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Analysis and Multi-objective Optimisation of Surface Modification Phenomenon by EDM Process with Copper-Tungsten Semi-sintered P/M Composite Electrodes

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Abstract In the present experimentation work, attempts have been made to model, analyse and optimise the surface modification phenomenon in electrical discharge machining process using response surface methodology. The central composite second order rotatable design has been chosen for designing the experiments and response surface methodology was applied for developing the mathematical models. Efforts has been made to correlate the four input process parameters; peak discharge current, pulse-on time, pulse-off time and tool electrode powder compaction pressure with two output responses; surface deposition rate and surface roughness. Results obtained were presented in the form of three dimensional surface plots. Analysis of variance had been performed to check the adequacy of the developed mathematical models as well as significance of each term comprising the models. Statistical software was used to construct the plots to analyse the influence of individual input process parameter on output responses. Composite desirability function approach was used for multi-objective optimisation of the developed models. Optimal parameter combinations for achieving maximum surface deposition rate and minimum surface roughness have been observed and presented in the form of contour plots. The optimal predicted results were experimentally verified, matched well with the predicted results.

Keywords: *electrical discharge machining, response surface methodology, analysis of variances, surface deposition rate, surface roughness, design of experiment*

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1. Introduction

Electrical Discharge Machining (EDM) is a well-established non-traditional material removal process. It is most extensively used for machining complicated contours in electrically conductive parts regardless of their hardness. Thus electrical and non-electrical process variables in EDM have received quite a substantial amount of research interest. Efforts have been made from a few decades to explore new and different ways of delivering a more efficient and stabilized sparking process that improves the performance measures of EDM. Though, it is a well-accepted concept of machining used in die and mould making industry as well as for finished parts for aerospace industry, automotive industry and surgical components for a few decades. Still the tool wear and formation of brittle and cracked white layer are two major disadvantages of conventional die sinking EDM process. It is almost impossible to achieve a condition without tool wear, but it can be minimised to some extent.

The EDM is an isothermal process, obviously some alternations in surface integrity takes place due to the formation of recast layer called white layer. During the study on effects of materials on the mechanism of EDM, Erden [1] observed that the solidified layer was actually an alloy composed of both electrode tool materials and decomposed products of dielectric like carbon. The re-solidified alloyed material on the surface and in the heat affected zone (HAZ) induces changes in surface integrity of workpiece material. The above phenomenon has inspired researchers to explore the possibility of new methods for surface modification by EDM process as a replacement of other existing surface modification techniques such as Physical Vapour Deposition (PVD), Chemical Vapour Deposition (CVD), Electro Plating and others.

Various researchers have conducted rigorous experimentation work to study the effects of dielectric fluids used in EDM process and reporting the formation of hardened and carbonized layer on a machined surface while using kerosene as the dielectric, and a softened and de-carbonized layer when using distilled water as dielectric [2].

In some recent studies, the machining performance has also been explored by adding conductive powders into the dielectric fluid [3m4]. The investigators found that mixing the various powders likes carbon, silicon, nickel, chromium and titanium with the dielectric, resultedin improvement in electrical discharge machined (EDMed) surface properties such as corrosion, wear resistance and hardness along with better surface quality and lesser surface cracks. Kruth et al. [5] developed an adaptive control system capable to optimise the machining parameter settings, such as servo-reference voltage, pulse duration, pulse interval and dielectric flow rate. In 1979 Jeswani [6] used the dimensional analysis model to predict tool wear in EDM process. Model equation relates the volume of material eroded from the tool electrode to the energy and density, thermal conductivity, specific heat and latent heat of vaporisation of tool electrode material. In another study using dimensional analysis Wang and Tsai [7] developed semi-empirical models for material removal rate and tool wear rate with different materials. The peak current, pulse duration, electric polarity and material properties were taken as input parameters. The final results show that the average error between experimental and model predicted values was less than 20% for MRR and 10% for TWR models.

While doing experimentation work and theoretical investigations on workpiece surface profiles in electrical discharge machining process, Cogun et al. [8] observed an increase in surface roughness value with the increase in electric discharge current, pulse duration and dielectric flushing pressure. Further, the surface profile information obtained was digitised and then it was modeled in the form of Fourier series.

In the past decade, it was reported that an artificial neural network (ANN) is a highly flexible modeling tool with greater capabilities on learning the mathematical mapping between input variables and output responses for nonlinear systems. Gopal and Rajurkar [9] developed 9-9-2 size back propagation neural network by taking machining depth, pulse-on time, pulse-off time and discharge current as input variables. They have conducted the experiments to validate an ANN model and concluded that an ANN model can provide faster and more accurate results. Tsai and Wang [10] have established six different neural network models and a neuro-fuzzy network model to illustrate the comparisons in MRR and surface finish of various materials machined by EDM process by changing tool electrode polarity. It was concluded that the adaptive-network fuzzy interference system (ANFIS) model is more accurate having lowest average error of 16.33%. By combining the capabilities of ANN and genetic algorithm (GA), Kesheng et al. [11] developed a hybrid intelligent method to model and optimise MRR and SR in EDM process. Mandal et al [12] used back propagation neural network for modelling and GA for multi-objective optimization of MRR and TWR. Rao et al. [13] developed a hybrid model using ANN andGA to map the input variables; discharge current, pulse-on time, pulse-off time with output measures; MRR and TWR for die-sinking EDM process. Lin et al. [14] used the grey relation analysis based on an orthogonal array and fuzzy based Taguchi method for optimization of the EDM process with multi performance characteristics such as MRR and TWR. They have also used grey fuzzy logic for optimisation of EDM process with multi-responses, MRR, TWR and SR.

Samuel and Philip [15] compared the performance of powder metallurgy (P/M) tool electrodes with conventional electrodes in normal electrical discharge machining (using straight polarity, machining conditions not favouring surface modification) and established that P/M electrodes are technically viable for EDM machining and their related properties could be controlled by varying compaction and sintering parameters. In another study Lin et al. [16] found that under certain processing and operating conditions, the sintered P/M electrodes cause in net material addition on EDMed surface instead of material removal.

Recently, powder metallurgy turns out to be a viable alternative technique to form tool electrode in which the desirable properties of different materials can be combined. Moreover the thermal, electrical, mechanical and micro-structural properties of P/M electrodes can be controlled effectively by process variables such as compaction pressure and sintering temperature.

Seeking, the advantages of powder metrology technology, several investigators carried out some investigations to explore the surface modification phenomenon by EDM process using green compact electrodes and came with findings that the electrode elements could be transferred to the machined surface of the workpiece to increase hardness and improve corrosion resistant [17-24].Though surface modification was already achieved by EDM process but the various issues related to the surface modification phenomenon yet to be explored. Therefore, selection of input parameters, their levels and combination of parameters to achieve surface modification by EDM process still is a critical issue.

Efforts have been made by many researchers to intentionally modify the work surface using EDM process by depositing a layer on it. But any mathematical, physical or empirical model capable to explore the changes in the surface integrity by heat and mass transfer due to discharge, breaking of dielectric fluid and diffusion of electrode material has not been reported till now. Such studies need to combine two complex phenomena; one is electro discharge and another is mass transfer or diffusion process in electrical discharge and that again extremely complicates the model. Therefore, there is enough scope to explore the aspect of surface modification phenomenon by EDM process.

The available literature indicates that most of the published work is concerned with correlating the machining parameters onlyto the output responses. But it is also necessary to include tool electrode parameters along with machine parameters to explore the combined effects on process performance. Few researchers have attempted to develop empirical models for normal EDM process. But, the mathematical model for surface modification phenomenon by EDM process with RSM has not been developed and reported. So, an attempt has been made to develop a reliable RSM model to predict the performance characteristics of die sinking EDM as surface modification process.

