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Parametric optimization of nano powder blended electrical spark machining process on AISI D3 DIE steel employing grey relational analysis

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- ✓ Material Removal Rate,
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- ✓ Taguchi Method.

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Abstract

The main objective of this research paper is to present the results of multi response optimization performed for nano powder blended electrical spark machining operations on AISI D3 Die steel based on Taguchi method coupled with grey relational analysis. Different sets of experiments planned as per Taguchi technique were carried out by varying four parameters such as peak current, pulse-on time, spark voltage and powder concentration. Material removal rate(MRR), electrode wear rate (EWR) and surface roughness (SR) are selected as output parameters for this research. Results showed that powder concentration and peak current were the influencing parameters on MRR, EWR, and SR as per Grey relational grade. The optimal combination parameters were identified as peak current at 7 A, pulse on-time at 50µs, gap voltage at 100 V and powder concentration at 0.5g/L. The confirmation test performed to validate the result obtained by grey relational analysis revealed a satisfactory enhancement in the response.

1. Introduction

In recent years, among available non-traditional machining techniques, Electric Spark Machining (ESM) otherwise called Electric Discharge Machining gained prominence due to its effectiveness in machining precise, complex shapes with special micro-features on the difficult-to-cut tool, die and mould materials irrespective of their hardness [1–4]. This process is based on controlled thermal erosion of electrically conductive material immersed in dielectric and initiation of quick, recurring spark discharges between the tool electrode and workpiece in the absence of physical contact between them [5]. This machining approach is currently being implemented extensively in press tools as well as dies, aerospace, automotive, together with surgical equipment manufacturing companies[6]. Despite astounding process capacities, low volumetric material extraction rates, as well as poor surface quality, are some of the limitations linked with conventional electrical discharge machining. In order to address these issues, researchers followed three different approaches. In the first approach, termed as Powder Blended Electric Spark Machining (PBESM), fine powder either in micro or nano size is suspended in the dielectric fluid which improves homogeneous disbursement of sparking among the powder particles creating shallow craters on the workpiece exterior surface causing enrichment in surface finish. Also, the ploughing action of conductive material in dielectric fluid enhances the material extraction rate [7]. The second approach is tool rotation that creates flushing effect and reduces debris accumulation within the discharge gap thereby improving material subtraction rate [8]. The third approach is vibrating the workpiece which enhances the machining time[9]. Out of three methods, the first approach offers better-machined surface quality and imparts functional properties to the machined surface [8,10].

All the influencing process variables in PBESM can be categorized under four headings viz., non-electrical parameters (like gain, lift and flushing pressure), powder properties (like particle size, shape, concentration, thermal conductivity, melting point), electrode material properties and electrical parameters (like gap voltage, pulse-ON time, peak current) [11,12]. Just like many other machining techniques, the quality of machined parts is substantially influenced by input process conditions. For this reason, promoting the quality of the process by establishing an exhaustive understanding of the relationship between these parameters for much better-machined surfaces has become a major research concern.

Unlike traditional Electric Discharge Machining, Powder Blended Dielectric based Electric Discharge Machining has a different machining technique[11] as shown in Figure. 1. Upon applying 80–320V voltage in the gap of 25–50 microns present between the electrode and the workpiece an electric field in the range of 10^5–10^7V/m is generated. Due to this, the powder particles not only gain energy but also come close to each other and arrange themselves in a crisscross series fashion forming an interlock among them[13]. This series configuration promotes in linking the discharge gap between both the electrodes. Also, the developed electric field accelerates the charged particles to behave like conductors which prop up the breakdown in the gap and increase the spark gap between the tool and the workpiece. Owing to linking effect, a reduction in insulating strength of the dielectric fluid is observed. A premature explosion in the gap takes place due to developed 'short circuit.' The applied fine-grained powder changes (expands and broadens) the plasma channel. Thus, the sparking is uniformly disbursed among the powdered particles; in consequence electric density of the spark diminishes. As a result of homogeneous disbursement of sparking among the powder particles, shallow craters are created on the workpiece exterior surface. This will cause enrichment in surface finish[7].

