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Modeling and Multi-objective Optimization of Green WEDM Characteristics on H21 Steel Using TOPSIS-CRITIC Technique

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Abstract

In this research work, TOPSIS (technique for the order of preference by similarity to ideal solution)-CRITIC (criteria importance through criteria inter-correlation) technique was used to determine the effectiveness of optimization of multiple response parameters of green wire electrical discharge machining (GWEDM) on H_{21} using deionized water as dielectric fluid. The effects of process parameters such as peak current (PC), pulse on time (T_{on}), pulse off time (T_{off}), wire tension (WT), wire speed (WS), and polarity (P) on the response parameters: cutting speed (CS), gap current (I_g), and surface roughness (SR) were investigated. Initially, the experimentation was performed based on Taguchi's design of the experiment (DOE) - L_{18}-orthogonal array and responses were recorded. In addition, analysis of variance (ANOVA), P-value hypothesis test, and F-test were performed to evaluate the influential process parameters at the 95% confidence level. Also, the regression analysis was implemented on the obtained preference values to develop the mathematical model that explained the correlation among the machining characteristics. The parametric optimization, intending to maximize the CS and minimize the I_g and SR, achieved PC = 18 A, T_{on} = 128 µs, T_{off} = 48 µs, WT = 6 gm, WS = 5 m/min and reverse polarity as the optimal parameters to increase CS, and peak current = 12 A, T_{on} = 120 µs, T_{off} = 52 µs, WT = 7 gm, WS = 5 m/min, and straight polarity for I_g, PC = 12 A, T_{on} = 120 µs, T_{off} = 56 µs, WT = 7 gm, WS = 5 m/min and straight polarity as the optimal parameters to decrease I_g and SR. The optimal conditions for GWEDM characteristics for multi-response optimization using TOPSIS-CRITIC method were, PC = 12 A, T_{on} = 128 µs, T_{off} = 48 µs, WT = 7 gm, WS = 5 m/min, and straight polarity. Additionally, ANOVA was performed on the preference values (in the case of TOPSIS-CRITIC), and it was found that PC was the most influential process parameter with the highest contribution of 56.56%.

Keywords

Green WEDM, Design of experiments, CRITIC, TOPSIS, Analysis of variance, Regression analysis

Introduction

The H_{21} hot work steel is immensely used in the manufacturing of tools, die, and mold due to its excellent dimensional stability, mechanical, wear, and corrosion properties [1]. The conventional machining of H_{21} steel to achieve the desired dimensional accuracy and improved production rate are not suggested for complex and intricate geometrical shape parts because the contact of work and tool at the interface experiences an intermittent force and residual stress results in wear of tool and damage or breakage of work material. Additionally, the conventional machine generates fine dust chip particles released to surrounding and as a result, ecological harms are arising once the toxic essence goes into the body of operators and nearby people. The manufacturing process is a power and energy exhaustive activity that seriously affects the environment. The high and economical production rate with excellent quality of products is still a challenging task for recent industries. Thus, green manufacturing (GM) is contributing to all industrial conditions to increase efficiency and reduce the harmful depositions of industrial waste (solid and gaseous) during manufacturing operation. GM uses modern machining processes with green dielectric fluids such as tap water, deionized water, and dry air, and are economical and ecofriendly. Includes efficient use of recourses resources, minimum environmental impact, minimum energy deterioration, producing negligible pollution [2]. Therefore, GWEDM is an excellent and popular nontraditional machining method used for machining of H_{21} hot work tool steel to enhance the efficiency and reduced the emission of harmful poisonous gases which is serious for occupational health and environmental conditions during machining [3].

