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Experimental Analysis of EDM Parameters on D2 Die Steel Using Nano-aluminum Composite Electrodes

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ABSTRACT

This paper presents an experimental study on the electrical discharge machining (EDM) of AISI D2 die steel using an Al-Ni composite electrode. The investigation focuses on the influence of input parameters like current, pulse duration, and pulse interval, on key output parameters such as material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR). EDM oil was employed as the dielectric fluid. Grey relational analysis (GRA) was utilized for designing and conducting the experiments using the Taguchi L9 method. The ANN model showed excellent predictive accuracy with a perfect correlation coefficient (R) of 1.00, indicating strong capability in forecasting MRR based on machining parameters. GRA further confirmed that higher current settings and longer pulse-off times effectively reduce tool wear, suggesting that the ANN model accurately reflects the conditions that minimize TWR. The ANN model achieved strong predictive accuracy for SR, with high correlation coefficients, although with slightly higher mean squared error (MSE) in testing.

Keywords: EDM machining; GRA; ANN; MRR; EWR; SR.

1. INTRODUCTION

The material removal rate (MRR) was greatly influenced by the optimization of EDM process parameters by (Jeykrishnan *et al.* 2018). Recent research revealed that the applied current contributed 69.7% of the variance in MRR, underscoring the importance of accurate current management in improving EDM performance (Anbuchezhiyan *et al.* 2022). Powder-mixed EDM and Nanopowder-mixed EDM have been developed as advanced methods for improving machining performance in difficult-to-cut materials, such as Al-Z-Mg composites reinforced with Si3N4, particularly when using nickel-coated and uncoated brass electrodes. The process of micro-hole machining, taking into account variables like pulse on time, voltage, input current, and capacitance, has demonstrated significant effects on MRR and EWR, with SEM analysis providing valuable insights into surface morphology alterations (Jana *et al.* 2021). Taguchi's L9 orthogonal array and multi-criteria decision-making techniques, such as TOPSIS and grey relational analysis, were used in this study to improve die-sinking EDM settings for AISI D2 steel machining using a copper electrode. With canola oil acting as the dielectric, the research found that the optimal settings provided enhanced output responses. These settings included a level 3 pulse on time, level 2 peak current, and level 2 servo voltage (Padhi *et al.* 2020) to maximize wire EDM of EN-31 alloy steel. This research used the grey-Taguchi technique, paying particular attention to cutting rate, surface roughness, and dimensional deviation. The study determined the ideal process parameters using Taguchi's L27 orthogonal array and grey relational analysis. A confirmatory test verified the enhanced machining performance. Najm *et al.* (2023) optimized the hybrid electrochemical discharge machining process for tungsten carbide using grey relation analysis and artificial neural networks, achieving significant enhancements in MRR and machining depth. Analysis revealed that electrolyte concentration and current were the most influential factors, with a resulting average surface roughness of 0.9275 µm, and confirmation of surface composition was done with Energy-dispersive X-ray spectroscopy. Paswan *et al.* (2023) found that using a carbonated liquid as an electrolytic solution in EDM significantly increased discharge energy density and material removal rate compared to EDM oil, primarily due to the liquid's higher viscosity. Higher peak currents and optimized pulse-on-time values enhanced MRR, although increased viscosity led to higher micro-crack density.