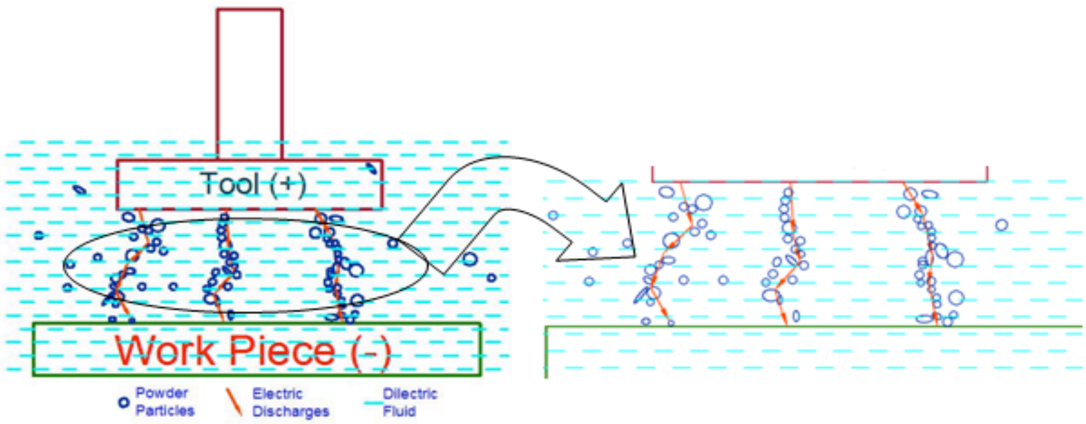

Figure. 1 Schematic depicting nano powder blended based dielectric EDM technique

Early in 1980 A. Erden and S. Bilgin[14] stated that intentionally added artificial impurities to dielectric have a significant effect on EDM performance. Since then several researchers focused on investigating the influence of artificial additives in dielectric when machining materials through electric discharge machining. Baljinder Singh[15] studied the effect of concentration of 325µm aluminum powder in the dielectric fluid along with other electrical parameters on H11 steel surface roughness employing L_{18} array and reported that polarity, suspended powder play a major role in the response. Abhishek Abrol[16] mixed 45-55µm chromium powder in kerosene to examine the simultaneous effect of powder concentration along with peak current, pulse on time and pulse off time when machining AISI D2 die steel and found that current is the most significant factor for MRR and TWR. Mohd. Junaid Mir[17] presented the discharge current, pulse time and aluminum powder (46µm) concentration optimized levels for surface roughness study on H11 steel and revealed that the peak current and concentration are most influential parameters affecting surface roughness. Suspending 37, 44 and 74µm sized aluminum powder of quantities 0-12g/L in EDM oil supplied by the manufacturer Anil Kumar et al.[18] fabricated circular holes on Inconel 718 using copper electrode. It is stated that powder concentration and size influenced EDM efficiency. It was also mentioned that highest Material Removal Rate (MRR) is obtained for 44µm powder at 6g/L concentration. H K Kansal et al.[19] utilized 0-6 g/L quantity of 20-30µm aluminum powder into kerosene available commercially to machine Al-10%SiCp material for 40minutes time. It was reported that added aluminum powder enhanced MRR up to certain (3g/L) concentration. Also, it was stated that most influential parameters on the performance of EDM are peak current and concentration of added powder.