The GWEDM is a contact-free thermo-electric erosion process, in which the erosion of material occurs due to a series of discrete sparks between inner electrodes gap caused by discharge voltage difference and motion of wire electrode in green dielectric fluids [4]. The performance parameters of the GWEDM such as cutting speed (CS), wire wear, surface roughness (SR), kerf width, microhardness, recast layer, dimensional deviation, and gap current (I_g) are widely influenced by process parameters like pulse on time (T_{on}), pulse off time (T_{off}), discharge voltage (Vd), polarity, peak current (PC), wire tension (WT) and wire feed (WF) which directly affect the economics, accuracy, and efficiency of machining [5, 6] and selection of process parameters are significantly essential. Thus, many researchers attempted to modify the wire electrical discharge machining conditions to obtain the desired response at optimal cost.

For this reason, the influence of various process parameters (PC, T_{on}, I_g, servo voltage, WF, WT, flushing pressure, taper angle, and vibration frequency) was investigated on the machining several response characteristics (MRR, SR, Kerf width and TWR) during machining of Al-7075 alloy and it was found that the wire feed, T_{on} and T_{off} had maximum impact on MRR, and SR since the discharge energy is related to T_{on}, causing the material to melt and evaporate and obtain faster cut. The flushing pressure and WT revealed the minor effects on the MRR and SR [7, 8]. The study of the impact of process parameters (T_{on}, capacitance, discharge peak current, and T_{off}) on the response parameters (CS and SR) was conducted during WEDM of tungsten carbide cobalt composites. It was found that SR and CS increase with the increase in capacitance and T_{on} time [9]. WEDM was carried out on HSLA steel as work material with moly wire and the results showed achieved the highest CS at low pulse frequency and T_{off} with maximum power [10]. Experimental analysis in WEDM of armor materials showed that MRR increased, and SR decreased with an increase in current and T_{on}. Also, higher peak current is caused by wire breakage during experimentation [11]. The investigation of WEDM characteristics on cementation alloy steel demonstrated that material removal rate and SR increase with rise in discharge current and pulse frequency. The Maximum CS led to decrease SR and increase the MRR [12] The investigation of WEDM parameters on Inconel 625 was conducted with cryogenic zinc coated and simply zinc coated wire. The results showed that the MRR and SR were extensively affected by the type of wire [13]. The investigation of WEDM parameters while Inconel 718 were examined with deep cryogenically treated wire and simple wire. It was observed that the cryogenically treated wire enhanced the CS and SR [14]; The CS affected material removal mechanism, which is directly influenced by the wire feed rate [15]. Hence, the above literature reveals that the T_{on}, T_{off}, WF, PC, polarity, WT, and SV have a major contribution to machining quality characteristics (MRR, SR, CS, TWR, KW, SG, and so on). The machining quality characteristics are related to production rate, process efficiency, functional requirements, physical characteristics, and other process parameters. Additionally, Green WEDM is a multi-input-output machining process, and the multi-objective optimization of machining parameters refers to the selection of appropriate machining conditions that could maximize or minimize all objective functions. However, multi-response optimization of machining parameters is performed with many statistical tools grey relational analysis (GRA), TOPSIS, teaching learning-based algorithm (TLBO), genetic algorithm (GA), particle swarm optimization (PSO), computational statistics (CS), etc. to find out the suitable machining conditions that optimize the machining quality characteristics. GRA with ANOVA technique was used for the optimization of EDM parameters with DMLS electrode on EN-24 steel. The desirability function approach was used for the optimization of EDM parameters on EN-31 [16]. ANN, and non-dominating sorting GA were used for the optimization of EDM parameters on SiC [17]. Finite element method-ANN-GA approaches were used for optimization of machining parameters on AISI P20 [18]. GA-ANN methods are used to optimize the machining characteristics on steel [19]; Neuro-fuzzy-ANN approach is use for optimization of machining characteristics on D2 steel [20] Thus, the reported literature appears to be insufficient in terms of modeling and multi-objective optimization of green WEDM process parameters.

The main aim of this research paper was to execute the modeling and optimization of GWEDM characteristics while processing H_{21} steel using technique for the order of preference by similarity to ideal solution (TOPSIS)-CRITIC method to achieve enhanced machining performance characteristics (CS, SR, and I_g).

