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Optimization of Production and Quality Attributes of SKD11 Material by Desirability Approach

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ABSTRACT
This research paper investigates the optimization of production and quality attributes of SKD11 material using Wire Electrical Discharge Machining (WEDM). The study experimentally examines the influence of six process parameters (pulse on time, peak current, servo voltage, wire tension, pulse off time, and wire feed rate) on material removal rate (MRR) and surface roughness (SR) during WEDM of SKD11, a high-carbon, high-chromium tool steel. Response Surface Methodology (RSM) is employed to develop regression models correlating these parameters with MRR and SR, enabling process optimization. A desirability approach is then used for multi-objective optimization, balancing MRR maximization and SR minimization. The results provide optimal process parameter settings for achieving both high productivity and superior surface quality in WEDM machining of SKD11. The developed quadratic models for MRR and SR offer predictive capabilities for improved process control.

Keyword: WEDM, SKD11, Material removal rate, surface roughness, RSM, desirability

Introduction

Wire electrical discharge machining (WEDM), also known as the spark erosion process, is utilized to fabricate highly detailed and complex shapes on materials that conduct electricity, using a wire. This process involves generating sparks between the wire, which acts as an electrode, and the workpiece, both of which are immersed in a dielectric fluid. The outstanding surface quality and dimensional accuracy achieved through WEDM are essential for applications in the production of dies and molds, as well as in industries such as aerospace, medical, surgical, and automotive [1]. Due to the unique properties of WEDM, it is capable of machining intricate and precise shapes [2]. In the current study, the WEDM process for SKD11 is both modeled and optimized. The findings have the potential to greatly improve manufacturing conditions and the quality of the machined workpiece, aligning with the varied needs of manufacturing companies [3].

Several studies have focused on modeling and enhancing the efficiency of the WEDM process. Datta and Mahapatra utilized Response Surface Methodology to create quadratic mathematical models that illustrate the behavior of the WDM operation. Their experiments involved varying six input process variables—dielectric flow rate, wire tension, discharge current, pulse frequency, wire speed, and pulse duration—across three different levels. Performance metrics such as SR and KW were recorded for each experimental trial[4]. In another study, Rao, Ramji, and Satyanarayana optimized process variables for cutting Aluminum-24345 using WEDM and RSM. They developed multiple linear regression models to link process parameters with machining performance [5]. Rajesh and Anand attempted to model the Material Removal Rate (MRR) and Surface Finish (Ra) in the wire EDM process using response surface methodology and a Genetic Algorithm (GA). The working current, working voltage, oil pressure, spark gap pulse-on time, and pulse-off time were selected as the input parameters [6].

Ghodsiyeh et al. deliberate the performance of three input process variables during machining of titanium alloy on WEDM with 0.25 mm diameter of zinc coated brass wire by use of response surface methodology as a design of experiment as well as to perform ANOVA to find significant parameters affecting MRR, SR and sparking gap (SG) [7]. Sharma, Khanna, and Gupta investigated the effect of input-controlled parameters on the MRR for WEDM using high-strength and low-alloy workpieces and brass wire as the electrode. The central composite response surface methodology was utilized to create a design matrix for the final experimentations and to formulate a mathematical model that correlates the independent process parameters with the desired surface roughness and material removal [8]. Lusi et al. [9] proposed a hybrid approach combining fuzzy logic and grey relational analysis with the Taguchi technique to predict optimal process parameters—such as open voltage, off time, servo voltage, arc-on time, and on time—in the WEDM machining of SKD61 tool steel. The objective was to optimize multiple performance characteristics, including surface roughness (SR), kerf width, and material removal rate (MRR). Sudhakara and Prasanthi [10]conducted a comprehensive review of various research methodologies applied in WEDM studies. They analyzed how different input parameters—such as on time, off time, voltage, wire tension, wire feed, dielectric pressure, and current—influence output responses like surface finish, material removal rate, dimensional accuracy, and the heat-affected zone (HAZ).

