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Parametric Optimization of WEDM Process for AISI 1026 Steel Using Taguchi-TOPSIS Hybrid Method

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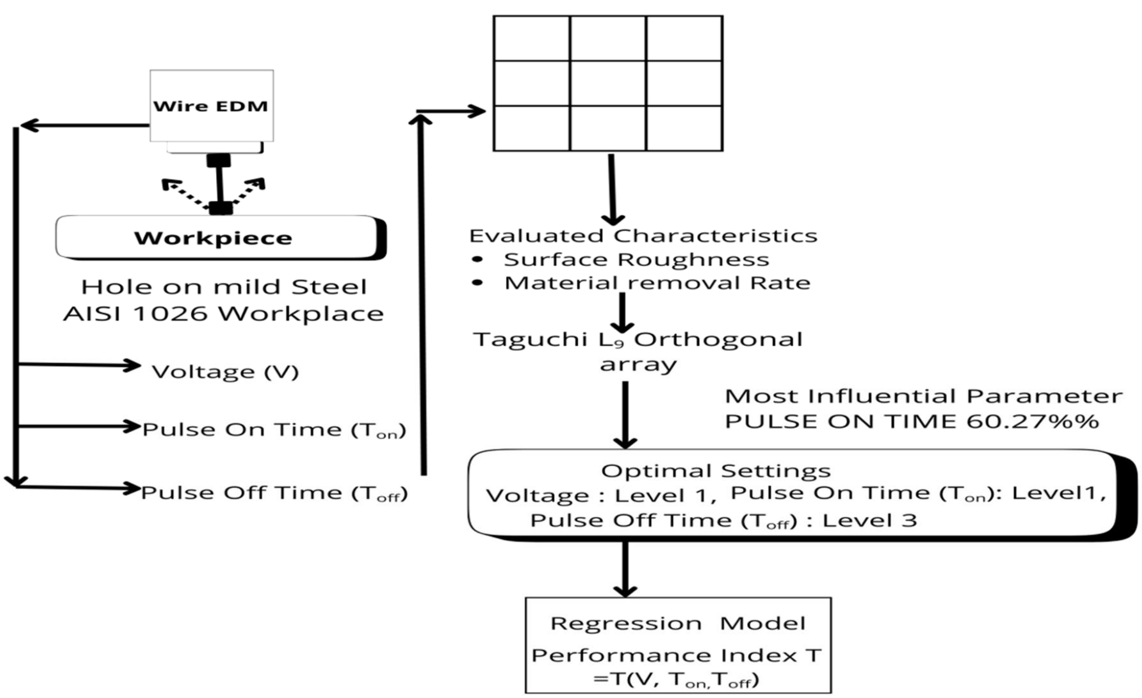
***Abstract:** In this research, holes were created in a mild steel AISI 1026 work piece using a Wire EDM (Electrical Discharge Machining) machine. The goal was to evaluate and look at the machined holes' quality characteristics. The control parameters of Wire Electrical Discharge Machining (WEDM) like voltage, pulse-on time, and pulse-off time have been taken into consideration in this work. Surface Roughness (SR) and Material Removal Rate (MRR) have been considered in the assessment of the quality characteristics. The Taguchi L_9 orthogonal array was used to set the control settings at different levels during the experiments. Present research has established rankings on various experimental sets by using the TOPSIS approach for combined response analysis. Optimal parameter settings were found using the Signal-to-Noise (S/N) ratio. The research showed that voltage at level 1, pulse on time at level 1, and pulse off time at level 3 were the optimal parameters. The most significant factor was determined using ANOVA, and Pulse on Time provided the highest proportion (60.27%). The performance index is calculated using the regression equation, which also shows the relationship between the machine's control variables and performance index. The S/N ratio value of -0.8569 obtained in the confirmation test, that shows successful implementation of the Taguchi-TOPSIS approach.*

***Keywords:** Wire EDM; AISI 1026; TOPSIS; Voltage; Pulse on time; Pulse off time; Material removal rate; Surface roughness.*

Graphical Abstract



Nomenclature	
ANOVA	Analysis of Variance
f_T	Total degree of freedom
f_Y	Degree of freedom of parameter Y
f_e	Error of degree of freedom
I_{rw}	Range of Solar Radiation (W/m^2), Winter
I_{rr}	Range of Solar Radiation (W/m^2), Rainy
N	Total no. of experiments
N_{Y1}, N_{Y2}, N_{Y3}	Repeating no. of each level (1, 2, 3) of parameter Y
P_Y	Percentage contribution of parameter Y
P_e	Percentage contribution of error term
Pi	Performance index
S/N	Signal-to-noise ratio
S_Y	Sum of the squares of due to parameters Y (Y= T_t, W_{fr}, $I_{rw/rr}$,)
S_T	Total sum of squares to total variance
S_e	Sum of square of error terms
S_Y'	Pure sum of square
S_i^+	Positive ideal solution
S_i^-	Negative ideal solution
T	Total of all result
T_t	Tube tilt angle (Degree)
T_{wo}	Maximum Outlet Water Temperature (^oC)
V_Y	Variance of parameter Y
V_e	Error of variance
W_{fr}	Water Flow Rate (kg/s)
X_{Y1}, X_{Y2}, X_{Y3}	Values of a result of each level (i.e. 1, 2, 3) of parameters Y
X_i	Value of result of each experiment (i =1 to 9)