The literature review also indicates that a few studies have been reported for multi-objective optimisation of process parameters of the surface modification by EDM process using powder metallurgy composite tool electrodes. Hence, attempts have been made to determine the possibility of using tool electrodes as feed stock material. Therefore in the present work attempts have been made to;

- Evaluate the process performance characteristics such as surface deposition rate (SDR) and surface roughness (SR) for surface modification phenomenon by EDM process considering; peak discharge current, pulse-on time, pulse-off time and tool electrode compaction pressure as input parameters.
- Develop a response surface methodology (RSM) model to correlate the input process parameters such as peak current, pulse-on time, pulse-off time and tool electrode compaction pressure with output responses like SDR and SR for surface modification by EDM process. These models would help in predicting the SDR and SR values for a large number of input parameter combinations.
- Analyse the influence of various input parameters on output responses.
- Analyse the three dimensional response surfaces to acquire further insight information on the correlation between the input process variables and the output responses.
- Optimise the process parameters for multi-objective performance of surface modification by EDM process.

The P/M semi-sintered tool electrodes formed at different powder compaction pressure was used in experimentation. The Peak discharge current, pulse-on time, pulse-off time and electrode powder compaction pressure were considered as input parameters for EDM machining process to evaluate the process performance characteristics such as SDR and SR.

2. Experimentation

In the present work output parameters, SDR and SR have been considered for evaluating the performance of surface modification process by EDM. Attempts have been made to correlate SDR and SR with input process parameters, such as, peak discharge current (I_p), pulse-on time (T_{on}), pulse-off time (T_{off}) and tool electrode compaction pressure (P_c).

2.1. Equipment and Procedure

Experiments were conducted on A25 spark generator integrated type TOOLCRAFT (India) die-sinking EDM machine. It can run either in normal polarity or in reverse polarity, but reverse polarity has been used for present experimentation work. Semi-sintered powder metallurgy tool electrodes made up of 8% copper, 92% tungsten metal powder (average grain size less 20 meshes) were formed at different compaction pressure and same were used for deliberate transfer of electrode material on work-piece surface by EDM process. The workpiece specimen used in the experimentation work was made up of EN-31 die steel material with dimensions 30×15×6 mm. The criterion for the choice of this material is purely based on its extensive use in tool and die making industry. Table 1 depicts the chemical composition for EN-31 die steel. During EDM process, EDM oil (EDM-30) was used as dielectric fluid with side flushing technique. The machining time for each experiment was kept constant and taken as 3 minutes.

Table 1. Chemical composition of EN-31 steel

Elements	C	Si	Mn	P	S	Cr	Fe
Wt. %	1.3	0.3	0.5	0.024	0.025	1.4	Balance

The input process parameters, machining conditions and output measures obtained were listed in Table 2. These were chosen based on literature reviews and some preliminary experimental investigations.

Table 2. Machining conditions used for experimentation

Working Conditions	Description
Work piece material	AISI EN- 31die steel
Electrode composition	8% Cu - 92% W
Sintering Temperature	300 °C
Compaction Pressure	500 -1300 MPa
Peak current	3 - 9 A
Pulse-on time	5 - 25 µsec
Pulse-off time	50 - 250 µsec
Polarity	Negative
Dielectric fluid	EDM-30
Dielectric flushing	Side flushing
Processing time	3 min

The work-piece was cleaned with acetone before and after each experiment, then dried with a dryer and precisely weighed. A digital balance (Make: EssaeTeraoka) with 0.1 mg resolutions was used to measure the weight. Surface deposition per unit time is known as surface deposition rate (SDR) and expressed as mg/min. The centre-line average value (R_a) for SR was measured by portable roughness tester 'Surftest SJ-301' (Make: Mitutoyo). The cut-off length was set at 2.5 mm for an evaluation length of 10 mm. The average value of six SR measurements was recorded in different directions for each specimen and these values were used for developing SR model. The observed surface roughness (R_a) values lie in the range of 5.18 to 7.95 µm.

2.2. Experimental Design Based on CCD

In present work, the range of peak discharge current, pulse-on time, pulse-off time and tool electrode powder compaction pressure (P_c) settings were chosen by conducting a number of pilot experiments. Each input parameter has five levels of variation (±2, ±1, 0) within the chosen range. The input process parameters along their levels used in present experimentation work are listed in Table 3.

Table 3. Experimental input variables along with selected levels

Process parameters	Units	Levels				
		-2	-1	0	+2	+2
Peak current	Amp	3	4.5	6	7.5	9
Pulse-on time	µs	5	10	15	20	25
Pulse-off time	µs	50	100	150	200	250
Compaction pressure	MPa	500	700	900	1100	1300

Experiments were carried out strictly as per pre-designed experimental plan based on design of experiment (DOE) technique. Central composite design (CCD) is the most popular class of second-order designs suggested by Boxand Wilson [25]. A central composite rotatable second order design (CCD) was chosen The rotatable CCD was composed of total numberof 30 experiments per set, it further consisted of 2β fractional runs with 24 corner points, six centre points and eight axial runs located at 2α levels. Design of experiment (DOE) matrix depicting actual and coded values of the input process variables along with two output responses are shown in Table 4.

Table 4. Design of Experiment matrix and machining characteristics

Exp.No.	Input process parameters								Observed responses	
	I_p		T_{on}		T_{off}		P_c		SDR (mg/min)	SR (μm)
	Actual	Coded	Actual	Coded	Actual	Coded	Actual	Coded		
1	4.50	-1	10	-1	100	-1	700	-1	31.58	7.511
2	7.50	1	10	-1	100	-1	700	-1	45.78	6.352
3	4.50	-1	20	1	100	-1	700	-1	35.65	7.954
4	7.50	1	20	1	100	-1	700	-1	49.30	6.401
5	4.50	-1	10	-1	200	1	700	-1	17.55	5.808
6	7.50	1	10	-1	200	1	700	-1	25.78	5.460
7	4.50	-1	20	1	200	1	700	-1	19.08	6.250
8	7.50	1	20	1	200	1	700	-1	27.68	5.517
9	4.50	-1	10	-1	100	-1	1100	1	28.05	6.313
10	7.50	1	10	-1	100	-1	1100	1	42.75	5.772
11	4.5	-1	20	1	100	-1	1100	1	30.95	7.022
12	7.5	1	20	1	100	-1	1100	1	42.92	6.147
13	4.5	-1	10	-1	200	1	1100	1	14.92	5.583
14	7.5	1	10	-1	200	1	1100	1	23.75	6.058
15	4.5	-1	20	1	200	1	1100	1	15.72	5.908
16	7.5	1	20	1	200	1	1100	1	24.35	7.098
17	3.0	-2	15	0	150	0	900	0	18.40	5.735
18	9.0	2	15	0	150	0	900	0	39.13	5.663
19	6.0	0	5	-2	150	0	900	0	29.60	6.493
20	6.0	0	25	2	150	0	900	0	32.83	6.997
21	6.0	0	15	0	50	-2	900	0	46.48	5.179
22	6.0	0	15	0	250	2	900	0	14.13	6.662
23	6.0	0	15	0	150	0	500	-2	32.17	5.893
24	6.0	0	15	0	150	0	1300	2	26.75	6.133
25	6.0	0	15	0	150	0	900	0	34.67	6.159
26	6.0	0	15	0	150	0	900	0	34.30	6.169
27	6.0	0	15	0	150	0	900	0	33.40	6.107
28	6.0	0	15	0	150	0	900	0	34.33	6.120
29	6.0	0	15	0	150	0	900	0	34.28	6.144
30	6.0	0	15	0	150	0	900	0	34.30	6.120