Materials and Methods

Materials

In this research, three rectangular plates of H_{21} die tool steel of dimension 50 x 50 x 10 mm were used as the work material with elemental composition (in wt. percentage) of C: 0.3; Mn: 0.3; Si: 0.2; Cr: 3.6; Ni: 0.3; W: 8.5; V: 0.4; Cu: 0.25; P: 0.03; S: 0.03; and remaining Fe. Further, the other properties of the same were density: 8.19 g/cm^3; Poisson's ratio at 25 °C: 0.27 - 0.3; thermal conductivity: 27 W/mK; specific heat (cal/g °C): 0.11; Rockwell hardness: 44; and modulus of elasticity: 196 GPa [1].

Design of experiment (DOE)

In this work, Taguchi's technique of DOE is a statistical tool for designing the experiments and find out the response of input parameters on response parameters Taguchi's DOE with its L_{18-} orthogonal array (OA) was used to investigate the GWEDM characteristics. The six independent parameters polarity, T_{on}, T_{off}, PC, WS, and WT were varied at three levels to study the influence on response variables like CS, SR, and I_g. The parameters and their levels used in experimental trials were decided primarily on the basis of pilot experiments and past literature. The same is displayed in table 1.

Experimental details and response measurement

The experimental trials were performed using CNC WEDM as shown in figure 1. The deionized water was used as a dielectric fluid having kinematics viscosity 0.294 x 10^{-6} m^2/s, dielectric strength 80 kV/m, and density 0.9982 g/ml. The half-hard brass wire of diameter 0.24 mm was used, and a 0.025 to 0.5 mm inner-electrode gap was maintained during experimentation. The ELCAM software was used to generate the required CNC program coding.

Figure 1: WEDM set-up.

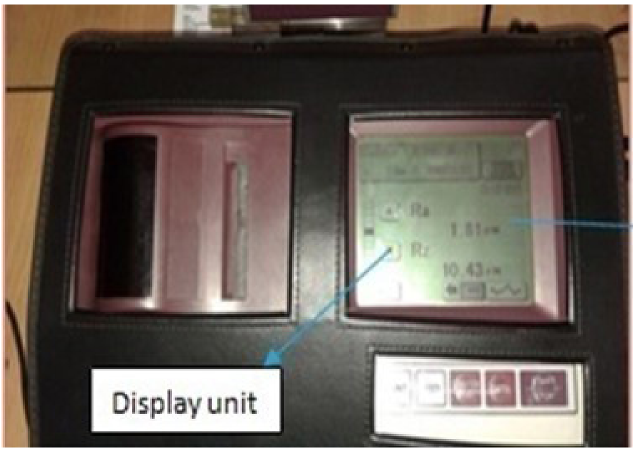

Figure 2: Mitutoyo surftest SJ-301.

In this experimental study, the CS was measured through the monitor of WEDM, and I_g was measured using an ammeter of WEDM at 2 mm, 4 mm, and 6 mm distance from an initial cutting position along the normal direction of the workpiece for all the four sides of the work surface (as shown in figure 2) and the average of twelve readings was taken as a performance measure (as illustrated in table 2).The surface roughness (Ra) was assessed at 3 locations normal to material cutting after each experimental trials, by using Mitutoyo surf test SJ-301 (shown in figure 2) for all the four cutting surfaces and the average of twelve readings was calculated (as shown in table 2).The DOE and experimental results of response parameters are described in table 2.

Multi-response optimization

Criteria importance through criteria inter-correlation (CRITIC)

In the midst of the multiple and conflicting responses, problems assignment of the same weight may bring up dissatisfaction amongst the consumers and manufacturer since the manufacturers are highly concerned about the inexpensive manufacturing (i.e., energy consumption, excellent surface quality, and high material cutting speed). Thus, the CRITIC method is used to calculate the weights of each objective function. The assessment of the process for easy decision-making using the CRITIC method does not require human involvement [23]. This approach is incorporated to calculate the weights of conflicting assignments [24]. The calculated weight criteria for the response variables: CS, SR, and I_g, were determined as 0.44, 0.27, and 0.29, respectively, using the CRITIC method.

