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Optimization of Material Removal Rate and Electrode Wear Rate in EDM Machining of D2 Steel Using Al–Cu–SiC Nanocomposite Powder Metallurgy Electrodes: a Taguchi and ANN-based Approach

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ABSTRACT

In this research study, a novel Al–Cu–SiC composite tool, created using the powder metallurgy (P/M) technique, was used for the electrical discharge machining of D2 steel, and the effects of important process parameters were investigated. The experimental runs were organized using a Taguchi-based design, and prediction models were constructed using artificial neural network techniques. This study was focused on machining performance, employing material removal rate (MRR) and electrode wear rate (EWR) as essential performance indicators and peak current, dielectric flushing pressure, and pulse on time as crucial input parameters. To evaluate the significance and suitability of the regression models created, an Analysis of Variance was conducted. The results showed that Al–Cu–SiC P/M electrodes were more sensitive to peak current and pulse duration. Increasing pulse duration significantly influenced MRR and EWR, with optimal values (MRR of 0.5880 g/min and minimal EWR) attained at a current of 9 A and a pulse length of 80 µs. Taguchi analysis identified pulse duration as the primary determinant; Regression equations emphasized pulse duration and current as critical factors for MRR, whereas ANN optimization effectively forecasted EDM results (R > 0.97), demonstrating decreased errors and reliable model performance across datasets.

Keywords: Taguchi L_{27}; ANN; MRR; EWR; Novel Composite; EDM.

1. INTRODUCTION

For hard materials, EDM is a popular non-traditional machining technique when accurate material removal and tool wear management are essential. In this work, a unique Al–Cu–SiC nanocomposite electrode, created using powder metallurgy (P/M) methods was used to examine the effects of important EDM parameters on D2 steel. The study optimized material removal rate (MRR) and tool wear rate (TWR) using Taguchi and ANN-based models, providing information on the composite electrode's increased sensitivity to certain machining parameters. Walia *et al.* 2021 successfully optimized machining parameters using Taguchi techniques, showing a notable increase in tool wear and machining efficiency during EDM. Artificial neural networks have also been used to forecast machining results, improving the precision of parameter changes and facilitating better management of tool shape changes in hardened steels (Singh *et al.* 2020). Studies have used Taguchi techniques to improve surface roughness and overall machining performance by optimizing machining parameters in EDM. Furthermore, the combination of an adaptive neuro-fuzzy inference system (ANFIS) and ANN has shown efficacy in modeling and forecasting machining results, with ANFIS demonstrating higher accuracy in evaluating roughness compared to conventional ANN techniques. Ramesh and Satish, (2022) investigated the EDM of aluminum alloy, reinforced with 10% silicon carbide, and have shown that copper electrodes of diverse geometries substantially influence machining efficiency. Utilizing Taguchi in conjunction with Principal Component Analysis (PCA), Cuckoo Search (CS), Firefly Algorithm (FA) optimization methods, researchers attained elevated removal rates while reducing electrode wear and recast layer thickness, which are critical for high-performance applications.