In another attempt by H K Kansal et al.[13] to optimize process parameters utilizing Taguchi design, 25mm diameter blind holes were drilled on AISI D2 Die steel when dipped in Kerosene doped with 0-4g/L 30µm silicon powder. It was highlighted that effect of nozzle flushing at inter electrodes gap on machining efficiency is negligible. Tzeng Yih-Fong et al.[20] proclaimed that 70–80nm powder blended Hercules ed 320h resulted in the better surface finish of skd-11. MP Jahan et al.[2] experimented with 55nm Gr blended total final elf edm3 oil when machining cemented tungsten carbide. GS Prihandana et al.[3] experimented with ultrasonicated 55nm Gr blended kerosene on silver-tungsten and reported that surface quality of machined surface improved. PC Tan et al.[5] reported that 40-47nm SiC and 45-55nm Al_2O_3 blended Idemistu Daphene cut oil on stainless mold steel reduced the average surface roughness. Houriyeh Marashi et al.[21] concluded that 40-60nm Ti powder blended hydrocarbon oil on D2 steel resulted in an enhancement in MRR.

From the review of literature available on PBESM, it is observed that only fundamental research work has been carried on the improvement of machining efficiency of PBESM. The aim of the present research work is multi characteristic optimization of Material Removal Rate (MRR), Electrode Wear Rate (EWR) and surface roughness (SR) when machining AISI D3 steel using copper electrode with and without suspended Silicon carbide nano powder in commercially available EDM oil dielectric medium using Taguchi Method and grey relation analysis. Taguchi methodology was applied to plan and analyze the experiments. The most efficient controllable factors in PBESM are determined using grey relation grade.

2. Experiment Set-up and Method

2.1 Machine

The experiments were conducted on the Electric Discharge Machine model S-50 ZNC of ELECTRONICA MACHINE TOOLS (Pvt. Ltd). Several input variables like spark voltage, pulse on time, % Duty factor, polarity, peak current and type of flushing can be varied in this machine. Also, this machine is equipped with a machining tank occupying a volume of 140liters of EDM Oil as supplied by the manufacturer. In order to reduce the amount of dielectric used and to avoid the damage of filtering system due to clogging of nano powder in filters, a new experimental set-up for nano powder blended EDM (NPBEDM) is fabricated. The newly fabricated set-up presented as a schematic in Figure. 2 consists of a small tank occupying a volume of 10liters accompanied with a motorized stirrer and dielectric recirculation pump, dielectric supply tank fitted with filters and mono block pump (not shown in the schematic) in chronological order. An in-line magnetic filter is used to filter the debris.

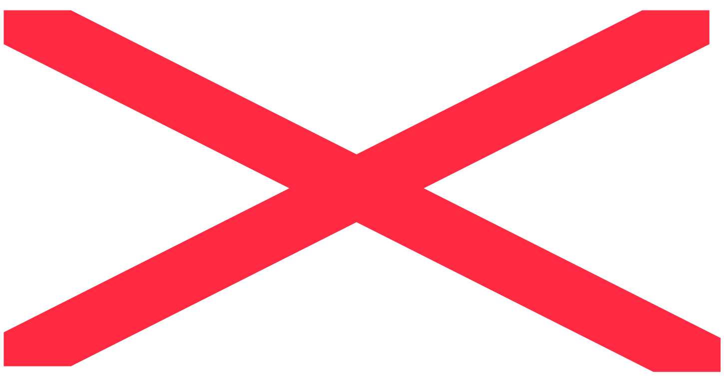

Figure 2: Schematic of fabricated experimental set-up

2.2 Work piece, Electrode, and Powder Material

AISI D3 die-Steel, Copper of dimensions 45mm×32.5mm×12mm (Figure. 3a) and 150mm×ϕ9.5mm (Figure. 4) respectively are considered as work piece and tool in this experimentation. The chemical composition of work piece material is as depicted in Table 1. Figure. 3b illustrates the workpiece with a set of experiments. Powder opted for present investigation is Silicon Carbide (Conductive) of 50nm size procured from Sisco Research Laboratories Pvt. Ltd. (SRL) - India. XRD spectra of Silicon Carbide powder is presented in Figure 5.

