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ORIGINAL ARTICLE

Optimization of process parameters using graphene-based dielectric in electric discharge machining of AISI D2 steel

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Abstract

Hard to machine materials have growing demand in industrial sector especially in nuclear, automotive, and aerospace industries for sustainable production. These materials cannot be machined by typical machining methods or conventional methods, and for machining such materials, nonconventional machining method are usually used. Electric discharge machine is widely used for machining such materials and complex geometries. This research aims to optimize the process parameters while electric discharge machining of AISI D2 steel using nanofluids. The effects of four most influencing factors including pulse-off time, discharge current, pulse-on time, and conc. of nanoparticles have been investigated. Graphene nanoplatelets mixed with kerosene oil were used as a dielectric. Box-Bhenken design based on response surface methodology (RSM) was used for experimentation. Regression models for performance measures such as material removal rate, surface roughness, and white layer thickness have been developed using RSM. ANOVA has been carried out for identifying the most significant factors. Multi-objective optimization has been carried out in terms of desirability function by establishing a compromise between maximum material removal rate and minimum surface roughness and white layer. ANOVA results shows that conc. of nanoparticles is the most significant parameter affecting the performance measures followed by the discharge current. The confirmatory tests were run for verifying and validating the results, and improvements in the performance measures such as MRR, R_a, and WLT up to 21.93 mm^3/min, 3.98 μm, and 19.13 μm, respectively, at an optimum have been observed. Multi-response optimization yielded compound desirability of 85.7% for the selected levels of process parameters for machining of AISI D2 steel.

Keywords Powdered-mixed EDM · Graphene nanoplatelets · Material removal rate · Surface roughness · White layer thickness · RSM

1 Background

Conventional machining processes are unable to machine hard materials with high strength and complex part geometries. In conventional machining, the cutting tool and work piece are always in physical contact, with a relative motion against each other, which results in friction and a significant tool wear. Also, material removal rate of the traditional processes is limited by the mechanical properties of the work material. While non-conventional or non-traditional machining leads to very high hardness (above 400 HB) and strength of the material [1]. Surface finish or tolerances are better than that obtainable from conventional processes. In non-traditional processes, there is no physical contact between the tool and work piece. Non-traditional processes easily deal with such difficult-to-cut materials like ceramics and ceramic-based tool materials, fiber reinforced materials, carbides, and titanium-based alloys. Electric discharge machining (EDM) is non-conventional machining process in which material is removed by sharp edge/edges or by some abrasive mechanism and by using some kind of energy sources without a physical contact between tool and material which have to cut. Today, EDM is the best machining option for harder materials that machine even brittle material with ease and accuracy. Its important advantages include absence of machining/cutting forces as compared to conventional ways of machining [2].

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In non-conventional machining like die-sinking electric discharge machining (EDM), the properties (such as thermal conductivity) of dielectric need to be enhanced. Due to improved properties, the performance measures in EDM are required to be investigated. The properties can be improved by doping the materials (nano-sized) that have high electrical conductivity. So, a relatively new class of fluids which consist of a base fluid with nano-sized particles (1–100 nm) suspended within them are known as nanofluids. Such thermal nanofluids for heat transfer applications represent a class of its own difference from conventional machining for other applications [3].

Nanofluids have high thermal conductivity at low temperature, lowest viscosity, thermal diffusivity, stability, and compatibility. Additionally, these materials are inexpensive and do not settle under gravity [4]. By varying the concentration of nanoparticles, it can be used for different applications. In EDM, there are some problems, which need to be observed such as the flushing of unwanted materials that is removed from the work part (called debris). This can be done by increasing the gap distance between the work part and electrode by using nanofluids. As a result, surface roughness and white layer thickness has to be minimized [5]. Another problem is the temperature of dielectric that is required is be controlled [6]. High peak current (much higher than spark temperature) to remove material results in thermal damage to the electrode [7]. For that, nanoparticles have been mixed with dielectric as it has high thermal conductivity. Various researchers have used different nanoplatelets such as silicon, copper, titanium, aluminum, and graphite in different dielectrics [8–11]. As a result, fast erosion of materials has been done under the sparking area, which increased the material removal rate. Due to its property of thermal diffusivity, it will stabilize the temperature of dielectric after the erosion of materials. Different researchers worked to improve the productivity [12], to minimize the surface roughness of machined surface [13, 14], and to control the cost of process. Similarly, some researchers focused on dielectrics to improve performance, either using powdered-mixed dielectrics or water-based or gaseous dielectrics [15–17].

In EDM, flushing of materials that is removed from the work part called debris is the one of the major problems. When gap distance between electrode and work piece is small, then it becomes difficult to remove the debris [18]. As a result, it will affect the performance of EDM. Another main problem is the temperature of dielectric that needs to be controlled. As when using high discharge current, higher spark temperature is produced, this is much higher than the required temperature to remove material, which ultimately can lead to thermal damage. As a result, recast layer can be formed after re-solidification. There is need to optimize and sustain the surface roughness (R_a), white layer thickness, and the material removal rate (MRR) by controlling the EDM process parameters like pulse-off time, pulse-off time, discharge current, and gap distance. In addition to this, improving the properties of dielectric by adding the graphene nanoplatelets can also be one of the solutions. To overcome these mentioned problems, it needs to optimize the process parameters using graphene-based dielectric in electric discharge machining of AISI D2 steel. So, considering the nano-dielectric as medium, optimization models have been developed for performance measures that will give the best optimal setting of the process parameters to have maximum MRR (productivity), minimum R_a (cost), and white layer (WLT). It has been concluded from the detailed literature that still no work has been done for AISI D2 steel with graphene-nano-dielectric on EDM process to predict the performance measures. For this purpose, experiment will be design for different levels of the selected parameters and DOE techniques will be applied.

2 Experimental Details

The section provides the details about the materials, experimental design, and preparation of sample. Powdered-Mixed CNC Die sinking EDM machine (model-CM 655C CNC) has been used for machining AISI D2 steel. It has been shown in Fig. 1. AISI D2 steel was used in this study as a work material being machined in graphene-based dielectric with having 2–10-nm average particle size. Optical emission spectrometer was used to measure the composition of AISI D2 steel as provided in Table 1. A cylindrical shaped copper tool having 26-mm external diameter (50-mm length) has been used as an electrode, because it gives best performance as compared to aluminum, brass and graphite in terms of hardness, melting point, economy (cost), and quality [19]. Graphene nanoparticles suspended in kerosene oil have been used as a dielectric, because of its good thermal conductivity. Specimens of work material ($215 \times 450 \times 12$ mm^3) were prepared using milling machine. As mentioned earlier, the process parameters selected for this research included pulse-on time, pulse-off time, discharge current, and concentration of nanoparticles.

2.1 Experimental design

Ranges and levels of the chosen parameters (pulse-on time, pulse-off time, discharge current, and conc. of nanoparticles) were considered based on trial runs keeping machine specifications (Table 2). The constant parameters throughout the experimentation are given in Table 3. In the current study, experiments were designed using response surface methodology (RSM) employing Box-Bhenken Design (BBD). Using Design Expert 7.0.0 software, 29 runs were designed having 24 factorial and five center points per block. Original levels of process parameters and measured responses are given in design matrix (Table 4). The responses considered in this study for the evaluation of the performance of machining were material removal rate (MRR), surface roughness (SR), and white layer thickness (WLT).

