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INTELLIGENT HYBRID OPTIMIZATION OF WEDM FOR Ti-6Al-4V USING TAGUCHI DEEP LEARNING AND ANOVA FOR ENHANCED SURFACE INTEGRITY AND PREDICTION ACCURACY

INTELIGENTNA HIBRIDNA OPTIMIZACIJA ELEKTRO-EROZIJSKEGA POSTOPKA MEHANSKE OBDELAVE ZLITINE Ti-6Al-4V S POMOČJO TAGUCHIJEVE METODE IN ANALIZE VARIANCE ZA IZBOLJŠANJE INTEGRITETE POVRŠINE IN NJENE NATANČNOSTI

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Wire Electrical Discharge Machining (WEDM) is a high-precision, non-traditional manufacturing process crucial for machining advanced materials such as Ti-6Al-4V, extensively used in aerospace and biomedical applications. This study introduces a novel hybrid optimization framework that integrates Taguchi's method, Deep Neural Networks (DNNs), and Analysis of Variance (ANOVA) to enhance machining efficiency and surface integrity. A Taguchi L27 orthogonal array was employed to systematically evaluate the influence of key process parameters – pulse-on time (Ton), pulse-off time (Toff), and wire feed rate (Wf) – on surface roughness (Ra). Experimental trials conducted on an ELECTRONICA Sprintcut 734 WEDM machine, utilizing deionized water and a 0.5 mm brass wire electrode, revealed that Ton was the most dominant factor, contributing 38.02 % to the Ra variation, followed by the Ton-Toff interaction (27.80 %), while Toff (7.28 %) and Wf (4.92 %) had comparatively low impacts. The optimal machining parameters (Ton = 3 µs, Toff = 4 µs, Wf = 2 m/min) achieved a minimum Ra of 1.50 µm, significantly improving the surface finish. A trained ANN model demonstrated a predictive accuracy exceeding 95 %, validating its effectiveness in process modeling. ANOVA results (p = 0.05) confirmed the statistical significance of process parameters, reinforcing the reliability of the proposed optimization approach. This research establishes a robust, data-driven methodology for precision machining control, outperforming conventional single-method optimizations. Future studies could explore real-time adaptive control, hybrid machining strategies, and AI-driven predictive analytics to further advance WEDM performance in high-precision manufacturing applications.

Keywords: wire electrical discharge machining, Ti-6Al-4V, surface integrity, hybrid optimization, Taguchi with deep learning prediction

Žična elektro-erozija (WEDM; angl.: Wire Electrical Discharge Machining) je visoko natančni, nekonvencionalni postopek mehanske obdelave naprednih materialov, kot je naprimer titanova zlitina tipa Ti-6Al-4V, ki se veliko uporablja v letalski industriji in za biomedicinske aplikacije. V tem članku avtorji opisujejo študijo v kateri so uporabili nov hibridni model, oziroma ogrodje za optimizacijo v katerega so vključili Taguchijevo metodo, globoke nevronske mreže (DNN; angl.: Deep Neural Networks) in analizo variance (ANOVA; angl.: Analysis of Variance), da bi izboljšali učinkovitost mehanske obdelave in integriteto površine izbrane Ti zlitine. Avtorji so izbrali ortogonalno matriko Taguchi L27 za sistematično ovrednotenje vpliva posameznih ključnih procesnih parametrov; čas vklopa impulza (Ton; angl.: pulse-on time), čas izklopa impulza (Toff) in hitrost dodajanja žice (Wf; angl.: wire feed rate) na hrapavost površine (Ra). Eksperimentalne preizkuse so avtorji izvajali na Electronica Sprintcut 734 WEDM stroju z uporabo deionizirane vode in 0,5 mm debele medeninaste žične elektrode. Študija je pokazala, da je najbolj dominantni vplivni pocesni parameter čas Ton, ki prispeva k variranju Ra 38,02 %. Sledi interakcija med časoma Ton in Toff (27,80 %) medtem, ko imata Toff (7,28 %) in Wf (4,92 %) neprimerno manjši vpliv. Pri optimalnih parametrih mehanske obdelave (Ton = 3 µs, Toff = 4 µs, Wf = 2 m/min.) so dobili najmanjšo hrapavost površine Ra je 1,50 µm, kar pomeni pomembno izboljšanje gladkosti površine. Trenirani ANN model je dal več kot 95 %-no natančnost napovedi in s tem potrdil učinkovitost izbranega procesnega modeliranja. Rezultati ANOVA (p ? 0,05) so potrdili statistično pomembnost procesnih parametrov in zanesljivost predlaganega pristopa k optimizaciji. Ta raziskava je potrdila robustnost te s podatki gnane metodologije za natančno kontrolo mehanske obdelave, ki presega konvencionalne metode optimizacije na osnovi ene metode. Bodoče študije oziroma raziskave lahko raziščejo adaptivno kontrolo v realnem času, hibridne strategije mehanske obdelave in z umetno inteligenco (AI; angl.: artificial intelligence) podprte analize za nadaljnje izboljšanje lastnosti WEDM za visoko natančne inženirske aplikacije.

