in Reference 5. Singh and Yeh [6] evaluated the multiple performance characteristics for aluminium matrix composite during APM-EDM using grey relational analysis and found an improvement of material removal rate (MRR), tool wear rate, (TWR) and surface roughness (SR). Tzeng and Lee [7] reported the addition of different powders to kerosene for examining the discharge gap, MRR and TWR while machining SKD 11 using copper tool. Chow et al. [8] found that on addition of SiC powder, utmost machining rates were achieved with an increase in machining gap whereas adding aluminium powder improves the surface texture. Singh et al. [9] investigated that the machining of 6061 Al/Al_2O_3/20P using copper tool and SiC powder mixed to the dielectric decreases the TWR and SR while MRR improves appreciably. A slight increase in the dimensional overcut occurred due to the abrasive effect. Kumar and Batra [10] studied the response of three die steel materials to surface modifications when machined using tungsten powder mixed dielectric. Assarzadeh and Ghoreishi [11] implemented response surface methodology combined with desirability approach for modelling and optimization of the process parameters during EDM of CK-45 die steel using Al_2O_3 powder suspension into dielectric. The optimal condition of process parameters was found to maximize the MRR. Kansal et al. [12] proposed a simplified model based on Taguchi and Utility approach for multi-characteristics optimization of the process parameters to obtain the optimal setting during machining of H-11 die steel using Si powder and copper tool. Bhattacharya et al. [13] proposed a suitable set of parameters for rough and finish machining on EN-31, H-11 and HCHCr die steel using aluminium and graphite powders with different combinations of tool and dielectric. Senthil et al. [14] used TOPSIS to optimize multiple responses while machining Al-$CuTiB_2$ to attain the best possible set of process parameters for machining. Singh et al. [15] investigated the impact of input parameters on surface roughness while machining H-11 die steel using copper tool with addition of Al powder to the dielectric. The surface roughness was improved and negative polarity of the tool electrode was found desirable for lowering the surface roughness. Talla et al. [16] conducted the multi-objective optimization of PMEDM using Taguchi, GRA and Principal Component Analysis to control the process parameters. Apart from that multi-objective optimization using Taguchi-based Grey relational analysis, Grey relational Analysis and ANFIS have also been carried out for EDM and wire EDM as reported by Lal et al., Raghuraman et al. and Azhiri et al. [17–19]. Ojha et al. [20] investigated the parametric optimization of PMEDM on EN-8 steel using suspension of chromium powder to dielectric fluid. Sarabjeet et al. [21] optimized collectively MRR, TWR, SR and surface integrity for three different metal matrix composites using TOPSIS, and the ranking was done as per the severity of surface defects.

Past work reveals that PMEDM involves a large number of input process variables that control the quality of the machined component. Therefore, the relative significance of the process variables on output responses is worth investigating. Though several works have been reported using different powders mixed to the dielectric fluid, not much effort has been made to explore the combined effect of input parameters affecting the performance of the PMEDM process for H-11 die steel. The effect of adding chromium powder to the dielectric fluid in varying concentrations has not yet been investigated for H-11 material. The optimum set of input parameters should be identified such that the machining process improves in terms of performance characteristics and surface quality. Chromium powder was selected because of the high wear and corrosion resistant properties it imparts to the machined elements. Multi-attribute decision making techniques like TOPSIS and GRA have not been implemented to find the optimal setting during PMEDM of H-11. Thus, the analysis of improvement occurring in the process using multi-attribute optimization techniques is desirable. The present work is a step in this direction. An attempt to find out the best possible set of process variables through multi-objective optimization using TOPSIS and GRA to acquire maximum MRR and minimum TWR, EWR and SR using chromium powder mixed to the dielectric fluid has been made. Analysis of variance (ANOVA) was used to locate the statistically significant input parameters affecting the output responses. Furthermore, comparison between the two multi-objective optimization processes has been done by estimating the improvements in their preference values. The microstructural examination showing the deposition of material due to powder particles and electrode material has been carried out for the obtained optimal setting.

2. Materials and methods

2.1. Set-up

Experiments were performed on EDM, model Electronica Smart ZNC EDM (Die sinking type) with positive polarity and servo-head. Dielectric fluid used was commercial grade EDM oil having freezing point 94 °C and specific gravity 0.763. The current and voltage waveforms were recorded on a “Digital Storage Oscilloscope”. Functional tank of the machine had a capacity of 300 litres for the circulation of dielectric fluid. Thus, a detachable machining tank was designed with a capacity of 20 litres to avoid the wastage of the dielectric fluid and for the effective use of powder particles leading to cost minimization as shown in Fig. 1. In the newly designed and adapted system, to ensure proper distribution of powder and to avoid the settling down of powder in dielectric fluid, a pump and stirring arrangement was installed. Each run was carried out for time duration of 15 minutes. The arithmetic mean of the SR was measured with a “Surface Roughness Tester (Talysurf, Rank Taylor Hobson, England)” Model-Surtronic S-100 series (M-112-4568-10). The SR was also measured as the actual deviation from the nominal surface by considering the microstructural analysis using the Inverted Trinocular Metallurgical Microscope along with Advanced Image Analyser (Make: Leica DMI 3000M).