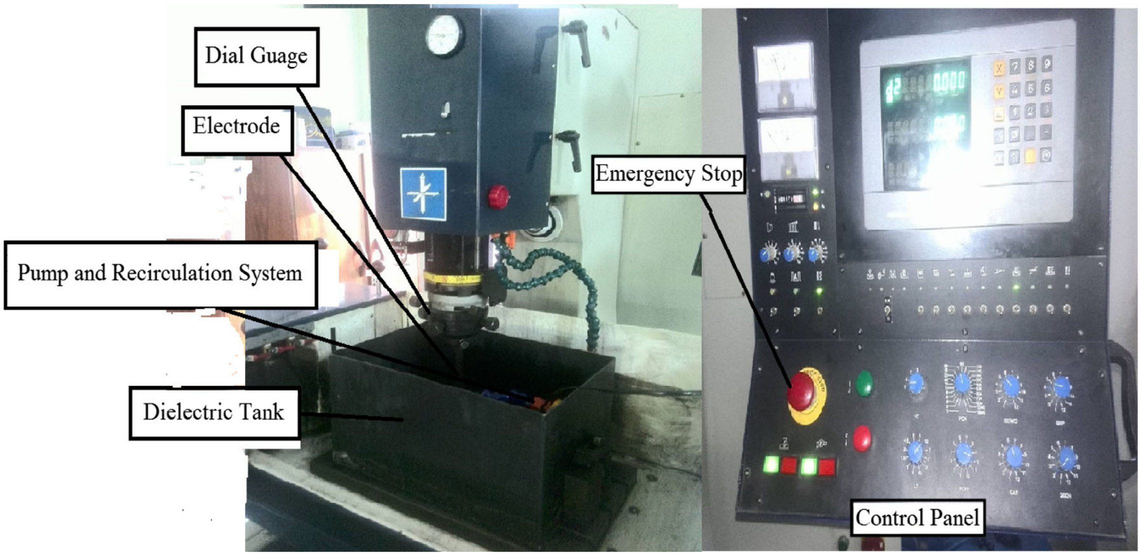


Fig. 1 Powdered-mixed EDM

2.2 Measurement of responses

2.2.1 Material removal rate

MRR can be calculated by multiplying electrode area with depth of cut taken and dividing with time taken for machining [20]. Multiplying the electrode area with the depth of cut gives the volume removed from the work piece. It can be determined using Eq. (1):

$$\mathrm{MRR} = \text{volume removed}/\text{machining time} = \nabla V/t \tag{1}$$

where ∇V represents the volume (mm^3) removed from the work piece during machining and t is the machining time (s) of the process.

2.2.2 Surface roughness

Surftest SJ-410 series 178-portable Surface meter[1] was used for measuring the surface roughness value. Snap shot of meter setting has been displayed in Fig. 2. The measured surface roughness has been given in Table 4, along with respective process parameters. For example, for order run #1, the machining has been performed at pulse-on time of 11 μs, current at 12 A, pulse-off time at 90 μs, and conc. of nanoparticles at 3 g/l, resulted surface roughness of 5.1194 μm. The value of surface roughness was measured five times at different places of the work piece, and average of all five values was used in this study.

[1] Surftest SJ-410 series 178-portable Surface is used for roughness of work piece measurement. Manufacturer: Mitutoyo America Corporation Facility available at Industrial Department, University of Engineering & Technology, Taxila

2.2.3 White layer thickness

Scanning electron microscope (SEM) was used for measuring white layer thickness. Some SEM images has been shown in Fig. 3. For SEM analysis, sample of 10 × 10 × 5 mm was prepared. WLT has been measured in micrometer.

2.2.4 Response surface methodology

Response surface methodology (RSM) is a collection of statistical and mathematical practices that is used for modeling, and analysis of problems in which a response, which is under consideration, is influenced by several variables. It gives enormous information about the responses in a small number of experiments. In addition, to analyze the effect of independent variables individually and interaction with each other, it develops a mathematical model for describing the relationship of inputs with response. The relation between process parameters and responses can be shown by Eq. (2).

$$Z = f(A, B, C, D) \tag{2}$$

where Z shows the responses, f shows the surface of responses, A shows the pulse-on time, B shows the pulse-off time, C shows the discharge current, and D shows the conc. of nanoparticles. For prediction of responses, second-order model was used for developing the mathematical models for better analyzing the interaction effects of parameters on the performance of electric discharge machining as presented as:

Table 1 Chemical composition of D2 steel

Elements	C	Si	Mn	Chr.	Mo	V
%	1.55	1.55	1.55	1.55	1.55	1.55

Table 2 Ranges and levels of input parameters

Process parameters	Ranges	Levels		
		Low	Medium	High
Pulse-on time (*A*)	60–120 μs	60	90	120
Pulse-off time (*B*)	7–11 μs	7	9	11
Discharge current (*C*)	9–15 A	9	12	15
Conc. of nanoparticles (*D*)	0–3 g/l	0	1.5	3

$$y=\beta_0+\sum_{i=1}\beta_i x_i+\sum\beta_{ii}{x_i}^2+\sum_{i<j}\sum\beta_{ij}x_ix_j+\varepsilon \tag{3}$$

where y shows the corresponding responses; and x_i, ${x_i}^2$, x_ix_j, and ε are the input process variable, square term, interaction term, and error term of the model, respectively. Similarly β_0, β_i, β_{ii}, and β_{ij} are the coefficients of regression for respective terms.

3 Results and discussion

In this section, a detailed description of results has been provided including corresponding mathematical models development, validation of models, 3D plots for analysis, and optimization of parameters in machining.

3.1 Mathematical models

Commercial statistical software (Design Expert 7.0.0) has been used for the development of mathematical models of responses. Analysis of variance (ANOVA) was employed for checking the adequacy of models and investigating the effects of parameters as well as their interaction effects on the responses such as MRR, SR, and WLT. To check the adequacy of developed models, different measures, i.e., coefficient of correlation (R^2), R^2 (predicted), and R^2 (adjusted) were employed.

3.2 Material removal rate

The measured values of MRR have been analyzed to investigate the effects of process parameters on the material removal rate and to develop an empirical model, which can predict the material removal rate. The summary for material removal rate regarding the comparison of models, analysis of variance (ANOVA), and model adequacy has been presented in Table 5. Suitable model for response can be selected based on p value. It can be observed that quadratic model is the most suitable model for explaining the results of material removal rate among the other polynomials because it exhibits least p value. ANOVA was performed at 95% confidence interval, reveals that that pulse-off time, discharge current, concentration of nanoparticles, interaction effect of pulse-off time and discharge, interaction effect of pulse-off time and conc. of nanoparticles, interaction effect of discharge current and conc. of nanoparticles, and quadratic terms of discharge current and conc. of nanoparticles are the most significant factors. It is cleared that pulse-off time, current, and conc. of nanoparticles significantly affect the material removal rate (MRR) for machining AISI D2 steel.