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

TOPSIS is a simple ranking MCDM technique adopted to find out the appropriate option amongst the finite sets by obtaining the solution of a multi-response optimization problem. TOPSIS is based on the concept of selecting the criteria or preference value among the alternatives which are nearest to the positive finest result, and furthermost from the negative best solution. The best solution has a relative nearness

Table 1: GWEDM process parameters and their levels.

Sl. No.	Machining parameters	Levels of parameters			Units	Symbols
1.	Peak current	12	15	18	A	PC
2.	Pulse on time	120	124	128	µs	T_{on}
3.	Pulse off time	48	52	56	µs	T_{off}
4.	Wire tension	6	7	8	gm	WT
5.	Wire speed	3	4	5	m/min	WF
6.	Polarity	Positive (1)	Reverse (2)		-	P
7.	Dielectric pressure		12		LPM	-
8.	Angle of cut		Vertical		-	-

Table 2: L_{18} (2^1 x 3^5) Taguchi's DOE and responses.

Sl. No.	Process parameters						Response parameters				
	Polarity	PC (A)	T_{on} (μs)	T_{off} (μs)	WT (gm)	WS (m/min)	Cutting Speed (m/min)	Gap current (μA)	Surface roughness (μm)	Preference value	Rank
1	1	12	120	48	3	6	2.61	1.91	2.5	0.814	4
2	1	12	124	52	4	7	2.54	2.01	2.74	0.727	6
3	1	12	128	56	5	8	2.53	2.31	2.21	0.754	5
4	1	15	120	48	4	7	2.41	2.51	2.77	0.571	8
5	1	15	124	52	5	8	2.51	2.71	2.78	0.572	7
6	1	15	128	56	3	6	2.54	3.21	2.73	0.521	9
7	1	18	120	52	3	8	2.03	3.86	3.76	0.148	16
8	1	18	124	56	4	6	2.00	4.26	4.16	0.082	17
9	1	18	128	48	5	7	3.72	4.71	4.61	0.453	10
10	2	12	120	56	5	7	1.49	2.02	2.513	0.319	14
11	2	12	124	48	3	8	3.05	2.12	2.753	0.862	2
12	2	12	128	52	4	6	2.86	2.42	2.223	0.842	3
13	2	15	120	52	5	6	1.94	2.62	2.783	0.366	13
14	2	15	124	56	3	7	2.08	2.82	2.793	0.392	12
15	2	15	128	48	4	8	3.83	3.32	2.743	0.865	1
16	2	18	120	56	4	8	1.68	3.97	3.773	0.065	18
17	2	18	124	48	5	6	3.20	4.37	4.173	0.401	11
18	2	18	128	52	3	7	3.15	4.82	4.623	0.309	15

to the perfect solution. TOPSIS technique provides a logical and reliable route using multiple attributes optimizations, where the contradictory outputs are changed to single-objective optimization problems using preference values. The experimental trial noticed with the maximum preference value is considered to be the optimum desired value among all the alternatives [25].

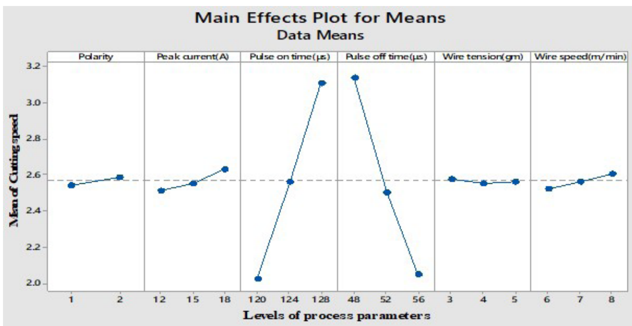

Figure 3: Main effect plot for CS for different process parameters.