Jeykrishnan *et al.* (2016) found that the incorporation of tungsten powder into the dielectric medium significantly enhanced the MRR in PMEDM of D2 die steel. Optimization using taguchi techniques and validation through confirmation experiments indicated that adjusting the applied input factors further improved MRR, with ANOVA highlighting the individual contributions of these parameters. Naveen *et al.* (2023) examined how solar energy may be integrated into thermochemical processes for biomass conversion and presented the techno-economic and life cycle evaluations. Sharma *et al.* (2021) demonstrated that a grey-fuzzy logic approach effectively optimized EDM parameters for hexagonal hole formation in pearlite SG iron, identifying peak current, pulse duration, and gap settings as key factors. The optimal settings for improved MRR and reduced overcut were established, and the developed regression model for predicting responses showed reliable performance with minimal prediction error. Raza *et al.* (2018) found that current intensity significantly affected output responses in EDM of Al6061-SiC composites. Among the electrodes tested, brass offered superior MRR and surface finish compared to stainless steel, while stainless steel provided a lower EWR than brass. Venkateswaran *et al.* (2023), based on different coating techniques and nanoparticle concentrations, examined how nanomaterial coatings affect the performance of fin and tube condensers and showed notable gains in heat transfer efficiency and system effectiveness. Ansari *et al.* (2023) found that for Wire-EDM of Al-10% SiC composites, pulse duration and sparking voltage were crucial for optimizing MRR and SR, while tool wear rate and spark gap were majorly influenced by sparking voltage. The multi-variable optimization identified the optimal parameters for high-precision microchannel fabrication. With input factors like Ip, Ton, and Toff, two neuro-fuzzy models and a neural network model were created to predict MRR, TWR, and radial overcut (G) in EDM for AISI D2 tool steel (Pradhan *et al.* 2010). The models showed excellent accuracy and useful prediction skills for these EDM process responses when verified against experimental data. Rizwee *et al.* (2019) reviewed the use of EDM for machining reinforced metal matrix composites, highlighting methodologies such as ANOVA, RSM, and Taguchi for process optimization. The review identified key process parameters affecting machining performance and suggested future research directions in optimizing EDM for MMCs. Nano-coating on electrodes significantly enhances the EDM machinability of Inconel 825, with graphene and CNT coatings, improving MRR, EWR, and surface roughness using silicon powder-mixed deionized water as dielectric (George *et al.* 2021). Raj *et al.* (2024) examined how different dielectric fluids and nanocomposite electrodes were used in EDM, with an emphasis on how they affected the machining of tougher materials. Important technical features were analyzed, highlighting improvements in EDM for challenging and complicated applications. Using RSM and ANOVA for parameter optimization, Y. Justin Raj *et al.* (2024) examined the effects of Al-Ni Nano-electrodes on surface roughness and machining time in Inconel 625 EDM. The findings provided valuable information for improving EDM efficiency and surface quality, as they showed that pulse-off time mostly impacted machining time, while current primarily affected surface roughness. Naveenprabhu *et al.* (2023) investigated how finned heat exchangers with different cooling pads might improve the performance of water chillers. Jute fiber, when positioned between the fan and condenser, exhibits better heat rejection and quicker chilling rates. Naveenprabhu *et al.* (2023) based on experimental data collected in a variety of climate settings, assessed the performance of evaporative heat exchangers in a range of designs and provided correlations for Sherwood and Nusselt numbers. The dual strategy of hydrogen generation and dye degradation using photocatalysis was reviewed, emphasizing the need for improvements in hydrogen storage and transportation as well as the efficacy of different photo catalysts (Priyadharsini *et al.* 2023).

The goal of this study is to enhance the output machining performance of Inconel 718, a hard super alloy, by EDM. To optimize the process, experimental trials were carried out using different discharge input parameter settings. The Taguchi L9 with Grey Relational Analysis technique was used. The best settings were determined via the use of confirmation experiments. The investigation showed that Inconel 718's EDM performance was significantly enhanced, especially when using a unique Cu-Ni-B4C composite electrode. This resulted in lower wear, better surface polish, and higher MRR. The intended function technique made it easier to determine the ideal EDM factor values for the least amount of electrode wear, and main effect graphs helped identify the important elements driving electrode wear. This work contributes significantly to the area of advanced material processing by addressing important issues in super alloy machining.

2. MATERIALS AND METHODS

2.1 Electrode Materials

The powder metallurgy process was used to create the Al-Ni electrode, which is 15 mm in diameter and 30 mm in length. This ensures a uniform combination and the ideal qualities for EDM machining. The procedure started with the selection of 10% by weight of nickel powder, with an average particle size of 40 microns, and high-purity aluminum powder, 90% by weight, with an average particle size of 50 microns. To get a consistent dispersion, these powders were meticulously weighed and combined in a ball mill running at 200 rpm for 4 hours. The resultant mixture was compressed to improve density and decrease porosity in a die cavity at a pressure of 600 MPa using a uniaxial hydraulic press. The compressed green body was then carefully cooled to room temperature after being sintered for two hours at 600 °C in an argon environment to avoid oxidation. To achieve the required dimensions and surface smoothness for efficient EDM application, the sintered electrode was lastly machined. Fig. 2 shows the electrode image.

Fig. 1: EDM setup

Fig. 2: EDM aluminum electrode tool

2.2 Work piece Material

D2 die steel, valued for its remarkable hardness and wear resistance, was the material utilized to create the work piece. A Sinker EDM EMS 350 machine, which provides exact control over several process parameters, was used to do the EDM machining. EDM oil's superior cooling and flushing qualities made it suitable for use as a dielectric fluid. The work piece measured 30 mm in diameter and 10 mm in thickness as shown in Fig. 3. It was aimed to use the powder metallurgy-fabricated composite Al-Ni electrode to drill a 3 mm hole. The electrode's particular size and material composition allowed for regulated conditions to be met when machining the D2 die steel efficiently and accurately.