This is because, as the current and conc. of nanoparticles, more heat will be transferred to the surface of work piece, and as a result, material will be removed rapidly. It can be observed that for adequacy measure, value R-squared is 0.9239, which is close to unity. It shows the more accuracy of the model. It has been observed from that adjusted R-squared and predicted R-squared values are in the range of 20% shows that 70.35% variability in new data and show a good compromise. The value of adequate precision is 13.57 which is greater than 4 [21]. The reliability of results has been assured by the value of coefficient of variance, which is 15.7899%. The regression model was developed to predict the material removal rate that has been presented using Eq. (4).

$$\begin{aligned}\text{Material removal rate} &= 2.30689+1.39924\\ &\times \text{pulse}_{\text{off}}\ \text{time}-1.42607\times\text{discharge current}\\ &+0.26155\times\text{pulse}_{\text{on}}\text{time}-3.03400\\ &\times\text{Conc.of nanoparticles}-0.37462\times\text{pulse}_{\text{off}}\ \text{time}\\ &\times\text{discharge Current}-0.019054\times\text{pulse}_{\text{off}}\ \text{time}\\ &\times\text{pulse}_{\text{on}}\text{time}+0.71128\times\text{pulse}_{\text{off}}\ \text{time}\\ &\times\text{Conc.of nanoparticles}+2.65820\text{E}{-003}\\ &\times\text{discharge current}\times\text{pulse}_{\text{on}}\text{time}-0.59518\\ &\times\text{discharge current}\\ &\times\text{Conc.of nanoparticles}-0.025994\times\text{pulse}_{\text{on}}\text{time}\\ &\times\text{Conc.of nanoparticles}+0.10534\times\text{pulse}_{\text{off}}\ \text{time}^2\\ &+0.27264\times\text{discharge current}^2-2.68974\text{E}{-004}\\ &\times\text{pulse}_{\text{on}}\text{time}^2+1.70655\times\text{Conc.of nanoparticles}^2\end{aligned}\tag{4}$$

Table 3 Constant parameters

Process parameters	Base fluid	Flushing method	Servo speed	Jump time distance	H.V	Nanofluid pressure	Working t ime	Depth of cut
Values	kerosene	Jet flushing method	50%	1 mm	240 V	17 Psi	3 s	1 mm

Table 4 Design matrix for parameters and responses

Order	Parameters				Responses		
Run Order	Pulse-on time (μs)	Pulse-off time (μs)	Discharge current (A)	Conc. of nanoparticles (g/l)	MRR (mm^3/min)	SR (μm)	WLT (μm)
1	90	11	12	3	8.53	5.12	20.76
2	60	11	12	1.5	6.03	4.83	30.17
3	90	11	15	1.5	8.37	5.29	39.26
4	90	9	12	1.5	6.93	5.83	26.38
5	90	9	15	0	22.61	5.53	45.29
6	60	9	12	0	12.22	5.98	43.53
7	90	7	9	1.5	12.15	4.11	25.15
8	90	9	9	3	11.30	3.98	15.38
9	90	7	15	1.5	21.29	5.28	32.45
10	90	9	15	3	13.58	5.57	21.37
11	90	9	9	0	9.62	5.39	32.36
12	60	9	12	3	12.65	5.28	17.98
13	90	11	9	1.5	8.22	4.28	26.35
14	120	9	9	1.5	8.02	4.58	24.93
15	60	7	12	1.5	8.84	4.55	29.37
16	90	9	12	1.5	10.74	5.58	25.38
17	60	9	9	1.5	5.32	4.22	26.35
18	120	9	12	3	11.90	5.14	23.97
19	120	9	15	1.5	15.88	5.26	37.28
20	120	7	12	1.5	12.58	4.88	38.19
21	120	9	12	0	16.15	5.86	45.37
22	120	11	12	1.5	5.20	4.57	38.67
23	90	11	12	0	7.63	5.94	41.32
24	90	9	12	1.5	10.49	5.81	28.35
25	90	9	12	1.5	7.78	5.88	27.36
26	90	9	12	1.5	7.01	5.64	26.26
27	90	7	12	3	12.92	5.33	21.35
28	90	7	12	0	20.55	5.87	43.26
29	60	9	15	1.5	12.22	5.37	25.84

3.3 Surface roughness

The measured values of surface roughness have been analyzed to investigate the effects of process parameters on the surface roughness and to develop an empirical model, which can predict the surface roughness. The summary for surface roughness regarding the comparison of models, analysis of variance (*ANOVA*), and model adequacy has been presented in Table 6.

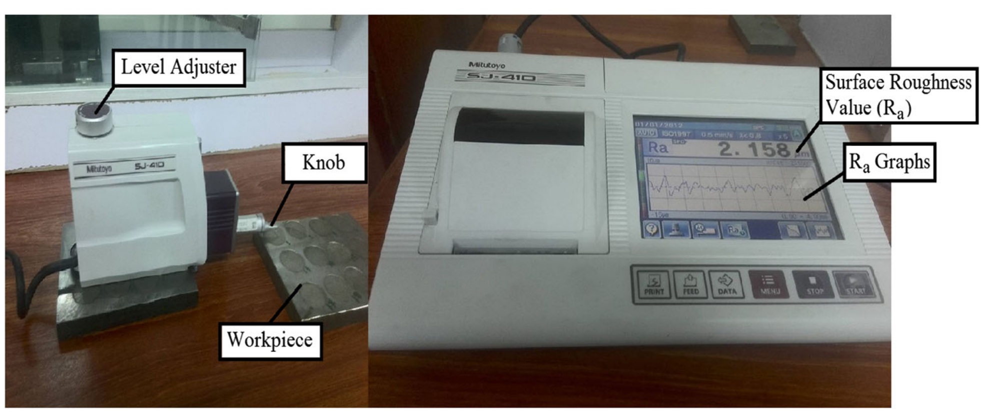
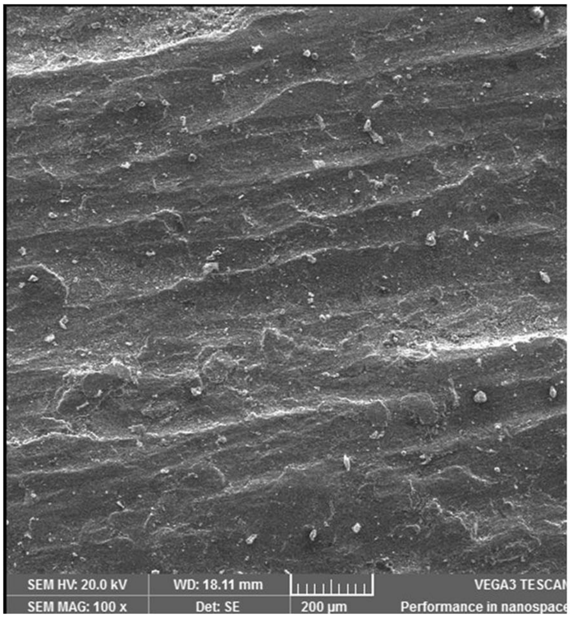


Fig. 2 Roughness tester meter



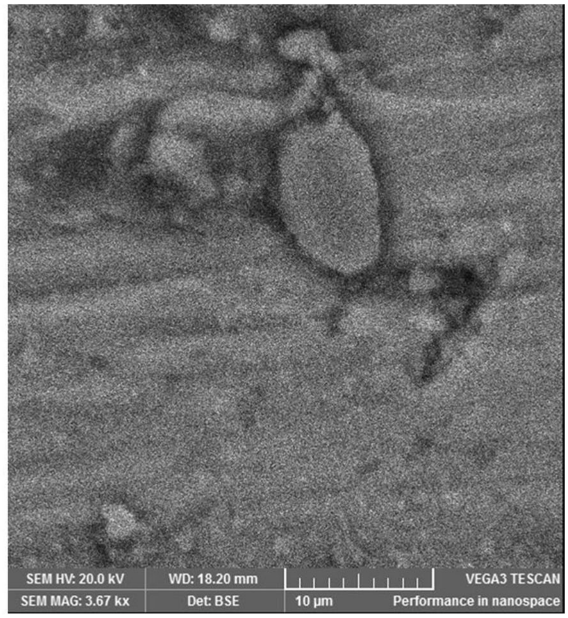


Fig. 3 SEM images

It can be observed from Table 6 that quadratic model is the most suitable model for explaining the results of surface roughness among the other polynomials as it exhibits least p value. ANOVA results reveal that