3. Response Surface Methodology

Response surface methodology (RSM) is a collection of statistical and mathematical techniques that are useful for developing, analysing, improving and optimising the processes in which an output response is influenced by several independent input variables [26]. Response surface methodology (RSM) was adopted for developing the surface deposition model and surface roughness model. DOE technique was used to conduct experiments for data collection. Then surface deposition and surface roughness prediction models are obtained by applying regression processes in which an output response is influenced by several independent input variables. Response surface methodology (RSM) was adopted for developing the surface deposition model and surface roughness model. DOE technique was used to conduct experiments for data collection. Then surface deposition and surface roughness prediction models are obtained by applying regression analysis. If all variables are assumed to be measurable, then the mathematical model can be expressed by equation prediction models are obtained by applying regression analysis. If all variables are assumed to be measurable, then the mathematical model can be expressed by equation (1) as below:

$$Y_i = f(I_p, T_{on}, T_{off}, P_c) + \varepsilon \quad (1)$$

Where Y_i is the surface modification response function and I_p,T_{on}, T_{off}, P_c, are the coded values of the machining input parameters with the fitting error 'ε' of the i[th] observation.The first step in RSM is to find a suitable approximation for the true functional relationship between the response and the set of input independent variables. Then a second order polynomial regression model is proposed. This is so called quadratic model of any output response which can be written as equation (2) as follows:

$$\begin{aligned} Y = \beta_0 + \beta_1 I_p + \beta_2 T_{on} + \beta_3 T_{off} + \beta_4 P_c + \beta_5 I_p T_{on} \\ + \beta_6 I_p T_{off} + \beta_7 I_p P_c + \beta_8 T_{on} T_{off} + \beta_9 T_{on} P_c \\ + \beta_{10} T_{off} P_c + \beta_{11} I_p^2 + \beta_{12} T_{on}^2 + \beta_{13} T_{off}^2 + \beta_{14} P_c^2 \end{aligned} \quad (2)$$

Where I_p, T_{on}, $T_{off}$and P_c are the input variables which have an influence on the response Y. The set of regression coefficients β's are known parameters and estimated by least squares, where 'ε' is random error which is normally distributed with mean as per observed response. The coefficients of regression model were estimated by using data obtained from the experimental results. Design-expert 8.01 statistical software programming was used for analysis. Statistical tests such as lack of fit test (F-test), and normal probability plot of residuals versus predicted response was used to test the validity of the modelsbefore using them in optimization problem.

3.1. Mathematical Modelling Based on RSM

In mathematical modelling, the model parameters are determined with the aid of methods such as regression analysis on the bases of numerous measurable values. The experiments which have to be carried out in order to determine to coefficients of the model are recorded in Table 4. Surface deposition model and surface roughness model have been developed to predict the responses using the significant input parameters and these are presented below as in equation (3) and (4) respectively.

$$\begin{aligned} SDR = +34.38 + 5.43 I_p + 0.91 T_{on} - 8.48 T_{off} \\ -1.67 P_c - 0.19 I_p T_{on} - 1.26 I_p T_{off} - 0.034 I_p P_c \\ -0.36 T_{on} T_{off} - 0.41 T_{on} P_c + 0.39 T_{off} P_c - 1.44 I_p^2 \\ -0.83 T_{on}^2 - 1.02 T_{0ff}^2 - 1.29 P_c^2 \end{aligned} \quad (3)$$

$$\begin{aligned} SR = +6.14 - 0.33 I_p + 0.20 T_{on} - 0.46 T_{off} \\ -0.19 P_c - 0.093 I_p T_{on} + 0.19 I_p T_{off} + 0.15 I_p P_c \\ -3.604^{03} I_{on} T_{off} + 0.070 T_{on} P_c + 0.18 T_{off} P_c \\ +0.069 I_p^2 - 0.016 T_{on}^2 - 0.013 T_{off}^2 + 0.034 P_c^2 \end{aligned} \quad (4)$$

3.2. Adequacy Check for the Developed Models

The adequacy of the models as well as the significance of the individual parameters in the developed models was checked by performing the analysis of variance (ANOVA) and Fisher's statistical test (F-test). As per this technique, if the calculated F-ratio values of the developed models do not exceed the standard tabulated values of F-ratio for desired level of confidence (99.80% and 99.93% for SDR and SR, respectively) then the models are considered to be at confidence level [26]. The ANOVA results for the proposed surface deposition model and surface roughness model are shown in Table 5 and Table 6 respectively.

Table 5. ANOVA results for surface deposition model

Source	SS	df	MS	F-Value	P-value Prob> F
Model	2660.09	14	190.01	540.25	< 0.0001 *
I_p	707.09	1	707.09	2010.49	< 0.0001 *
T_{on}	20.08	1	20.08	57.08	< 0.0001 *
T_{off}	1724.66	1	1724.66	4903.75	< 0.0001 *
P_c	67.30	1	67.30	191.36	< 0.0001 *
I_pT_{on}	0.60	1	0.60	1.72	0.2096**
I_pT_{off}	25.58	1	25.58	72.73	< 0.0001 *
I_pP_c	0.019	1	0.019	0.054	0.8198**
$T_{on}T_{off}$	2.12	1	2.12	6.04	0.0266 *
$T_{on} P_c$	2.68	1	2.68	7.62	0.0146 *
$T_{off} P_c$	2.47	1	2.47	7.03	0.0181 *
I_p^2	56.82	1	56.82	161.55	< 0.0001 *
T_{on}^2	18.75	1	18.75	53.31	< 0.0001 *
T_{off}^2	28.36	1	28.36	80.63	< 0.0001 *
P_c^2	45.50	1	45.50	129.38	< 0.0001 *
Residual	5.28	15	0.84		
Lack of Fit	5.17	10	0.52	23.52	0.0002
Pure Error	0.11	5	0.022		
Cor Total	2665.37	29			

SS: sum of squares, df: degree of freedom, MS: mean squares,
(*): Significant terms, (**): non-significance terms

Table 6. ANOVA results for surface roughness model

Source	SS	df	MS	F-Value	P-value Prob> F
Model	11.49	14	0.82	1433.85	< 0.0001 *
I_p	2.58	1	2.58	4507.01	< 0.0001 *
T_{on}	0.94	1	0.94	1646.08	< 0.0001 *
T_{off}	5.19	1	5.19	9068.20	< 0.0001 *
P_c	0.89	1	0.89	1555.94	< 0.0001 *
I_pT_{on}	0.14	1	0.14	240.02	< 0.0001 *
I_pT_{off}	0.61	1	0.61	1061.75	< 0.0001 *
I_pP_c	0.37	1	0.37	654.08	< 0.0001 *
$T_{on}T_{off}$	$2.078E^{-04}$	1	$2.078E^{-04}$	0.36	0.5557**
$T_{on}P_c$	0.077	1	0.077	135.32	0.0001 *
$T_{off}P_c$	0.50	1	0.50	882.49	0.0001 *
I_p^2	0.13	1	0.13	226.29	< 0.0001 *
T_{on}^2	6.952^{-03}	1	6.952^{-03}	12.15	0.0033 *
T_{off}^2	$4.940E^{-03}$	1	$4.940E^{-03}$	8.63	0.0102 *
P_c^2	0.032	1	0.032	55.27	0.0001 *
Residual	$8.582E^{-03}$	15	$5.722E^{-04}$		
Lack of Fit	$6.520E^{-03}$	10	$6.520E^{-04}$	1.58	0.3202
Pure rror	$2.063E^{-003}$	5	$4.126E^{-04}$		
Cor Total	11.49	29			

SS: sum of squares, df: degree of freedom, MS: mean squares,
(*): significant terms, (**): non-significant terms

The p-values in ANOVA analysis Table 5 for SDR model and in Table 6 for SR model are less than 0.05, implies that both models are significant. The main effect of each linear factor and square effect of peak discharge current (I_p), pulse-on time (T_{on}) and tool electrode compaction pressure (P_c) is also significant in SDR model. Additionally SDR model contains single two-way significant interaction terms such as (I_pT_{off}), ($T_{on}T_{off}$), ($T_{on}P_c$) and ($T_{off}P_c$). Similarly p-values for I_p, T_{on}, T_{off}, P_c, I_p^2, T_{on}^2, T_{off}^2, P_c^2, (I_pT_{on}), (I_pT_{off}), (I_pP_c), ($T_{on}P_c$) and ($T_{off}P_c$) shown in Table 6 are less than 0.05, which implies that these are significant terms for the developed SR model. The remaining insignificant model terms was removed from the models that resulted in improved SDR and SR models. These models are shown in equation (5) and equation (6).