Table 1: AISI D3 Die-Steel's chemical composition used in experimentation

Elements	Fe	Cr	C	Si	Mn	Ni	V	Mo	W	P	S
Wt %	85.74	11.125	2.078	0.395	0.223	0.152	0.106	0.06	0.056	0.031	0.03

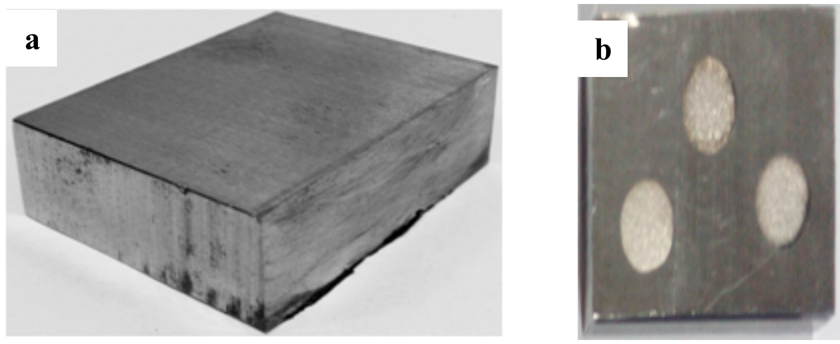

Figure 3: AISI D3 die-steel workpiece before and after machining

Figure 4: Copper Electrode used in experimentation

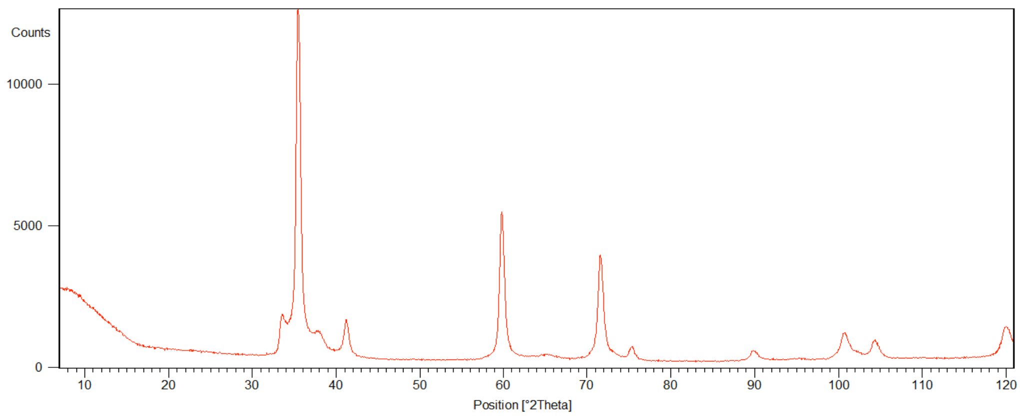

Figure 5: SiC nanopowder XRD spectra

2.3 Parameters and Experiment Plan

Four quantitative type process variables (peak current, gap voltage, pulse-ON time, and powder concentration) with three levels are considered as process variables. It could require a whole of eighty-one (3^4) sets of experiments to optimize the variables if a full factorial design is carried out [22] which remains a significant challenge. To address this challenge the Taguchi method utilizes orthogonal arrays designed to contemplate the whole parameter space and its influence on response with just a little number of examinations[23,24]. As suggested by Datta et al[25] and Harmesh Kumar et al. [12] experiments were conducted based on an L9 orthogonal array. Throughout the experiments, positive polarity, 30min machining time, 10% duty factor are fixed. Standard L9 orthogonal array with actual values and experimental findings are shown in Table 3. The levels of the process variables are fixed after conducting pilot experiments and presented in Table 2. Each machining case was repeated three times to achieve accurate surface roughness values as shown in Figure. 3b.