Table 5 ANOVA for material removal rate

Source	SS	DOF	MS	F-value	p value	Remarks
Mean vs total	3680.816	1	3680.816			
Linear vs mean	332.330	4	83.0825	7.979	0.0003	
2FI vs linear	78.045	6	13.008	1.362	0.282	
Quadratic vs 2FI	127.552	4	31.888	10.076	0.0005	Suggested
Cubic vs quadratic	16.985	8	2.123	0.466	0.843	Aliased
Residual	27.318	6	4.553			
Total	4263.047	29	147.001			
Model	537.928	14	38.423	12.142	< 0.0001	Significant
A-P-off	163.919	1	163.919	51.799	< 0.0001	
B-Current	128.814	1	128.814	40.706	< 0.0001	
C-P-on	12.900	1	12.900	4.076	0.0631	
D-Conc. of nanoparticles	26.697	1	26.697	8.436	0.0115	
AB	20.209	1	20.209	6.386	0.0242	
AC	5.228	1	5.228	1.652	0.2195	
AD	18.213	1	18.213	5.755	0.0309	
BC	0.229	1	0.229	0.072	0.7919	
BD	28.693	1	28.693	9.067	0.0093	
CD	5.473	1	5.473	1.729	0.2096	
A^2	1.152	1	1.152	0.364	0.5560	
B^2	39.053	1	39.053	12.341	0.0034	
C^2	0.380	1	0.380	0.120	0.7341	
D^2	95.634	1	95.634	30.220	< 0.0001	
Residual	44.303	14	3.164			
Lack of fit	30.173	10	3.017	0.854	0.6198	Not significant
Pure error	14.129	4	3.532			
Cor total	582.231	28				
Std. dev.	1.779			R-squared	0.924	
Mean	11.266			Adj. R-squared	0.848	
C.V. %	15.789			Pred. R-squared	0.704	
PRESS	195.877			Adeq. precision	13.571	

Table 6 ANOVA results for surface roughness

Source	SS	DOF	MS	*F*-value	*p* value	Remarks
Mean vs total	786.1631	1	786.1630695			
Linear vs mean	4.190846	4	1.047711429	4.425643	0.0080	
2FI vs linear	0.686242	6	0.114373589	0.412121	0.8613	
Quadratic vs 2FI	4.451951	4	1.112987671	28.67021	< 0.0001	Suggested
Cubic vs quadratic	0.073841	8	0.009230111	0.117921	0.9959	Aliased
Residual	0.469644	6	0.078273995			
Total	796.0356	29	27.44950318			
Model	9.329038	14	0.66636	17.16522156	< 0.0001	Significant
A-P-off	1.65E-05	1	1.65E-05	0.000426168	0.9838	
B-Current	2.752621	1	2.752621	70.9066681	< 0.0001	
C-P-on	0.000273	1	0.000273	0.007030834	0.9344	
D-Conc. of nanoparticles	1.437935	1	1.437935	37.04075092	< 0.0001	
AB	0.007413	1	0.007413	0.190961973	0.6688	
AC	0.085439	1	0.085439	2.20088941	0.1601	
AD	0.018508	1	0.018508	0.476766531	0.5012	
BC	0.054803	1	0.054803	1.411703259	0.2545	
BD	0.520057	1	0.520057	13.39651411	0.0026	
CD	2.07E-05	1	2.07E-05	0.000532119	0.9819	
A^2	1.370927	1	1.370927	35.31465844	< 0.0001	
B^2	2.384811	1	2.384811	61.43197587	< 0.0001	
C^2	1.04203	1	1.04203	26.84237157	0.0001	
D^2	0.157525	1	0.157525	4.057788508	0.0636	
Residual	0.543485	14	0.03882			
Lack of fit	0.475151	10	0.047515	2.781345953	0.1681	Not significant
Pure error	0.068334	4	0.017083			
Cor total	9.872523	28				
Std. dev.	0.197029			R-squared	0.94495	
Mean	5.206637			Adjusted R-squared	0.889899	
C.V.%	3.784185			Predicted R-squared	0.711964	
PRESS	2.843641			Adequate precision	12.31673	

discharge current and concentration of nanoparticles, interaction effect of discharge current and conc. of nanoparticles, quadratic terms of pulse-on time, pulse-on time, and discharge current are significant factors. It clears that discharge current, and conc. of nanoparticles significantly affects the surface roughness (SR) for machining AISI D2 steel. This is because of as the current and conc. of nanoparticles; more heat will be transferred to the surface of work piece and as a result would affect the surface quality. Accuracy/adequacy of model has been measured by R-squared value. As it has observed that R-squared value is 0.9450 which is close to unity. It shows the more accuracy of the model. It can be observed that adjusted R squared and predicted R-squared values that are in the range of 20% show 71.20% variability in new data and show a good compromise. The value of adequate precision is 12.3167 which is greater than 4. The reliability of results has been assured by the value of coefficient of variance which is 3.7842. The mathematical model has been developed for the prediction of surface roughness (SR) is presented using Eq. (5):

$$
\begin{aligned}
\text{surface roughness} = & -21.31516 + 2.40753 * \text{pulse}_{\text{off}}\text{time} \\
& +1.83801 * \text{discharge current} + 0.11793 * \text{pulse}_{\text{on}}\text{time} \\
& -1.19148 * \text{Conc.of nanoparticles} - 7.17500\text{E} \\
& -003 * \text{pulse}_{\text{off}}\text{time} * \text{discharge current} - 2.43583\text{E} \\
& -003 * \text{pulse}_{\text{off}}\ \text{time} * \text{pulse}_{\text{on}}\text{time} \\
& -0.022674 * \text{pulse}_{\text{off}}\text{time} * \text{Conc.of nanoparticles} - 1.30056\text{E} \\
& -003 * \text{discharge current} * \ \text{pulse}_{\text{on}}\text{time} \\
& +0.080128 * \text{discharge current} * \text{Conc.of nanoparticles} 5.05000\text{E} \\
& -005 * \ \text{pulse}_{\text{on}}\text{time} * \text{Conc.of nanoparticles} - 0.11493 * \text{pulse}_{\text{off}}\text{time}^2 \\
& -0.067372 * \text{discharge current}^2 \\
& -4.45341\text{E}-004 * \ \text{pulse}_{\text{on}}\text{time}^2 + 0.069261 * \text{Conc.of nanoparticles}^2
\end{aligned} \tag{5}
$$

3.4 White layer thickness

The measured values of white layer thickness were analyzed to find the significant parameters that can influence the white layer thickness. The summary for white layer thickness regarding the comparison of models, analysis of variance