$$\begin{aligned}SDR = {} & +34.38 + 5.43I_p + 0.91T_{on} - 8.48T_{off} - 1.67P_c \\ & -1.26I_pT_{off} - 0.36T_{on}T_{off} - 0.41T_{on}P_c + 0.39T_{off}P_c \\ & -1.44I_p^2 - 083T_{on}^2 - 1.02T_{0ff}^2 - 1.29P_c^2\end{aligned} \quad (5)$$

$$\begin{aligned}SR = {} & +6.14 - 0.33I_p + 0.20T_{on} - 0.46T_{off} \\ & -0.19P_c - 0.093I_pT_{on} + 0.19I_pT_{off} + 0.15I_pP_c \\ & +0.070T_{on}P_c + 0.18T_{off}P_c + 0.069I_p^2 - 0.016T_{on}^2 \\ & -0.013T_{off}^2 + 0.034P_c^2\end{aligned} \quad (6)$$

The “lack of fit F-value” of 23.52 for SDR model implies that the lack of fit is not significant relative to pure error. There is only a 0.14% chances, that a “lack of fit F-value” this large could occur due to noise. In case of SR model “lack of fit F-value” of 1.58 indicates that the lack of fit is not significant relative to the pure error.

Further the propertiessuch as R-squared (Multiple correlation), adjusted R-squared and predicted R-squared of developed models for SDR and SR were recorded in Table 7 and Table 8.

Table 7. Multiple correlation for adequacy of Surface Deposition Model

R-Squared	0.9980
Adj R-Squared	0.9962
Pred R-Squared	0.9888
Adeq Precision	83.978

Table 8. Multiple correlation for adequacy of Surface Deposition Model

R-Squared	0.9993
Adj R-Squared	0.9986
Pred R-Squared	0.9965
Adeq Precision	165.100

The R-squared is used as a measure of agreement to fit and it is defined as the ratio of variability explained by the model to the total variability in the actual data. The R-squared value of 0.9980 and 0.9993 for SDR and SR model respectively means that 99.80% and 99.93% of the variance in the SDR and SR model is explained uniquely or jointly by the independent variables. Thus both developed models are fairly strong enough to be used to predicting the SDR and SR in the full range of process. The predicted R-square of 0.9888 is in reasonable agreement with adjusted R-squared of 0.9962; this means we could expect this SDR model to explain about 98.88% of the variability in predicting new observations, as compared to the 99.62% of the variability in the original data explained by the least square. It can also be noted from Table 8, that the difference inpredicted R-square of 0.9965 and adjusted R- square of 0.9986 for SR model is within 0.2 as recommended for model to be adequate.

Further the adequacy of developed models was checked from the normal probability plot and actual versus predicted response plot. The Figure 1 and Figure 2 show the normal probability plot of residuals and plot of the actual versus the predicted response for the second order SDR model respectively.

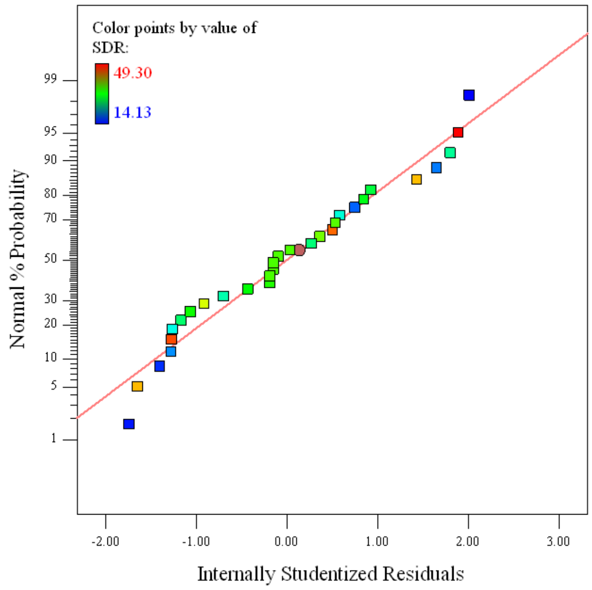

Figure 1. Normal Probability Plot of the Residuals for Surface Deposition Model

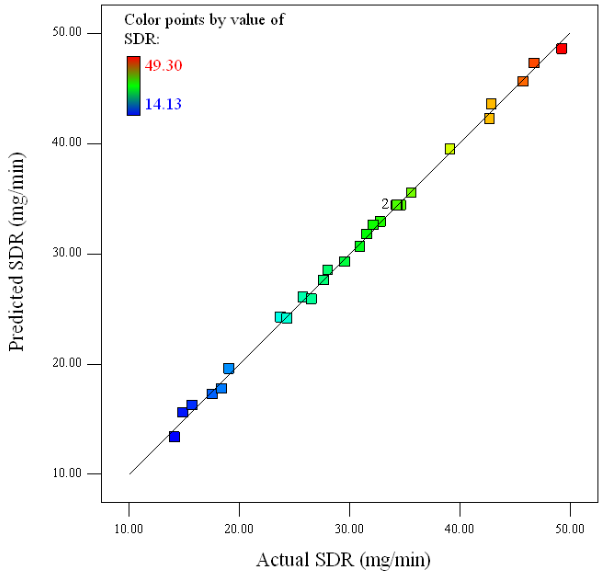

Figure 2. Variance of Actual V/s Predicted Response for Surface Deposition Model

It is observed from these plots that the residuals and actual data falls along a straight line, implies that the errors are distributed normally the proposed SDR model is adequate.

Similarly Figure 3 and Figure 4 depict the residual plot and plot of the actual versus the predicted response for the surface roughness model respectively. In the normal probability plot, it can be noted that the spread of data points is approximately along a straight line. Also Figure 4 reveals that residuals fall on a straight line. This shows a good correlation between model fitted and model predicted values for SR model. Hence from above statistical tests, it can be concluded that the developed models for both the responses are adequate and these can be used for further analysis to determine the effects of various parameters on the output responses.

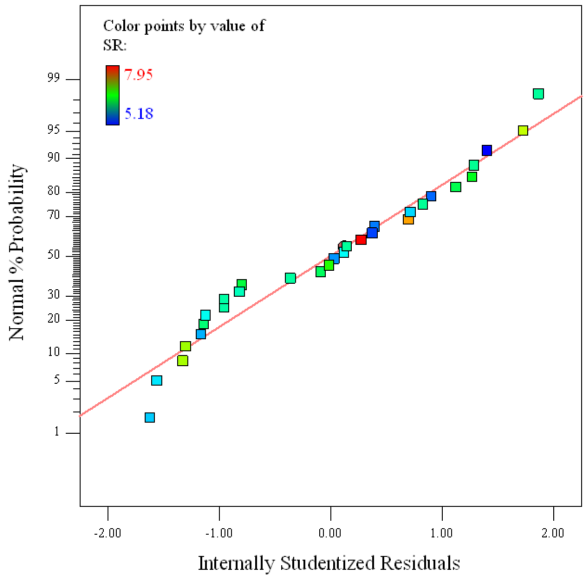

Figure 3. Normal Probability plot of the Residuals for the Surface Roughness Model

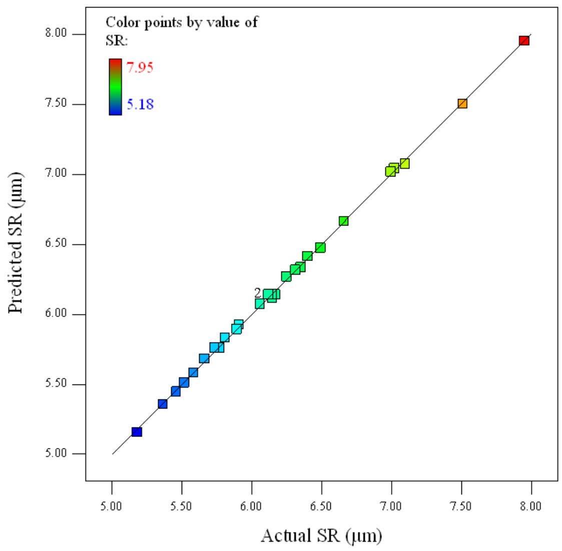

Figure 4. Variation of Actual V/s Predicted Response for SDR

4. Parametric Analysis

The parametric analysis has been carried out to study the effects of input process parameters such as peak discharge current, pulse-on time, pulse-off time and tool electrode compaction pressure on the output responses such as surface deposition rate and surface roughness during surface modification phenomenon by EDM process. The Design Expert 8.01 software was used to generate the three dimensional response surface plots for SDR and SR second order RSM models. Analysis of the response surface provides further insight information on the correlation between the input process variables and the output responses.