Fig. 3: EDM D2 Die steel workpiece

2.3 Process Parameters

Three variables make up the EDM input factors: pulse duration at 60, 90, and 120 µs, pulse interval at 10, 20, and 30 µs; and current (Ip) set at 4, 8, and 12 A. To investigate the impact of these combinations on machining performance, they were methodically changed.

2.4 Output Responses

MRR and TWR were determined by measuring the weight loss of the work piece and electrode with a precision balance. Surface roughness was assessed using a surface profilometer.

2.5 Grey Relational Analysis (GRA)

Grey relational analysis is a methodological tool used in engineering and optimization research to evaluate and improve the performance of complex systems. To get the greatest quality features, several input factors are optimized using GRA. When assessing or reviewing the performance of a large project with little information, grey relational analysis is often used. By assigning weights to each answer, GRA may be used to determine the ideal situation for multi-objective issues.

3. RESULTS AND DISCUSSION

Table 1 displays the findings of the EDM experiment, emphasizing how roughness, wear rate, and removal rate of material are affected by changes in input factors.

Table 1. Output Response of EDM Experiment

Ip, A	Pulse on (T_{on}), µs	Pulse off (T_{off}), µs	MRR	TWR	SR
4	60	10	0.1321	0.0444	3.342
4	90	20	0.3465	0.0611	4.434
4	120	30	0.7649	0.0523	5.523
8	60	20	0.3765	0.0869	3.501
8	90	30	1.1122	0.0742	6.609
8	120	10	0.2014	0.0378	5.736
12	60	30	0.7602	0.1639	5.341
12	90	10	0.5826	0.0539	5.525
12	120	20	0.5568	0.0339	6.251
		min	0.1321	0.0339	3.342
		max	1.1122	0.1639	6.609

The TWR varied from 0.0339 to 0.1639 mm^3/min, the SR from 3.342 to 6.609 µm, and the MRR from 0.1321 to 1.1122 mm^3/min. These outcomes show how the machining performance measures and the input parameters are related.

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad \ldots..(1)$$

The equation (1) is used for normalization in Grey Relational Analysis (GRA). It transforms the original data into a dimensionless value between 0 and 1, facilitating comparison. This method is applied when higher values are better, scaling the values relative to the minimum and maximum within the dataset. The process ensures that the lowest value becomes 0 and the highest becomes 1, standardizing the data for further analysis.

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \quad \ldots.(2)$$

Equation (2) normalizes data in Grey Relational Analysis (GRA) where lower values are better. It scales the original value $x_i^0(k)$ to a range between 0 and 1, with the highest value becoming 0 and the lowest value becoming 1. This standardization facilitates comparison across different criteria by transforming the data into a dimensionless form, ensuring uniformity in multi-criteria decision-making processes.

$$\Delta_{0i}(k) = \|x_0^*(k) - x_i^*(k)\| \ldots\ldots\ldots\ldots(3)$$

Equation (3) calculates the absolute difference between the normalized reference sequence and the comparative sequence for the k-th criterion in GRA. It quantifies the deviation of each alternative from the reference, essential for computing the Grey relational coefficient (GRC). Smaller differences indicate closer similarity to the reference sequence, aiding in performance comparison and ranking. The grey relational coefficient correlation between the comparative and reference sequences is shown in Table 2. The deviation sequences and normalized values are used in the calculation.

$$\Delta_{max} = \underset{\forall j\epsilon i}{\max}\ \underset{\forall k}{\max} \left\|x_0^*(k) - x_j^*(k)\right\| \ldots(4)$$

$$\Delta_{min} = \underset{\forall j\epsilon i}{\min}\ \underset{\forall k}{\min} \left\|x_0^*(k) - x_j^*(k)\right\| \ldots(5)$$

Table 2. Normalized and Deviation GRA analysis

NORMALIZED VALUE			DEVIATION		
MRR	EWR	SR	MRR	EWR	SR
0.0000	0.0808	0.0000	1.0000	0.9192	1.0000
0.2188	0.2092	0.3343	0.7812	0.7908	0.6657
0.6456	0.1415	0.6676	0.3544	0.8585	0.3324
0.2494	0.4077	0.0487	0.7506	0.5923	0.9513
1.0000	0.3100	1.0000	0.0000	0.6900	0.0000
0.0707	0.0300	0.7328	0.9293	0.9700	0.2672
0.6409	1.0000	0.6119	0.3591	0.0000	0.3881
0.4596	0.1538	0.6682	0.5404	0.8462	0.3318
0.4333	0.0000	0.8904	0.5667	1.0000	0.1096
0	0	0	0	0	0
1	1	1	1	1	1