Table 7 ANOVA results for white layer thickness

Source	SS	DOF	MS	F-value	p value	Remarks
Mean vs total	26,684.03	1	26,684.03			
Linear vs mean	1738.656	4	434.664	36.13128	< 0.0001	
2FI vs linear	66.04068	6	11.00678	0.889707	0.5227	
Quadratic vs 2FI	164.4466	4	41.11165	9.883325	0.0005	Suggested
Cubic vs quadratic	41.66933	8	5.208667	1.886464	0.2275	Aliased
Residual	16.56645	6	2.761074			
Total	28,711.41	29	990.0486			
Model	1969.143	14	140.6531	33.81329	< 0.0001	Significant
A-P-off time	3.808133	1	3.808133	0.915483	0.3549	
B-Current	216.4951	1	216.4951	52.04586	< 0.0001	Significant
C-P-on time	103.0774	1	103.0774	24.78002	0.0002	Significant
D-Conc. of nanoparticles	1415.275	1	1415.275	340.235	< 0.0001	Significant
AB	7.868025	1	7.868025	1.891489	0.1906	
AC	0.0256	1	0.0256	0.006154	0.9386	
AD	0.455625	1	0.455625	0.109533	0.7456	
BC	41.3449	1	41.3449	9.939398	0.0071	Significant
BD	12.0409	1	12.0409	2.894657	0.1110	
CD	4.305625	1	4.305625	1.035081	0.3262	
A^2	95.31117	1	95.31117	22.913	0.0003	Significant
B^2	1.331085	1	1.331085	0.319996	0.5806	
C^2	68.59786	1	68.59786	16.49107	0.0012	
D^2	26.94787	1	26.94787	6.478323	0.0233	
Residual	58.23578	14	4.159698			
Lack of fit	53.04986	10	5.304986	4.091838	0.0934	Not significant
Pure error	5.18592	4	1.29648			
Cor. total	2027.379	28				
Std. dev.	2.039534			R-squared	0.971275	
Mean	30.33379			Adj. R-squared	0.942551	
C.V. %	6.723636			Pred. R-squared	0.845283	
PRESS	313.6702			Adeq precision	20.59895	

(ANOVA), and model adequacy has been presented in Table 7.

It can be observed from Table 7, quadratic model is the most suitable model for explaining the results of white layer thickness among the other polynomials as it exhibits least p value. ANOVA results reveal that pulse-on time, discharge current, concentration of nanoparticles, interaction effect of pulse-off time and discharge, interaction effect of pulse-off time and conc. of nanoparticles, interaction effect of discharge current and pulse-on time, quadratic terms of pulse-off time, and conc. of nanoparticles are the most significant factors. It clears that pulse-off time, discharge current, and conc. of nanoparticles significantly affect the white layer thickness (WLT) for machining AISI D2 steel. Therefore, as the discharge current, more heat will be transferred to the surface of work piece, and as a result, material will be removed rapidly, and recast layer will be produced. Accuracy of model has been measured by R-squared value. As it can be observed that R-squared value is 0.9713, which is close to unity, it shows the more accuracy of the model. It has been observed that adjusted R squared and predicted R-squared values that are in the range of 20% show 84.53% variability in new data and show a good compromise. The value of adequate precision is 20.599, which is greater than 4. The reliability of results has been assured by the value of coefficient of variance, which is 6.7236. Regression models that have been developed to predict the white layer thickness for the given parameters are presented using Eq. (6):

$$\begin{aligned}
\text{WLT} = {} & +171.40631 - 19.82171 \ {}^*\text{pulse}_{\text{off}}\ \text{time} - 2.11658 \ {}^*\text{discharge current} \\
& -1.00396 \ {}^*\text{pulse}_{\text{on}}\ \text{time} - 8.41850{}^*\text{Conc.of nanoparticles} \\
& +0.23375 \ {}^*\text{pulse}_{\text{off}}\ \text{time}{}^*\text{discharge current} \\
& -1.33333\text{E}{-}003{}^*p_{\text{off}}\ \text{time}{}^*\text{pulse}_{\text{on}}\ \text{time} \\
& +0.11250 \ {}^*p_{\text{off}}\ \text{time}{}^*\text{Conc.of nanoparticles} \\
& +0.035722{}^*\text{Current}{}^*\text{pulse}_{\text{on}}\ \text{time} \\
& -0.38556 \ {}^*\text{discharge current}{}^*\text{Conc.of nanoparticles} \\
& +0.023056{}^*\text{pulse}_{\text{on}}\ \text{time}{}^*\text{Conc.of nanoparticles} \\
& +0.95831{}^*\text{pulse}_{\text{off}}\ \text{time}^2 - 0.05033 \ {}^*\text{discharge current2} \\
& +3.61333\text{E}{-}003{}^*\text{pulse}_{\text{on}}\ \text{time}^2 \\
& +0.90589{}^*\text{Conc.of nanoparticles2}
\end{aligned} \tag{6}$$

3.5 Validation of regression models

The proposed models for material removal rate, surface roughness, and white layer thickness have been validated by performing the additional experiments. The selection of additional nine experiments has been designed in such a way that the combinations of process parameters do not belong to the

Table 8 Validation of proposed models

Process parameters					Material removal rate			Surface roughness			White layer thickness		
Run	Discharge current	Pulse-off time	Pulse-on time	Conc. of nanoparticles	Experimental	Predicted	Error %	Experimental	Predicted	Error %	Experimental	Predicted	Error %
1	11	10	80	0.5	11.23	10.84	3.60	6.02	5.78	4.15	33.13	33.92	2.33
2	11	10	80	2.5	21.72	20.87	4.08	4.98	5.12	2.73	19.23	19.97	3.71
3	11	12	80	0.5	11.47	12.05	4.81	5.11	4.97	2.82	39.92	41.48	3.76
4	11	12	150	2.5	23.18	22.59	2.61	2.16	2.24	3.57	44.83	46.31	3.2
5	14	10	150	0.5	11.37	11.67	2.57	3.76	3.94	4.57	59.32	61.59	3.69
6	14	10	150	2.5	27.18	26.03	4.42	3.92	3.75	4.53	46.93	48.55	3.34
7	14	12	80	0.5	16.61	15.88	4.60	4.75	4.98	4.62	46.82	47.77	1.99
8	14	12	150	2.5	28.03	28.95	3.18	2.35	2.46	4.47	55.23	57.78	4.41

design matrix designed based on RSM. The calculations are provided in Table 8. Experimentally obtained values are compared with those predicted value to estimate the error using the following formula [22] given in Eq. (7):

$$\Delta = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{Y_{\mathrm{i,experiental}} - Y_{\mathrm{i,predicted}}}{Y_{\mathrm{i,predicted}}} \right| \tag{7}$$

where Δ is the error estimator, Y_{i} is the response value, N is the total number of runs, and i is the run number. $Y_{\mathrm{i,\ experiental}}$ is the response value obtained from additional experiments. $Y_{\mathrm{i,\ predicted}}$ is the response value obtained from mathematical models.

Results shown in Table 8 show that experimentally measured values of material removal rate, surface roughness, and white layer thickness, and their predicted values are very close to each other which is an evidence of the accuracy of the model. The estimate of error should be less than 5% [23]. Average prediction errors of material removal rate, surface roughness, and white layer thickness are 2.7%, obtained from the validation.

3.6 3D response surface plots

The following section interprets the influence of process parameters which are pulse-on time, pulse-off time, discharge current, and conc. of nanoparticles on responses, material removal rate, surface roughness, and white layer thickness. 3D plots explain the interaction effect of two variables simultaneously on the responses.

3.7 Material removal rate

The influence of process parameters on material removal rate has been presented in Fig. 4. The 3D plot of pulse-on time vs. pulse-off time is shown in Fig. 4. It has been observed that MRR increases with increase of pulse-on time and pulse-off time. Pulse-off time has almost negligible effect on MRR, while pulse-on time has direct relation with material removal rate. It has been observed that MRR increased with increase in pulse-off time and conc. of nanoparticles. As conc. of nanoparticles increase, gap distance between work piece and electrode decreases, so more energy will be transferred to the gap; rapid removal of materials will occurred. The 3D plot of discharge current vs. conc. of nanoparticles is shown in Fig. 4. The interaction effect of both the parameters on MRR is significant. MRR increased significantly with increase in discharge current and conc. of nanoparticles. Discharge gap will be energized at every moment, and removal of materials will be taken place largely.