I. INTRODUCTION

Wire EDM (Electrical Discharge Machining) is a specialized form of EDM that uses a thin, electrically charged wire as the cutting tool. In this process, the wire is continuously fed through the work piece, and electrical discharges between the wire and the material cause precise erosion of the metal. This non-contact method allows Wire EDM to machine hard, conductive materials into complex and intricate shapes with extreme accuracy, making it ideal for industries such as aerospace, medical devices, and tool manufacturing. Unlike traditional machining, Wire EDM can produce tight tolerances and fine finishes without generating heat or mechanical stress on the material, making it suitable for delicate or high-precision applications.

Grey relational analyses are used to optimize machining parameters in Wire-EDM processes, addressing uncertainty, multi-input, and discrete data problems. table feed rate, gap width, and surface roughness influence optimal parameters(Huang & Liao, 2003) Taguchi methods to optimize process parameters on Al-10%SiCP composites, focusing on metal removal rate, tool wear rate, taper, radial overcut, and surface roughness(Singh et al., 2004).Wire electrical discharge machining of γ-titanium aluminise alloy, focusing on selecting the optimal cutting condition and wire offset setting for desired surface finish and dimensional accuracy, using an additive model (Sarkar et al., 2005). EDM parameters using direct metal laser sintering (DMLS) electrodes for EN 24 steel machining. Grey relational analysis and ANOVA techniques reveal effective control of performance characteristics, with current being the most affective parameter (Meena & Nagahanumaiah, 2006).

EDM using magnetic force assisted standard machines has been developed, enhancing efficiency and surface integrity. Magnetic force assisted EDM had higher material removal rate, lower relative electrode wear ratio, and smaller surface roughness compared to standard EDM (Lin et al. 2009). It uses response surface modelling and artificial bee colony to optimize WEDM parameters, focusing on machining speed and surface roughness, to achieve maximum efficiency(R. V. Rao & Pawar, 2009). A model and optimization for micro-electric discharge machining using artificial neural networks and genetic algorithms. The model is effective in estimating material removal rate and improves with optimized parameters (Somashekhar, Ramachandran, and Mathew 2010).The impact of EDM parameters on surface roughness of titanium alloy is explored. It develops a mathematical model for surface finish using response surface method and evaluates machining settings. Results show increasing pulse on time leads to fine surface; while 200 µs pulse off time produces superior finish (Rahman et al 2011).Electric discharge machining (EDM) is crucial for intricate shapes in electrically conductive materials. Parametric design and optimization are essential. Biogeography-based optimization (BBO) algorithm outperforms other population-based algorithms in optimizing process responses (Mukherjee & Chakraborty, 2012).Micro-electric discharge machining (micro-EDM) of Ti- 6Al-V alloy using tungsten carbide electrodes is investigated. It examines the impact of input parameters on output parameters like metal removal rate, tool wear rate, and overcut, using grey relational analysis and ANOVA (Meena and Azad 2012). It analyses past experimental data on Electrical Discharge Machining (EDM) processes using four principal component analysis (PCA)-based optimization methods. Results show that PCA-based approaches generally lead to better optimization performance, with the PCA-based proportion of quality loss reduction method showing the best performance (Chakravorty et al., 2012).A fuzzy-based algorithm for predicting material removal rate, tool wear ratio, and surface roughness in electrical discharge machining (EDM) and ultrasonic-assisted EDM processes, achieving over 90% accuracy is introduced (Shabgard et al., 2013).A hybrid method of a back-propagation neural network, genetic algorithm, and response surface methodology to analyse material removal rate, electrode wear ratio, and work piece surface finish in SKD61 EDM Manufacturing is used (Tzeng & Chen, 2013).The effects of EDM input parameters and tool geometry on Inconel 718 machining using a copper Electrode is investigated. Five parameters were optimized using desirability approach and ANOVA. The rectangular tool geometry was found to be successful, with current being the most influencing factor. Validation tests for the Fuzzy Logic Model showed a closer relationship with experimental results (Sengottuvel et al., 2013). The use of Grey relational theory and Taguchi optimization technique to optimize cutting parameters in Wire EDM for SS304, aiming to achieve minimum kerf width and best surface quality simultaneously and separately is discussed. The study also uses ANOVA to identify important factors (Durairaj et al., 2013). Mechanical properties of EN8 and D3 steel work pieces using an Electrical discharge machine, analysing parameters like peak current, pulse on time, die electric pressure, and tool diameter is examined (Balasubramanian & Senthilvelan, 2014).It examines the impact of wire EDM parameters on aluminium alloy quality, focusing on heavy and light metals. Parametric analysis and hybrid genetic algorithm optimization are used, ensuring good agreement with experimental values(P. S. Rao et al., 2014).Support vector Machine is used (SVM) to develop models for electrical discharge machining (EDM), utilizing Gaussian radial basis function and ε-insensitive loss function . Particle swarm optimization is employed to optimize parameter settings (Aich & Banerjee, 2014).Optimal parametric data-set for maximum material removal rate and minimum electrode wear ratio during Electrical discharge machining of AISI 316LN Stainless Steel using three desirability-based multi-objective particle swarm optimization algorithms is predicted (Majumder et al., 2014).The impact of input process parameters like pulse ON time, discharge current, and voltage on surface roughness in EN41 material is explored. It optimizes 5 output parameters using the Grey-Taguchi method, finding that current has the largest impact (Vikas et al., 2014).Optimizing cutting conditions for Wire-EDM to improve surface roughness and material removal rate. It uses pulse-on time, pulse off time, and wire feed rate as parameters. Surface characteristics are studied using SEM, and the Box-Benched approach is used. The optimal conditions are 1. µs pulse on time, 17. µs pulse off time, and 3.85 mm/min wire feed rate(Raj & Senthilvelan, 2015).The impact of graphite powder concentration in dielectric fluid on Ti-6Al-4V alloy electric discharge machining is investigated. The Taguchi parameter design approach was used to optimize parameters like peak current, pulse on time, and pulse off time, resulting in optimal performance characteristics like material removal rate and surface roughness (Gugulothu et al., 2015).Optimizing Electrical Discharge Machining process parameters of Aluminium-multiwall carbon Nanotube composites (AL-CNT) model has been focused. Optimal levels for material removal rate, wear electrode ratio, and average surface roughness are found using Response Surface Methodology and Genetic Algorithm (Hegab et al., 2015). It optimizes process parameters in Electrical discharge machining of Al- 18wt.%SiCp metal matrix composite using VIKOR and Entropy weight measurement methods. The VIKOR Index is optimized, validated through conformation test and ANOVA techniques (Bhuyan & Routara, 2016). The impact of EDM parameters on material removal rate, electrode wear rate, and surface roughness in aluminium boron carbide composite machining is examined. Results show current is the most significant factor for MRR and SR(P. Kumar & Parkash, 2016).