2.2. Electrode and workpiece material

Workpiece material selected for the experiment is H-11 die steel having a composition of “5% Cr, 0.35% C, 1% Si, 0.4% Mn, 0.03% P,

Fig. 1. PMEDM set-up.

0.02% S, 1.5% Mo, 0.01% Co, 0.01% Cu, 0.45% V" and the rest being Fe. It is a hot work steel having high hardenability, toughness, high abrasion resistance, excellent wear resistance and high compressive strength. The dimension of the workpiece is $120 \times 60 \times 25$ mm obtained in proper annealed condition. The tool electrode selected for the experiment is electrolytic copper having a dimension of $20 \times 20 \times 60$ mm. "Optical Emission Spectrometer" was used to measure the chemical composition of the tool and workpiece material. Each workpiece was ground before the operation for proper alignment between the tool and workpiece surface. Chromium powder with size <53 µm was mixed to the dielectric fluid with varying concentrations. The microstructural analysis of the selected samples was carried out using SEM at a magnification of 500×.

2.3. Design of experiments

Taguchi's Technique was implemented to find the impact of process variables on the PMEDM performance. In the present work, the important input parameters selected were concentration of chromium powder 'C_p' (gm/l), peak current 'I_p' (Amp), pulse on time 'T_{on}' (µs), duty cycle 'DC' (%) and gap voltage 'V_g' (V) varying at three levels based on certain pilot experiments performed for selection of process parameters and their levels as shown in Table 1.1. To determine the effect of powder addition, experiments without powder were also performed at one level. The influence of input parameters on response variables like MRR, TWR, EWR and SR was examined. Considering the number of factors and their levels an L_{27} Taguchi's orthogonal array was used to conduct the experiments as shown in Table 1.2. Taguchi's process uses means to normalize the functions.

Srivastava and Pandey [22] considered MRR and TWR as "the ratio of the volume of material removed from the workpiece and tool surface with respect to the machining time" and can be expressed as:

$$MRR\,(mm^3/min) = \frac{\text{"Volume of material removed from workpiece"}}{\text{density} \times \text{time}} \tag{1}$$

$$TWR\,(mm^3/min) = \frac{\text{"Volume of material removed from tool"}}{\text{density} \times \text{time}} \tag{2}$$

EWR can be defined as "the ratio of weight of the electrode wear to the weight of the workpiece wear after machining" and is expressed as:

$$EWR\,(\%) = \frac{\text{"Wear weight of the tool"}}{\text{"Wear weight of the workpiece"}} \times 100 \tag{3}$$

2.4. Multi-objective optimization

2.4.1. Technique for order of preference by similarity to ideal solution (TOPSIS)

TOPSIS helps to determine the most suitable alternative from a finite set. The principle of the technique is that the selected criteria should be nearest from positive best solution and farthest from negative best solution, the finest solution being the one having the most relative closeness to the ideal solution. The steps involved in carrying out TOPSIS are expressed as:

Step 1: Lan and Tian-Syung [23] reported that decision matrix is the first step of TOPSIS which consists of 'n' attributes and 'm' alternatives and can be represented as:

$$D_m = \begin{bmatrix} q_{11} & q_{12} & q_{13} & \cdots & \cdots & q_{1n} \\ q_{21} & q_{22} & q_{23} & \cdots & \cdots & q_{2n} \\ q_{31} & q_{32} & q_{33} & \cdots & \cdots & q_{3n} \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ q_{m1} & q_{m2} & q_{m3} & \cdots & \cdots & q_{mn} \end{bmatrix} \tag{4}$$

where q_{ij} is the performance of ith alternative in relation to the jth attribute.

Step2: The normalized matrix can be obtained by using the following expression

$$r_{ij} = \frac{q_{ij}}{\sqrt{\sum_{i=1}^{m} q_{ij}^2}} \quad j = 1, 2, \ldots, n. \tag{5}$$

Step 3: The weight of each attribute was assumed to be $w_j (j = 1, 2, \ldots, n)$. The weighted normalized decision matrix $U = [u_{ij}]$ can be obtained by

$$U = w_j r_{ij} \tag{6}$$

where, $\sum_{j=1}^{n} w_j = 1$.

Step 4: The positive-ideal and negative-ideal solutions have been obtained from the following expressions:

$$U^+ = \left\{ \left(\sum_i^{max} u_{ij} \middle| j \in J \right), \left(\sum_i^{min} | j \in J | i = 1, 2, \ldots . m \right) \right\} = \{u_1^+, u_2^+, u_3^+, \ldots\ldots, u_n^+\} \tag{7}$$

Table 1.1
Selection of levels for the factors.

Factors with symbol and units	Levels		
	Level 1	Level 2	Level 3
Concentration of chromium powder 'C_p' (gm/l)	0	3	6
Peak current 'I_p' (Amp)	3	6	9
Pulse on time 'T_{on}' (µs)	100	150	200
Duty cycle 'DC' (%)	7	8	9
Gap voltage 'V_g' (V)	30	40	50

Table 1.2
L_{27} experimental design with response variables.