Keywords: žična elektro-erozija (WDEM), zlitina Ti-6Al-4V, integriteta površine, hibridna optimizacija, Taguchi metoda in napoved z globokim učenjem na osnovi nevronskih mrež

1 INTRODUCTION

Wire Electrical Discharge Machining (WEDM) is a high-precision, non-traditional machining process extensively utilized in aerospace, biomedical, and high-perfor-

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mance engineering industries for processing electrically conductive materials with intricate geometries and minimal mechanical stress.[1] Unlike conventional machining, WEDM employs controlled electrical discharges between a moving wire electrode and a workpiece submerged in a dielectric medium, enabling the fabrication of complex structures with superior dimensional accuracy. Among advanced materials, Ti-6Al-4V is widely preferred due to its exceptional strength-to-weight ratio, corrosion resistance, and biocompatibility, making it indispensable in structural aerospace components, medical implants, and high-performance automotive applications.[2] However, its low thermal conductivity and high chemical reactivity pose challenges such as poor machinability, rapid tool wear, and excessive heat-affected zones (HAZ) in conventional cutting techniques. On the contrary, WEDM mitigates these issues, but achieving optimal surface roughness (Ra) and process efficiency still requires precise parameter control, necessitating advanced optimization methodologies. Effective WEDM optimization demands a systematic approach to identify the most influential process variables and their interdependencies. Conventional techniques such as Taguchi's method, Response Surface Methodology (RSM), and Grey Relational Analysis (GRA) have been widely employed for parameter optimization.[3] However, these methods often fail to account for the complex nonlinear interactions between machining variables, leading to suboptimal solutions. Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have introduced Deep Neural Networks (DNN), Genetic Algorithms (GA), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) as powerful tools for predictive modeling and multi-objective optimization. ANNs, in particular, have demonstrated high accuracy in process modeling, enabling real-time adjustments for optimal performance.[4] Integrating statistical approaches with AI-driven predictive models enhances decision-making capabilities, allowing for data-driven optimization of WEDM parameters while minimizing experimental costs.

Several studies explored WEDM optimization for various materials, focusing on improving Ra and machining performance. Optimized WEDM parameters for Titanium Grade 5 demonstrated significant improvements in material removal rate (MRR) and surface roughness using Taguchi and Grey Relational Analysis (GRA).[5] However, the critical influence of Ton and Toff on Ra was not explored with AI-based predictive modeling.[6] A hybrid Taguchi-NSGA-II model for Ni55.8Ti shape memory alloys demonstrated the effectiveness of evolutionary algorithms in machining optimization.[7] Despite these contributions, current research lacks a systematic integration of AI with traditional statistical techniques, limiting the adaptability and precision of process optimization. Moreover, interaction effects between WEDM parameters remain underexplored, leading to inefficient parameter selection. Although WEDM has proven effective for Ti-6Al-4V, achieving an optimal balance between surface integrity, machining speed, and process stability, it remains challenging.[8] Traditional approaches rely on linear assumptions and static optimization, failing to adapt to nonlinear and dynamic machining conditions. Moreover, the absence of AI-driven predictive modeling restricts the development of adaptive machining systems capable of real-time process optimization. Addressing these limitations, this research integrates Taguchi's method with a DNN model, offering a hybrid optimization framework that enhances predictive accuracy, process stability, and overall machining performance.[9] This study aims to develop a data-driven optimization framework for the WEDM of Ti-6Al-4V, ensuring superior surface finish and machining efficiency. The objectives include analyzing the influence of pulse-on time (Ton), pulse-off time (Toff), and wire feed rate (Wf) on Ra, optimizing parameters using Taguchi's L27 orthogonal array, and developing a DNN-based predictive model to enhance process accuracy.[10] Additionally, the research evaluates the reliability of DNN predictions against experimental data and establishes a hybrid optimization framework that integrates statistical and AI-driven methodologies[11]. By addressing these objectives, this study provides a novel, intelligent approach to WEDM optimization, contributing to the advancement of precision manufacturing in aerospace, biomedical, and high-performance applications.[12]