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The optimal machining parameters for electric discharge machining (EDM) in manufacturing sectors, focusing on high material removal rate (MRR) and low tool wear rate (TWR) is analysed. Using Taguchi technique, optimized parameters were found through ANOVA, validating error percentages and parameter contributions (Jeykrishnan et al., 2016). A selective modification of aluminium surfaces using electric discharge machining, resulting in a hard layer of tungsten and copper is presented. The modified surface exhibits improved performance and characterization (Rahang & Patowari, 2016).Experimental work on wire electrical discharge machining of porous nickel titanium (Ni40Ti60) alloy reveals process parameters affecting cutting rate, dimensional shift, and surface roughness. Results show successful single-cutting operation, but surface projections appear after first cut(Sharma et al., 2017).The machinability of copper, graphite, and brass electrodes for machining Inconel 718 super alloy are compared. Data from Taguchi's L27 orthogonal array and analysis of machining parameters reveal that electrode material, discharge current, and pulse-on-time are crucial for performance measures (Mohanty et al., 2017). The optimization of material removal rate and roughness parameter in Electrical Discharge Machining (EDM) using particle swarm optimization (PSO) and biogeography based optimization (BBO) techniques is explored. Results show linear increases in MRR and Ra when discharge current is mid-range, with BBO outperforming PSO in terms of computational time and accuracy(Faisal & Kumar, 2018).It evaluates the integration of Taguchi and TOPSIS in multi-response optimization of powder mixed electrical discharge machining (PMEDM) process. Results show that titanium powder mixed dielectric fluid improves efficiency, with powder concentration having the strongest influence(Nguyen et al., 2018). Metal Matrix Composites (MMCs) have unique properties that make conventional machining difficult. To address this, Electrical Discharge Machining (EDM) was used, with grey relational analysis revealing optimal conditions for enhancing machinability and surface quality. ANOVA results showed peak current as the most contributing parameter. A verification test validated the optimal conditions (Senthilkumar & Muralikannan, 2019). Unconventional machining methods like electrical discharge machining, focusing on optimizing process variables for improved material removal and surface finish is investigated. It identifies research gaps and provides insights for future research in unconventional EDM (M. Y. Khan & Sudhakar Rao, 2019).It investigated the effect of process parameters on performance parameters like material removal rate, surface roughness, and white layer thickness in NiTi60 (Smart Material Alloy). The results show that optimum settings for these parameters result in a 7.63% error rate in material removal rate (Gaikwad & Jatti, 2019). The optimal parametric combination of wire electro discharge machining (WEDM) on EN31 steel using grey-fuzzy logic technique, focusing on factors like pulse-on-time, pulse-off-time, material removal rate, and surface roughness is explored (Das et al., 2019). The radial basis function (RBF) to approximate EDM parameters and performance responses for 304 steel is introduced. It conducts multi-objective optimization using NSGA-II method, considering energy consumption, air pollution indices, and pulse current, time period, and duty cycle (Li et al., 2019). ANOVA and the signal-to-noise (S/N) ratio were utilized to determine the ideal amounts of independent factors. The response variables MRR (A-7 A, Ton-20 µs, V-125 V), TWR (A-1 A, Ton-10 µs, V-100 V), and SR (A-1 A, Ton-10 µs, V-150 V) have the best parameters, respectively (F. Khan et al., 2019). The use of Electrical Discharge Machining (EDM) method to reduce tool wear rate and surface quality in titanium alloys used in orthopaedic implants, focusing on pulse on time and voltage is investigated (Soundhar et al., 2019).A combination of grey relational analysis and principal component analysis to optimize the process input parameters during Electric Discharge Machining (EDM) of Inconel 825, resulting in significant enhancements in performance characteristics is used (Payal et al., 2019).The optimization of WEDM machining parameters using techniques like Taguchi Method, ANOVA, GRA, ANN, and PCA to improve material removal rate and surface roughness on super alloys, primarily driven by aerospace and npower industries are reviewed (Marelli et al., 2019).Process control parameters for wire-cut electrical discharge machining of D2 steel using Taguchi quality design concept is optimized. Results show current impacts material removal rate, wire speed affects surface roughness(A. Kumar et al., 2020). The Micro-electrical discharge machining process of Ti-6Al-4V alloy using Fuzzy TOPSIS and MCDM approaches is optimized. Results show MRR is directly proportional to capacitance and inversely proportional to over-cut, improving geometric accuracy and precision in micro-manufacturing applications (Dewangan et al., 2020). The impact of cutting parameters on component dimensions and shape tolerances using DIN 1.2316 plastic mild steel and Sumitomo Denko SBG type wire is examined. The optimal machinability was determined using GRA, achieving 9 mm/min table feed rate (Ay & Etyemez, 2020). A variation of EDM called magnetic field aided powder mixed electrical discharge machining (MFAPM-EDM) uses an electric and magnetic field in conjunction with fine powder added to the dielectric to enhance surface quality, machining speed, and process stability. Because of its increasing use in the automotive, marine, and aviation industries, aluminum 6061 alloy was chosen as the work piece. Parametric analysis and optimization were performed on MFAPM-EDM machined aluminum 6061 in this work(Rouniyar & Shandilya, 2021). Among the nonconventional machining process, the less heat affected zone with more accuracy of machining can be obtained from the WEDM process.