Run	C_p	I_p	T_{on}	DC	V_g	Avg MRR	Avg TWR	Avg EWR	Avg SR
1	0	3	100	7	30	2.564	0.017	0.671	3.8
2	0	3	100	7	40	2.649	0.019	0.735	4.1
3	0	3	100	7	50	2.735	0.022	0.821	4.5
4	0	6	150	8	30	4.529	0.027	0.611	4.87
5	0	6	150	8	40	5.470	0.030	0.561	5.45
6	0	6	150	8	50	6.666	0.036	0.550	5.86
7	0	9	200	9	30	9.401	0.389	4.143	6.5
8	0	9	200	9	40	10.256	0.486	4.747	7.47
9	0	9	200	9	50	10.940	0.524	4.792	9.2
10	3	3	150	9	30	2.735	0.008	0.300	2.86
11	3	3	150	9	40	3.076	0.009	0.318	3.14
12	3	3	150	9	50	5.475	0.007	0.140	3.54
13	3	6	200	7	30	6.666	0.017	0.257	4.07
14	3	6	200	7	40	7.222	0.010	0.146	4.56
15	3	6	200	7	50	7.435	0.026	0.360	4.91
16	3	9	100	8	30	8.511	0.045	0.529	5.2
17	3	9	100	8	40	11.829	0.057	0.489	5.63
18	3	9	100	8	50	15.947	0.082	0.516	5.97
19	6	3	200	8	30	6.239	0.004	0.076	2.4
20	6	3	200	8	40	7.435	0.003	0.046	2.84
21	6	3	200	8	50	8.376	0.007	0.088	2.98
22	6	6	100	9	30	12.820	0.003	0.026	3.12
23	6	6	100	9	40	13.076	0.007	0.054	3.36
24	6	6	100	9	50	14.017	0.009	0.069	3.68
25	6	9	150	7	30	16.153	0.034	0.214	4.07
26	6	9	150	7	40	16.692	0.042	0.256	4.68
27	6	9	150	7	50	17.0684	0.049	0.289	5.04

$$U^- = \left\{\left(\sum_i^{\min} u_{ij} \middle| j \in J\right), \left(\sum_i^{\max} | j \in J | i = 1, 2, \ldots . m\right)\right\} = \left\{u_1^-, u_2^-, u_3^-, \ldots\ldots\ldots, u_n^-\right\} \quad (8)$$

Step 5: Separation between alternatives were determined from the "ideal" solution and is given by:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (u_{ij} - u_j^+)^2}, \quad i = 1, 2, \ldots . m \quad (9)$$

Separation of alternatives from "negative-ideal" solution is expressed as:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (u_{ij} - u_j^-)^2}, \quad i = 1, 2, \ldots . m \quad (10)$$

Step 6: Relative nearness of the distinct alternative to the positive-ideal solution is calculated which is given as:

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad i = 1, 2, \ldots . m \quad (11)$$

Step 7: The P_i value was ranked in descending order to identify the set of alternatives having the most preferred and the least preferred solutions.

2.4.2. *Grey relational technique*

In order to obtain the required output utilizing minimum resources, it is very much essential to follow optimal combination of process parameters. The optimal parameter setting for a particular response may be unfavourable for other responses. So, a multi-objective optimization needs to be carried out to obtain an optimal parameter setting. In GRA, the experimental values of the measured quality feature are normalized within a range of zero to one. This can be identified as "grey relational generation". The "grey relational coefficient (GRC)" is then computed. Overall performance characteristic depends on the computation of the "grey relational grade (GRG)". Thus, a multi-attribute process optimization is transformed to a single objective problem as suggested by Datta et al. [24]. The highest GRG will be evaluated as the optimal parametric combination. For "grey relational generation", the MRR consequent to "higher the better" principle is given as:

$$x_i(l) = \frac{y_i(l) - \min y_i(l)}{\max y_i(l) - \min y_i(l)} \quad (12)$$

TWR, EWR and SR subsequent to "lower the better" condition are specified as:

$$x_i(l) = \frac{\max y_i - y_i(l)}{\max y_i(l) - \min y_i(l)} \quad (13)$$

where $x_i(l)$ is obtained "grey relational generation", $\min y_i(l)$ is the least value of $y_i(l)$ for the lth response and $\max y_i(l)$ is the highest value for the lth response where $l = 1,2,3,4$ for the various output responses considered in a sequence. The data after normalization for "grey relational generation" are presented in Table 2.1. GRC is computed to establish a correlation between the finest data and the definite normalized data. The GRC is calculated as:

$$\xi_i(l) = \frac{\Delta_{\min} + \psi\Delta_{\max}}{\Delta_{0i}(l) + \psi\Delta_{\max}} \quad (14)$$

where $\Delta_{0i}(l) = |x_0(l) - x_i(l)|$, ψ is the distinctive coefficient lying between $0 \le \psi \le 1$, $\Delta_{\min}$ is the minimum value for Δ_{0i} and $\Delta_{\max}$ is the maximum value for Δ_{0i}. The GRG can now be formulated as:

Table 2.1
Estimation of preference value with rank order.