Equations (4) and (5) define the maximum and minimum Grey relational differences in grey relational analysis. Equation (4), identifies the greatest absolute difference across all criteria k and all alternatives j, establishing the upper bound of the differences. Conversely, Equation (5), determines the smallest absolute difference, setting the lower bound. These bounds are crucial for calculating the Grey relational coefficient, as they normalize the differences, ensuring comparability across different criteria and alternatives.

$$\zeta_i(k) = \frac{\Delta_{min} + \zeta.\Delta_{max}}{\Delta_{oi}(k) + \zeta.\Delta_{max}} \ldots\ldots\ldots(6)$$

Equation (6), calculates the Grey relational coefficient in grey relational analysis. Here, Δ_{min} and Δ_{max} are the minimum and maximum Grey relational differences, respectively while $\Delta_{oi}(k)$ represents the absolute difference between the reference and comparative sequences for the k-th criterion. The coefficient ζ is a distinguishing coefficient, typically set between 0 and 1, used to adjust the sensitivity of the analysis. This equation normalizes the differences, providing a relative measure of how closely each alternative matches the reference sequence, with higher values indicating a closer relationship.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} i\zeta_i(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Equation (7) calculates Grey relational grade (GRG) in GRA Here, ζi(k) is the Grey relational coefficient for the i-th alternative and k-th criterion, and n is the total number of criteria. The Grey relational grade γi is the average of the GRCs across all criteria, providing an overall measure of the performance of each alternative relative to the reference sequence. Higher values of γi indicate better overall performance and closer similarity to the reference sequence. This metric is essential for ranking and selecting the best alternative among multiple options in multi-criteria decision-making processes.

Table 3 illustrates the grey relational coefficient values for output responses for 9 experiments, alongside their corresponding grey relational grades and rankings. The GRC values for MRR range from 0.3333 to 1.0000, for EWR from 0.3333 to 1.0000, and for SR from 0.3333 to 1.0000. The GRG, which is the mean of these coefficients, ranges from 0.3397 to 0.8067. Experiment 5, with a GRG of 0.8067, ranks highest, indicating superior overall performance, whereas experiment 1, with a GRG of 0.3397, ranks lowest. This evaluation highlights the most effective experimental setup by integrating the performance metrics of MRR, EWR, and SR.

Table 3. Gray relation coefficient GRA analysis

MRR	Gray Relation Coefficient (GRC)			
	EWR	SR	GRG	GR RANK
0.3333	0.3523	0.3333	0.3397	9
0.3902	0.3874	0.4289	0.4022	7
0.5852	0.3681	0.6007	0.5180	4
0.3998	0.4577	0.3445	0.4007	8
1.0000	0.4202	1.0000	0.8067	1
0.3498	0.3401	0.6517	0.4472	6
0.5820	1.0000	0.5630	0.7150	2
0.4806	0.3714	0.6011	0.4844	5
0.4687	0.3333	0.8202	0.5408	3

3.1 ANN analysis of MRR

The ANN model demonstrated high accuracy in predicting the MRR of D2 die steel machined by EDM with an aluminum composite electrode, as evidenced by low mean squared error values and high correlation coefficients (R). The model effectively captured the impact of machining parameters on MRR, indicating its potential for optimizing EDM processes. The analysis at epoch 4 shows (Fig. 4) a gradient of 2.5344×10−122.5344 \times 10^{-12}2.5344×10−12, and zero validation checks, indicating highly stable and well-converged training at this early stage.