Navuluri *et al.* (2024) studied the machining of hardened D2 steel with copper-silicon carbide composite tools and found a substantial decrease in wear and roughness. Optimization using response surface methods and central composite design(CCD) design determined ideal settings, resulting in a tool wear rate of 0.39 gm/min and a surface roughness of 2.8 µm, hence assuring great accuracy and cost-effectiveness. Raza *et al.* (2018) studied the EDM of Al6061-SiC composites and found that the choice of electrode material substantially influences machining results, with brass yielding a 23.2% increase in MRR and a 20.3% enhancement in surface polish compared to stainless steel. Singh *et al.* 2017 focused on EDM of Al6061-SiC composites with sintered Cu-W electrodes, demonstrating enhanced output performance attributable to material transfer phenomena. Optimization using response surface methods have shown that peak current, pulse length, and gap voltage greatly influence machining results, improving surface integrity and recast layer properties. Jose *et al.* (2024) focused on EDM and Near-dry EDM of aluminum alloy hybrid composites and found that the features of tool materials, such as thermal conductivity and bonding strength, significantly influence the removal rates and roughness. The TOPSIS approach discovered ideal conditions for the use of copper composite tools with Al_2O_3 powder concentration to enhance MRR and SR, leading to smoother surfaces and less tool wear. Surya *et al.* (2017) studied WEDM of Al7075-TiB_2 in-situ composites using Taguchi's L27 orthogonal array and have shown that the input factors and bed speed substantially influenced machining results. The ANN model optimized predictions of the removal rate of metal, dimensional inaccuracy, and roughness, closely matching experimental outcomes. Ponappa *et al.* (2019) investigated the EDM of Al7075/TiC/B_4C hybrid composites indicating that pulse current is essential for optimizing metal removal rates, reducing electrode wear, and decreasing roughness. The research used a complete factorial design and genetic algorithm for multi-objective optimization, resulting in optimum parameter settings for high-performance machining with enhanced surface characteristics. Bhowmick *et al.* (2023) investigated the EDM of Al7075/TiC/B_4C hybrid composites and found that the pulse current is essential for optimizing metal removal rates, reducing electrode wear, and decreasing roughness. The research used a complete factorial design for multi-objective optimization, resulting in optimum parameter settings for high-performance machining with enhanced surface characteristics. The investigation carried out by Mathan *et al.* (2024) on the EDM of titanium alloy using a Cu–TiB_2 composite electrode revealed that current and pulse length considerably influence the output responses. RSM optimization found optimal settings (15 A current, 150 µs pulse duration, 50 V) for enhanced MRR, while reverse polarity increased surface smoothness, EDS analysis verified efficient material transfer with 63.13 wt. % boron on the machined surface. Ramdatti *et al.* (2021) investigated the EDM of die steel with a copper composite electrode fabricated by powder metallurgy, with the optimization output factors accomplished *via* response surface methodology and composite attractiveness. The results demonstrated that the ideal process parameters provide MRR and TWR forecasts with errors of 5.19% and −3.33%, respectively. Dey *et al.* (2017) investigated the EDM machining of compo-casted Al6061/cenosphere AMCs, a hybrid optimization strategy including RSM- and PSO-optimized critical parameters, current and pulse duration, resulting in improved MRR, SR, and EWR. The Taguchi L_{27} design and mathematical modeling produced dependable multi-response optimization, with experimental outcomes closely aligning with expected values under diverse processing circumstances. Justin, R. Y *et al*. (2024), in their work, emphasized the improved EDM machining of D2 die steel with a cost-efficient aluminum-based nanocomposite electrode, to optimize removal rate and minimize wear. Optimal settings established by RSM resulted in a maximum MRR of 0.0099 mm³/min at 12 A, with a pulse ON duration of 70 µs and a pulse OFF time of 90 µs, highlighting the electrode's efficacy in die-sinker EDM applications. Justin *et al.* (2024) focused on optimizing EDM settings for Inconel 718 using a Cu-Ni-B_4C nanocomposite electrode to increase MRR, EWR, and SR, showcasing significant improvements in machining efficiency. At 8 A, with a pulse length of 50 µs and a pulse interval of 90 µs, the MRR rose to 0.0118 g/min, whilst the EWR and SR decreased to 0.001 g/min and 3.108 µm, respectively, with convolutional neural network models attaining the maximum prediction accuracy ($R^2 = 0.9999$). Justin *et al.* (2024) explored the EDM machining of AISI D2 die steel with an Al-Ni composite electrode, investigating the impacts of current, pulse length, and interval on material removal rate, tool wear rate, and surface roughness. The findings demonstrated that increased current and extended pulse-off durations significantly decreased TWR, with an ANN model attaining an R-value of 1.00, indicating exceptional prediction precision for machining results. Naveenprabhu *et al*. (2024) analyzed the thermal properties of SiC- and MgO-reinforced aluminum matrix composites (AMCs), emphasizing their enhanced thermal fatigue resistance, microstructural stability, and appropriateness for high-temperature applications in the automotive and aerospace sectors. Ramu *et al*. (2023) examined e-glass fiber/epoxy composites with different concentrations of aluminum powder and MWCNTs, attaining a maximum thermal conductivity of 0.3057 W/m-K and exhibiting an optimal balance of tensile and impact strengths, with slight reductions in the mechanical properties as MWCNT content increased. De *et al.* (2023) developed an environmentally sustainable Al-ZrO_2 alloy composite from waste Al/Mg scrap by stir casting, demonstrating a 57.7% enhancement in impact toughness and a 13.66% increase in hardness with the incorporation of 15 wt. % ZrO_2 relative to the base material.

This research is aimed at improving the electrode wear and material removal rate in the EDM machining of D2 steel. Various EDM input parameter settings were tested experimentally using a new Al–Cu–SiC composite electrode made by P/M techniques. To maximize process results, a Taguchi-based design in conjunction with ANN and Taguchi approaches was used. Confirmation experiments were used to identify and verify the ideal parameter values, which showed a significant increase in MRR and decreased tool wear. Thus, this study made a valuable contribution to material processing methods for hard alloys by providing important insights into the use of composite electrodes in EDM.