V. Kumar et al. [11] investigated the influence of machining parameters including peak current (Ip), pulse-on time (Ton), pulse-off time (Toff), and servo voltage (SV) on cutting speed (CS), surface roughness (SR), and radial overcut (RoC) during the WEDM of Nimonic-90. Their study employed Design of Experiments (DoE) using Response Surface Methodology (RSM) and applied a desirability function for multi-objective optimization. Mohapatra, Satpathy, and Sahoo [12] investigated the influence of WEDM process parameters—such as wire feed rate, servo voltage, wire tension, and pulse-off time—on achieving minimum surface roughness (SR) and maximum material removal rate (MRR) during the machining of copper spur gears. They employed a combination of grey Taguchi technique with desirability function and Taguchi's quality loss function to optimize the responses. Chakraborty and Bose [13] applied entropy-based grey relational analysis to determine the optimal cutting parameters—gap voltage, pulse-on time, corner angle, servo feed, peak current, and pulse-off time—for enhancing cutting velocity, surface roughness (SR), material removal rate (MRR), and minimizing corner inaccuracy during the WEDM of Inconel 718. Their experiments were designed using the Taguchi L27 orthogonal array. Silverman, Eswaramoorthy, and Shanmugham [14] studied the effects of control parameters—pulse-on time, pulse-off time, and wire tension—on the WEDM performance of titanium. Using Response Surface Methodology (RSM), they aimed to maximize metal removal rate and improve surface finish.

Extensive research has been conducted on Wire EDM using various conductive metals. In the present study, SKD11 steel was selected as the workpiece material for experimentation. SKD11 is of particular interest due to its higher carbon and chromium content compared to other steels, offering excellent wear resistance, corrosion resistance, and strength—making it a preferred choice in the tool and die manufacturing industry. Despite its widespread use, WEDM processes often lack comprehensive operating data specific to each material. This data gap necessitates performance analysis to determine the optimal set of process parameters that can effectively balance both productivity and quality.This study focuses on developing mathematical models to establish the relationship between key WEDM process parameters—pulse-on time (Ton), pulse-off time (Toff), servo voltage (SV), peak current (IP), wire tension (WT), and wire feed (WF)—and their effects on material removal rate (MRR) and surface roughness (SR) during the machining of SKD11. The analysis is based on the Response Surface Methodology (RSM), which enables the creation of empirical models that can assist in selecting the most efficient combination of machining parameters.

Materials and methods

A series of preliminary trials was conducted following the principles of Response Surface Methodology (RSM). The subsequent sections provide detailed explanations of the experimental setup, the workpiece material, measuring instruments, the design of experiments, and the selection of input process variables along with their respective levels[15].

Workpiece Material

The SKD11 steel [16] used for the experimentation was sourced from M/s Bansidhar Steel Corporation, Rakhiyal, Ahmedabad. The chemical composition of the SKD11 material is presented in Table 1. For all experiments, the workpiece had a constant height of 12 mm, and a brass wire electrode with a diameter of 0.25 mm was used as the cutting tool.

Table 1. Chemical composition of SKD11

Element	Standard (Max Weight)	Actual (Max Weight)
C	1.40 – 1.60 %	1.55 %
Mn	0.60 % max	0.35 %
Si	0.60 % max	0.25 %
V	1.10 % max	0.9 %
Mo	0.7 -1.20 %	0.8 %
Cr	11.0 -13.0%	12.0 %
Fe	Balance	Balance

Experimental setup and performance measuring devices

The experiments were carried out using a 4-axis Electronica Sprint Cut-734 WEDM machine, located at Jay Tech Industries, Odhav, Ahmedabad. During the machining process, key input parameters—including pulse-off time (Toff), pulse-on time (Ton), wire feed (WF), peak current (IP), wire tension (WT), and servo voltage (SV)—were varied to examine their influence on material removal rate (MRR) and surface roughness (SR). The brass wire electrode was connected to the negative terminal, while the workpiece was connected to the positive terminal. The wire diameter was maintained constant throughout all trials. A specialized fixture was employed to securely hold the workpiece on the machine table, minimizing any risk of misalignment. Both the electrode and the workpiece were submerged in dielectric fluid during machining. MRR, a key indicator of machining productivity and cost-effectiveness, was calculated using the following formula [17].

$$\text{MRR (mm3/min)} = \text{Average machining rate} \times \text{thickness of plate} \times \text{width of cut} \qquad (1)$$