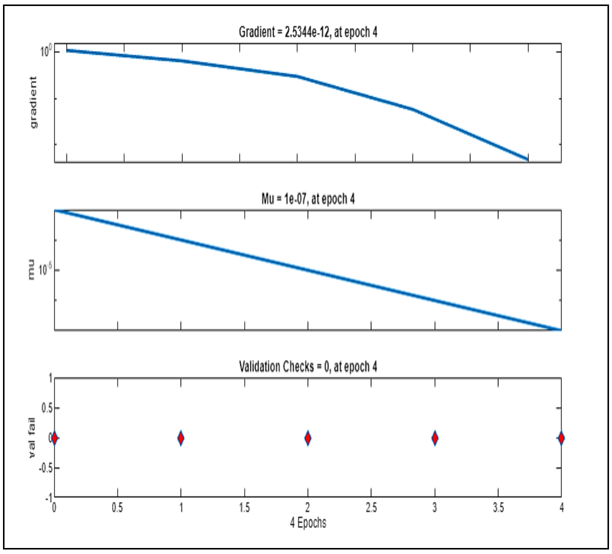

Fig. 4: ANN analysis of MRR

Fig. 5 displays a line graph that demonstrates the performance of a machine learning model across four epochs. The number of epochs is represented by the horizontal axis, while the vertical axis represents the mean squared error on a logarithmic scale. Three distinct data sets' MSE values are shown versus the number of epochs in the graph:

- Train (blue line): The MSE on the training data is shown here, showing how well the model can match the training set over time.
- Validation (green line): To keep an eye on the model's performance on untested data and avoid over fitting, this line displays the MSE on the validation set.
- Test (red line): After training, the model's performance is assessed by this line, which displays the MSE on the test set of data.
- Top Validation Results: The best validation performance is 0.0011946 at epoch 4. This indicates that at this stage, the model may have reached its lowest validation error. With the use of this graph, one may examine the model's performance across the epochs and determine the optimal location on the validation set.

The histogram image (Fig. 6) shows the distribution of prediction errors from an ANN model, indicating the frequency of errors within specific ranges. It provides insight into the model's accuracy and performance by highlighting the concentration of errors around the mean value.

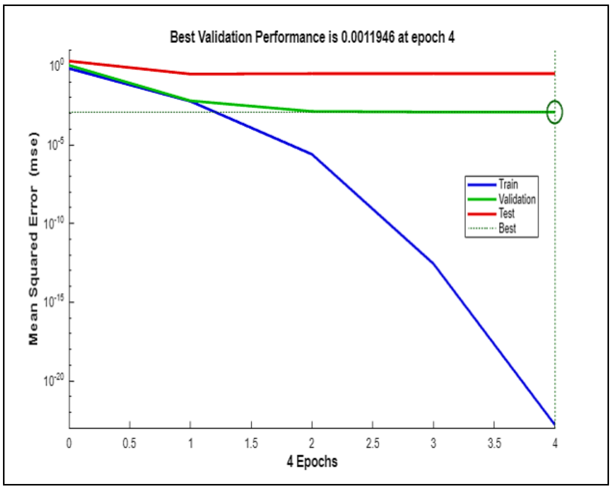

Fig. 5: ANN best validation performance analysis of MRR

MRR, TWR, and SR were assessed for nine experimental runs in the study's ANN analysis of MRR using Minitab. The training (6 samples), validation (2 samples), and testing (2 samples) sets of the dataset were separated. The correlation coefficient and mean squared error were used to assess the ANN model's performance. A perfect linear connection between the predicted and real MRR values was shown by the training, validation, and testing MSE values of 0.0000, 0.0012, and 0.3289, respectively, in Fig. 7. These results showed a high level of model accuracy with an R-value of 1.00. Significant differences in MRR were found to occur when machining settings were altered, with the lowest and greatest MRR values being recorded at 0.1321 and 1.1122, respectively.

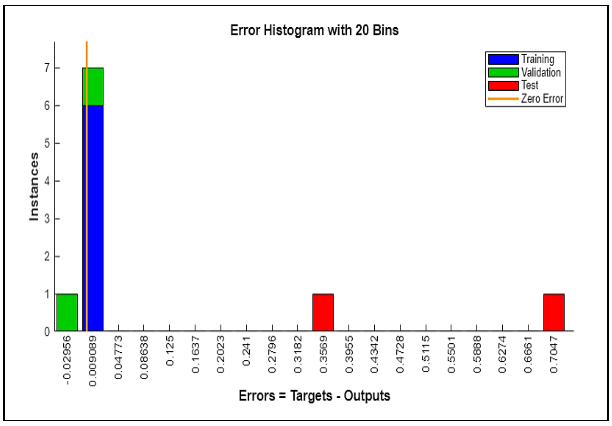

Fig. 6: ANN error histogram analysis of MRR

3.2 ANN analysis of EWR

This study explores the application of artificial neural networks to predict the tool wear rate of D2 die steel machined by electrical discharge machining using an aluminum composite electrode. The objective is to improve the accuracy and reliability of TWR predictions in advanced EDM operations. The ANN TWR analysis at epoch 4 (Fig. 8) shows a gradient value and three validation checks, indicating moderate convergence and stability with early signs of overfitting.