2. MATERIALS AND METHODS

2.1 Tool Materials

Electrode wear rate and metal removal rate were chosen as the study's primary metrics to evaluate machining performance. Peak current, pulse on time, and pulse off time were the input machining parameters that were examined in connection with MRR and TWR. To conduct the experiments, an EMS 350 die-sinking EDM machine was used. A sintered Al–Cu–SiC composite, created by P/M and hot extrusion to decrease porosity, served as the EDM tool electrode. All of the compacted electrodes in this composite have particle sizes under 50 µm and are made of an aluminum matrix with 5% Cu and 10% SiC. An electrolytic copper rod having a negative polarity, measuring 15 mm by 30 mm, was connected to the sintered electrode. Several studies were then carried out using this extruded sintered electrode to look at surface changes using EDM. Fig. 1 shows the tool electrode.

Fig. 1: Aluminum composite tool electrode

2.2 Workpiece Materials

This experiment examined the performance of EDM machining on a 30 mm diameter D2 die steel specimen that was 10 mm thick. The steel was cut with a 2 mm diameter hole utilizing the Al–Cu–SiC composite electrode. The electrode was connected to an electrolytic copper rod in negative polarity. To evaluate their impact on the machining results, the EDM process parameters: peak current, flushing pressure, and pulse-on time were changed. This configuration offered a controlled setting for assessing surface properties and machining performance in D2 steel with cutting-edge composite electrodes.

Table 1. Input parameters for EDM machining

S. No.	Current	Pulse-on	Pulse-off
1	3	40	100
2	6	80	150
3	9	120	200

1.3 Input Parameters

Three experimental settings with different input factor levels are shown in Table 1 along with a set of machining parameters employed in the EDM process. In the initial configuration, 3 A of current, 40 µs of pulse duration, and 100 µs of pulse interval were applied; in the second condition, these values were raised to 6 A, 80 µs, and 150 µs, respectively. These parameters were subsequently increased to 9 A, 120 µs pulse duration, and 200 µs pulse time in the third condition. A methodical examination of the effects of increased current and different pulse durations on EDM machining performance was made possible by this sequence of parameter adjustments.

2.4 Output Parameters

Before and after each experiment, the workpiece and tool electrode were properly cleaned, dried, and weighed on a precision scale with an accuracy of 0.1 mg. MRR and TWR were determined by dividing the weight loss of each component by the overall machining duration.

2.5 EDM Machining Oil

Kerosene served as the dielectric fluid for the EDM technique in this experiment. When enough power is given, kerosene's insulating properties allow for steady spark production while avoiding premature discharges. Additionally, it aids in cooling the electrode and workpiece, avoiding excessive heat accumulation that might change the material's characteristics and the precision of the machining. Kerosene also helps remove debris that can obstruct regular sparking by washing away the degraded material particles from the spark gap.

It is appropriate for applications requiring D2 steel and composite electrodes because of its particular advantages in EDM, which include minimizing electrode wear and producing smooth surface finishes.

Table 2. EDM Machining - Experimental inputs and outputs

Run	Current (A)	Pulse-on (B)	Pulse-off (C)	MRR (g/min)	EWR (g/min)
1	3	40	100	0.3101	0.0564
2	3	40	150	0.3416	0.0561
3	3	40	200	0.4380	0.0563
4	3	80	100	0.4268	0.0562
5	3	80	150	0.4996	0.0687
6	3	80	200	0.5638	0.0731
7	3	120	100	0.4250	0.0673
8	3	120	150	0.4378	0.0572
9	3	120	200	0.4716	0.0677
10	6	40	100	0.3210	0.0577
11	6	40	150	0.3516	0.0531
12	6	40	200	0.4490	0.0653
13	6	80	100	0.4268	0.0562
14	6	80	150	0.4716	0.0687
15	6	80	200	0.5468	0.0761
16	6	120	100	0.4690	0.0653
17	6	120	150	0.4528	0.0562
18	6	120	200	0.4826	0.0667
19	9	40	100	0.3231	0.0731
20	9	40	150	0.4273	0.0526
21	9	40	200	0.2660	0.0532
22	9	80	100	0.5770	0.0724
23	9	80	150	0.3660	0.0754
24	9	80	200	0.4810	0.0525
25	9	120	100	0.4346	0.0535
26	9	120	150	0.4028	0.0565
27	9	120	200	0.4348	0.0556

2.6 Optimization Techniques

In this study, the EDM process parameters for milling D2 steel using Al composite electrodes were optimized using the Taguchi technique and ANN. The effects of changing input on performance were methodically examined using an experimental design in the Taguchi technique. The S/N ratio analysis of the findings allowed for the identification of the best parameter values to improve machining performance. Using the experimental data, an ANN model was created concurrently to capture intricate, non-linear interactions between the input parameters and the results of the machining process. A thorough grasp of how to maximize EDM performance while reducing electrode wear was made possible by this combination strategy, which enabled effective parameter space exploration and produced precise forecasts.