Wheree Width of cut = (X-Y), X = Desired size of work piece = 8 mm, Y = Real size of the work piece obtained after machining, which is measured by Mitutoya digital Vernier caliper having one micron least count. The dimensions of the workpiece were measured at two random points along each of the sides AB, BC, and CD, and the average of these six readings was taken as the actual size of the workpiece. Surface roughness was evaluated using the Centre Line Average (CLA) parameter, denoted as Ra. A contact-type Mitutoyo Surftest SJ-410 roughness tester, with a least count of 0.001 µm, was used for the measurements. The instrument was set with a cutoff length of 0.8 mm and an evaluation length of 4 mm. Ra values were recorded at three different locations perpendicular to the cutting direction, and the average of these readings was considered as the surface roughness (SR). The setup used for surface roughness measurement is illustrated in Fig. 1.

Fig. 1. Set up for Surface roughness measurement

Level of input process parameters selection

In the present study, the influence of various input process parameters—pulse-on time (Ton), pulse-off time (Toff), servo voltage (SV), peak current (IP), wire tension (WT), and wire feed (WF)—on performance measures such as surface roughness and MRR has been thoroughly examined. The selection of these parameters and their respective levels was based on preliminary screening experiments, machine capability, a detailed literature review, and guidelines from the manufacturer's manual[18]. The chosen parameters were varied systematically to analyze their effects, and both actual and coded values of the input variables are summarized in Table 2.

Table 2. Process variables and their ranges[19]

Coded Factors	Real Factors	Parameters	Levels				
			-α	-1	0	+1	+α
A	Ton	Pulse on Time	110	112	115	118	120
B	Toff	Pulse off Time	50	52	54	56	58
C	IP	Peak Current	160	170	180	190	200
D	SV	Spark Gap Set Voltage	10	20	30	40	50
E	WF	Wire Feed Rate	4	6	7	8	10
F	WT	Wire Tension	4	6	7	8	10

Design of Experiments

In this study, the Response Surface Methodology (RSM) was employed to design the experiments and carry out the optimization process using Design Expert 7.0 software. RSM was utilized to develop a second-order regression model that establishes the relationship between the process variables and the response characteristics [20]. This approach, combined with regression analysis, allows for effective modelling of the desired responses based on multiple input parameters. The experimental design facilitates the evaluation of interaction and quadratic effects, providing valuable insights into the shape and behaviour of the response surface.

A total of 52 experimental runs were conducted using a Central Composite Design (CCD) with half replication for six input parameters, where the axial distance (α) was set to 1.565 (α = k^1/4), also referred to as practical α. This value is particularly advantageous when working with more than five variables [21]. The design comprises 32 factorial points (runs 1 to 32), 12 axial points (runs 33 to 44) used to estimate curvature, and 8 centre points (runs 45 to 52) at the zero level for replication and pure error estimation. The corresponding performance measures for Material Removal Rate (MRR) and Surface Roughness (SR) are summarized in Table 3.

Table 3. Performance measure

Std order	Run order	Response I MRR mm^3/min	Response II Surface Roughness µm
1	15	4.428	2.627
2	40	8.7348	3.312
3	26	4.0656	2.683
4	9	8.2584	3.215
5	31	6.498	3.09
6	38	10.44	3.564
7	8	5.1642	3.038
8	45	8.2764	3.493
9	34	3.996	2.642
10	30	6.948	2.907
11	51	3.3108	2.254
12	14	5.7096	3.085
13	33	5.256	2.922
14	27	8.28	3.176
15	11	4.347	2.644
16	36	6.8076	3.08
17	20	4.5936	2.655
18	35	6.9552	2.931
19	24	3.6288	2.368
20	6	6.0876	2.79
21	47	5.1072	2.586
22	12	8.4216	2.968
23	46	3.975	2.512
24	28	6.6864	2.755
25	13	3.696	1.991
26	1	5.6448	2.522
27	18	2.772	1.835
28	48	4.6032	2.502
29	37	3.564	2.084
30	4	6.3684	2.62
31	44	3.42	1.89
32	22	5.4912	2.386
33	32	3.06	1.491
34	41	6.048	2.624
35	3	5.22	2.49
36	10	4.026	2.131
37	39	4.536	2.308
38	42	5.112	2.432
39	7	4.8048	2.737
40	49	3.7422	1.702
41	5	5.487	2.4
42	16	5.184	2.433
43	25	5.1642	2.571
44	43	5.673	2.432
45	19	5.4984	2.484
46	21	5.7462	2.542
47	17	5.664	2.46
48	52	5.394	2.395
49	50	5.796	2.475
50	29	5.724	2.539
51	2	5.5998	2.29
52	23	6.1236	2.38

Results and discussion

The Analysis of Variance (ANOVA) was conducted to evaluate the adequacy of the fitted model and to support both regression and graphical analysis.