This WEDM has widely used to cut hard and complicated to machine. This can be able to machine the high corrosion resistant materials like super alloys in the application of aerospace, marine, and high temperature application(Natarajan et al., 2022). A comparative analysis of the algorithms showed that models based on the Support Vector Regression algorithm perform the best in predicting the roughness parameter Ra and machining time separately. SVR performs better with nonlinear data, making it more accurate in predicting machining time values than simpler regression models(Łomozik et al., 2023). The process parameters of die-sinking EDM are optimized for a variety of output responses in this study, utilizing copper electrodes and American Iron and Steel Institute (AISI) P20 tool steel work pieces(Tran et al., 2023). A novel technique that greatly increases prediction accuracy and machining results is the integration of Artificial Neural Network (ANN) modeling with various network structures for prediction and optimization with the CRITIC (Criteria Importance Through Inter criteria Correlation) -WASPAS (Weighted Aggregated Sum Product Assessment) multi-objective optimization method(Kavimani et al., 2024). The two primary categories of aluminum alloys are wrought alloys and cast alloys. Alloys are treated solidly in the first instance, but later they are liquefied in a furnace before being poured into molds. Aluminum alloys can be classified as either heat-treatable or non-heat-treatable based on the methods of strengthening that are employed(Juliyana et al., 2024). Ti-6Al-4 V alloy, which is favored in many industries because of its remarkable hardness, can be machined with the use of a new process called wire electric discharge machining (WEDM)(Agdale et al., 2025). A novel approach to metal cutting, Wire Electric-Discharge Machining (WEDM) offers the benefit of precision manufacturing above existing techniques. By using WEDM in both additive and subtractive manufacturing processes, the metal machining sector has benefited greatly in recent years in terms of high speed and accuracy(Afridi et al., 2025).

II. EXPERIMENTAL PLAN

A. Base Material and Sample Specimen

The goal of the experiment is to optimize machining parameters for Wire Cut EDM (WEDM) on a Mild Steel work piece to achieve the desired surface roughness, material removal rate (MRR), and dimensional accuracy. AISI 1026 Mild Steel is used as base material in the dimensions 50 × 50 × 20mm thickness. Figure 1 displays a schematic of the base metal work pieces. Figure 2 is the image of the plates. The hardness of Mild Steel (MS) AISI 1026 in Annealed Condition 120-160 HV. Prepared 9 work pieces and measured the weight of each MS work piece, and all the work pieces have the same weight. In WEDM, the wire used is brass-coated copper wire a thickness of 0.25 mm. Drilling will be performed on Wire EDM machine for 9 Mild Steel (AISI 1026) work pieces (50 × 50 × 20 mm) by cutting a 20 mm diameter circular profile using different machining parameters.