3. RESULTS AND DISCUSSION

With the maximum MRR and lowest electrode wear at a peak current of 6 A and a pulse duration of 182 µs, the findings show that the Al composite electrode improves EDM performance on D2 steel. Compared to traditional choices, the electrodes exhibit increased sensitivity to changes in peak current and pulse on time. Understanding the complex interactions between process parameters was made possible by optimizing using ANN and the Taguchi technique. Regression model validation verified that the predictions were reliable. Fig. 2 shows the workpiece after machining with EDM.

Table 2 summarizes the experimental results of EDM using varying settings of input factors, presenting the removal rates of metal and tool wear for each combination of parameters. The data indicates that MRR generally increases with higher pulse duration and current levels, while EWR exhibits slight variations but tends to remain relatively low, reflecting efficient machining with the Al composite electrode. For example, at a current of 9 A and a pulse duration of 80 µs, the MRR reached its peak value of 0.5880 g/min, showcasing the effectiveness of optimizing these parameters. Overall, the findings illustrate the relationship between EDM parameters and machining efficiency.

Fig. 2: D2 Workpiece after EDM machining

Table 3. Material Removal Rate Response Table for Signal-to-Noise Ratios

Level	Current	Pulse-on	Pulse-off
1	-7.356	-9.031	-7.852
2	-7.206	-6.381	-7.671
3	-7.882	-7.033	-6.922
Delta	0.675	2.649	0.930
Rank	3	1	2

Table 3 presents the material removal rate signal-to-noise (S/N) ratios for an EDM process where a "larger-is-better" criterion is applied. Among the factors, Pulse duration has the greatest effect on performance, with the highest delta (2.649), ranking it as the most influential parameter. Current shows the least influence, with the smallest delta (0.675), ranking it third in significance.

Table 4. Material removal rate responset for means

Level	Current	Pulse-on	Pulse-off
1	0.4349	0.3586	0.4126
2	0.4412	0.4844	0.4168
3	0.4125	0.4457	0.4593
Delta	0.0287	0.1257	0.0467
Rank	3	1	2

Table 4 shows the mean responses for each parameter level in an EDM process. Pulse duration has the highest influence on the outcome, with the largest delta value (0.1257), making it the most significant factor. Current has the smallest delta (0.0287), ranking it as the least influential parameter.

Table 5. Electrode wear rate response table for signal-to-noise ratios

Level	Current	Pulse On	Pulse Off
1	24.18	24.75	24.21
2	24.09	23.61	24.43
3	24.46	24.38	24.10
Delta	0.37	1.14	0.34
Rank	2	1	3

This response Table 5 shows the signal-to-noise (S/N) ratios of electrode wear rate for an EDM process, following a "smaller is better" approach. Among the parameters, Pulse-on has the highest influence on the response with a delta of 1.14, making it the most significant factor. Current has a moderate effect with a delta of 0.37, while Pulse-off has the least influence, ranking third.

Table 6. Electrode wear rate response table for means

Level	Current	Pulse-on	Pulse-off
1	0.06211	0.05820	0.06201
2	0.06281	0.06659	0.06050
3	0.06053	0.06067	0.06294
Delta	0.00228	0.00839	0.00244
Rank	3	1	2

Table 6 displays the mean values for each parameter level in an EDM process. Pulse-on has the largest effect, with a delta of 0.00839, ranking it as the most influential parameter. Pulse-off has a moderate impact with a delta of 0.00244, while Current has the smallest effect, ranking third in significance.

This regression equation (1) models the removal rate of material in grams per minute for EDM based on specific values of input settings. Each coefficient represents the effect of a particular level of these parameters on MRR, with positive values indicating an increase and negative values indicating a decrease in MRR. The equation allows the prediction of MRR by plugging in the levels for each parameter.

3.4 Regression Equation of MRR

$$\begin{aligned} \text{MRR (g/min)} = {} & 0.4296 + 0.0054\ \text{Current (A)\_3} \\ & + 0.0117\ \text{Current (A)\_6} \\ & - 0.0170\ \text{Current (A)\_9} \\ & - 0.0709\ \text{Pulse On (B)\_40} \\ & + 0.0548\ \text{Pulse On (B)\_80} \\ & + 0.0161\ \text{Pulse On (B)\_120} \\ & - 0.0170\ \text{Pulse Off (C)\_100} \\ & - 0.0128\ \text{Pulse Off (C)\_150} \\ & + 0.0297\ \text{Pulse Off (C)\_20} \end{aligned} \quad \ldots.\ (1)$$