Table 2: Process variables and levels

Process variable	Code	Levels		
		Level 1	Level 2	Level 3
Peak Current, I_p, (A)	K	5	6	7
Pulse-ON time, T_{ON}, (µs)	X	50	100	150
Gap Voltage, V_g, (V)	M	50	60	70
Powder Concentration, PC, (g/L)	N	0	0.5	1

Table 3: Experimental findings using orthogonal array

Experiment Trail	I_p (A)	Ton (μs)	V_g (V)	Powder Concentration (g/L)	Decision Matrix [D]		
					MRR (mm^3/min)	EWR (mm^3/min)	SR (μm)
1	5	50	50	0	0.45	0.074	6.575
2	5	100	60	0.5	1.31	0.187	4.550
3	5	150	70	1	0.77	0.374	5.105
4	6	50	60	1	1.17	0.374	4.630
5	6	100	70	0	0.70	0.299	4.555
6	6	150	50	0.5	1.41	0.224	4.720
7	7	50	70	0.5	1.60	0.112	4.975
8	7	100	50	1	1.45	0.262	4.970
9	7	150	60	0	1.20	0.080	6.590

2.4 Machining Performance Assessment

Material Removal Rate (MRR), Electrode Wear Rate (EWR) and Surface Roughness (SR) are considered as responses. The difference in weights of workpiece and tool, before and after experimentation are measured on SHIMADZU (AUX 200) analytical balance respectively. Numerical values are then substituted in Eqs. (1)[26] and (2)[26] to calculate MRR and EWR.

$$\text{MRR} = \frac{[(W_{bm} - W_{am}) \times 1000]}{(D_w \times t)} \qquad (1)$$

where MRR – Material Removal Rate (mm^3/min), W_{bm} – weight of workpiece before machining (g), W_{am} – weight of workpiece after machining (g), D_w – density of the workpiece (7.7 g/cm^3), t – machining time (minutes).

$$\text{EWR} = \frac{[(E_{bm} - E_{am}) \times 1000]}{(D_e \times t)} \qquad (2)$$

MRR – Material Removal Rate (mm^3/min), E_{bm} – weight of electrode/tool before machining (g), E_{am} – weight of electrode/tool after machining (g), D_e – density of the electrode/tool (8.9 g/cm^3), t – machining time (minutes).

Surface Roughness calculated in terms of arithmetic mean roughness (R_a) is defined as $R_a = \frac{1}{S}\int_0^S |h(z)dz|$ where $h(z)$ is the value of roughness profile, and S is evaluation length. It is measured along horizontal, vertical diameters on the facade of blind holes using Mitutoyo make (SJ-201) surface roughness tester and the average value is considered for analysis.

3. Results and discussion

3.1 Grey relational technique

Grey Relation Technique (GRT) is an important technique that not only predicts quandary behavior of systems but also interprets correlation among systems and corroborates models. In this technique, the complex multi-response optimization predicament is simplified as the optimization of Single Response Gray Relational Grade (SRGRG). This approach was initially established by Deng [27] and then has been efficiently employed in several disciplines of machining processes. Suman Kalyan Das [28] implemented Taguchi based grey relational analysis to optimize coating parameters when determining wear characteristics of electroless Nickle-Boron coatings. Hsuan-Liang Lin[29] deployed Taguchi method coupled with grey relational analysis to perform multi-criterion (penetration depth, fusion area, DWR of weld bead) optimization of a novel Gas Metal Arc welding process.

B Satyanarayana [30] applied Taguchi procedure together with grey relational technique to find out effective levels of feed, depth of cut and speed when performing simultaneous minimization of surface roughness, cutting force and tool flank wear. K.F.Tamrin[31] used grey relational analysis to determine optimum levels of power consumed, stand-off distance and welding speed for multi-performance (mean weld width, mean kerf width, weld tensile strength) analysis in CO_2 laser joining of dissimilar materials. In an attempt to perform multi response optimization of wear characteristics of a hybrid composite, Saravanakumar[32] used grey relational analysis. In another effort to model and optimize multi-response (cutting force, vibration signals, and surface roughness) of milling characteristics Murat Sarıkaya[33] implemented Taguchi based gray relational analysis. Hence it was observed that GRT had found its existence in a wide range of machining applications. On the other hand literature on multicriteria optimization of NPBEDM variables implementing GRT is still in developing stage. In the current experimental exploration, the grey relation has been applied to determine the optimal process input variables that give maximum MRR with an enhanced surface finish in NPBEDM of tool steel.