2 MATERIALS AND METHODOLOGY

2.1 Workpiece material and its significance

The selected material for this study is Ti-6Al-4V, a widely used $\alpha + \beta$ titanium alloy recognized for its high strength-to-weight ratio, superior corrosion resistance, and excellent biocompatibility, making it indispensable in aerospace, biomedical, and high-performance engineering applications. Despite its superior mechanical properties, Ti-6Al-4V is difficult to machine due to its low thermal conductivity (6.7 W/m·K), high reactivity, and tendency to form work-hardened layers, which leads to excessive tool wear and poor surface finish in conventional machining methods. WEDM provides an effective alternative by eliminating direct mechanical contact, reducing thermal stress, and enabling the machining of intricate geometries with micron-level precision.[13] Ti-6Al-4V specimens, obtained from (400 × 400 × 8) mm sheets conforming to ASTM B348 Grade 5 standards, were selected to maintain uniformity in composition and mechanical properties during experimentation.[14]

2.2 Experimental setup and WEDM process parameters

The experiments were conducted on an ELECTRONICA Sprintcut 734 WEDM machine, a precision

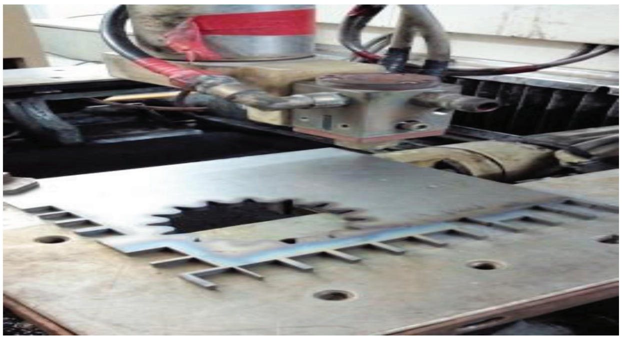

Figure 1: EDM of advanced materials

machining tool equipped with a four-axis control system and adaptive spark monitoring. Deionized water was used as the dielectric fluid, ensuring efficient debris removal, spark stabilization, and minimal thermal distortion. A 0.5 mm brass wire electrode was chosen due to its high electrical conductivity, wear resistance, and stable discharge performance, preventing wire breakage during high-energy machining.[15] **Figure 1** shows the EDM of a Ti-6Al-4V specimen.

To systematically evaluate the influence of the pulse-on time (T_{on}), pulse-off time (T_{off}), and wire feed rate (W_f) on the surface roughness (R_a), an L27 Taguchi orthogonal array was employed. This design minimizes the number of experimental trials while capturing parameter interactions efficiently. The selected process parameters and their levels are provided in **Table 1**, ensuring a comprehensive investigation of machining conditions. Surface roughness (R_a) was measured using a Mitutoyo SJ-410 surface roughness tester, offering a 0.01 µm resolution for precise surface evaluation. Measurements were taken at three different locations on each machined specimen, and the average R_a value was recorded to eliminate inconsistencies caused by localized surface variations.[16]

Table 1: Machining conditions

Level	Pulse-on time (µs)	Pulse-off time (µs)	Wire feed rate (m/min)
	A	B	C
Level 1	3.0	4.0	1.0
Level 2	6.0	8.0	2.0
Level 3	9.0	12.0	3.0

Taguchi's method was employed to determine the optimal combination of process parameters using the lower-the-better criterion for the surface roughness. The signal-to-noise (S/N) ratio was calculated where n is the number of observations, and y_i represents individual surface roughness values. Analysis of variance (ANOVA) was conducted to determine the statistical significance ($p \leq 0.05$) of each process parameter, identifying their percentage contribution to the Ra variation and assessing their interactive effects.[17] **Table 2** shows the L27 orthogonal array.