3.5 Regression Equation of EWR

$$\begin{aligned} \text{EWR (g/min)} = {} & 0.06182 + 0.00029\ \text{Current (A)\_3} \\ & + 0.00099\ \text{Current (A)\_6} \\ & - 0.00129\ \text{Current (A)\_9} \\ & - 0.00362\ \text{Pulse On (B)\_40} \\ & + 0.00477\ \text{Pulse On (B)\_80} \\ & - 0.00115\ \text{Pulse On (B)\_120} \\ & + 0.00019\ \text{Pulse Off (C)\_100} \\ & - 0.00132\ \text{Pulse Off (C)\_150} \\ & + 0.00113\ \text{Pulse Off (C)\_200} \end{aligned} \quad \ldots.\ (2)$$

The regression equation (2) predicts the wear rate of the tool in grams per minute for EDM, based on specific levels of input settings. Each term represents how different settings of these parameters impact EWR, with positive coefficients increasing EWR and negative ones reducing it. By inputting parameter levels, the equation provides an estimated EWR value.

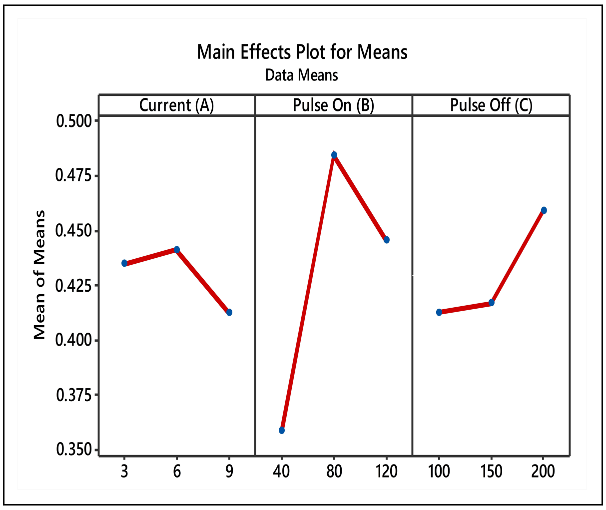


Fig. 3: Main Effects Plot for MRR

The Main effects plot (Fig. 3) shows the influence of input factors on the mean response in an EDM process. Pulse-on has the most significant effect, with a peak at 80, indicating the highest mean response at this level. Pulse-off also shows an increasing trend, especially at the 200 level, while Current (A) has a smaller and relatively flat effect.

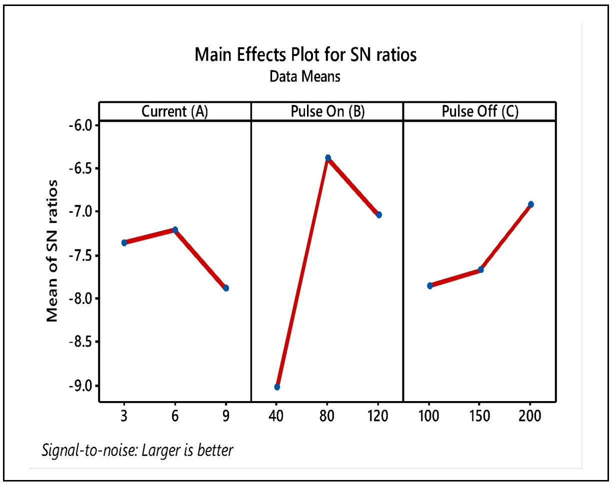


Fig. 4: Signal-to-Noise Ratio Plot for MRR

The Signal-to-Noise Ratio Plot for MRR S/N ratios (Fig. 4) demonstrates the impact of factors settings on process performance under a "larger is better" criterion. Pulse duration has the greatest effect, showing a peak at level 80, indicating optimal S/N performance at this level. Current has the smallest impact, while Pulse interval shows improvement at level 200.

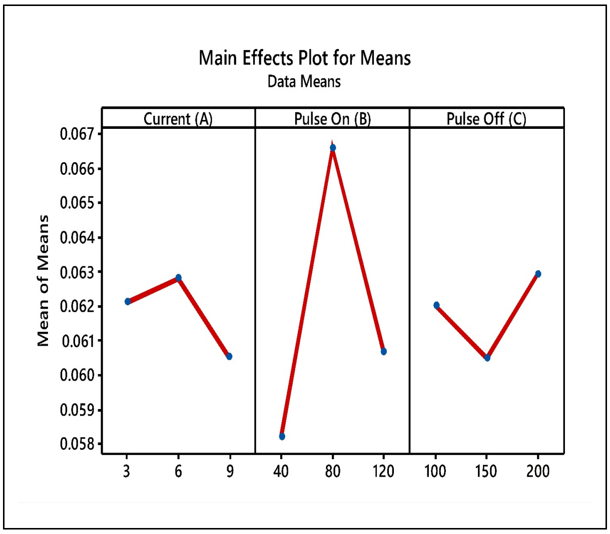


Fig. 5: Signal-to-Noise Ratio Plot for EWR

The plot shown in Fig. 5 follows a "smaller is better" criterion, illustrating the influence of input on the response. Pulse duration has the most significant effect, with a minimum S/N ratio at level 80, indicating the highest impact on reducing variability. Current and pulse intervals have less pronounced effects, showing smaller changes across their levels.