4.1. Effects of Machining Parameters on Surface Deposition Rate

Based on RSM model, the effects of I_p and T_{on} on SDR while holding the values of other two parameters; T_{off} and P_c at specific level are shown in Figure 5 as surface plots.

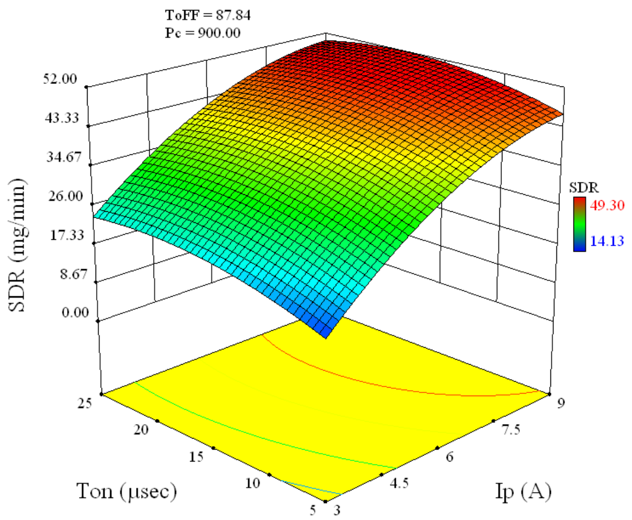

Figure 5. Surface plot of SDR V/s Pulse-on Time and Peak Discharge Current

The nonlinear nature of variation of SDR with I_p has been observed and it can also be noted that for an increase in I_p from 3 Amp to 9 Amp there is sharp increase in SDR from 14.13 to 44.20 mg/min. This increase in SDR with the increase in peak discharge current is due to the fact that spark discharge energy is increased, that facilitate the phenomenon of melting and vaporising in the spark gap. The discharge energy for EDM process mainly depends upon peak discharge current. The higher peak current produces the larger discharge heat energy. Therefore, more heat is transferred into the spark gap as the peak discharge current increases and causes the more and more disintegration of electrode elements that do mixed with the molten zone of workpiece resulted in increased SDR.

It is observed from Figure 5 that an increase in pulse-on time from 5 µsec to 25 µsec (keeping current at 3 Amp and T_{on} as 20 µsec) leads to an increase in the SDR value from 14.13 to 26.33 mg/min and the variation is also nonlinear in nature. This increase in SDR value (while holding peak discharge at 3 Amp) can be attributed to the fact that an increase in T_{on} leads to an increase in rate of heat energy generated, which increases the rate of melting and evaporation for both P/M tool electrode and work surface. Furthermore, the increase in the T_{on} means applying the same heating temperature for a longer time, which thereby leads to increase in SDR value for the same machining time with increased pulse-on time.

The effects of pulse-off time and tool electrode compaction pressure while holding other two parameters;

peak discharge current and pulse-on time at constant level is shown in Figure 6 as surface plots. Almost similar nonlinear nature of variation of the SDR value with pulse-off time and P/M tool electrode compaction pressure has been observed. From the surface plot for SDR, it is found that there is sharp effect on SDR value with change in pulse-off time and moderate effect with change in P/M tool electrode compaction pressure. The decrease in SDR from 46.80 to 14.13 mg/min with the increase in pulse-off time from 50 µsec to 250 µsec and holding P_c at 700 MPa was observed. This decrease in SDR is due to the fact that an increase in pulse-off time leads to decrease in rate of heat energy generated within the spark zone consequently decreases the melting and evaporation of both electrode and work material.

Further, it can be observed that an increase in tool electrode compaction pressure from 500 MPa to 1300 MPa leads to a decrease in SDR from the value 49.30 to 36.40 mg/min while holding T_{off} at 50 µsec. This 26% decrease in SDR may be attributed to the bonding strength between the elements of P/M electrodes. Hence more input energy would be required to disintegrate the elements of electrodes during melting stage, which further leads to decrease in SDR during EDM process.

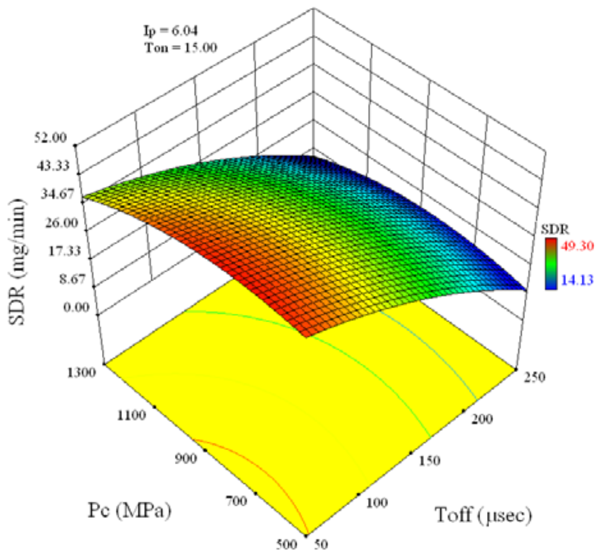

Figure 6. Surface plot of SDR V/s Pulse-off Time and Tool Compaction Pressure

From the surface plots for SDR and F-values from ANOVA of SDR, it can be observed that the influence of T_{off} is more as compared to remaining three input parameters. Hence it was concluded that T_{off} is the most significant input parameter with greater influence on SDR, subsequently followed by I_p, P_c and finally by Pulse-on time.

4.2. Effects of Machining Parameters on Surface Roughness

The three dimensional surface plot in Figure 7 depicts the effects of T_{on} and I_p on the surface roughness value, while keeping the other parameters at specific levels. The non-linear nature of the SR with T_{on} and I_p has been observed. It has been observed from the surface plot that there is an increase in SR value from 5.18 to 7.95 µm when T_{on} increases from 5 µsec to 25 µsec, holding peak discharge current at 9Amp. This might be due to the fact that an increase in T_{on} leads to an increase in the rate of heat energy dissipated in machining zone implies that applying same heating energy for longer time, which further enhances the evaporation, resulting in increase in SR.