Analysis of material removal rate

To assess the adequacy of the model for surface roughness, three statistical tests were performed: model summary statistics, sequential model sum of squares, and the lack-of-fit test. Based on these evaluations, the quadratic model was found to be the most appropriate and was selected for further analysis.

Table 4 presents the ANOVA results for the quadratic model at a 95% confidence level. The model's F-value of 81.88 and corresponding p-value of less than 0.0001 indicate that the model is statistically significant. There is only a 0.01% probability that such a large F-value could be due to random noise. Additionally, the lack-of-fit F-value of 7.43 further suggests that the lack of fit is also statistically significant, with only a 0.01% chance of such a result occurring due to noise. This confirms the relevance of the quadratic model at the 95% confidence level.

The model's coefficient of determination (R^2) approaching unity implies a strong fit to the actual data, reflecting minimal variation between predicted and observed values. The predicted R^2 value of 0.8812 is in close agreement with the adjusted R^2 value of 0.8963, further validating the model's accuracy. Figure 2 illustrates the normal probability plot of residuals for surface roughness, showing that the residuals are normally distributed, as most points lie close to the straight line.

Table 4. Analysis of Variance for the Quadratic Model of Material Removal Rate

Source	SS	df	MS	F Value	p-value Prob > F	
Model	226.88	11	20.62	81.88	< 0.0001	significant
A-TON	134.17	1	134.17	532.72	< 0.0001	significant
B-TOFF	19.08	1	19.08	75.77	< 0.0001	significant
C-IP	13.89	1	13.89	55.17	< 0.0001	significant
D-SV	26.95	1	26.95	107.00	< 0.0001	significant
E-WF	19.57	1	19.57	77.72	< 0.0001	significant
F-WT	0.24	1	0.24	0.98	0.3245	
AD	1.97	1	1.97	7.82	0.0063	
AE	3.38	1	3.38	13.45	0.0004	significant
D^2	1.87	1	1.87	7.45	0.0076	
E^2	2.27	1	2.27	9.03	0.0034	significant
F^2	3.39	1	3.39	13.49	0.0004	significant
Residual	23.17	92	0.25			
Lack of Fit	18.67	33	0.56	7.427	< 0.0001	significant
Pure Error	4.49	59	0.07			
Cor Total	250.0	103				

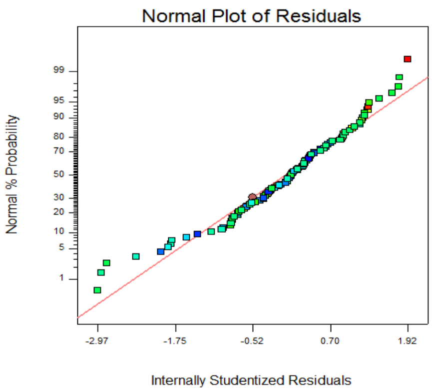

Fig. 2. Normal probability plot for MRR

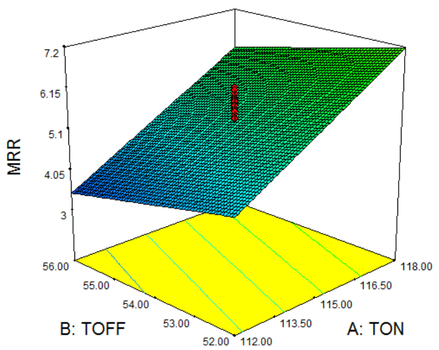

Fig. 3. Combine effect of TON and TOFF on MRR

Based on the developed second-order polynomial model, the influence of input process variables on the material removal rate (MRR) was analyzed using Design Expert 7.0. A regression equation in terms of actual (real) factors was derived from the experimental data to represent the MRR. Insignificant factors, identified through statistical analysis, were excluded from the final quadratic equation to enhance model accuracy and simplicity.