Results and Discussion

Parametric optimization

The effects of input variables on CS

The effects of independent process parameters T_{on}, T_{off}, PC, polarity, WT, and WS on the CS amid the machining of H_{21} steel was illustrated in figure 3 and it was found that CS increased in proportion with T_{on} because of high spark energy is generated at higher T_{on} duration, leading to produce the large heat energy and larger crater size. The increase in T_{off} will decrease CS since the rate of discharge energy decreases and the cooling effect of dielectric (as a result of reduction in the intensity of spark energy) [26]. The CS increases with an increase in PC because a higher PC generates larger heat energy due to increase in the melting amount of material removal and produces deeper crater size. In the reverse polarity, the size of sparks is relatively larger, and due to larger spark size, bigger and deeper craters are produced. Hence the CS increases in the reverse polarity as compared to the straight polarity. The WS increases the rate of sparks between the workpiece and the wire. The high rate of sparks increases the melting amount of work materials and thus slows down the WS, leading to the wire breakage. Hence, as the CS increases, the WS increases. As the WT increases, CS decreases due to a decrease in I_g and then increases due to an increase in I_g [27].

The optimal parametric combination of machining variables for optimal CS is reverse polarity, PC = 18 A, T_{on} = 128 μs, T_{off} = 48 μs, WT = 3 gm, and WT = 8 m/min. The influential parameters were calculated by the difference of the highest and the smallest mean values. The parameters of higher mean differences have higher rank and were thus identified as the most significant process parameters. Hence, T_{off} was recognized as the most influencing process parameters, followed by T_{on}, PC, WS, and polarity.

The effect of process parameters on Ig

The effect of independent process parameters T_{on}, T_{off}, PC, polarity, WT, and WS is shown in figure 4. It was noted that the I_g rises with rise in T_{on} because spark energy increases to sustain the machining. Hence, more I_g will be required to increase the I_g. On the other hand, a reverse trend was noticed where, with an increase in T_{off}, the need of I_g was decreased to maintain the machining. I_g increases with PC increase and reverse polarity because discharge current and discharge energy increase to continue the machining and hence I_g increase [28]. WT is an insignificant process parameter for I_g thus it is neglected. WS increase I_g increase because the rate of contact of wire and workpiece increase due to high contact rate, sparking rate increase, and produced more heat energy for machining and hence to maintain the requirement of energy the I_g increase.

The optimal parametric combination of machining variables for optimal I_g was straight polarity, PC 12 A, T_{on} 120 µs, T_{off} 52 µs, WT 4 gm, and WS 8 m/min. The influential parameters were calculated by the difference of highest and smallest mean values. The parameters of higher mean difference were given the higher rank and were thus identified as the most significant process parameters. Hence, PC was found to be the most influential parameter followed by T_{on}, polarity, WS, T_{off}, and WT.

The effects of input variables on SR

The effects of T_{on}, T_{off}, PC, polarity, WT, and WS on the SR is displayed in figure 5. It was found that SR increases with rise in in T_{on} because higher T_{on} produces higher discharge energy, leading to more heat energy. Further, the SR of the machined surface depends on heat energy ratio observed per pulse. Hence, higher discharge energy, causing more material erosion, can produce more and deeper craters. Also, if the melted material is not eliminated adequately, then it gets re-solidified, leading to a rougher surface. Further, with the increase in T_{on}, the heat energy ratio decreases. The SR is maximum at the minimum value of T_{off} and then gets reduced with rise in T_{off} as a result of very short duration of T_{off}. Hence, there is no sufficient time to take away the melted material from the inter-electrode gap, and thus, the SR increases with the increase in T_{off}. In addition, since more discharge energy is required to establish the plasma channel, higher electrode wear and SR are noticed. Also, SR increases with an increase in the WS due to the high feed rate. Also, as the new wire comes in contact with the workpiece at a faster rate, it first leads to increase in the surface roughness and later decrease in the same because at high-speed, the wire breakage is reduced and due to smooth machining surface roughness gets decreased [29]. In the reverse polarity, the size of sparks is larger and produces deeper and larger size of the crater and hence, higher surface roughness of the machined surface is noticed as compared with the straight polarity. With the rise in peak current, surface roughness increases, leading to an increase in the number of discharges, and thus, enhancing the discharge energy. Thus, due to larger discharge energy more material is melted and produces larger and deeper crater size. Hence SR is increasing. The vibration and the deflection of tool wire get reduced when WT increases and thus reduced the surface roughness to a minimum value as a result of starch and breakage in the wire.