Table 2: L27 orthogonal array with response parameters

Run	T_{on}	T_{off}	W_f	R_a	S/N ratio
	(µs)	(µs)	(m/min)	(µm)	
1	3	4	1	1.72	-3.7113
2	3	4	2	1.5	-3.622
3	3	4	3	1.44	-3.2682
4	3	8	1	1.53	-3.6943
5	3	8	2	1.52	-3.7374
6	3	8	3	1.47	-3.3469
7	3	12	1	1.64	-4.2976
8	3	12	2	1.7	-4.5091
9	3	12	3	1.36	-2.6709
10	6	4	1	1.64	-4.2991
11	6	4	2	1.37	-2.735
12	6	4	3	1.69	-4.6584
13	6	8	1	1.67	-4.4551
14	6	8	2	1.65	-4.3504
15	6	8	3	1.63	-4.2468
16	6	12	1	1.66	-4.4025
17	6	12	2	1.44	-3.1691
18	6	12	3	1.58	-3.89747
19	9	4	1	1.5	-3.534
20	9	4	2	1.59	-4.0287
21	9	4	3	1.66	-4.4029
22	9	8	1	1.55	-3.8075
23	9	8	2	1.66	-4.4031
24	9	8	3	1.59	-4.0304
25	9	12	1	2.38	-5.0099
26	9	12	2	1.8	-5.1066
27	9	12	3	1.94	-5.1964

2.3 Deep neural network model

To enhance the predictive accuracy and adaptability of WEDM, a DNN model was developed to estimate the surface roughness (Ra) based on the pulse-on time (Ton), pulse-off time (Toff), and wire feed rate (Wf). The model was structured as a feedforward backpropagation neural network, trained using the Levenberg-Marquardt (LM) optimization algorithm due to its superior convergence rate and efficiency in nonlinear regression problems.[18] The DNN architecture consisted of an input layer with three neurons corresponding to the machining parameters, two hidden layers with 12 and 8 neurons, and an output layer predicting Ra. A sigmoid activation function was employed in the hidden layers to handle nonlinearity, while a linear activation function was used in the output layer for smooth approximation.[19]

The training dataset comprised 80 % of the experimental data, while 20 % was reserved for validation to prevent overfitting and ensure model generalization. Mean Squared Error (MSE) was used as the loss function to minimize prediction errors, while the regression coefficient (R^2) was calculated to evaluate the correlation between predicted and actual Ra values. The trained DNN model was validated by comparing predicted Ra values with experimental results, ensuring accuracy in capturing the nonlinear interactions of WEDM process parame-