$$\text{Material removal rate} = -88.78042 + 1.16180 * TON - 0.25428 * TOFF + 0.043395 * IP + 0.76260 * SV + 4.44255 * WF - 4.77725 * WT - 5.84948E\text{-}003 * TON * SV - 0.076693 * TON * WF - 2.50575E\text{-}003 * SV^2 + 0.27586 * WF^2 + 0.33710 * WT^2 \quad (2)$$

The quadratic terms of wire feed (WF) and wire tension (WT) have a significant influence on the material removal rate (MRR) and can be effectively used to predict MRR within the specified range of controlled variables. In this analysis, the model terms A, B, C, D, E, AD, AE, D^2, E^2, and F^2 were found to be statistically significant, as indicated in Table 4. Model terms with a p-value (Prob > F) greater than 0.1000 are considered insignificant and do not have a meaningful impact on the response.

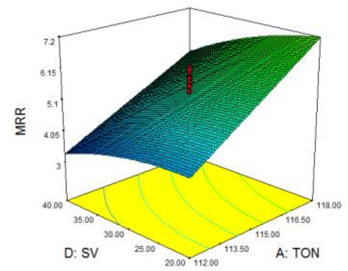

Fig. 4. Combine effect of TON and SV on MRR

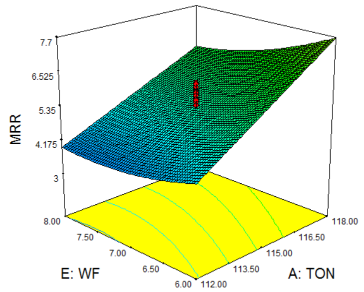

Fig. 5. Combine effect of TON and WF on MRR

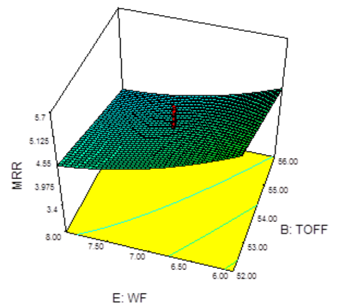

Fig. 6. Combine effect of TOFF and WF on MRR

As shown in Fig. 3, the material removal rate (MRR) increased from 2.811 mm^3/min to 6.10 mm^3/min with an increase in pulse-on time from 112 µs to 118 µs and a simultaneous decrease in pulse-off time from 56 µs to 52 µs. This is attributed to the longer duration of discharge energy at higher pulse-on times, which results in rapid melting and evaporation of the material, thereby increasing MRR.Fig. 4 illustrates a similar trend, where MRR increased from 2.811 mm^3/min to 6.10 mm^3/min as the pulse-on time was increased from 112 µs to 118 µs and the servo voltage was reduced from 40 V to 20 V. A lower servo voltage narrows the spark gap, leading to more frequent discharges and higher MRR. Conversely, a higher spark gap reduces discharge frequency, slowing the machining process and decreasing MRR.As observed in Fig. 5, MRR increases with an increase in pulse-on time and a decrease in wire feed rate. Fig. 6 further shows that MRR increased from 3.4 mm^3/min to 5.7 mm^3/min when pulse-off time decreased from 56 µs to 52 µs and wire feed rate decreased from 8 m/min to 6 m/min. A shorter pulse-off time increases the number of discharges per unit time, thus enhancing the energy delivered to the workpiece and raising the MRR. In contrast, longer pulse-off durations reduce the discharge frequency and, consequently, the rate of material erosion.

Analysis of Surface Roughness

To assess the adequacy of the model for surface roughness, three statistical tests were conducted: model summary statistics, sequential model sum of squares, and the lack-of-fit test. Based on these evaluations, the quadratic model was found to be the most suitable and was selected for further analysis.

Table 5 presents the ANOVA results for the quadratic model at a 95% confidence level. The model's F-value of 42.88, with a corresponding p-value of less than 0.0001, indicates that the model is statistically significant. There is only a 0.01% probability that such a high F-value could occur due to random noise. Additionally, the lack-of-fit F-value of 7.76 confirms that the lack of fit is also statistically significant, with just a 0.01% chance that such a result is due to noise. This confirms the reliability and significance of the quadratic model at the 95% confidence level. Furthermore, the coefficient of determination (R^2) is close to unity, indicating that the model fits the experimental data well and reflects minimal variation between actual and predicted values. The predicted R^2 value of 0.7804 is in good agreement with the adjusted R^2 value of 0.8173, with a difference of less than 0.03—further validating the model's accuracy. Figure 7 shows the normal probability plot of residuals for surface roughness, which clearly demonstrates that the residuals are approximately normally distributed, as most points lie close to the straight line.