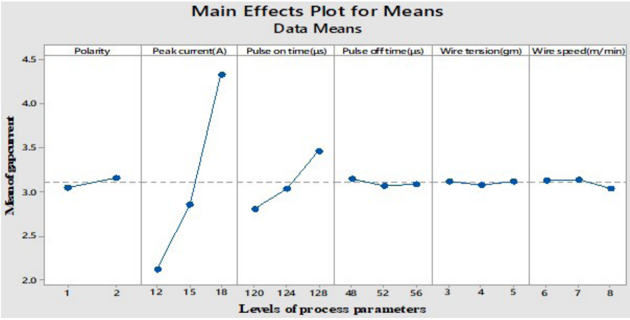

Figure 4: Main effect plot for I_g for different process parameters.

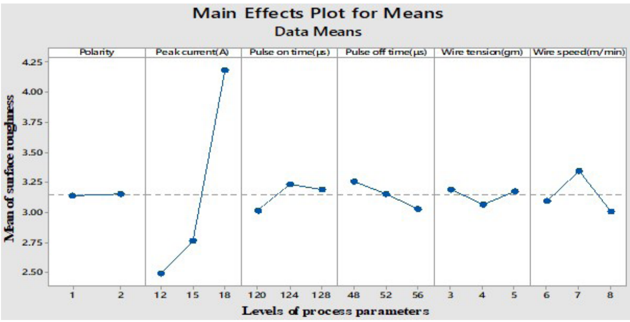

Figure 5: Main effect plot for SR for different process parameters.

The optimal parametric setting of machining characteristics for SR is straight polarity, PC 12 A, T_{on} 120 µs, T_{off} 56 µs, WT 4 gm, and WS 8 m/min. The influential parameters are calculated by the difference of highest and smallest mean values. The parameters of higher mean difference have higher rank and most significant process parameters. Hence, PC is the most significant process parameter followed by WS, T_{off}, T_{on}, WT, and polarity.

Multi response optimization using TOPSIS-CRITIC method

The multi-objective optimization of GWEDM characteristics was executed using the TOPSIS-CRITIC method on the experimental response characteristics obtained during experimental trials. The preference values of all the parametric settings of the experimental trials were obtained using some equations and each response variable was assigned the weights calculated by CRITIC. In the TOPSIS method, multiple responses are converted into single response characteristics and the same are further used to calculate the preference values of all the experiments (as illustrated in table 2). The relative closeness to the positive finest solution is determined as the largest preference value of response measure. Thus, it was observed that experimental trial 15 had an excellent response, displaying the maximum preference value, followed by trials 11 and 12. The optimal parametric setting achieved was PC = 15 A, T_{on} = 128 µs, T_{off} = 48 µs, WT = 4 gm, WS = 8 m/min, and reverse polarity.

This experimental investigation also evaluated the response of GWEDM parameters on the preference values by calculating the means of preference values for all the levels of machining parameters (as shown in table 1) and thus, the maximum mean of preference values of the process parameters was: PC = 12 A, T_{on} = 128 μs, T_{off} = 48 μs, WT = 4 gm, WS = 8 m/min, and straight polarity. The most influential GWEDM parameters were estimated by evaluating the difference between the largest and smallest mean of preference values and comparing the same. The difference of mean values was 0.4767 for PC, 0.3055 for T_{off}, 0.2435 for T_{on}, 0.0825 for WS, 0.0478 for WT, and 0.0246 for polarity. Hence, the results revealed that PC (0.4767) has the maximum influence on the multiple responses, and the sequence of influence on the multi-response characteristics is: PC (rank 1), T_{off} (rank 2), T_{on} (rank 3), WS (rank 4), WT (rank 5), and polarity (rank 6). The highest preference value gives the optimal machining parameter for WEDM.