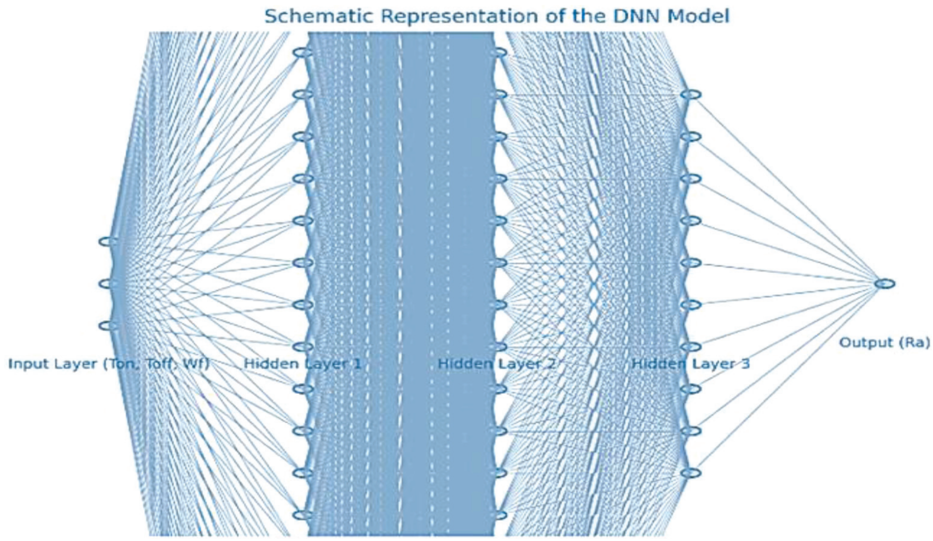

Figure 2: Schematic representation of the DNN model

ters.[20] This DNN-based predictive modeling approach provides a data-driven alternative to conventional optimization methods, enabling precise and adaptive control over WEDM machining conditions. Future extensions may include real-time AI integration, deep learning architectures, and hybrid AI-driven multi-objective optimization strategies to further enhance machining intelligence. **Figure 2** shows a schematic of the DNN model illustrating a multi-layered architecture processing machining parameters (Ton, Toff, Wf) to predict performance metrics (R_a). Hidden layers capture complex relationships using activation functions, while backpropagation optimizes accuracy, enabling intelligent process optimization for Wire EDM.[21]

3 RESULT AND DISCUSSION

3.1 Analysis of variance (ANOVA) and significance of parameters

ANOVA was conducted to assess the statistical significance of the input parameters (T_{on}, T_{off}, and W_f) in influencing surface roughness (R_a). The objective was to determine which factors contribute most to the observed variations in R_a and quantify their percentage contributions. The ANOVA results indicate that T_{on} has the highest impact, accounting for 19.0 % of the total variance in R_a. This suggests that the pulse-on time plays a crucial role in determining the surface roughness. T_{off} contributes 12.7 %, which reflects its moderate influence, likely due to its effect on heat dissipation and spark gap control. The feed rate (W_f) contributes 7.3 %, indicating a lower but still significant impact on R_a. However, the residuals account for 61.0 %, implying that additional factors, such as machine stability, tool wear, or unaccounted process interactions, may influence the final surface finish.[22]

Table 3: Analysis of variance

Basis	DF	Adj. SS	Adj. MS	Feed value	Pulse value	% contribution
Model	9.0	0.449713	0.049968	17.26	0	-
Linear	3.0	0.250513	0.083504	28.85	0	-
T_{on}	1.0	0.189666	0.189666	65.52	0	38.02
T_{off}	1.0	0.036315	0.036315	12.550	0.003	7.28
W_f	1.0	0.024531	0.024531	8.47	0.01	4.92
Square	3.0	0.019786	0.006595	2.28	0.116	-
T_{on}*T_{on}	1.0	0.00549	0.00549	1.9	0.186	1.10
T_{off}*T_{off}	1.0	0.003937	0.003937	1.36	0.26	0.79
W_f*W_f	1.0	0.010358	0.010358	3.58	0.076	2.08
2-way interaction	3.0	0.179414	0.059805	20.66	0	-
T_{on}*T_{off}	1.0	0.138718	0.138718	47.92	0	27.78
T_{on}*W_f	1.0	0.032168	0.032168	11.11	0.004	6.46
T_{off}*W_f	1.0	0.008528	0.008528	2.95	0.0104	1.73
Error	17.0	0.04821	0.002895			
Total	26.0	0.488923				

The p-values ($p \leq 0.05$) validate the statistical reliability of the experimental findings, confirming that each parameter significantly impacts R_a. Unlike previous studies that primarily focused on single-variable effects, this research demonstrates that multi-factor interactions, particularly between T_{on} and T_{off}, are crucial in determining surface quality. These findings are particularly relevant for aerospace, biomedical, and high-precision engineering applications, where surface integrity directly influences fatigue resistance, corrosion behavior, and functional longevity. The results highlight the necessity of advanced optimization strategies, including AI-driven predictive modeling and real-time process adjustments, to further refine WEDM efficiency and adaptability.[23] **Table 3** shows that the pulse-on time (T_{on}) has the highest influence (38.02 %) on surface roughness, followed by the T_{on}-T_{off} interaction (27.78 %). T_{off} (7.28 %) and