3.8 Surface roughness

The influence of process parameters on surface roughness has been presented in Fig. 5. The 3D plot of discharge current vs.

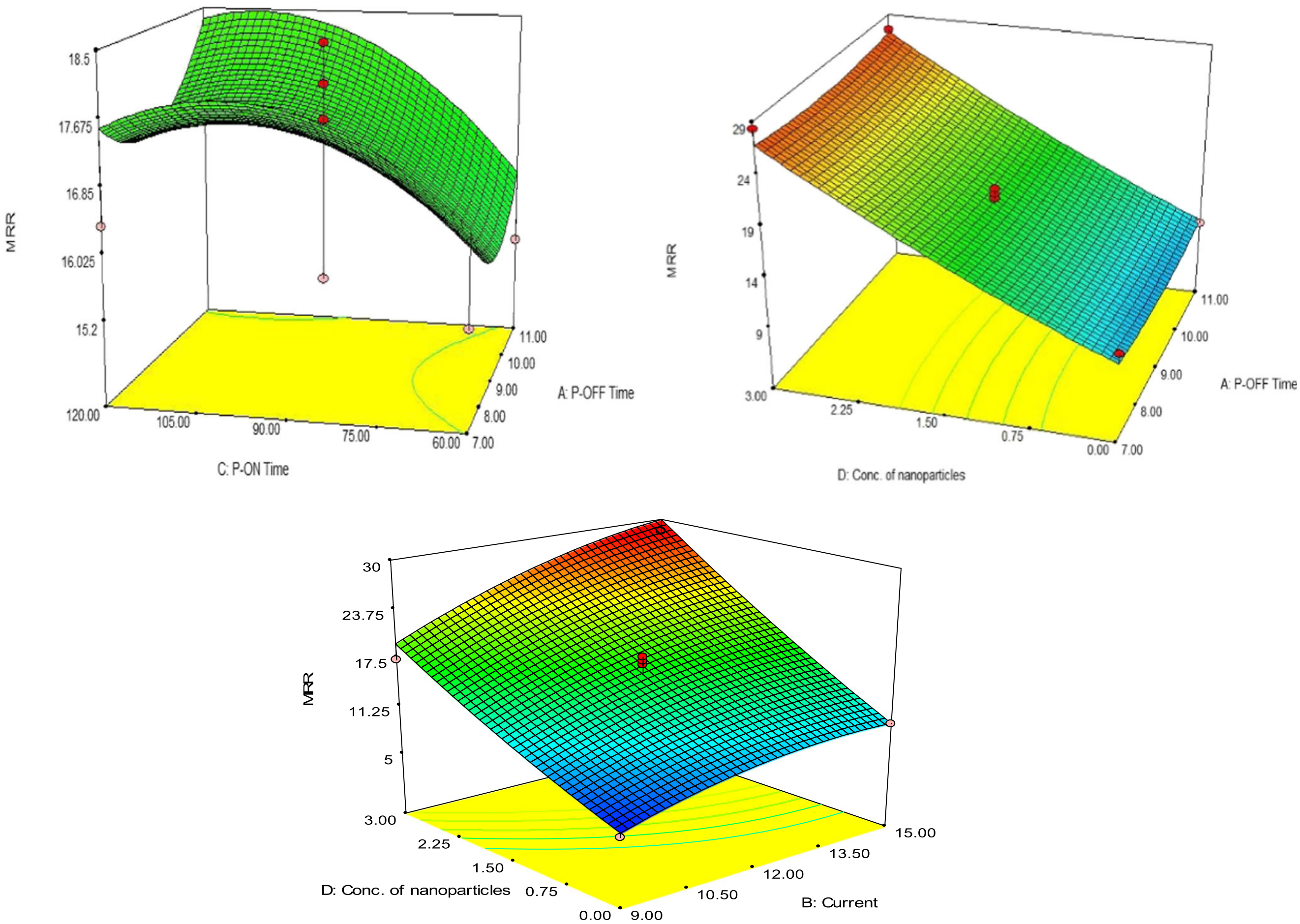


Fig. 4 3D plots for MRR

pulse-off time is shown in Fig. 5. It has been observed that surface roughness increases with increase in discharge current and pulse-off time. This is because more energy will be provided to the gap and as a result its quality will be affected. The 3D plot of pulse-on time vs. pulse-off time is shown in Fig. 5. It has been observed that surface roughness decreases at higher level of pulse-on time and pulse-off time. The 3D plot of discharge current vs. conc. of nanoparticles is shown in Fig. 5. It has been observed that surface roughness increases with increase in discharge current but decreases with the increase in conc. of nanoparticles because it will maintain the temperature of dielectric used for machining.

3.9 White layer thickness

The influence of process parameters on white layer has been presented in Fig. 6. Figure 6 shows that with increase in discharge current and pulse-on time, the white layer thickness increases. The value of WLT increases when discharge current increased from 12 to 15 A, because higher values of discharge current provide more energy to the discharge gap, resulting in more quantity of molten material from the work piece, thus increasing re-solidification layer thickness, which results in increment in white layer thickness and product life [24]. Pulse-on time has less effect on white layer as compared to discharge current. The 3D plot of pulse-on time and conc. of nanoparticles is shown in Fig. 6. This figure shows that white layer thickness decreases with increase in conc. of nanoparticles but increases with increase in pulse-on time. Both have significant effect on white layer.

3.10 Optimization of performance measures

Optimization can be achieved by producing better quality parts at higher production rate. The performance measures include material removal rate, surface roughness, and white layer thickness. All these performance measures need to be expressed in the form of a single objective function to optimize simultaneously as expressed in Eq. (8). Desirability function is used for optimization for improving sustainability. Performance measures such as MRR, SR, and WLT have been optimized simultanously for all the responses.