ANOVA

The ANOVA was used to ascertain the influence and individual contribution of each machining process parameter on the response variables. In this process, fisher's ratio test was conducted to evaluate the deviation and importance of the process parameters which show the extreme change in the response variables. Also, the probability test (P-value) was incorporated to illustrate the importance of the process parameters. Parameters with P-value smaller than 0.05 (alpha value) were identified as the significant ones.

To determine the sufficiency and fitness of the mathematical model, coefficient of determination R^2 and adjusted-R^2 were calculated. The ANOVA was performed on the Minitab 17-software [29]. The results of the ANOVA on preference values are presented in table 7 at 95% confidence level using larger is better response characteristics. PC was identified as the most significant process parameter with the highest

Table 3: Mean of CS.

Process parameters	Level 1	Level 2	Level 3	Max –min	Rank
Polarity	2.543	2.587	-	0.043	5
Peak current (A)	2.513	2.552	2.630	0.117	3
Pulse on time (μs)	2.027	2.563	3.105	1.078	2
Pulse off time (μs)	3.137	2.505	2.053	1.083	1
Wire tension(gm)	2.577	2.553	2.565	0.023	6
Wire speed (m/min)	2.525	2.565	2.605	0.080	4

Table 4: Mean of I_g.

Process parameters	Level 1	Level 2	Level 3	Max –min	Rank
Polarity	3.054	3.132	-	0.110	3
Peak current (A)	2.132	2.865	4.332	2.200	1
Pulse on time (μs)	2.815	3.048	3.465	0.083	2
Pulse off time (μs)	3.157	3.073	3.098	0.083	5
Wire tension (gm)	3.123	3.082	3.123	0.042	6
Wire speed (m/min)	3.132	3.148	3.048	0.100	4

Table 5: Mean of SR.

Process parameters	Level 1	Level 2	Level 3	Max –min	Rank
Polarity	3.140	3.153	-	0.013	6
Peak current (A)	2.490	2.766	4.183	1.693	1
Pulse on time (μs)	3.017	3.233	3.190	0.217	4
Pulse off time (μs)	3.258	3.152	3.030	0.228	3
Wire tension (gm)	3.193	3.068	3.178	0.125	5
Wire speed (m/min)	3.095	3.342	3.003	0.338	2

Table 6: Mean of preference value.

Process parameters	Level 1	Level 2	Level 3	Max –min	Rank
Polarity	0.5158	0.4912	-	0.0246	6
Peak current (A)	0.7197	0.5478	0.2430	0.4767	1
Pulse on time (μs)	0.3805	0.5060	0.6240	0.2435	3
Pulse off time (μs)	0.6610	0.4940	0.3555	0.3055	2
Wire tension (gm)	0.5077	0.5253	0.4775	0.0478	5
Wire speed (m/min)	0.5043	0.4618	0.5443	0.0825	4

Table 7: ANOVA for preference value.

Source	DF	Seq.-SS	Adj-SS	Adj-MS	F_{Value}	P_{Value}	% Contribution
Regression	6	1.1497	1.1497	0.19162	38.12	0.00	95.41%
Polarity	1	0.0027	0.0027	0.00271	0.54	0.47	0.23%
Peak current	1	0.6816	0.6816	0.68163	135.5	0.000	56.56%
Pulse on time	1	0.17788	0.17788	0.177877	35.38	0.000	14.76%
Pulse off time	1	0.27999	0.27999	0.279991	55.69	0.000	23.23%
Wire tension	1	0.00273	0.00273	0.002730	0.54	0.477	0.23%
Wire speed	1	0.00480	0.00480	0.004800	0.95	0.350	0.40%
Error	11	0.05530	0.05530	0.005027			4.59%
Total	17	1.20504					100.00%
S = 0.0709034, R^2 = 95.41%, R^2-adj = 92.91%, R^2-predicted = 86.51%							

56.56% contribution, followed by T_{off} (23.23%), T_{on} (14.76%), WS (0.40%), WT (0.23%), and polarity (0.23%). The polarity, WT, and WS are insignificant (P-value > 0.05). Further, R^2 = 95.41%, R^2-adj = 92.91%, validated that the presented mathematical model was sufficient and fit for preference values.