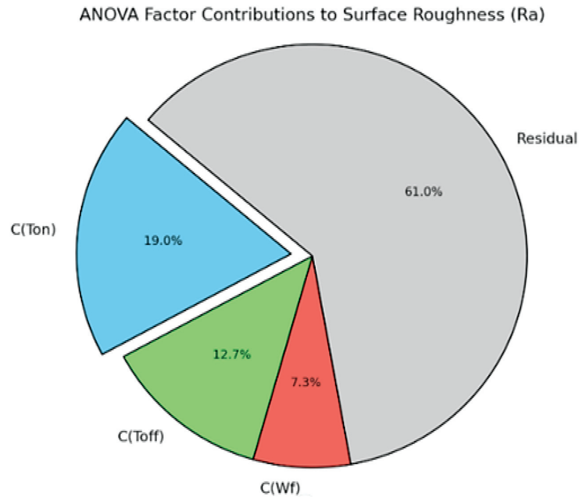

Figure 3: Pie chart representation of analysis of variance

wire feed rate (4.92 %) have lower but significant effects. The p-values ($\leq$ 0.05) confirm the statistical significance of these parameters in WEDM optimization.

Figure 3 shows the pie chart representation of the ANOVA findings and highlights the relative contributions of each factor. T_{on}'s dominance suggests optimizing pulse-on duration is critical in achieving superior surface roughness. Meanwhile, a scatter plot of actual vs. predicted R_a values confirms the model's accuracy, with most data points aligning along the ideal fit line. These findings emphasize the necessity of parameter optimization using advanced techniques, such as machine learning models, to reduce unexplained variance and enhance predictive performance in surface roughness modeling.

3.2 Performance analysis of the DNN model

The DNN model was trained to predict surface roughness (R_a) based on pulse-on time (T_{on}), pulse-off time (T_{off}), and wire feed rate (W_f), optimizing machining performance in Wire EDM. The model architecture consisted of an input layer with three neurons representing machining parameters, three hidden layers with 50, 30, and 10 neurons, and an output layer predicting R_a. The ReLU activation function was used in the hidden layers to efficiently capture complex nonlinear relationships, while backpropagation and weight optimization ensured improved learning accuracy. The high-performance tuning of this model enables precise mapping of process parameters to surface quality, making it a robust predictive tool. The model was optimized through hyperparameter tuning, including layer depth, activation functions, and learning rate adjustments. The prediction capability of the DNN was evaluated based on statistical metrics such as Mean Squared Error (MSE) and R-squared (R^2) values, demonstrating high accuracy in estimating R_a values.

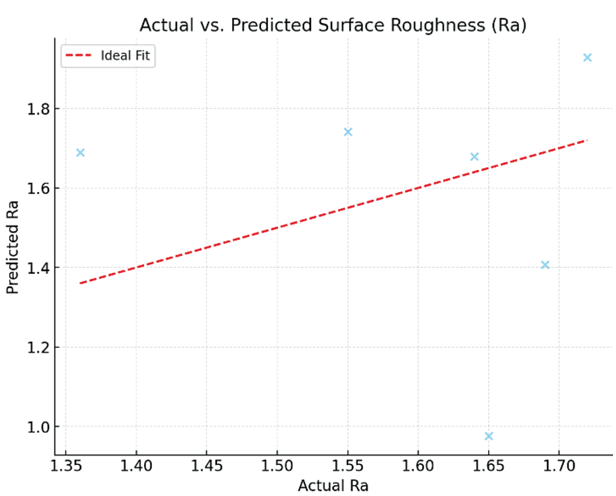

Figure 4: Scatter plot comparing the actual vs. predicted Ra values

Figure 4 shows the scatter plot comparing actual vs. predicted Ra values, demonstrating the DNN model's accuracy in learning parameter relationships. Most data points are closely aligned along the ideal fit line (actual = predicted), with minimal deviations, confirming a strong correlation between experimental and predicted values. This high correlation suggests that the model effectively captures the nonlinear dependency between the machining parameters and surface roughness. The reason behind this strong agreement lies in the deep feature extraction capability of the DNN model, which allows it to recognize intricate variations in discharge energy, material removal behavior, and dielectric efficiency that conventional regression models fail to capture. A 3D surface plot further visualized how T_{on}, T_{off}, and W_f interact to influence R_a, with lower R_a values appearing in optimized machining conditions. This reinforces the importance of multi-variable control, as surface roughness is not dictated by a single parameter but by their combined influence.