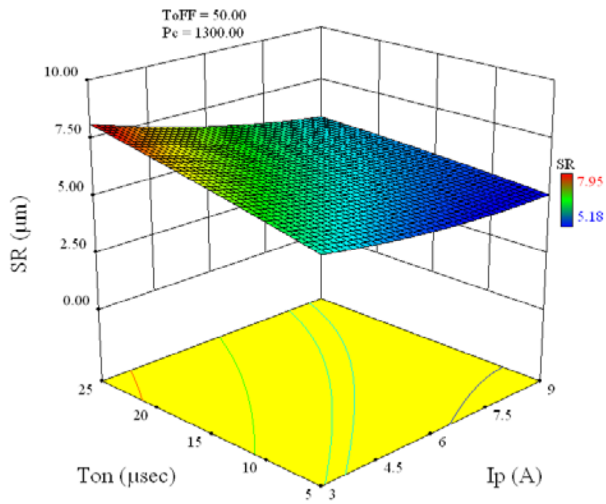

Figure 7. Surface plot of SR V/s Pulse-on Time and Peak Discharge Current

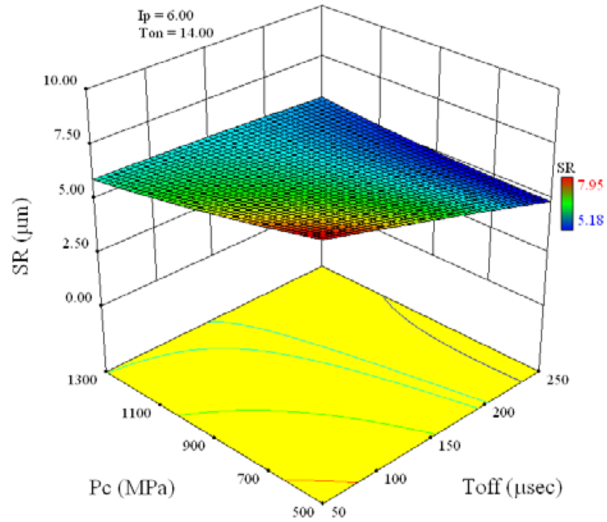

Figure 8. Surface Plot of SR V/s Tool Compaction Pressure and Pulse-off Time

The surface plot in Figure 8 shows that there is an increase in SR value from 5.18 to 7.95 µm when T_{on} increases from 5 µsec to 25 µsec, holding peak discharge current at 9 Amp. This might be due to the fact that an increase in Ton leads to an increase in the rate of heat energy dissipated in machining zone implies that applying same heating temperature for longer time, which further enhances the evaporation, resulted in increase in SR. The decrease in SR value from 6.67 to 5.18 µm was also observed with the increase in the value of peak discharge current from 3 Amp to 9 Amp while holding pulse-on time at 5 µsec. This decrease in the SR might be attributed to the slight difference between the melting rate and rate of re-solidification in the heat affected zone (HAZ) during EDM process. Further, the surface plot in Figure 8 reflects the nonlinear behaviour of variation of the SR with the variation in T_{off} and P_c. This may be attributed to the thermo-physical properties of P/M electrodes. The decrease in the SR value was observed from 7.95 µm to 5.18 µm when there is an increase in T_{off} from 50 to 250 µsec. Similarly the decrease in the SR value from 7.95 to 5.18 µm was also recorded from the experimental work when there was an increase in powder compaction pressure from 500 MPa to 1300 MPa.

Moreover the ANOVA analysis of surface roughness model in Table 5 depicts the influence of T_{off} on SR value that is little more as compared to other parameters. Therefore $T_{off}$is the most significant input variable effecting SR value, followed by I_p, T_{on} and then finally by P_c.

5. Micro-hardness

The micro-hardness of the EDMed surface was measured with a micro hardness testing machine (Make: Mitutoyo, Model HM-112) by choosing testing load of 500 mg. The micro-hardness distribution along the cross-section of the machined surface was depicted in Figure 9. Higher value of micro hardness (69.4 HRC)was recorded adjacent to the EDM machined surface. This isattributed to the presence of higher content of WC in the re-solidified layer after EDM process.

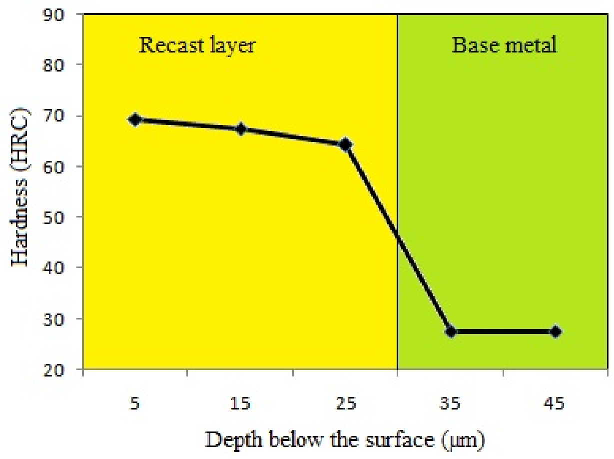

Figure 9. Variation of Micro-hardness along cross-section of modified layer

Further, there is decrease in the hardness value as the depth from the surface increases and then declines to a horizontal value that equals to the hardness of base metal (27.6 HRC). Thus 2.5 times increase in the micro-hardness of base metal implies the realisation of an improved wear and corrosion resistant surface. So by suitably adjusting the machining parameters of EDM process with P/M electrodes using negative polarity, modified surface with improved surface properties can be achieved.

6. Multiple-response Optimization

The SDR and SR are considered as two output responses to determine the machining performance of EDM as surface modification process. It is observed that both the responses are conflicting in nature. Hence, conventional optimal solution is inadequate to provide the best combination of parameter levels that produce the maximum SDR and minimum SR values. Attempts have been made to optimise the SDR and the SR obtained from the surface deposition and surface roughness models and these are represented by Equation (5) and Equation (6).

Derringer and Suich [27] described a technique called desirability approach that is useful to solve the optimization problems with multi-response quality characteristic situations in the industry. This technique makes the use of transformation of each predicted response $\hat{Y}_i$, to a dimensionless partial value called individual desirability (d_i), which varies over the range of 0 to 1. Either the value of (d_i) is one, if the response $\hat{Y}_i$ is at its target, or it is zero if one or more responses are outside their acceptable range. Castilloetel. [28] worked on multiple response optimisation problems and purposed general steps to achieve optimal solutions.

- Use response surface methodology to fit polynomial to each response.
- Specify the desirability function for each response.
- Compute the overall desirability function by taking the geometric mean of individual desirability functions.
- The overall desirability function is then optimised.

If any response $\hat{Y}_i$ is desirable to maximise, then the individual desirability (d_i) is defined as:

$$\begin{aligned} d_i &= 1 && \hat{y}_i > H_i \\ d_i &= \left(\frac{\hat{y}_i - L_i}{H_i - L_i}\right)^{w_i} && L_i \le \hat{y}_i \le H_i \\ d_i &= 0 && \hat{y}_i < L_i \end{aligned} \tag{7}$$

If the response $\hat{Y}_i$ is to minimise, then the individual desirability (d_i) is defined as:

$$\begin{aligned} d_i &= 1 && \hat{y}_i < L_i \\ d_i &= \left(\frac{H_i - \hat{y}_i}{H_i - L_i}\right)^{w_i} && L_i \le \hat{y}_i \le H_i \\ d_i &= 0 && \hat{y}_i > H_i \end{aligned} \tag{8}$$

Similarly the individual desirability can be defined as follows, when the response $\hat{Y}_i$ is at a target (T_i) value or is in a given range.

$$\begin{aligned} d_i &= 0 && \hat{y}_i < L_i \\ d_i &= \left(\frac{\hat{y}_i - L_i}{T_i - L_i}\right)^{w_i} && L_i \le \hat{y}_i \le T_i \\ d_i &= \left(\frac{H_i - \hat{y}_i}{H_i - T_i}\right)^{w_i} && T_i \le \hat{y}_i \le H_i \\ d_i &= 0 && \hat{y}_i > H_i \end{aligned} \tag{9}$$

Where in equation (7), equation (8) and equation (9), $\hat{Y}_i$ is predicted value of i^{th} response, L_i and H_i are lowest and highest acceptable values for i^{th} response, w is assigned as importance or weight-age to each response and d_i are the individual desirability of i^{th} response.

The third step is to combine the individual desirability (d_i) for each response in order to obtain the single composite desirability (D), which is the weighted geometric mean of the individual desirability for the each response. The composite desirability is;

$$D = [d_1^{w1} \times d_2^{w2} \times ....d_n^{wn}]^{1/n} = \left[\prod (d_i^{w_i})\right]^{1/W} \quad (10)$$

Where '*n*' is the number of responses, value w_i ($0<w_i<1$ and $W=\sum w_i$) is the relative importance assigned to the i^th individual response and sum of w_1, w_2.......w_n equals to one. This relative importance w_i is a comparative scale for weighing each of the resulting d_i in the overall desirability product in equation (10), and it varies from '*0*' for least desirable to '*4*' for most desirable response respectively. One represents the ideal case; zero indicates that one or more responses are outside their acceptable limits. The value of composite desirability depends on the relative importance (w_i values) of the individual desirability for each response that was considered for process performance optimisation. Further the composite desirability was optimised and identification of the optimal input variable was done using optimisation algorithm.