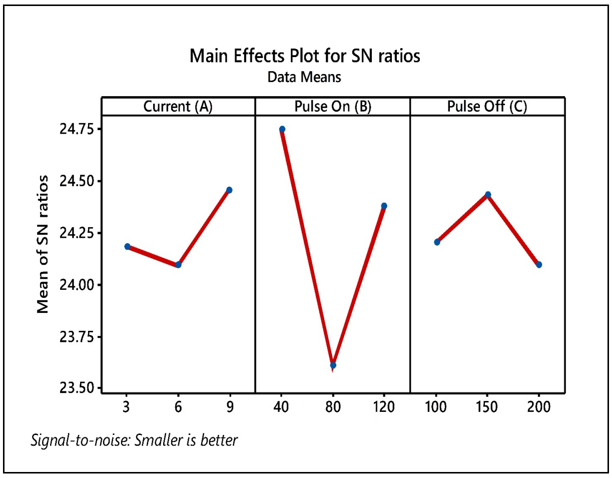
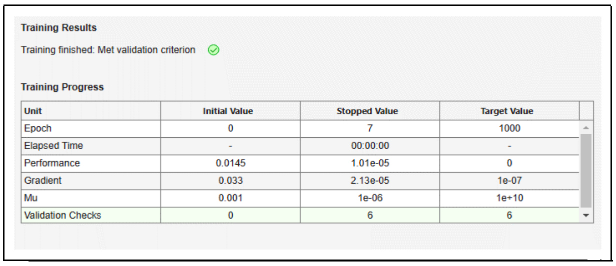


Fig. 6: Main Effects Plot for EWR

The main effects plot shown in Fig. 6 depicts the influence of the three factors on the mean response variable in a Taguchi experimental setup. Each factor has three levels, and the mean responses were plotted to identify which levels maximize or minimize the response. Pulse timing at level 80 has the highest mean, indicating it significantly impacts the response variable. This analysis helps in optimizing levels to improve the EDM machining output responses, such as reduced electrode wear rate.


Training Results

Training finished: Met validation criterion

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	7	1000
Elapsed Time	-	00:00:00	-
Performance	0.0145	1.01e-05	0
Gradient	0.033	2.13e-05	1e-07
Mu	0.001	1e-06	1e+10
Validation Checks	0	6	6

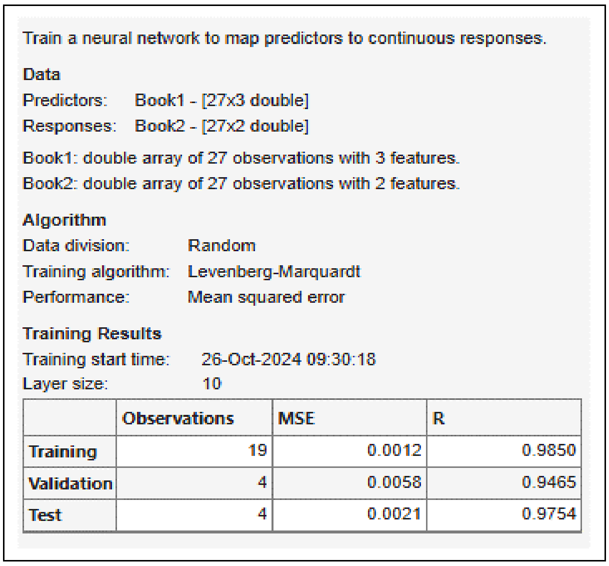
Fig. 7: ANN Training Result Analysis

3.6 ANN Optimization

The training results of an ANN model are shown in Fig. 7. The training stopped at epoch 7, meeting the validation criterion with a final performance of 1.01e^{-05}, close to the target of 0. The gradient reached 2.13 x 10^{-05}, above the very small target threshold of 1e^{-07}, and validation checks were completed at the sixth attempt, meeting the stopping criterion.

The ANN training summary (Fig. 8) shows model performance in predicting continuous responses using Leven Berg-Marquardt. The dataset has 27 observations, with 19 for training, 4 for validation, and 4 for testing. Mean squared error (MSE) values for training, validation, and testing are 0.0012, 0.0058, and

0.0021, respectively, indicating accuracy. The correlation coefficients (R) of 0.9850, 0.9465, and 0.9754 suggest strong predictive capability across all phases.