Table 5. ANOVA for Quadratic Model of surface roughness

Source	SS	df	MS	F Value	p-value Prob > F	
Model	16.19	11	1.47	42.88	< 0.0001	significant
A-TON	5.26	1	5.26	153.43	< 0.0001	significant
B-TOFF	0.13	1	0.13	4.02	0.0478	significant
C-IP	0.18	1	0.18	5.26	0.0241	significant
D-SV	2.95	1	2.95	86.16	< 0.0001	significant
E-WF	3.71	1	3.71	108.2	< 0.0001	significant
CE	0.18	1	0.18	5.21	0.0237	significant

DE	0.30	1	0.30	8.89	0.0037	significant
B^2	0.12	1	0.12	3.58	0.0616	
C^2	0.26	1	0.26	7.85	0.0062	
E^2	0.35	1	0.35	10.30	0.0018	significant
F^2	0.74	1	0.74	21.85	< 0.0001	significant
Residual	3.15	92	0.03			
Lack of Fit	2.56	33	0.07	7.76	< 0.0001	significant
Pure Error	0.59	59	0.010			
Cor Total	19.34	103				

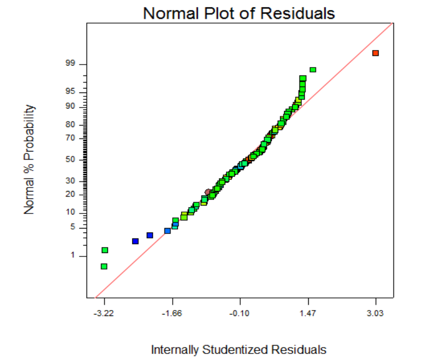

Fig. 7. Normal probability plot for SR

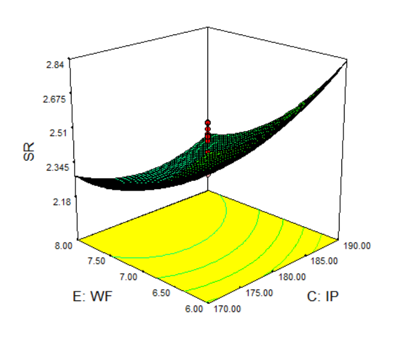

Fig. 8. Iteration effect of the wire feed and peak current on surface roughness

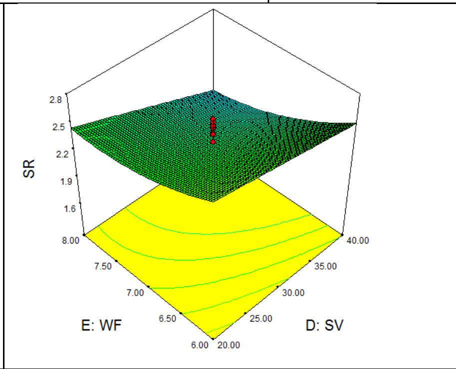

Fig. 9. Iteration effect of servo voltage and wire feed rate on surface roughness

Based on the developed second-order polynomial model, the effects of the input process variables on surface roughness (SR) were analyzed using Design Expert software. A regression equation, expressed in terms of actual values of the six input variables, was formulated from the experimental data to represent SR. The equation is provided below.

$$\text{Surface roughness} = +78.61910 + 0.089044 * TON - 1.78728 * TOFF - 0.30636 * IP + 0.028325 * SV - 0.61146 * WF - 2.24411 * WT - 5.32500E-003 * IP * WF - 6.90625E-003 * SV * WF + 0.016349 * TOFF2 + 9.68293E-004 * IP2 + 0.11091 * WF2 + 0.16154 * WT2 \quad (3)$$

The quadratic terms of peak current (IP), wire feed (WF), pulse-off time (Toff), and wire tension (WT) have a significant influence on surface roughness (SR) and can be effectively used to predict SR within the defined range of control variables. Among the main effects, pulse-on time (Ton), pulse-off time (Toff), peak current (IP), servo voltage (SV), and wire feed (WF), along with the interaction effects of WF with IP and WF with SV, were found to be statistically significant. The corresponding interaction plots are shown in Figs. 8 and 9.