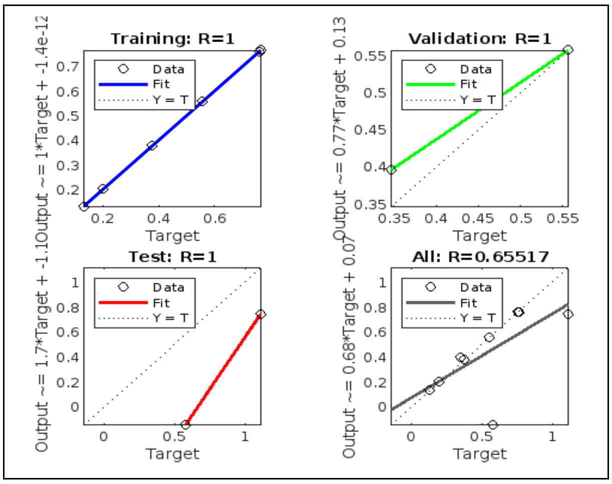

Fig. 7: ANN training and validation analysis of MRR

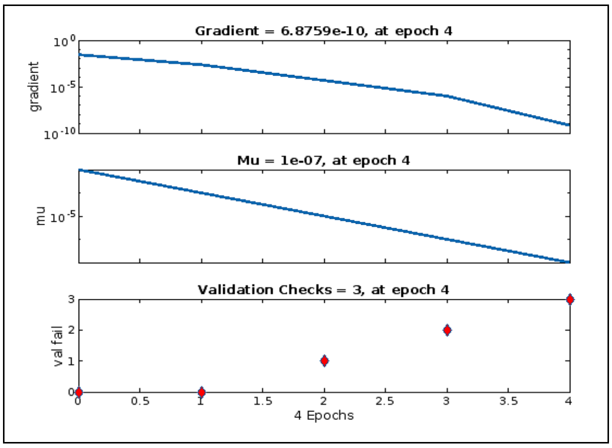

Fig. 8: ANN analysis of EWR

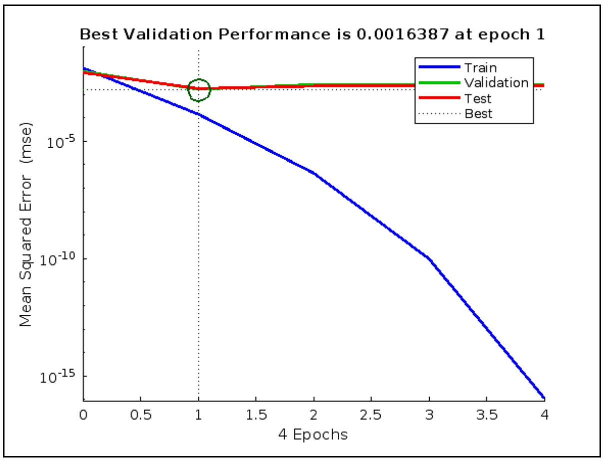

Fig. 9: ANN best validation performance analysis of EWR

Fig. 9 displays a training plot for a neural network showing MSE against epochs. The blue line represents training error, which decreases significantly over 4 epochs. The green and red lines represent validation and test errors, which remain relatively stable.

The best validation performance (0.0016387 MSE) is achieved at epoch 1, highlighted by a green circle.

In an artificial neural network analysis of tool wear rate with a histogram having 20 bins and zero error, shown in Fig. 10, the model accurately predicts TWR, showing no discrepancies between predicted and actual values. The zero error indicates perfect model performance and precise bin classification.