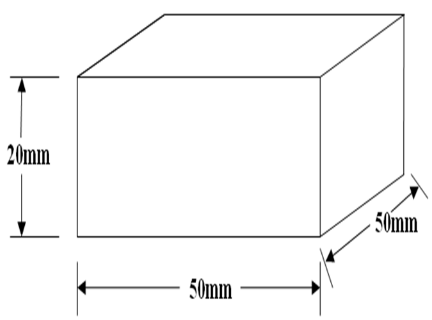

Fig. 1 - Schematic diagram of specimen

Fig. 2 – Sample Preparation of the work piece

Table 1: Chemical composition of AISI 1026

Base material	Chemical composition%			
	C	Mn	P	S
Mild steel	0.25	0.84	0.04	0.040

Fig. 3 Drilling Setup

Fig. 4 Wire-EDM Setup

Table 2: Level of parameters

Parameters	Unit	Level 1	Level 2	Level 3
Voltage	Volt	30	45	60
Pulse on time	µS	6	8	10
Pulse of time	µS	56	58	60

B. Selection of Response Parameters

Cutting Quality characteristics depend upon the response parameters MRR (Material Removing Rate), SR (Surface Roughness).

C. Selection of Input Process Parameters

Input parameter Are control factors influence the variation of response parameter based on considered literature review. Voltage, Pulse on time and Pulse off time are taken as input parameters.

D. Determination of Level Values

For the design of the experiment, three levels of process Parameters were used. And they are listed in table 2 the chosen voltage, pulse on time and pulse of time values have been determined by experience and literature review.

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III. METHODOLOGY

A. Taguchi Method

To analyze the result of the experiments for discharged water temperature, the signal-to-noise ratio (S/N) was utilized.
In this respect, higher-is-better characteristics for this response were selected to get maximum output temperature from evacuated tube collector.
The signal-to-noise ratio (S/N) was calculated using the Eq. (1)

$$S/N = -10log(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{r_i^2}) \qquad (1)$$

Using the larger-the-better criterion, the signal-to-noise ratio (S/N) is computed, where n is the total number of runs and r_i is the response at run number i.
Furthermore, a quantitative study employing variance analysis was carried out to evaluate these factors' efficacy and ascertain the degree of reliability associated with each parameter's ability to achieve the highest possible output water temperature. The ANOVA method was also used for statistical analysis to ascertain the statistical significance of each parameter. To determine which parameter had the greatest influence on the output water temperature and the highest ratio between the two variances, the F-test was used. Variances quantify how far data deviate from the mean. The larger the ratio, the greater the effect of the parameter on the evacuated tube collector response (FISHER, 1926). The ANOVA terms and formulas have shown in Table 3.

Table 3: ANOVA Terms and formulas (FISHER, 1926)

S. No.	Formula
1.	$C.F. = T^2/N$
2.	$S_T = \sum_{i=1\ to\ 18} X_i^2 - C.F.$
3.	$S_Y = \left(X_{Y1}{}^2/N_{Y1} + X_{Y2}{}^2/N_{Y2} + X_{Y3}{}^2/N_{Y3}\right)$
4.	$f_Y = (No.of\ levels\ of\ parameters\ Y) - 1$
5.	$f_T = (Total\ no.of\ results) - 1$
6.	$f_a = f_T + \sum f_Y$
7.	$V_Y = S_Y/f_Y$
8.	$S_e = S_T - \sum S_Y$
9.	$V_e = S_e/f_e$
10.	$F_Y = V_Y/V_e$
11.	$S'_Y = S_Y - (V_e \times f_z)$
12.	$P_z = S'_Y/S_T \times 100$
13.	$P_e = \left(1 - \sum P_Y\right) \times 100$

B. Topsis Method

The abbreviation TOPSIS represents the Technique for Order Preference by Similarity to Ideal Solution. Alternatives are selected and a normalized decision matrix is created in TOPSIS. As near to the ideal answer as possible and as far away from the negative-perfect solution as possible should be the chosen options. Any alternative's best performance values for each attribute combine to generate the positive ideal solution. Combining the poorest performance numbers yields the negative-ideal solution. Each attribute's optional weighting is used to measure proximity to each of these performances in the Euclidean sense (Muniappan et al., 2018).

C. Steps In Topsis Methods

1) Step -1 Create a standard decision matrix A. The decision matrix A for complete assessment questions with n evaluation units and m evaluation indexes is:

$$A = \begin{array}{c} \\ x_1 \\ x_2 \\ \dots \\ x_n \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & c_3 & c_m \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} \end{array}$$

In the equation $a_{pq} = c_q x_p$, the q^{th} assessment index of the p^{th} assessment unit (alternative project) is displayed p = 1,2,3……...,m; q = 1,2,3,……n . Transform matrix A into matrix B:

$$B = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \dots & \dots & \dots & \dots \\ b_{n1} & b_{n2} & \dots & b_{nm} \end{bmatrix}$$

$$b_{pq} = \frac{a_{pq}}{\sqrt{\sum_{p=1}^{n} a_{pq}^2}} \quad , q = 1,2,3\dots.m. \qquad (2)$$

2) Step -2 Create a weighted and standardized decision matrix D and a weight vector

W= $(w_1, w_2, w_3, \dots \dots \dots, w_n)$.

$$D = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1m} \\ d_{21} & d_{22} & \dots & d_{2m} \\ \dots & \dots & \dots & \dots \\ d_{n1} & d_{n2} & \dots & d_{nm} \end{bmatrix}$$

$$d_{pq} = w_j b_{pq}, \ p = 1,2,3\dots\dots..,n;\ q = 1,2,3,\dots\dots m. \qquad (3)$$