As illustrated in Fig. 8, lower values of peak current (170–190 A) combined with higher wire feed rates (6–8 m/min) result in reduced surface roughness. This is because higher IP increases discharge energy, which leads to excessive melting and evaporation, forming large craters on the machined surface. The depth and diameter of these craters grow with increasing IP, resulting in a rougher finish. In contrast, a higher wire feed rate helps dissipate excess heat from the machining zone, thereby reducing material removal and improving surface finish. Similarly, Fig. 9 shows that higher values of servo voltage (20–40 V) along with increased wire feed rates (6–8 m/min) yield lower surface roughness. This combination helps maintain a more stable spark gap and efficient cooling, leading to better surface quality.

Multi-Objective Optimization Using Desirability Approach

Derringer and Suich (1980) introduced a multi-response optimization technique known as the desirability approach, which is widely adopted in industry for solving problems involving multiple quality characteristics. This method employs an objective function, D(X), referred to as the desirability function. The overall desirability is calculated as the geometric mean of the individual desirability values corresponding to each transformed response [21]:

$$D = (d_1 \times d_2 \times d_3 \times \ldots\ldots\ldots\ldots\ldots \times d_n)^{1/n} = \left(\prod_{i=1}^{n} d_i \right)^{1/n} \quad (4)$$

Desirability is an objective function that ranges from zero (completely undesirable) to one (fully desirable), reflecting how well a particular solution meets the set goals. Statistical optimization aims to identify the point that maximizes this desirability function. In the present study, the optimization module in Design-Expert software was used to determine the optimal combination of input process parameters—namely, wire feed rate, pulse-off time, peak current, pulse-on time, servo voltage, and wire tension—that meet the specified criteria for each response and parameter. The optimization process was carried out with the goal of maximizing the material removal rate (MRR) while minimizing surface roughness (SR). The constraints applied to each response and input parameter are listed in Table 6. Using Design-Expert, the most favourable operating conditions for the process variables and their corresponding performance measures were determined and are presented in Table 7. To validate the optimization results, confirmatory experiments were conducted. The experimental outcomes (Table 7) closely matched the predicted values, demonstrating the reliability and accuracy of the optimized model.

TABLE 6. Range of input parameters and responses for desirability (CR, SR and MRR)

Process parameters	Goal	Lower Bound	Upper Bound	Lower Weight	Upper Weight	Importance
TON	is in range	112	118	1	1	3
TOFF	is in range	52	56	1	1	3
IP	is in range	170	190	1	1	3
SV	is in range	20	40	1	1	3
WF	is in range	6	8	1	1	3
WT	is in range	6	8	1	1	3
MRR	maximize	2.772	10.44	1	1	5
SR	minimize	1.431	3.606	1	1	3

TABLE 7. Optimum Process parameters for multi-objective optimizations and confirmation experiment results

Optimum Process Parameters						**Response Predicted**		**Response Experimental**		**Desirability**
Ton	**Toff**	**IP**	**SV**	**WF**	**WT**	**MRR**	**SR**	**MRR**	**SR**	
118	52.08	182.29	20	6.17	6.92	**8.582**	**3.098**	**8.520**	**3.127**	**0.5816**

Conclusions

In this paper influence of process parameters on MRR and SR were investigated. The parameters and their combinations affecting the process were obtained using ANOVA.

1. The blanking die material SKD 11 can be machined effectively byWEDMas higher MRR (10.44 mm3/min) and lower SR (1.491 µm) are acknowledged during cutting.
2. Machining parameters such asTon, Toff, IP, SV and WF are the significant parameters for obtaining maximum MRR. The combine effect of Ton x WF also show their considerable effect on maximum MRR.
3. Machining parametrs like Ton, Toff, IP, SV and WF are most significant parametrs for obtaining mimimum surface roughness. The combine effect of WF and IP, and WF and SV are found to be statistically important for minimum SR
4. The quadratic models for MRR and SR will provide guidelines for forecast of MRR and SR in advance. confirmation test outcome show that models are reasonably fit with the experimental trial outcome.

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