6.2. Multiple-response Optimisation Based on Desirability Approach

In the present work two responses has been considered, i.e., SDR and SR for optimization. Attempts have been made to identify the optimal input variable settings for achieving the maximum SDR and minimum SR. The two objective response functions are designed as below in equation (11) and equation (12):

$$SDR = \phi_1 \left\{ I_p, T_{on}, T_{off}, P_c \right\} \quad (12)$$

$$SR = \phi_2 \left\{ I_p, T_{on}, T_{off}, P_c \right\} \quad (13)$$

These objective functions are subjected to following conditions as in equation (13) to maximise SDR and minimise SR:

$$\left\{ \begin{array}{rl} 3 \le I_p \le & 9 \\ 5 \le T_{on} \le & 50 \\ 50 \le T_{off} \le & 250 \\ 500 \le P_c & \le 1300 \end{array} \right\} \quad (14)$$

The criteria selected for multi-objective optimization of objective functions, which includes the constraints of the output responses, goal and weights (*w*) assigned to each output parameter are shown in Table 9. The optimization of objective functions was resulting in 55 numbers of solutions that were recorded in Table 10. The solution numbers 1 to 7 have a highest value of composite desirability (D = 0.957). These seven solutions obtained are the most optimal solutions that yield out maximum SDR value of 49.30 and minimum SR value of 5.41 µm simultaneously.

It can be observed from the Table 10, that the solution number 36 gives the highest SDR value of 50.76 mg/min by holding the parameter settings at I_p= 9 Amp, T_{on}= 5 µsec, T_{off}= 50.03 µsec and P_c = 976.65 MPa. Hence, with proper choice of input parameters, the highest SDR can be obtained.

Table 9. Criteria selected for multiple-objective optimisation

Output Responses	Goal	Lowerlimit	Upper limit	Lower(w)	Upper (w)	Relative importance
SDR (mg/min)	Maximise	14.13	49.30	1	1	3
SR (µm)	Minimise	5.18	7.95	1	1	3

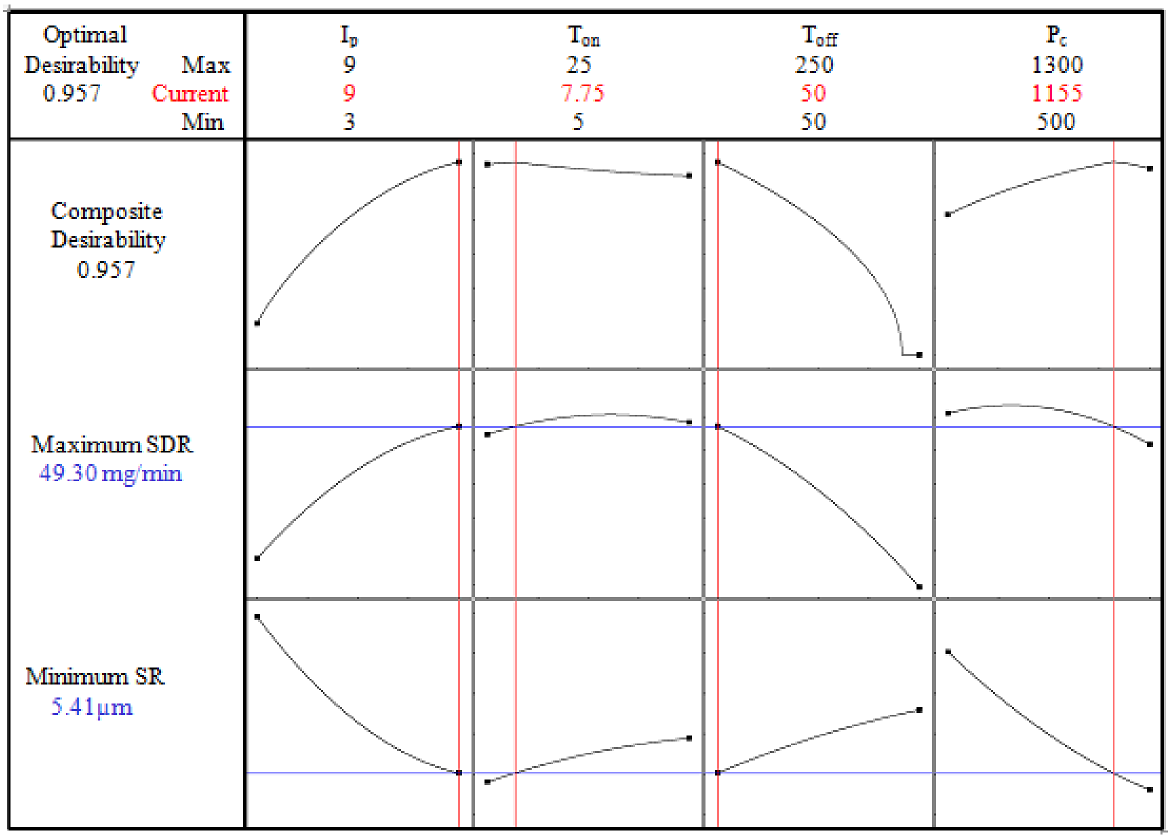

Figure 10. Multi response optimization results for maximum SDR and minimum SR

Table 10. Optimal combinations of process parameters for high value of Desirability

Solution Number	Input process parameters				Predicted responses		Desrability
	I_p (Amp)	T_{on} (μSec)	T_{off} (μSec)	P_c (Mpa)	SDR (gm/min)	SR (μm)	
1	9.00	7.75	50.00	1155.13	49.30	5.41	0.957*
2	9.00	7.79	50.00	1156.10	49.30	5.41	0.957
3	9.00	7.42	50.01	1147.00	49.30	5.41	0.957
4	9.00	7.40	50.00	1146.38	49.30	5.41	0.957
5	9.00	7.15	50.00	1139.99	49.30	5.41	0.957
6	8.99	7.64	50.00	1151.80	49.30	5.41	0.957
7	9.00	7.12	50.00	1139.02	49.30	5.41	0.957
8	9.00	6.61	50.00	1125.36	49.28	5.42	0.956
9	9.00	6.57	50.00	1123.35	49.30	5.42	0.956
10	8.95	7.28	50.00	1140.06	49.30	5.42	0.955
11	9.00	9.76	50.00	1194.90	49.30	5.43	0.954
12	9.00	10.10	50.24	1199.30	49.30	5.43	0.953
13	9.00	10.46	50.00	1205.42	49.30	5.44	0.952
14	9.00	10.52	50.00	1206.30	49.30	5.44	0.952
15	8.84	8.07	50.00	1151.95	49.30	5.44	0.952
16	9.00	10.63	50.00	1207.91	49.30	5.44	0.951
17	8.85	8.73	50.00	1170.05	49.22	5.44	0.951
18	9.00	5.37	50.00	1081.76	49.30	5.45	0.951
19	8.80	8.07	50.00	1149.33	49.30	5.45	0.950
20	8.84	8.02	50.85	1147.36	49.30	5.45	0.950
21	9.00	5.28	50.00	1077.79	49.30	5.45	0.950
22	9.00	9.57	50.00	1151.35	50.43	5.47	0.946
23	9.00	9.92	50.00	1232.58	48.22	5.39	0.946
24	8.70	9.40	50.00	1170.12	49.30	5.47	0.945
25	9.00	5.00	50.57	1047.46	49.58	5.49	0.942
26	9.00	13.14	50.01	1233.37	49.30	5.50	0.941
27	9.00	13.37	50.00	1235.00	49.30	5.50	0.940
28	9.00	13.51	50.00	1235.87	49.30	5.50	0.940
29	8.92	13.23	50.00	1230.38	49.30	5.51	0.939
30	9.00	8.8.00	59.76	1132.09	49.30	5.51	0.939
31	8.75	5.00	50.00	1040.53	49.30	5.53	0.935
32	9.00	14.53	50.00	1241.18	49.30	5.53	0.935
33	9.00	15.29	50.00	1243.72	49.30	5.55	0.931
34	9.00	5.00	58.41	1005.99	49.30	5.57	0.926
35	9.00	16.73	50.00	1245.50	49.30	5.59	0.924
36	9.00	5.00	50.03	976.65	50.76	5.61	0.919**
37	9.00	17.80	50.00	1241.11	49.41	5.62	0.918
38	9.00	19.50	50.00	1238.04	49.30	5.66	0.910
39	9.00	20.59	50.01	1192.76	50.66	5.69	0.903
40	9.00	21.58	50.00	1223.68	49.30	5.70	0.901
41	9.00	23.69	50.00	1201.27	49.30	5.74	0.894
42	9.00	25.00	101.66	669.43	49.30	5.74	0.893
43	9.00	25.00	101.60	689.69	49.30	5.74	0.893
44	9.00	25.00	101.52	701.89	49.30	5.74	0.893
45	9.00	25.00	101.49	704.06	49.30	5.74	0.892
46	9.00	25.00	100.97	605.63	49.30	5.75	0.892
47	9.00	25.00	102.65	716.23	49.03	5.74	0.890
48	9.00	25.00	100.13	572.45	49.30	5.76	0.889
49	9.00	25.00	99.62	783.68	49.30	5.76	0.889
50	9.00	23.95	102.42	596.02	49.30	5.77	0.887
51	9.00	24.29	100.42	801.65	49.30	5.77	0.887
52	9.00	23.18	103.44	771.81	49.30	5.78	0.886
53	9.00	25.00	95.44	812.74	49.88	5.78	0.886
54	9.00	25.00	92.30	898.21	49.44	5.80	0.881
55	9.00	18.85	104.94	845.70	49.30	5.82	0.877