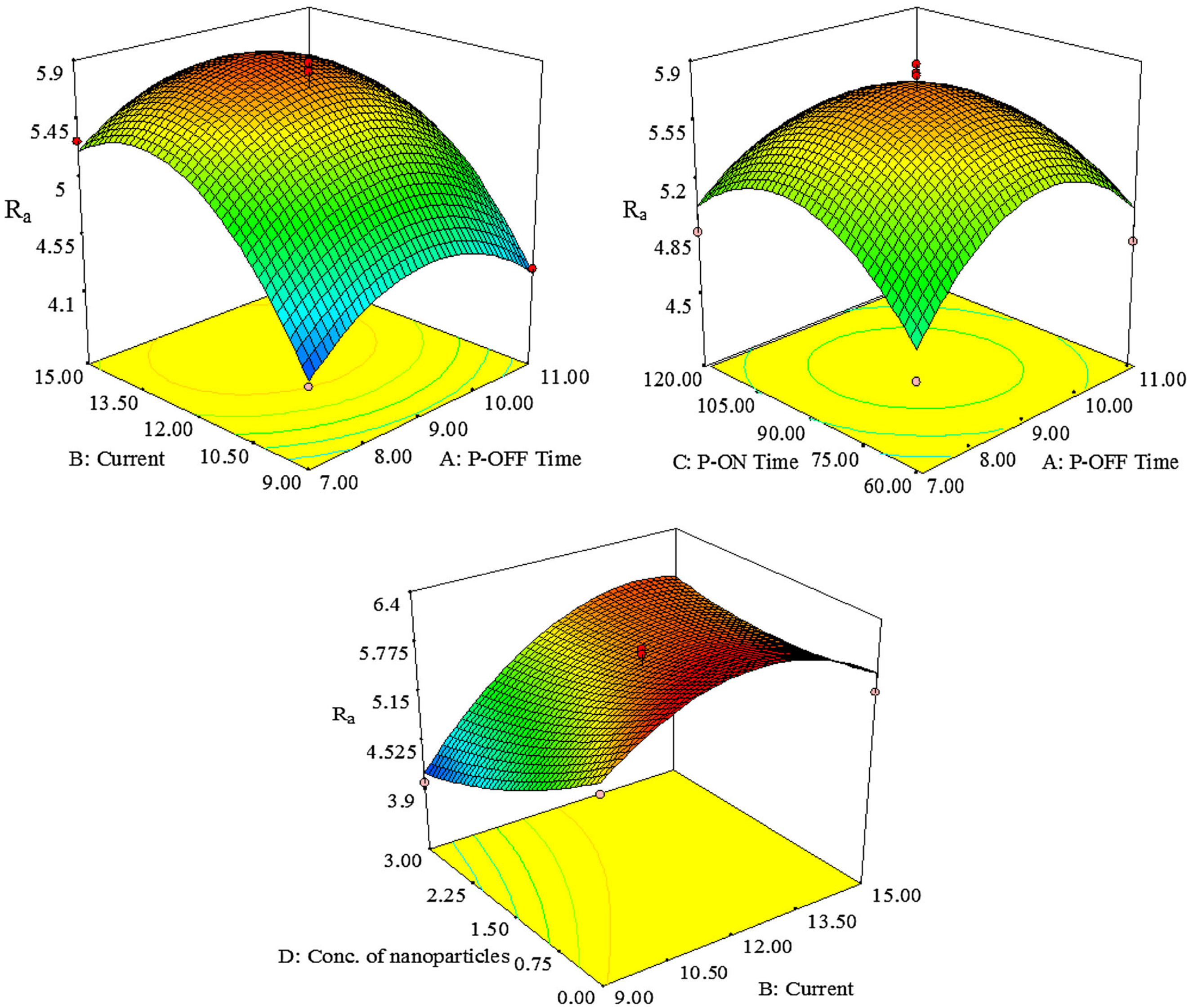


Fig. 5 3D plots for surface roughness

$$objective\ function = \begin{cases} Maximize\ Material\ Removal\ Rtae \\ Mininmize\ Surface\ Roughness \\ Minimize\ White\ Layer\ Thickness \end{cases} \quad (8)$$

The findings from the detailed analysis of 3D response surface plots in previous sections have been summarized. The figure shows effects of increasing the process parameters on performance measures. Two functions namely ‗As-is function'(achieved function) and ‗To-be function'(desired function) have been used. As-is function represents the achieved effects of increasing process parameters on performance measures. To-be function, on the other hand, depicts the benchmarked desired function as presented in Eq. (8). To-be function can be achieved by simultaneously maximizing material removal rate while minimizing surface roughness, and white layer thickness. In reality, by increasing any of the process parameter, this to-be function cannot be achieved. For example by increasing discharge current, all four performance measures (material removal rate, surface roughness, and white layer thickness) increase.

3.11 Desirability function

Desirability-based optimization approach is used to optimize multi-responses simultaneously. First step of this technique is to convert each individual response y_i into a desirability value d_i where d_i ranges from 0 to 1. A value of "0" indicates that the response is outside the range or has unacceptable value, while "1" indicates that

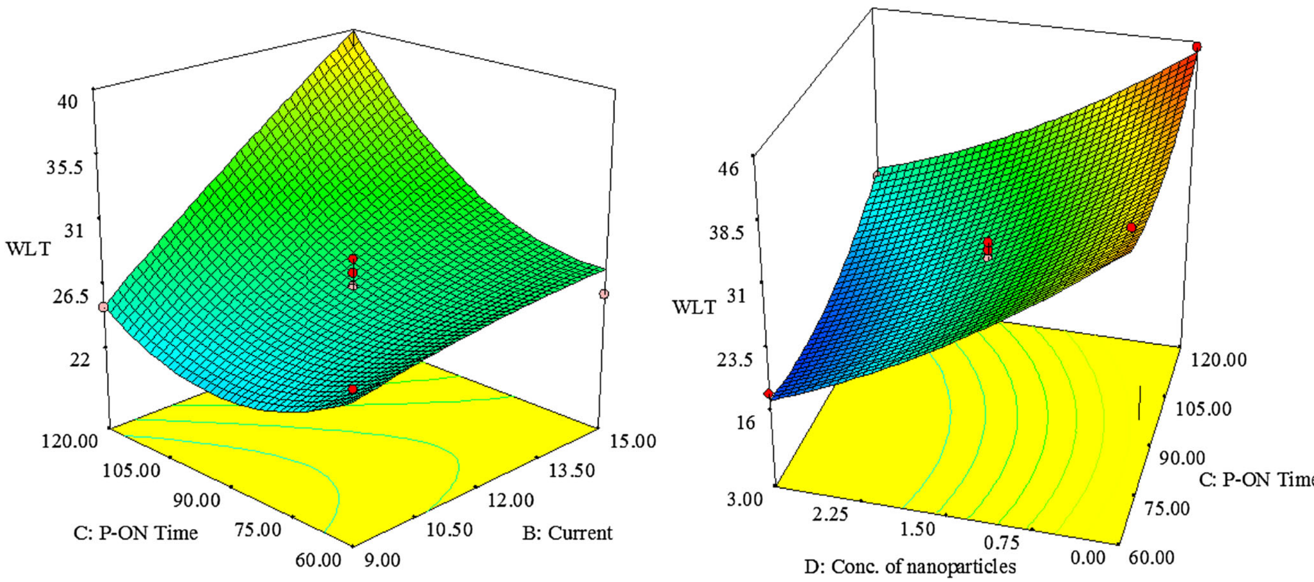


Fig. 6 3D Plots for white layer thickness

response is within the defined range or has acceptable value [22]. The desirability function is actually a mathematical transformation of multi-response problem into a single response problem using function $0 \le d_{\mathrm{i}} \le 1$. Another important factor is weight factor denoted by r having value of 1; if the chosen value for r is less than 1, then sensitivity of the desirability function reduces as found by the algorithm [25].

The following procedure is adopted for optimization in this research as developed by Derringer and Suich; firstly, individual desirability for each response is calculated. MRR desirability is calculated using maximization function as presented in Eq. (9) [26].

$$d_i = \begin{cases} 0, Y_i \le L_i \\ \left(\dfrac{H_i - Y_i}{H_i - L_i}\right)^w L_i < y_i < -H_i \\ 1, Y_i \le H_i \end{cases} \tag{9}$$

While for surface roughness and white layer thickness, minimization function is employed, as presented in Eq. (10).

$$d_i = \begin{cases} 0, Y_i \le L_i \\ \left(\dfrac{H_i - Y_i}{H_i - L_i}\right)^w L_i < y_i < H_i \\ 1, Y_i \ge H_i \end{cases} \tag{10}$$

where H_{i} indicates the higher value, L_{i} indicates the lower value, and w is the weight of particular value that show its importance. Secondly, composite desirability is calculated using Eq. (11) for MRR, SR, and WLT using weight geometric mean method.

$$DG = \left(d1 \times d1 \times \dots \dots \times {d_n}^{w_n}\right)^{\frac{1}{n}} \tag{11}$$

where DG represents the desirability value obtained from geometric mean method and n is the number of responses ($n = 3$). Optimization has been performed on Design Expert software.