Regression analysis

The regression analysis was used as a statistical tool to develop a mathematical model to explain the relation among the machining characteristics. The regression equation is expressed as:

$$Y = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 \qquad (1)$$

Where, Y is the predictor (output) variables i.e., preference value (P_i). x_1, x_2, x_3, x_4, x_5, and x_6 are criterion (input) variables, and α_0, α_1…. α_n are the regression coefficients. In this analysis, experimental results (Table 2) were further to derive the following corresponding prediction equation for the preference values (eq 1):

$$P_i = -0.136 - 0.0246\ \text{Polarity} - 0.07944\ \text{PC} + 0.03044\ T_{on} - 0.03819\ T_{off} - 0.0151\text{WT} + 0.0200\ \text{WS} \qquad (2)$$

The impact of process parameters on the preference values is shown in eq 1, where it was observed that T_{on} and WS had a positive impact and polarity, PC, T_{off}, and WT had a negative impact on preference values. Further, T_{on} was found to be the most influential parameters. The normal probability plot for the preference values (as a reference in figure 6) reflects the point's position which is much closer to the straight line, indicating that the normally distributed data and the larger slope of the figure inferring the process parameters have major effects on green WEDM response parameters. The residual of the mathematical model shows that the average error of this model is 4.59% (which is less than 10%). Hence the calculated accuracy of this model appears to be fit, accurate, and satisfactory.

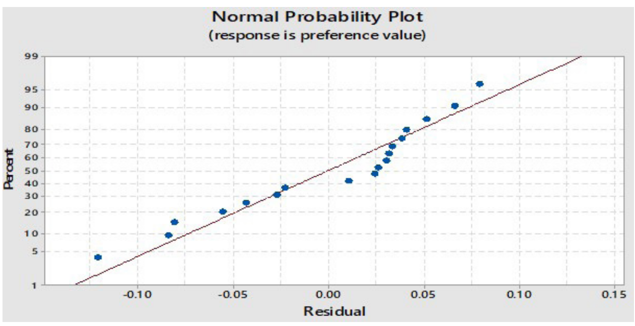

Figure 6: Probability plot of preference value.

Conclusion

The main findings of the present research work are as follows:

- The optimal settings for parametric optimization were PC = 18 A, T_{on} = 128 µs, T_{off} = 48 µs, WT = 6 gm, WS = 5 m/min and reverse polarity for maximum CS; PC = 12 A, T_{on} = 120 µs, T_{off} = 52 µs, WT = 7 gm, WS = 5 m/min and straight polarity for minimum I_g, and PC = 12 A, T_{on} = 120 µs, T_{off} = 56 µs, WT = 7 gm, WS = 5 m/min and straight polarity for minimum SR.
- The optimal set of input parameters using TOPSIS-CRITIC method was PC = 12 A, T_{on} = 128 µs, T_{off} = 48 µs, WT = 7 gm, WS = 5 m/min, and straight polarity. ANOVA was performed on the preference values, that revealed that the PC was the most significant variable with a maximum individual contribution of 56.56%.
- The developed mathematical model and regression analysis were found to be sufficiently accurate and acceptable as the coefficient of determination were R^2 = 95.41%, R^2-adj = 92.91%, R^2-predicted = 86.51%, and average error 4.59%.
- The minimization of gap current (I_g) was likely to minimize the energy consumption to achieve GWEDM.
- The finding of the present research work might be considered by the industry to improve the quality of processing using GWEDM.

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None.

Conflict of Interest

The authors have no relevant financial or non-financial interests to disclose.

Credit Author Statement

Abhishek Singh: Conceptualization, Writing - review and editing, Supervision; Sandeep Kumar: Resources, Experimentation, Writing - original draft preparation; Rahul Davis: Writing - review and editing. All the authors read and approved the manuscript.

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