* Optimal parameters; peak current = 9 A, Pulse-on time = 7.75 µsec, pulse-off time = 50 µsec and tool electrode compaction pressure = 1155.13 MPa for Max SDR = 40.30 mg/min and Min SR = 5.41µm. ** Highest SDR of 50.76 mg/min with slight increase in SR value from 5.41 to 5.61µm.

Further, the contour plots for overall composite desirability was drawn as. The sensitivities of the results were obtained by using shape of the contour lines and thus represented in Figure 11.

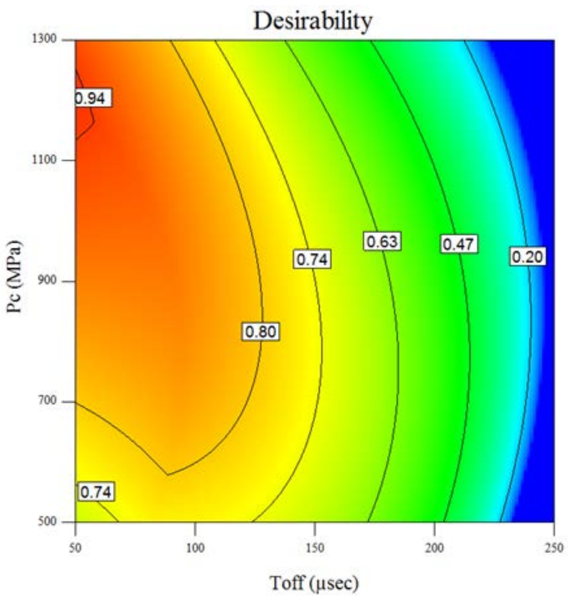

Figure 11. Contour Plot for overall Desirability Function (I_p= 9 Amp and T_{on} =10 μsec)

The near-optimum region was located close to the left hand top region of the plot having maximum composite desirability value of 0.957 that gradually reduced as we moved right and downwards. Also, the results show that optimal process performance can be achieved under relatively lower pulse-off time and higher tool compaction pressure when using by using Cu-W powder metallurgy composite electrodes and if both the output responses (SDR and SR) are given equal importance. Figure 10 represents the optimized graphs of the two responses (SDR and SR) and also the optimization results. The vertical red colour lines inside the cells represent current optimal parametric settings, and the horizontal blue colour lines represent the current response values.

7. Confirmation Experiments

Once the optimal level of the process parameters is selected, the final step is to predict and verify the improvement of the performance characteristic using the optimal level of the machining parameters. Some additional confirmation experiments were performed to validate the developed models by using optimal input parametric setting for SDR and SR. In order to estimate the accuracy of the prediction models, percentage error and average percentage error were used [29]. Table 11 shows the average of error percentage for experimental validation of the developed models for both the responses.

Table 11. Validation of developed models with optimal parameter setting

Output Responses	Desirability	Predicted value	Experimental value	Prediction Error (%)
SDR (mg/min)	0.957	49.30	45.46	7.78
SR (R_a)	0.957	5.41	5.12	5.36

From the Table 11, it can be observed that the calculated error is small.

The average error percentage between experimental and predicted values for SDR and SR models were found to lie within 7.78% and 5.36% respectively, which confirms adequacy for excellent reproducibility of the developed models for SDR and SR.

8. Conclusions

After analysing the results of the experiments on EN-31 tool steel with P/M semi-sintered composite electrodes, the following conclusions could be drawn:

- The experimental investigations show that the RSM is a powerful tool for modelling, developing, analysing and optimising the multi-response situations in the industry. It was applied successfully to the surface modification phenomenon by EDM process.
- The mathematical model for surface deposition rate (SDR) developed is:

$$
\begin{aligned}
SDR = &+34.38 + 5.43I_p + 0.91T_{on} - 8.48T_{off} \\
&-1.67P_c - 1.26I_pT_{off} - 0.36T_{on}T_{off} \\
&-0.41T_{on}P_c + 0.39T_{off}P_c - 1.44I_p^2 \\
&-083T_{on}^2 - 1.02T_{0ff}^2 - 1.29P_c^2
\end{aligned}
$$

- The second order polynomial mathematical model obtained by using response surface methodology for SR is:

$$
\begin{aligned}
SR = &+6.14 - 0.33I_p + 0.20T_{on} - 0.46T_{off} \\
&-0.19P_c - 0.093I_pT_{on} + 0.19I_pT_{off} + 0.15I_pP_c \\
&+0.070T_{on}P_c + 0.18T_{off}P_c + 0.069I_p^2 - 0.016T_{on}^2 \\
&-0.013T_{off}^2 + 0.034P_c^2
\end{aligned}
$$

- The predicted values match the experimental values reasonably well in the full design space with R^2 of 99.80% for surface deposition model and R^2 of 99.93% for the surface roughness model.
- It was found that pulse-off time was the most significant term in both surface deposition and surface roughness models, followed by peak discharge current, pulse-on time and then lastly tool electrode compaction pressure.
- The proposed Cu-W semi-sintered powder metallurgy electrode has found to offer 2.5 times more gain in the micro-hardness value to the base metal after EDMed process.
- From the multi-response optimization, the optimal combination of parameter settings are peak current of 9 A, Pulse-on time 7.75 μsec, pulse-off time of 50 μsec and tool electrode compaction pressure of 1155.13 MPa for achieving the required higher SDR and lower SR.
- Highest SDR value of 50.76 mg/min with parameter settings at I_p= 9 Amp, T_{on} = 5 μsec, T_{off} = 50.03 μsec and P_c = 976.65 MPa was observed. So with proper choice of input parameters, highest SDR can be obtained.

- The prediction error percentage for surface deposition model and surface roughness model fall within 7.78% and 5.36% respectively with optimal combination of parameters. This confirms excellent reproducibility of the experimental conclusions.

The research findings along with developed mathematical models will provide effective guidelines to select parameter settings for achieving desired surface characteristics of EDMed surface during EDM die sinking of EN-31 diesteel. This research work will open up further scope to study the machined surface quality and surface integrity for utilizing EDM die sinking process more effectively in tool and die making industry.

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