Table 9 Constraints for multi-optimization of performance measures

Name	Goal	Lower limit	Upper limit	Lower weight	Upper weight	Importance
P-off time	is in range	7	11	1	1	3
Current	is in range	9	15	1	1	3
P-on time	is in range	60	120	1	1	3
Conc. of nanoparticles	is in range	0	3	1	1	3
MRR	maximize	5.37552	28.3653	1	1	3
R_a	minimize	3.982	5.9847	1	1	3
WLT	minimize	15.38	45.37	1	1	3

Table 10 Achieved desirability of measures along with process parameters values

Solutions	P-off time	Discharge current	P-on time	Conc. of nanoparticles	Value responses			Desirability	
					MRR	R_a	WLT		
1	7.09	9.46	85.63	3.00	21.928	3.982	19.134	0.857	Selected
2	7.07	9.46	86.41	3.00	21.953	3.982	19.242	0.856	

Multi-objective optimization has been performed using desirability function to set values of parameters to develop a compromise between maximum MRR and minimum SR and WLT. Optimization has been performed simultaneously for maximization of MRR and minimization of the SR and WLT using in range values of the inputs pulse-off time, discharge current, pulse-on time, and conc. of nanoparticles. All parameters and performance measures have been optimized using equal importance and weightage.

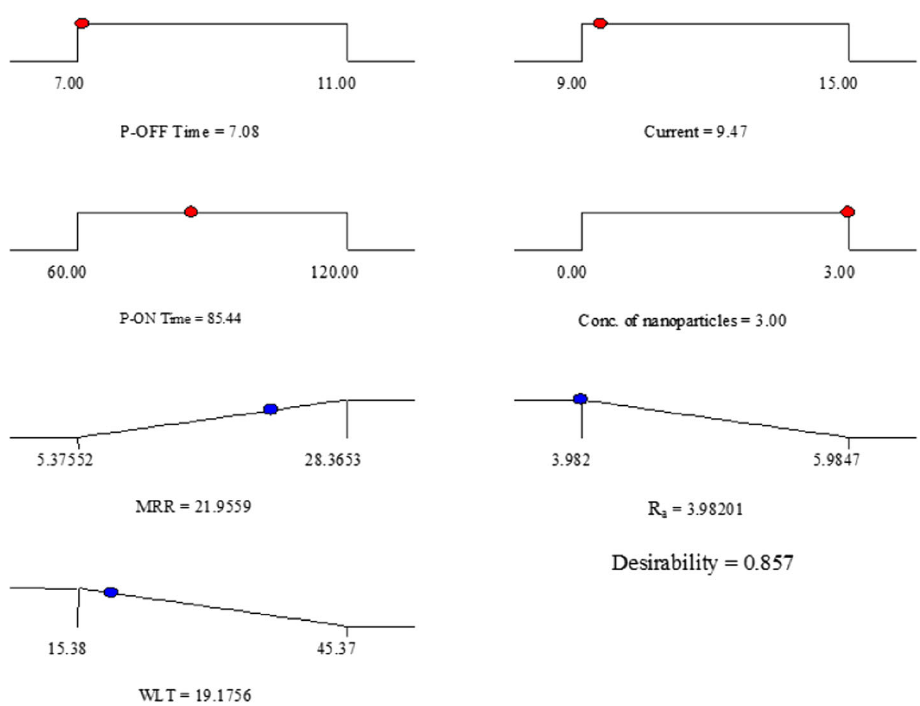
The constraints for multi-objective optimization of AISI D2 steel electric discharge machining have been presented in Table 9. The achieved desirability along with process parameters values has been provided in Table 10. It can be observed that desirability as high as 785.7% can be achieved when all performance measures have equal weights. The effectiveness of the process parameters has already been established in previous section and can be validated by comparing values of performance measures for a maximum desirability of 85.7% from Table 10.

Ramps for multi-objectives optimization have been shown in Fig. 7. It has been cleared that the desirability value for all the responses is 0.857, for which the optimum values for material removal rate, surface roughness, and white layer thickness are 21.92 mm^3/min, 3.98 μm, and 19.13 μm, respectively. The optimal values for the process parameters, i.e., pulse-off time, discharge current, pulse-on time, and conc. of nanoparticles are 7.08 μs, 9.47 Amp, 85.44 μs, and 3.00 g/l, respectively. The desirability value for sustainable production has also been shown in Fig. 8.

4 Conclusions and Recommendations

In this research work, the effects of significant process parameters related to powdered-mixed electric discharge machining including pulse-off time, discharge current, pulse-on time, and conc. of nanoparticles on responses variables such as MRR, SR, and WLT while machining AISI D2 steel have been investigated. Experiments were performed according to Box-Bhenken Design based on RSM. ANOVA has been performed for analysis. The optimization of performance measures was carried out

Fig. 7 Ramps for multi-objective optimization



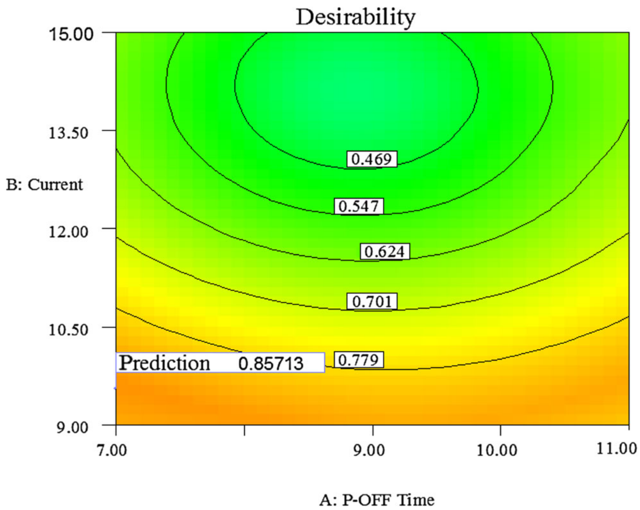


Fig. 8 Desirability plot for performance measures

through multi-objective optimization by establishing a compromise between productivity (material removal rate), quality (surface roughness), and cost (white layer thickness). Discharge current and conc. of nanoparticles are the most influencing factors affecting the material removal rate, surface roughness, and white layer thickness.

- Pulse-on time was the only factor that significantly affects the white layer thickness.
- Maximum material removal rate can be achieved at higher levels of discharge current and conc. of nanoparticles on the other hand; minimum surface roughness and white layer thickness were achieved at low levels of discharge current and high level of conc. of nanoparticles.
- All the process parameters behave in such a way that the response variables cannot be optimized simultaneously. Therefore, to overcome this difficulty, multi-objective optimization has taken place, which was achieved by desirability function.
- For desirability function, value achieved was 85.7% with maximum MRR value of 21.928 mm^3/min, minimum SR value of 3.982 μm, and minimum WLT value of 19.134 μm associated with sustainability.
- The contour plots have been presented which can be used by shop floor practitioners to achieve certain desirability suitable for their machines.
- It is possible for predicting MRR, SR, and WLT before conducting machining using proposed developed models. Furthermore, machining parameters that satisfy constraints of required quality (surface finish), productivity (material removal rate), and cost (white layer thickness) for a specific industrial applications can be easily selected.

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