3) Step -3 Find the ideal solution x^+ and minus ideal solutions x^-.

$$x^+ = \{(\max d_{pq} | q \in I), (\min d_{pq} | q \in I') | p = 1,2,3 \dots\dots n\} = \{x_1^+, x_2^+ x_3^+ \dots x_m^+\} \qquad (4)$$

$$x^- = \{(\min d_{pq} | q \in I), (\max d_{pq} | q \in I') | p = 1,2,3 \dots\dots n\} = \{x_1^-, x_2^- x_3^- \dots x_m^-\} \qquad (5)$$

4) Step-4 Determine the Euclidean distance S_i^+ with the Equation given below,

$$S_i^+ = \left[\sum_{j=1}^{m} (d_{pq} - x^+)^2\right]^{0.5} \qquad (6)$$

5) Step -5 Determine the Euclidean distance S_i^- with the Equation given below,

$$S_i^- = \left[\sum_{j=1}^{m} (d_{pq} - x^-)^2\right]^{0.5} \qquad (7)$$

6) Step -6 Determine the Performance score (Pi) with the equation given below

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \qquad (8)$$

The value of P_i lies between 0 and 1($0 \le P_i \le 1$)

7) Step -7 Rank the options of alternatives in decreasing order of P_i.

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IV. RESULT AND DISCUSSION

The TOPSIS method is one of the multi-criteria decision-making (MCDM) strategies. It serves as a kind of ranking system. It examines the problem from both a quantitative and qualitative perspective. Compared to the analytical hierarchy process (AHP) and fuzzy analytic hierarchy process (FAHP) approaches, the TOPSIS strategy provides the best and fastest answer in our real-life scenarios. The TOPSIS approach selects the sample with the best result from the nine experiments in the current study.

Table 4: Coded & decoded - Design of experiment based on L-9 orthogonal array

	Coded			Decoded		
Exp. No.	voltage	Pulse on time	Pulse off time	voltage	Pulse on time	Pulse off time
1	1	1	1	30	6	56
2	1	2	2	30	8	58
3	1	3	3	30	10	60
4	2	1	2	45	6	56
5	2	2	3	45	8	60
6	2	3	1	45	10	56
7	3	1	2	60	6	60
8	3	2	1	60	8	56
9	3	3	2	60	10	58

The coded or decoded wire EDM control parameter values are shown in Table 4. For a total of nine studies, it contains multiple parameter settings, with distinct control parameters being changed for every experimental run.

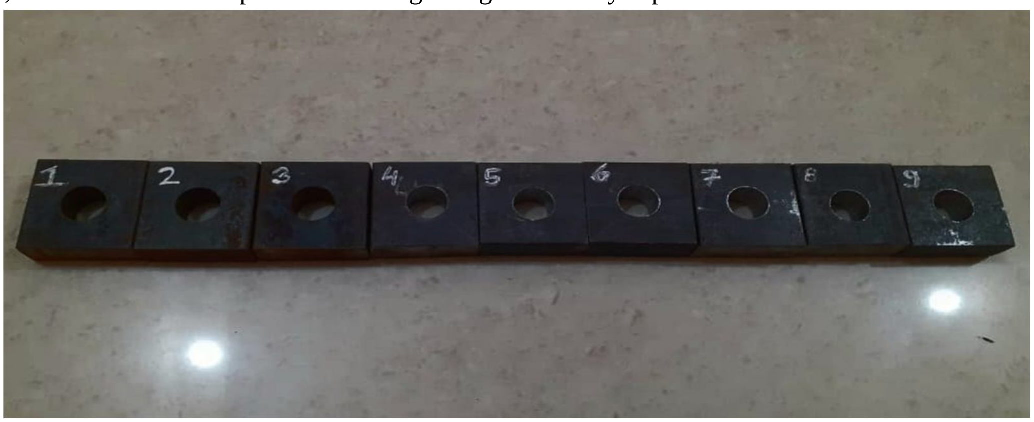

Fig. 5 Work piece after hole cutting

Nine work pieces with holes created using wire EDM in accordance with the Taguchi orthogonal array are shown in Figure 5.

Table 5: Responses - Material removing rate, surface roughness

S. No.	MRR	SR
1	0.3410	2.7999
2	0.3274	2.5866
3	0.3255	2.4896
4	0.3604	2.9876
5	0.3218	2.3796
6	0.3142	2.1967
7	0.3352	2.6857
8	0.3488	2.8756
9	0.3222	2.2567

Table 6: Normalised Matrix – Material removing rate, surface roughness

S. No.	MRR	SR
1	0.3412	0.3599
2	0.3275	0.3325
3	0.3256	0.3200
4	0.3606	0.3666
5	0.3219	0.3059
6	0.3143	0.2901
7	0.3354	0.3452
8	0.3490	0.3825
9	0.3223	0.2824

The MMR and SR observed values, derived from various trials, are shown in Table No. 5. The normalized values of MRR and SR, which were calculated using Equation No. 2, are displayed appropriately in Table No. 6.