Experiment no.	Preference value	Order
1	0.732646	22
2	0.728204	23
3	0.721152	24
4	0.745919	21
5	0.750752	20
6	0.756868	17
7	0.256988	25
8	0.166888	26
9	0.152767	27
10	0.754425	19
11	0.75668	18
12	0.790947	14
13	0.798046	15
14	0.803786	12
15	0.791854	13
16	0.78799	16
17	0.812234	10
18	0.814376	9
19	0.809128	11
20	0.826087	8
21	0.838593	7
22	0.912291	4
23	0.912397	3
24	0.919641	1
25	0.914893	2
26	0.890696	5
27	0.874719	6

$$\gamma_i = \frac{1}{n} \sum_{l=1}^{n} \xi_i(l) \quad (15)$$

with n being the number of output responses. The higher is the value of GRG, the closer is the subsequent arrangement of parameters to the optimum solution.

3. Results and discussion

3.1. *Rate of material removal from the workpiece and tool electrode*

The machining efficiency of the process can be characterised by the MRR and TWR. The main aim behind machining should be more amount of material removal with less tool wear. The tool material for machining is selected based upon the principle that the material should have low resistance to electricity and high melting point. From the experimental results it has been found that, when no powder is added to the dielectric and the current and pulse on time increase, MRR increases and the TWR also increases. This is because with the increase in electrical power, additional thermal energy is generated in the discharge channel. Addition of powder particles to the dielectric fluid causes decrease in insulating strength of the dielectric fluid and the inter-electrode gap increases, causing an easy removal of debris. Due to the bridging effect, quicker sparking occurs, resulting in faster erosion from the workpiece surface. This easy short circuit improves the machining rate of the process. The plasma channel gets widened and enlarged, producing stable and uniform sparks. Thus thin craters are formed on the workpiece which improves the surface quality. Experimental observations of MRR and TWR show that when Cr powder is added in 3 gm/l, the MRR increases and the TWR decreases. As the concentration of Cr powder increases to 6 gm/l, the MRR further increases and the TWR decreases with less damaged surfaces. It can be observed from Fig. 2.1 and Fig. 2.3 that with the increase in concentration of Cr powder from 3 gm/l to 6 gm/l, the MRR is showing an increase and TWR is showing a decrease, resulting in improved surface quality for H-11 die steel. The MRR and TWR increase with current independent of other factors as shown in Fig. 2.2 and Fig. 2.4. The variations of output

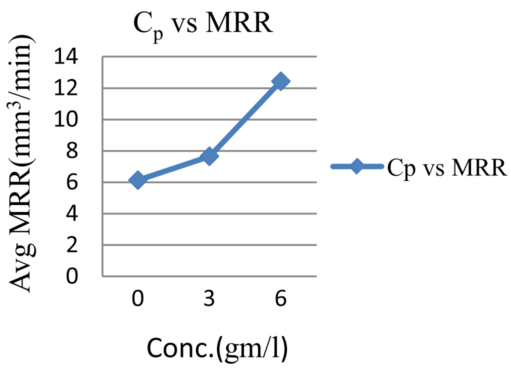

Fig.2.1 C_p vs MRR

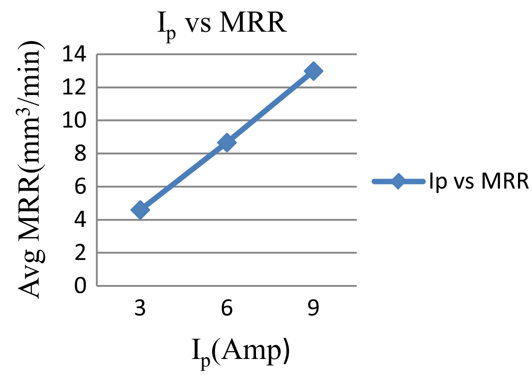

Fig.2.2 I_p vs MRR

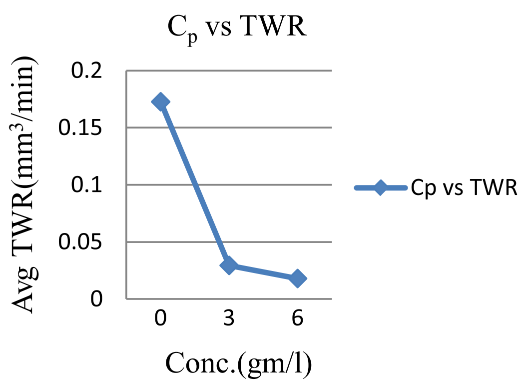

Fig.2.3 C_p vs TWR

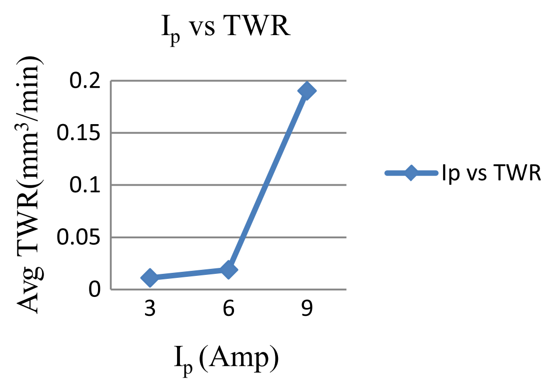

Fig.2.4 I_p vs TWR

Fig. 2. 2.1, 2.2, 2.3 and 2.4 Variations of MRR and TWR with C_p and I_p.