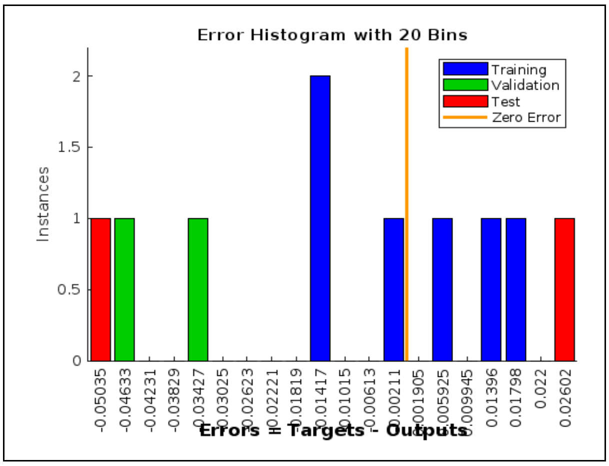

Fig. 10: ANN error histogram analysis of EWR

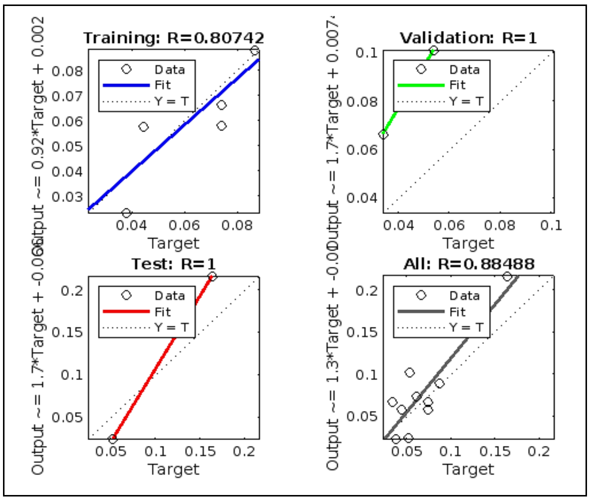

Fig. 11: ANN training and validation analysis of EWR

In the ANN analysis of wear rate using MATLAB, the model uses input parameters from a dataset of nine experiments. The performance metrics for the model include training, validation, and testing MSE values of 0.0001, 0.0016, and 0.0018, respectively. The training and testing correlation coefficients are both 1.00, indicating perfect linear relationships, while the validation R is 0.8074, showing a strong but slightly less perfect correlation. These results suggest that the model accurately predicts TWR with high precision, capturing the complex relationships between the input parameters and TWR. The TWR values in the dataset range from a minimum of 0.0339 to a maximum of 0.1639, highlighting the variability in tool wear based on different machining conditions (Fig. 11).

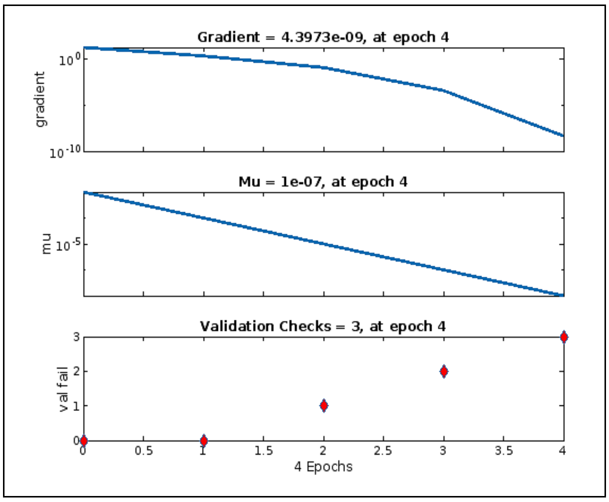

Fig. 12: ANN analysis of SR

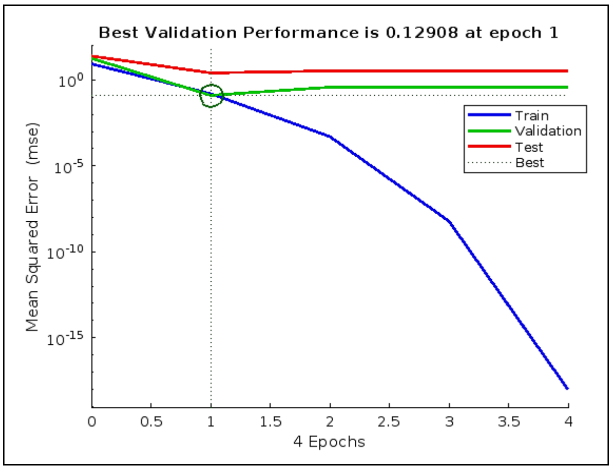

Fig. 13: ANN best validation performance analysis of SR

3.3 ANN analysis of SR

This study investigates the use of ANN to predict the surface roughness of D2 die steel machined by EDM using an aluminum composite electrode. The analysis aims to enhance the precision and efficiency of surface quality predictions in advanced machining processes.The ANN SR analysis at epoch 4 shows a gradient value and three validation checks, indicating reasonable convergence with potential overfitting concerns at this training stage in Fig. 12. The graph, shown in Fig. 13, illustrates the MSE over 4 epochs for training, validation, and test datasets. The blue line, representing training error, decreases significantly. The green and red lines show relatively stable validation and test errors. The best validation performance (0.12908 MSE) occurs at epoch 1, highlighted by a green circle.