Table 7: Summarized calculation of the TOPSIS with Rank

S. No.	MRR	SR	Si^+	Si^-	Pi	Rank
1	0.3412	0.3599	0.0297	0.0820	0.7341	3
2	0.3275	0.3325	0.0599	0.0518	0.4637	5
3	0.3256	0.3200	0.0717	0.0392	0.3534	6
4	0.3606	0.3666	0.0158	0.0960	0.8586	2
5	0.3219	0.3059	0.0857	0.0246	0.2230	7
6	0.3143	0.2901	0.1032	0.0077	0.0694	9
7	0.3354	0.3452	0.0450	0.0662	0.5953	4
8	0.3490	0.3825	0.0116	0.1059	0.9012	1
9	0.3223	0.2824	0.1071	0.008	0.0695	8
E^+	0.3606	0.3825				
E^-	0.3143	0.2824				

Table 8: S/N ratio of PI

S. No.	Voltage	Pulse on time	Pulse off time	PI	SNRA1
1	30	6	56	0.7341	-2.6849
2	30	8	58	0.4637	-6.6753
3	30	10	60	0.3534	-9.0347
4	45	6	58	0.8586	-1.3242
5	45	8	60	0.2230	-13.0339
6	45	10	56	0.0694	-23.1728
7	60	6	60	0.5953	-4.5053
8	60	8	56	0.9012	-0.9036
9	60	10	58	0.0695	-23.1603

Equation No. 7 was used to calculate the Positive Ideal Solution and Negative Ideal Solution, and Equation No. 8 was used to determine the Performance Index, which is shown in Table No. 7. Each experiment has been ranked according to the Performance Index. The experiment with the greatest Performance Index, Experiment No. 8, was carried out with a voltage of 60 volts, a pulse-on time of 8 microseconds, and pulse-off duration of 56 microseconds. So it has been given Rank 1.

Equation 1 has been used to determine the signal-to-noise ratio (S/N Ratio) for Performance Index in Table No. 8.

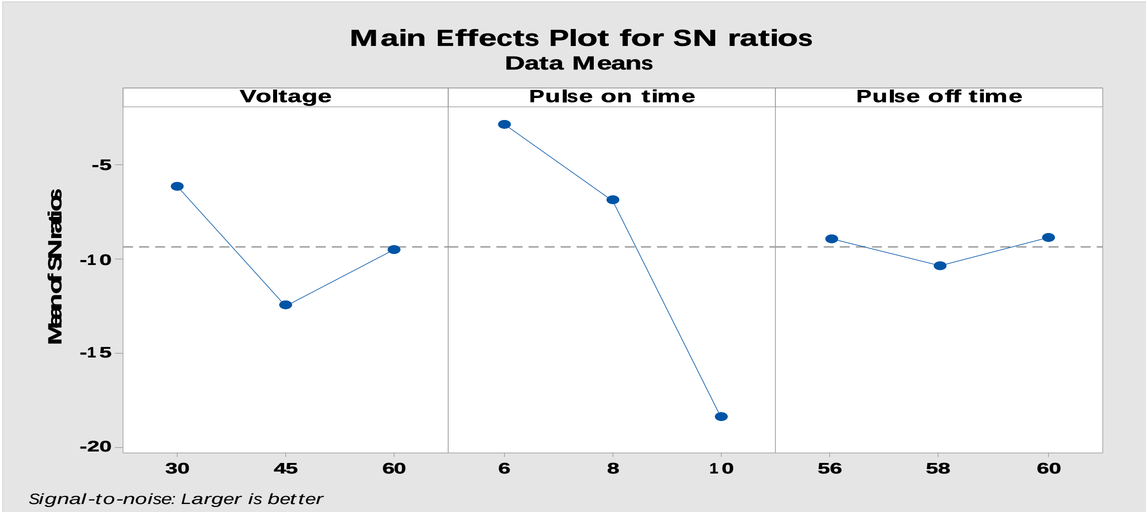

Fig. 6 Main Effects Plot for SN ratios

The best parameter settings were determined to be voltage at 30, pulse on time at 6, and pulse off time at 60, as shown in the main effect plot for the S/N ratio in Figure 6.

Table 9: ANOVA Table corresponding to S/N ratio

Source	DF	Seq SS	Contribution	Adj SS	Seq MS	F-Value	P-Value
Voltage	2	0.03696	4.52%	0.03696	0.01848	0.15	0.867
Pulse on time	2	0.49287	60.27%	0.49287	0.24644	2.05	0.328
Pulse off time	2	0.04783	5.85%	0.04783	0.02391	0.20	0.834
Error	2	0.24010	29.36%	0.24010	0.12005		
Total	8	0.81776	100.00%				

Regression Equation

S/N of PI = 0.474 + 0.043 Voltage_30 - 0.091 Voltage_45 + 0.048 Voltage_60 + 0.255 Pulse on time_6 + 0.055 Pulse on time_8 - 0.310 Pulse on time_10 + 0.094 Pulse off time_56 - 0.010 Pulse off time_58 - 0.084 Pulse off time_60 (9)

ANOVA is a technique frequently used to examine the extent to which each response's variation is caused by the total variance attributable to the factors. It displays the percentage impact of each process parameter on the output responses, evaluating the effects of parameters such as voltage, pulse-on time, and pulse-off time (as shown in Table 9). According to the ANOVA table, pulse-on time has the highest percentage contribution at 60.27%, making it the most significant parameter for all responses. Therefore, the output responses are largely influenced by pulse-on time. In contrast, among the experimental characteristics, voltage had the lowest percentage of contribution.