responses like MRR and TWR with respect to C_p and I_p indicate that with the increase in C_p, MRR increases and TWR decreases whereas with the increase in I_p, the MRR and TWR both tend to increase, which is clearly represented in Fig. 2.1–2.4.

3.2. Electrode wear ratio

The characteristic of a perfect tool should be the potential of removing maximum material from the workpiece with the capability to resist self-erosion. From the experimental findings it is clear that with an increase in I_p and T_{on}, the EWR increases during the machining without powder addition. With addition of powder, the EWR decreases because of less tool wear and more material removal from the workpiece.

3.3. Surface roughness

The roughness of the surface produced by electro-discharge machining is directly related to the size of the crater formed and the distribution of recast layer on the surface. The experimental investigations reveal that the roughness of the surface varies within a range of 3.8 µm to 9.2 µm when no powder is added to the dielectric fluid. It can be seen from Fig. 3.1 that with the rise in pulse current, the roughness of the surface also rises as the large dispersive energy causes violent sparks and impulsive forces which result in the formation of larger craters leading to the increase of SR. During flushing when the cooling takes place, some amount of molten material does not completely flush away and resolidifies on the surface, increasing the SR. While adding chromium powder to the dielectric, the surface quality improves as a

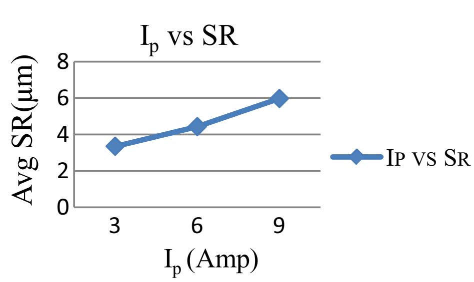

Fig.3.1 I_p vs SR

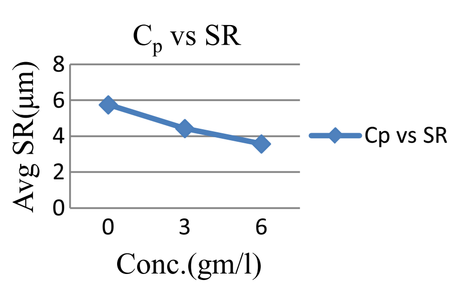

Fig.3.2 C_p vs SR

Fig. 3. 3.1 and 3.2 Variation of SR with I_p and C_p.

consequence to the reduction of SR as shown in Fig. 3.2. When 3 gm/l of powder is added, the roughness values are reduced to a range of 2.86 µm to 5.97 µm. On increasing the concentration of powder to 6 gm/l, the roughness further gets reduced to a range of 2.4 µm to 5.04 µm. It is observed that when T_{on} is increasing, there is a decrease in pulse intensity and increase in the diameter of plasma channel which creates smooth surfaces as compared to low values of T_{on} and higher pulse current combinations. Addition of powder particles in proper size and concentration reduce the SR during machining. Addition of more amount of powder will cause difficulty in stirring as it settles down in the tank. This will adversely affect the surface properties of the material.

3.4. TOPSIS

Optimization of PMEDM with multiple attributes like MRR, TWR, EWR and SR was performed using "TOPSIS". With the results obtained after the experimental runs, the preference value for each experimental combination can be achieved using equations (4–10). The preference value for each alternative can be calculated considering the comparative nearness to the best solution which is computed as the "ratio of negative ideal separation measure divided by the sum of negative ideal separation measure and the positive ideal separation measure" using equation (11). All the output responses are assigned equal weightage considering the performance parameters equally important when machined under ideal conditions. Multi-attribute optimization is thus converted into single objective optimization using a combined approach of Taguchi's design and TOPSIS. The preference values for TOPSIS obtained from each experimental run with the rank order are furnished in Table 2.1.The relative closeness to the ideal solution with respect to the optimal performance measure achieves the maximum preference value and highest rank and is thus considered as the best value for the performance measure.

It can be seen that experimental run #24 is the best multiple performance characteristics having the highest preference order, hence it is the optimal setting followed by run #25 and #23. The optimal parametric combination can be determined by considering the higher values of preference order. The optimal setting obtained is $\mathbf{C_{p3}I_{p2}T_{on1}DC_3V_{g3}}$.

3.4.1. Confirmatory experiment for TOPSIS

After the evaluation of optimal parameter setting, prediction and confirmation for the improvement of quality characteristic using the most suitable set of process variables is carried out.