Train a neural network to map predictors to continuous responses.

Data
Predictors: Book1 - [27x3 double]
Responses: Book2 - [27x2 double]

Book1: double array of 27 observations with 3 features.
Book2: double array of 27 observations with 2 features.

Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error

Training Results
Training start time: 26-Oct-2024 09:30:18
Layer size: 10

	Observations	MSE	R
Training	19	0.0012	0.9850
Validation	4	0.0058	0.9465
Test	4	0.0021	0.9754

Fig. 8: ANN Analysis of Output Performance

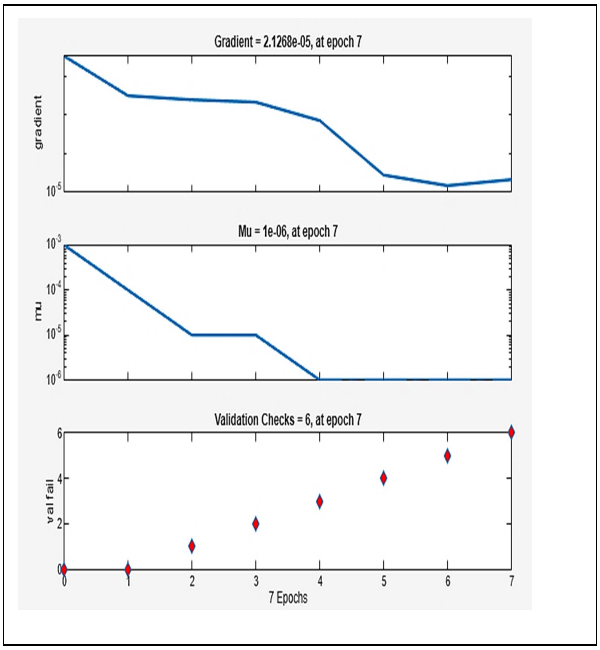


Fig. 9: ANN Training Progress

Fig. 9 shows the ANN training progress over 7 epochs. The top graph indicates the gradient decreasing to 2.1268e^{-05}, showing convergence. The middle graph displays Mu (learning rate parameter) reducing to 1e^{-06}, indicating stability in learning. The bottom graph shows validation checks reaching 6 at epoch 7, which triggers stopping based on the validation performance criteria.

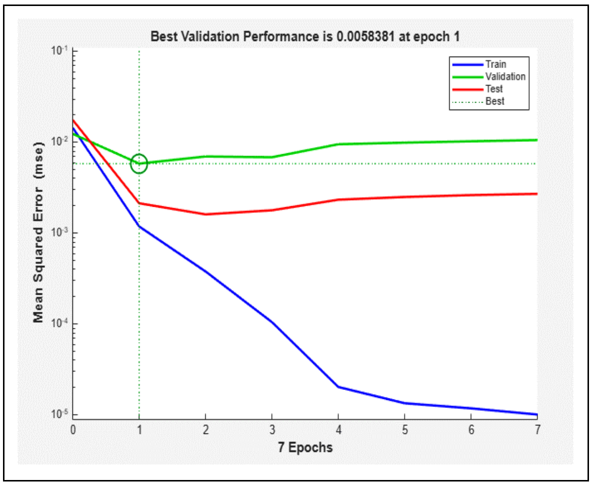


Fig. 10: ANN Analysis of MSE

Fig. 10 shows the mean square error across training, validation, and test sets over 7 epochs in an ANN model. The best validation performance, with an MSE of 0.0058, was achieved at epoch 1. After this point, validation and test errors (green and red lines) remain relatively stable, while training error (blue line) continues decreasing, indicating potential overfitting.

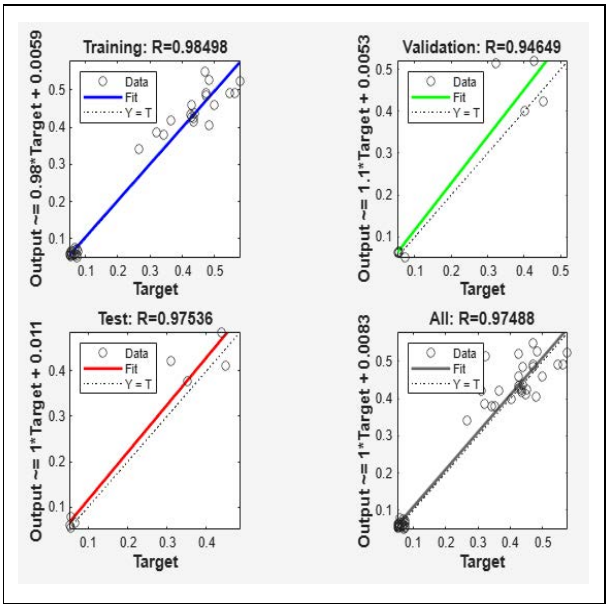


Fig. 11: ANN Analysis of Actual and Predicted Values

Fig. 11 presents the scatter plots depicting the relationship between the target variable and the predicted output for training, validation, and test datasets. The diagonal dotted line represents the ideal line where output equals target. The R-values indicate strong correlations for each dataset, with the respective linear equations for data fitting.