This study combines several quality attributes into a single performance factor, allowing for the determination of the optimal parameter combination using the traditional Taguchi approach. Additionally, the regression analysis indicates that the polynomial Equation 9 can be used to calculate the S/N ratio of the wire-cut performance score.

V. CONCLUSION

The study found that applying the Taguchi-TOPSIS technique to optimise WEDM process parameters for AISI 1026 mild steel is successful and results in notable performance gains. Surface roughness and material removal rate were combined into a single composite response using TOPSIS. With a performance ratio of -0.9012 and the highest score, Experiment No. 8 came in first place. The ideal parameters were voltage level 1, pulse-on time level 1, and pulse-off time level 3, according to Signal-to-Noise (S/N) ratios.

The percentage contribution of each parameter was calculated using ANOVA. To forecast performance index values, a regression equation was created. The efficacy of the approach was confirmed by confirmation tests with 30 V, 6 µs pulse-on time, and 60 µs pulse-off duration, which produced an S/N ratio of -0.8569.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article.

Disclosures and declarations

1. Funding: This research received no external funding.

2. Conflicts of Interest: The authors declare no conflict of interest.

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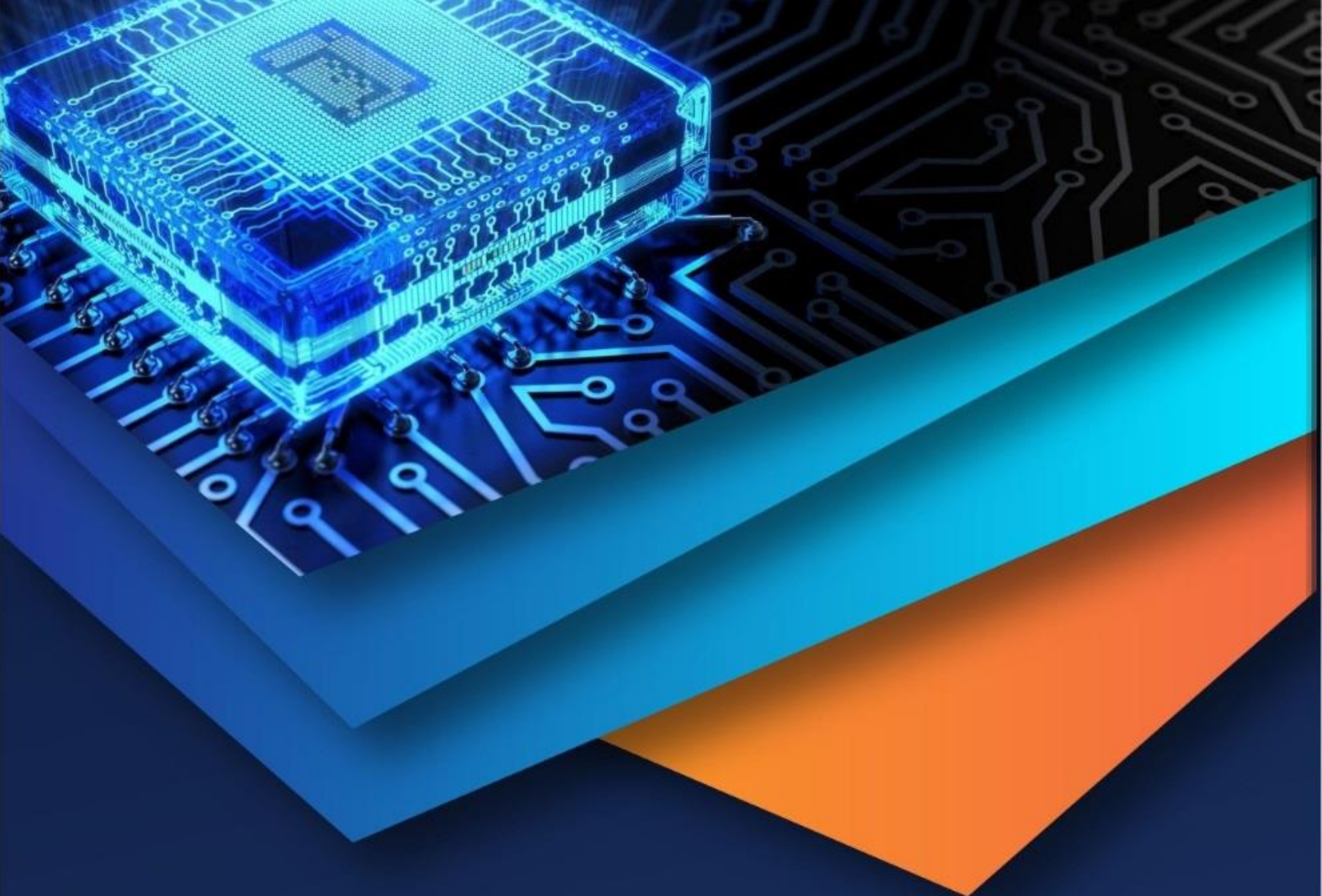

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