From Table 2.2 it can be observed that the optimal setting obtained from the TOPSIS gives an increased MRR with low TWR, EWR and SR, thus improving the performance of the quality characteristic and productivity. The concentration of chromium powder causing more amount of material removal is 6 gm/l. The improvement in preference value for ideal solution is 0.161689.

Table 2.2
Findings from the confirmatory experiment.

Initial factor setting		Optimal set
		Experimental
Level	$\mathbf{C_{p1}I_{p1}T_{on1}DC_1V_{g1}}$	$\mathbf{C_{p3}I_{p2}T_{on1}DC_3V_{g3}}$
Chromium powder concentration (gm/l)	0	6
Peak current (Amp)	3	6
Pulse on time (µs)	100	100
Duty cycle (%)	7	9
Gap voltage (Volts)	30	50
MRR (mm^3/min)	2.564	14.0171
TWR(mm^3/min)	0.0172	0.00981
EWR (%)	0.6718	0.069986
SR (μ)	3.8	3.68
Value of preferred solution	0.757952	0.919641

Improvement in preference value for ideal solution = 0.161689.

Table 2.3
ANOVA table for preference solution.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
C_p	2	0.49459	0.494588	0.247294	445.01	0.000
I_p	2	0.17782	0.177819	0.088909	159.99	0.000
T_{on}	2	0.25257	0.252566	0.126283	227.25	0.000
DC	2	0.18469	0.184694	0.092347	166.18	0.000
V_g	2	0.00026	0.000259	0.000129	0.23	0.795
Residual error	16	0.00889	0.008891	0.000556		
Total	26	1.11882				

S = 0.02357, R^2 = 99.2%, R^2 (adj) = 98.7%.

Table 2.4
Response table for preference solution.

Level	C_p	I_p	T_{on}	DC	V_g
1	0.5569	0.7731	0.8157	0.8062	0.7458
2	0.7900	0.8213	0.8040	0.7935	0.7386
3	0.8776	0.6302	0.6049	0.6248	0.7401
Delta	0.3207	0.1911	0.2108	0.1814	0.0072
Rank	1	3	2	4	5

3.4.2. ANOVA for TOPSIS

The considerable effect of process variables on the performance characteristics can be determined by using ANOVA. ANOVA result for preference solution is given in Table 2.3, considering 95% confidence interval as statistically significant. The results of factor responses are considered by using 'higher-the-better' expectation by means of MINITAB software. Table 2.4 indicates that C_p, T_{on}, DC and I_p are parameters which have significant contribution towards improvement in the value of preference solution while the role of V_g is insignificant.

3.5. Grey relational analysis

The experimental results obtained for the different output parameters as presented in Table 1.2 were first normalized using equations (12) and (13). GRC was calculated for each output response using equation (14). The GRC for each response were used to estimate the GRG using equation (15) which represents the overall performance characteristics of the machining process assuming equal weightage for all the performance characteristics considering ideal conditions. The values for GRC and GRG for each run with the rank order are furnished in Table 3.1. A multi-criteria optimization problem is thus converted to a single objective optimization problem using a combined approach of Taguchi design and GRA. Higher value of GRG leads to the optimum or close to the optimum combination of input parameters.

It can be seen that experimental run #22 is the most suitable set of performance characteristics having the highest GRG; hence it is the optimal setting followed by runs #23 and #24. Separating the effect of each parameter at different levels becomes possible in case of orthogonal experimental design. Optimal parametric combination can be determined by considering the higher values of GRG. The mean GRG for each level of input parameter can be determined by estimating the averages of GRG for the particular setting of levels from the obtained experimental results. For all the levels, mean GRG can be given in the similar manner as shown in Table 3.2. The average of all the GRG obtained in Table 3.1 gives the total mean GRG. The total mean GRG is calculated to be 0.7167.

3.5.1. Confirmatory experiment for grey relational analysis

After the estimation of optimal parameter setting, prediction and confirmation for the development of quality attribute using the optimal setting is carried out. From the optimal level of design parameters, the estimated GRG $(\breve{\gamma})$ is calculated as:

$$\breve{\gamma} = \gamma_m + \sum_{i=1}^{p}(\bar{\gamma} - \gamma_m) \tag{16}$$

Table 3.1
Estimation of Grey Relational Coefficient for performance features ($\psi = 0.5$) and Grey Relational Grade with rank order.