Fig. 14 shows an ANN analysis of surface roughness with a histogram having 20 bins and zero error. The model accurately predicts SR, showing no discrepancies between predicted and actual values. The zero error indicates perfect model performance and precise bin classification.

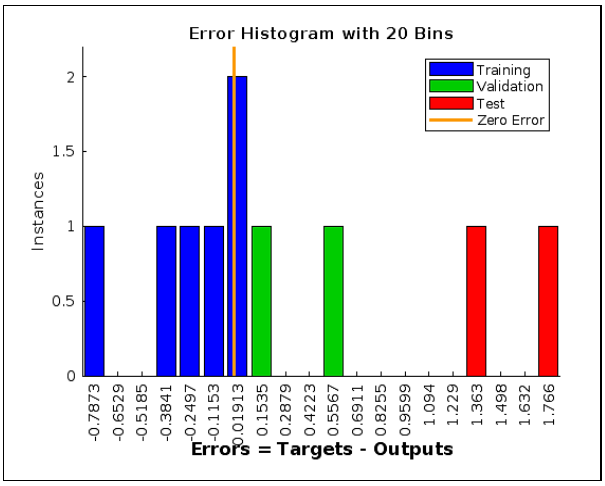

Fig. 14: ANN error histogram analysis of EWR

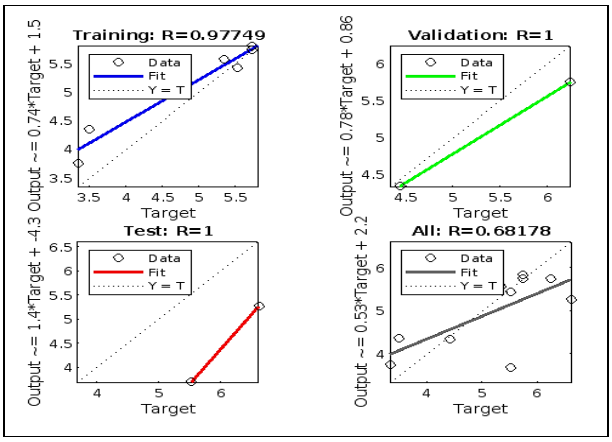

Fig. 15: ANN training and validation analysis of EWR

In Fig. 15 the model uses input parameters from a dataset of different experimental runs in the ANN analysis of roughness using MATLAB. The dataset has a range of SR values, from 3.342 at the least to 6.609 at the highest. Training, validation, and testing datasets are used to assess the model's performance; the corresponding MSE values are 0.1608, 0.1291, and 2.5913, respectively. For training, validation, and testing, the corresponding correlation coefficients are 0.9775, 1.00, and 1.00, respectively. According to these findings, the ANN model predicts SR with a high degree of accuracy and a strong linear connection between the predicted and actual values. The slightly higher MSE throughout the testing phase indicates that, overall, the model has excellent surface roughness prediction skills based on the supplied machining parameters, however there may be some fluctuation in the model's performance.

4. CONCLUSION

Based on the combined ANN and GRA of EDM machining of D2 die steel with an aluminum composite electrode, the following conclusions were drawn: Based on systematic testing and analysis, pulse on time was shown to be the key influencing factor for surface roughness, followed by pulse off time and current.

- Material removal rate (MRR): The ANN model showed excellent predictive accuracy with a perfect correlation coefficient (R) of 1.00, indicating strong capability in forecasting MRR based on machining parameters. Complementarily, GRA highlighted that higher current and pulse duration optimize MRR, underscoring the model's effectiveness in capturing the impact of these parameters on machining efficiency. The research focused on current as the most important parameter in terms of machining time reduction, highlighting its relevance in reducing the amount of time needed to mill Inconel 625.

- Tool wear rate (TWR): ANN results demonstrated high precision in predicting TWR, with perfect correlation coefficients (R) and minimal MSE values, reflecting reliable model performance. GRA further confirmed that higher current settings and longer pulse-off times effectively reduce tool wear, suggesting that the ANN model accurately reflects the conditions that minimize TWR.

- Surface roughness (SR)**:** The ANN model achieved strong predictive accuracy for SR, with high correlation coefficients, although with slightly higher MSE in testing. GRA results corroborated that optimal SR is achieved with balanced parameters, validating the model's capability in predicting surface quality and highlighting the importance of parameter optimization for improved surface finish.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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