Determining GRG (Grey Relational Grade) is the key point of GRT. Four steps involved to find out GRG for a multi-objective optimization are detailed in below flowchart (Figure. 6) followed by a brief explanation of each step.

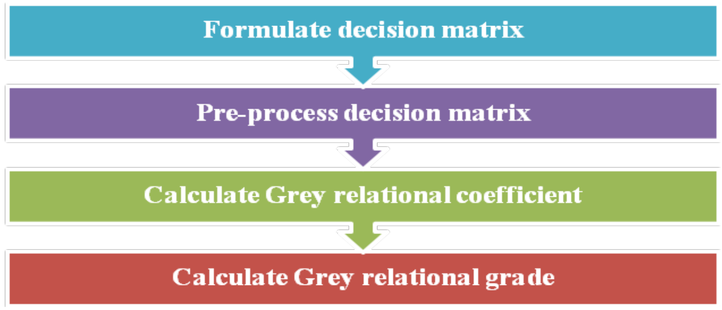

Figure 6: Four steps involved to find GRG

3.1 Decision matrix formation

In this stage, a m×n decision matrix [D] is constructed where m and n represent a number of experiment trails and performance responses values respectively. Here m = 9 and n = 3 (MRR, EWR & SR). [D] is shown in Table 3.

Table 4: Computed Normalized values, GRC and GRG

Experiment Trail	Normalized Values			GRC			GRG	Rank
	MRR	EWR	SR	MRR	EWR	SR		
1	0.000	1.000	0.007	0.333	1.000	0.335	0.556	8
2	0.748	0.623	1.000	0.665	0.570	1.000	0.745	2
3	0.278	0.000	0.728	0.409	0.333	0.648	0.463	9
4	0.626	0.000	0.961	0.572	0.333	0.927	0.611	6
5	0.217	0.250	0.998	0.390	0.400	0.995	0.595	7
6	0.835	0.500	0.917	0.752	0.500	0.857	0.703	3
7	1.000	0.873	0.792	1.000	0.798	0.706	0.835	1
8	0.870	0.373	0.794	0.793	0.444	0.708	0.648	4
9	0.652	0.980	0.000	0.590	0.962	0.333	0.628	5

3.2 Data pre-processing

Each numeral (y_{ij}) in Decision matrix [D] is normalized to scale down between 0-1 incorporating strategies (3) and (4).

Higher-the-better $$x_{ij} = \frac{\left(y_{ij} - \min\left(y_{ij}\right)\right)}{\left(\max\left(y_{ij}\right) - \min\left(y_{ij}\right)\right)} \quad (3)$$

Smaller-the-better $$x_{ij} = \frac{\left(\max\left(y_{ij}\right) - y_{ij}\right)}{\left(\max\left(y_{ij}\right) - \min\left(y_{ij}\right)\right)} \quad (4)$$

where y_{ij} = j^{th} performance response for i^{th} trail, $\max(y_{ij})$ and $\min(y_{ij})$ = maximum and minimum values of all j^{th} performance responses. x_{ij} = normalized numeral. Table 4 depicts normalized values for the EWR, MRR, and SR.

3.3 Grey relational coefficient calculation

Using normalized SNR values found in the preceding stage, the gray relational coefficients (GRCs) of performance responses are calculated after substituting in the equation (5)[26].

$$\gamma\left(x_{0j}, x_{ij}\right) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{ij} + \xi\Delta_{\max}} \text{ for } i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n \qquad (5)$$

where x_{0j} = reference value of *j*th response ($x_{0j} = 1$), $\Delta_{ij} = |x_{0j} - x_{ij}|$, $\Delta_{min} = \min\{\Delta ij, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\}$, $\Delta_{max} = \max\{\Delta_{ij}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n\}$ and ξ = distinguishing coefficient, $\xi \in (0, 1]$. In common $\xi = 0.5$ is applied when calculating GRCs[26,34]. Table 4 depicts GRC values for the EWR, MRR and SR.