Run	MRR	TWR	EWR	SR	Grey Relational Grade	Order
1	0.333	0.9495	0.7869	0.7083	0.6945	17
2	0.334	0.9418	0.7708	0.6666	0.6785	19
3	0.335	0.9317	0.7498	0.6181	0.6589	22
4	0.366	0.9146	0.8028	0.5792	0.6657	21
5	0.384	0.9050	0.8166	0.5271	0.6584	23
6	0.410	0.8866	0.8197	0.4956	0.6532	24
7	0.486	0.4028	0.3666	0.4533	0.4272	25
8	0.515	0.3501	0.3354	0.4014	0.4006	26
9	0.542	0.3333	0.3333	0.3333	0.3855	27
10	0.335	0.9817	0.8967	0.8808	0.7738	10
11	0.341	0.9759	0.8907	0.8212	0.7573	12
12	0.384	0.9836	0.9541	0.7488	0.7678	11
13	0.410	0.9496	0.9114	0.6706	0.7356	15
14	0.424	0.9731	0.9519	0.6115	0.7401	13
15	0.429	0.9175	0.8771	0.5752	0.6998	16
16	0.458	0.8619	0.8256	0.5483	0.6736	20
17	0.580	0.8269	0.8373	0.5128	0.6894	18
18	0.866	0.7672	0.8294	0.4878	0.7376	14
19	0.401	0.9947	0.9794	1	0.8438	5
20	0.429	0.9998	0.9918	0.8854	0.8266	8
21	0.454	0.9848	0.9746	0.8542	0.8171	9
22	0.630	1	1	0.8252	**0.8639**	**1**
23	0.645	0.9857	0.9882	0.7798	0.8497	2
24	0.703	0.9759	0.9820	0.7264	0.8471	3
25	0.888	0.8927	0.9267	0.6706	0.8445	4
26	0.950	0.8686	0.9120	0.5985	0.8325	6
27	1	0.8500	0.9007	0.5629	0.8284	7

Table 3.2
Estimation of mean Grey Relational Grade.

Factors		Grey Relational Grade		
	Level 1	Level 2	Level 3	Delta
C_p	0.5803	0.7306	0.8393	0.259
I_p	0.7576	0.7459	0.6466	0.111
T_{on}	0.7437	0.7535	0.6529	0.0098
DC	0.7459	0.7295	0.6748	0.0711
V_g	0.7247	0.7148	0.7106	0.0141

Total Mean Grey Relational Grade = 0.7167.

where γ_m is the total mean GRG, γ_i is the mean GRG at the most favourable setting and p is the number of major variables affecting the performance feature. Thus, the predicted GRG is equivalent to the mean GRG and the sum of the difference of mean GRG of each factor at the optimal level and the total mean GRG.

From Table 3.3, it can be observed that the MRR increased from 2.564 mm^3/min to 9.87 mm^3/min and the TWR gets reduced from 0.0172 mm^3/min to 0.0034 mm^3/min. The EWR shows a reduction from 0.6718% to 0.0305% and SR decreases from 3.8 µm to 1.57 µm. The results of confirmation test show good agreement with the predicted values. The improvement in GRG after validation is 0.2593.

Table 3.3
Findings from the confirmatory experiment.

Initial factor setting		Optimal set	
		Predicted	Experimental
Level	$\mathbf{C_{p1}I_{p1}T_{on1}DC_1V_{g1}}$	$\mathbf{C_{p3}I_{p1}T_{on2}DC_1V_{g1}}$	$\mathbf{C_{p3}I_{p1}T_{on2}DC_1V_{g1}}$
Concentration of chromium powder (gm/l)	0		6
Peak current (Amp)	3		3
Pulse on time (µs)	100		150
Duty cycle (%)	7		7
Gap voltage (Volts)	30		30
MRR (mm^3/min)	2.564		9.87
TWR(mm^3/min)	0.0172		0.00302
EWR (%)	0.6718		0.0305
SR (μ)	3.8		1.57
GRG	0.69680	0.9542	0.9561

Improvement in GRG = 0.2593.

3.5.2. ANOVA for grey relational analysis

ANOVA, a statistical tool, is used to identify any differences in the average performance of the set of items under test. The significant effect of process variables on the response parameters can be specified using ANOVA at a 95% confidence interval. The results of factor responses are calculated by using 'higher-the-better' expectation using MINITAB software. ANOVA result for means of GRG is given in Table 4.1. Table 4.2 indicates that C_p, T_{on}, DC and I_p are the parameters having statistically significant contribution towards improvement in GRG while the role of V_g is insignificant.

From the obtained optimal setting it can be assumed that as the powder concentration increases, the bridging effect causes more amount of material removal, resulting in better MRR. Thus the optimal powder concentration is 6 gm/l. Table 4.3 shows the final multi-objective optimization results of the confirmatory tests using TOPSIS and GRA and the improvement obtained using both the techniques.

3.6. Microstructure analysis

SEM analysis of machined surface for the optimal setting obtained using TOPSIS and GRA is shown in Fig. 4.1 and Fig. 4.2. It can be observed that the prevailing thermal conditions cause damages to the machined surface, making the surface profile uneven. The roughness profile obtained on the machined surface is directly dependent on the amount of material resolidified or the recast layer formed. Addition of Cr powder to the dielectric improves the surface properties. A small part of the molten material resolidifies when mixed with the carbon elements in the dielectric fluid, molten material from workpiece and electrode due to improper flushing by the dielectric fluid. The upper recast layer of this zone is called the white layer. Generally these layers

Table 4.1
ANOVA table for GRG.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
C_p	2	0.304485	0.30448	0.15224	522.02	0.000
I_p	2	0.066987	0.06698	0.03349	114.84	0.000
T_{on}	2	0.055352	0.05535	0.02767	94.90	0.000
DC	2	0.024953	0.02495	0.01247	42.78	0.000
V_g	2	0.000950	0.00095	0.00047	1.63	0.227
Residual error	16	0.004666	0.00466	0.00466	0.000292	
Total	26	0.457392	0.45739			

$S = 0.01708$, $R^2 = 99\%$, R^2 (adj) = 98.3%.