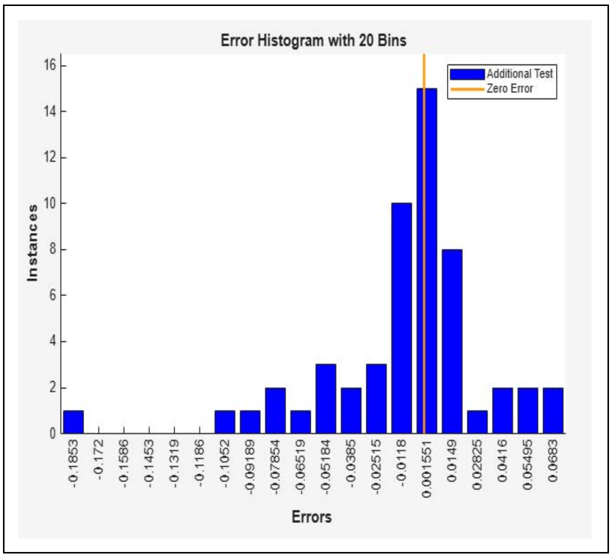


Fig. 12: ANN Analysis of Error Histogram

The histogram displays the distribution of errors from an artificial neural network analysis (Fig. 12), with errors binned into 20 intervals. The majority of the errors are concentrated near zero, as indicated by the peak at zero error. Additionally, the plot distinguishes between "Zero Error" and additional test data, with the former represented by an orange line showing the error concentration.

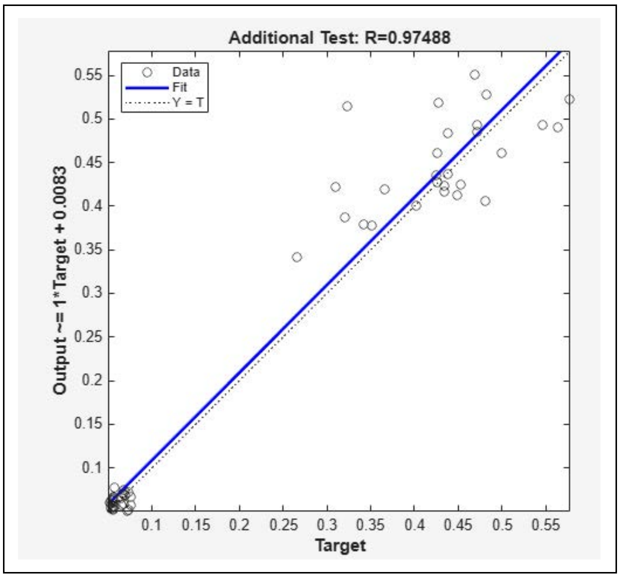


Fig. 13: ANN Analysis of Predicted Value (Additional test)

The scatter plot (Fig. 13) shows the relationship between the target values and the predicted output for the additional test data in the ANN analysis. The fitted line (blue) indicates a strong linear relationship between the output and the target, with an R-value of 0.97488, suggesting high predictive accuracy. The dotted line represents the ideal output where the target equals the prediction.

4. CONCLUSION

The findings demonstrated the significance of tuning the parameters in EDM machining by showing that raising input current and pulse timing considerably improved the removal rate of material and wear rate of the tool. The findings are:

The timing of the pulse had the most substantial influence on both MRR and EWR, resulting in increased MRR and consistent EWR values.

The maximum MRR (0.5880 g/min) and minimum EWR were attained using a 9 A current and an 80 µs pulse duration, indicating ideal machining parameters.

The Taguchi Analysis indicated that pulse on time exerted the most significant effect on MRR and EWR, while current showed the least influence in both signal-to-noise and mean response evaluations.

Regression equations were formulated for the removal rates of material and electrode wear, demonstrating that pulse on time and current were the critical determinants of MRR, while pulse on time influenced EWR.

The ANN optimization study enhanced the EDM process with great precision (R > 0.97), showing its efficacy in forecasting EDM results.

The ANN model demonstrated uniform performance across training, validation, and test datasets, exhibiting a reduction in MSE and steady gradient values.

The ANN model exhibited only a few mistakes, highlighting its notable accuracy and reliability in predicting outcomes for EDM.

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CONFLICT OF INTEREST

The authors declared no conflict of interest in this manuscript regarding publication.

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