3.4 Grey Relational Grade Calculation

The calculation strategy for quantification in grey relational space is termed grey relational grade. A grey relational grade or degree is a weighted sum of grey relational coefficients, and it is often computed implementing equation (6)[26]

$$\varsigma_i = \left(\frac{1}{n}\right)\sum_{k=1}^{n} \gamma(k) \qquad (6)$$

where ς_i is Grey Relational Grade for ith experiment, *k* is experimental trials. Table 4 depicts evaluated GRGs employing (6).

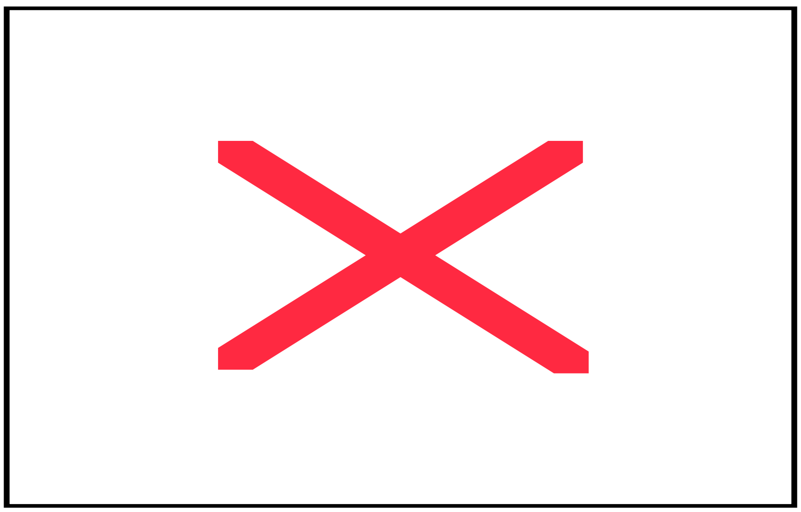

Figure 7: Variation in GRG for all nine trails

A careful observation of Figure. 7 reveals that GRG for the 7th experiment is highest which equals to 0.835 indicating that the corresponding experimental result is closer to the ideally normalized value and has the best multiple performance characteristics among nine experiments.

The mean of the grey relation grade for a unique level of machining parameters is computed using MINITAB 17 software and listed in Table 5. The influence of each cutting parameter can be more clearly understood by means of grey relation grade graph (Figure. 8).When the last row of Table 5 is compared, it is observed that the difference between the maximum and minimum value of the grey relational grade for factor N is bigger than other factors. This indicates that SiC nano powder addition has a stronger effect on multi performance characteristics than peak current, pulse on time, and gap voltage. From, Figure. 8 it is observed that $K_3X_1M_2N_2$ is the condition for maximum grey relation grade, i.e., optimal setting for maximum MRR, minimum Electrode wear rate and surface roughness.

Table 5: Response table for GRG

	Machining Parameters	**K**	**X**	**M**	**N**
Average GRG by parameter Level	L1	0.5882	**0.6672**	0.6358	0.5931
	L2	0.6363	0.6628	**0.6614**	**0.7608**
	L3	**0.7037**	0.5982	0.6310	0.5742
	High-Low	0.1156	0.0690	0.0304	0.1866