Table 4.2
Response table for GRG.

Level	C_p	I_p	T_{on}	DC	V_g
1	0.5803	0.7576	0.7437	0.7459	0.7248
2	0.7306	0.7460	0.7535	0.7295	0.7148
3	0.8393	0.6466	0.6530	0.6748	0.7106
Delta	0.2590	0.1110	0.1006	0.0711	0.0141
Rank	1	2	3	4	5

Table 4.3
Optimum level of significant process parameters for relative error estimation.

Response	Optimum level setting	Improvement In preferred grades
TOPSIS	$\mathbf{C_{p3}I_{p2}T_{on1}DC_3V_{g3}}$	0.161689
Grey Relational Analysis	$\mathbf{C_{p3}I_{p1}T_{on2}DC_1V_{g1}}$	0.2593

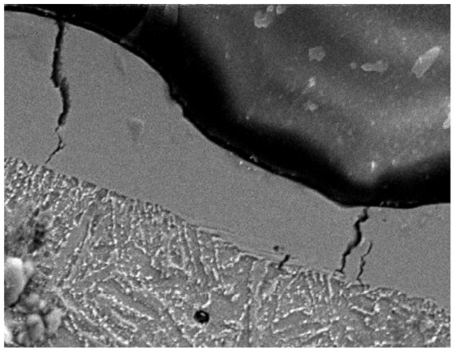

Fig. 4.1 SEM image for optimal set using TOPSIS

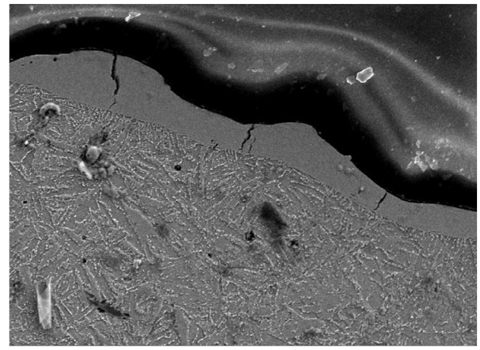

Fig. 4.2 SEM image for optimal set using GRA

Fig. 4. 4.1 and 4.2 SEM image for the obtained optimal set of parameters.

are rough, brittle in nature and are vulnerable to cracks. The roughness profile obtained on the machined surface is directly dependent on the amount of material resolidified or the Recast layer formed.

4. Conclusion

The present investigation aims at improving the surface quality and productivity by maximizing the MRR and minimizing the TWR, EWR and SR of H-11 die steel on the addition of chromium powder to the dielectric fluid and optimizing the process variables. Taguchi's Technique has been used to conduct the experiments by varying the concentration 'C_p', peak current 'I_p', pulse on time 'T_{on}', duty cycle 'DC' and gap voltage 'V_g'. Multi-attribute optimization has been performed using TOPSIS and GRA to determine the most significant set of process variables. The following are the findings from the present work:

1. The optimal setting of process parameters is found to be $C_p = 6$ g/l, $I_p = 6$Amp, $T_{on} = 100$ µs, DC = 90% and $V_g = 50$ V from TOPSIS and $C_p = 6$ g/l, $I_p = 3$Amp, $T_{on} = 150$ µs, DC = 70% and $V_g = 30$ V from GRA.
2. Confirmatory tests reveal that the improvement of preference values in the experimental and initial setting using TOPSIS and GRA are 0.161689 and 0.2593 respectively, which is satisfactory.
3. ANOVA was carried out to find out the significance of machining parameters affecting process characteristics at 95% confidence interval. C_p, T_{on}, DC and I_p are parameters which have significant contribution towards improvement in the value of preference solution while the role of V_g is insignificant.
4. From the experimental results it is observed that the roughness of the surface varies within a range of 3.8 µm to 9.2 µm when no powder is added to the dielectric fluid. When 3 gm/l of Cr powder is added, the roughness values are reduced to a range of 2.86 µm to 5.97 µm. On increasing the concentration of Cr powder to 6 gm/l, the roughness further gets reduced to a range of 2.4 µm to 5.04 µm. Thus, adding powder particles in proper size and concentration reduces the surface roughness during machining.
5. From the examination of the photomicrographs, it is found that adding conductive powder to the dielectric fluid improves the surface topography with less defects, cracks and surface roughness, which is directly related to the size of the crater formed and the distribution of recast layer on the surface.
6. Therefore, both the models are appropriate to establish the best possible solution for the set of input parameters depending upon the required performance characteristics.

The outcome of the present research work will be a considerable aid to the industries for quality improvement in processing using PMEDM.

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