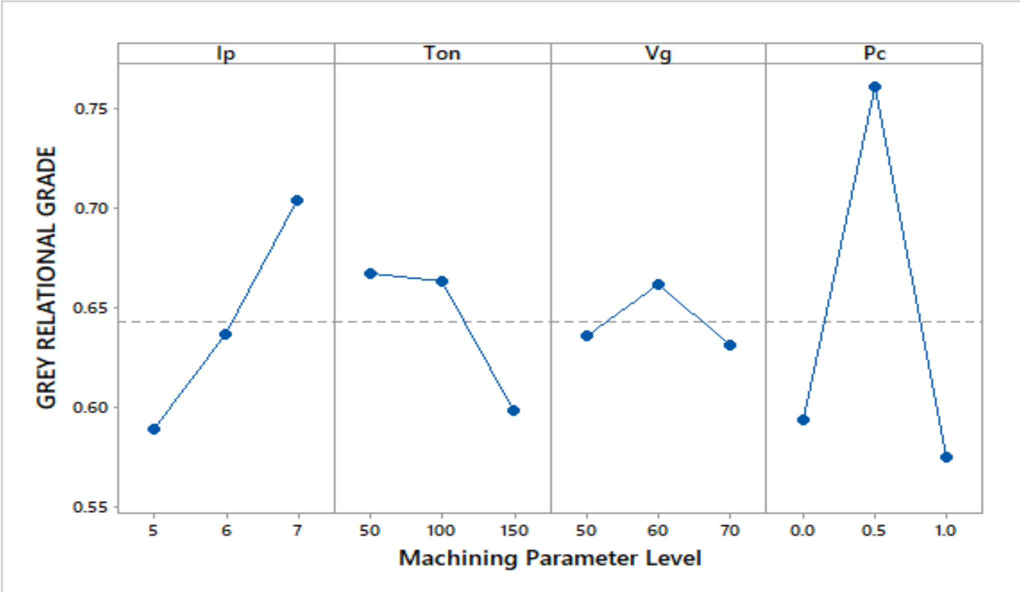

Figure 8: Influence of NPBESM parameters on GRG

3.5 Confirmation test

Once the optimal levels of the machining parameters are identified, the final step is to predict and verify the improvement of performance characteristic using optimal level of the machining parameters. The estimated grey relational grade using optimal level of the machining parameters can be calculated as follows[6,35]

$$\hat{\alpha} = \alpha_m + \sum_{i=1}^{q} \left(\bar{\alpha}_i - \alpha_m \right) \qquad (7)$$

Based on Eq. (7), the estimated grey relational grade using optimal machining parameters is obtained. Table 6 shows results of confirmation experiments using optimal experimental conditions. It is clearly shown that the multiple performance characteristics in the NPBESM process are greatly improved through grey relation technique.

Table 6: Results of GRG using initial and optimal machining parameter

	Preliminary machining parameters	**Optimal Machining parameters**	
	$K_1X_1M_1N_1$	Predicted $K_3X_1M_2N_2$	Experimental $K_3X_1M_2N_2$
Grey relational grade	0.556	0.865	0.866

Conclusions

The grey relational analysis has been used to optimize the weld parameters in NPBESM of AISI D3 Steel for multi-performance characteristics namely material removal rate, electrode wear rate, and surface roughness. Taguchi orthogonal array L9 has been used for the experiment work. Following are the observations from the present work.

1. The PBESM process parameters are optimized for material removal rate, electrode wear rate and surface roughness by grey relational analysis. The optimum levels of process parameters are peak current 7Amp, pulse-on time 50μs, gap voltage 50V and powder concentration 0.5g/L. These are therefore the recommended level of parameters for obtaining higher material removal, less electrode wear, and reduced surface roughness.
2. The experimental result for the optimal setting shows that there is considerable improvement in machining efficiency of the process and grey relation grade.
3. It is evident from the above study that the optimization of the complicated multi-performance characteristics can be greatly simplified through Taguchi and grey relational analysis approach.

4. It is also found that nano powder addition has a stronger effect on multi characteristics than peak current, pulse on time, and gap voltage.

Further, the technique presented in this study can be extended to different work materials and hybrid manufacturing techniques to improve performance characteristics simultaneously.

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