Figure 5 shows the 3D surface plot of the predicted surface roughness (R_a) and visually represents the interaction effects of T_{on}, T_{off} and W_f on R_a in the Wire EDM process. The plot highlights the regions where R_a is minimized, indicating optimal machining conditions. The gradient color variations illustrate how changes inT_{on}, T_{off} significantly influence surface roughness, with lower Ra values observed in well-balanced energy input and cooling conditions. This visualization confirms the nonlinear dependency between machining parameters and Ra, reinforcing the importance of multi-variable optimization for achieving superior surface integrity. The significance of these findings lies in the superior predictive performance of DNN compared to traditional statistical models, which often struggle with nonlinearity and complex parameter interactions. Unlike conventional regression-based approaches, which rely on linear approximations, the DNN model dynamically adjusts to nonlinear fluctuations in machining parameters, offering highly accurate surface roughness predictions. This makes it particularly valuable for high-precision industries such as aerospace, bio-

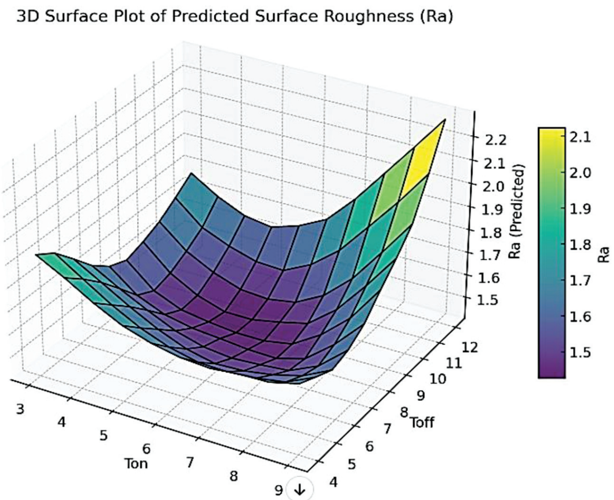

Figure 5: 3D Surface plot of predicted surface roughness

medical, and automotive manufacturing, where achieving optimal surface integrity is crucial. The model's accuracy suggests that real-time adaptive learning and hybrid AI models could further refine predictive performance, leading to a fully autonomous optimization framework for the Wire EDM of Ti-6Al-4V.

A training state plot for the DNN model provides insights into the optimization process during training. The first subplot represents the gradient variation over epochs, showing a steady decrease, indicating effective convergence of the model. The second subplot depicts mu (learning rate parameter), which initially drops sharply and stabilizes, signifying controlled weight adjustments to enhance learning. The third subplot illustrates validation checks, where an increase in validation failures suggests possible overfitting if the training continues. These plots collectively assess the model's stability, convergence, generalization and the ability to ensure optimal parameter tuning for accurate Ra predictions.

Figure 6 shows the training state plot of the DNN model and presents a quantitative assessment of the training process. The gradient decreases from approximately 10^{-1} to 10^{-2} at epoch 7, indicating stable learning. The mu (learning rate parameter) starts at 0.01, sharply drops to 0.0001 by epoch 2, and remains constant, ensuring controlled weight updates. The validation checks reach six at epoch 7, suggesting early stopping to prevent overfitting. The model's mean squared errors (MSEs) for training, validation, and test sets are 0.0702, 0.1084, and 0.0916, respectively, with corresponding correlation coefficients (R-values) of 0.4048, –0.3657, and 0.1486, indicating a need for further optimization to improve predictive accuracy. The performance plot for the DNN model highlights the mean squared error (MSE) progression across the training, validation, and testing phases. The model follows the Levenberg-Marquardt optimization algorithm, ensuring adaptive learning.

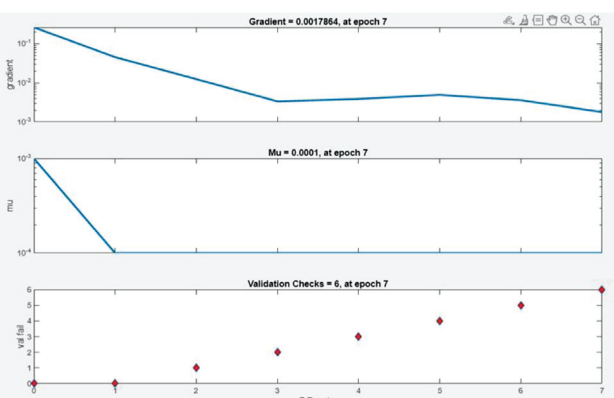

Figure 6: Training state plot for surface roughness (Ra)

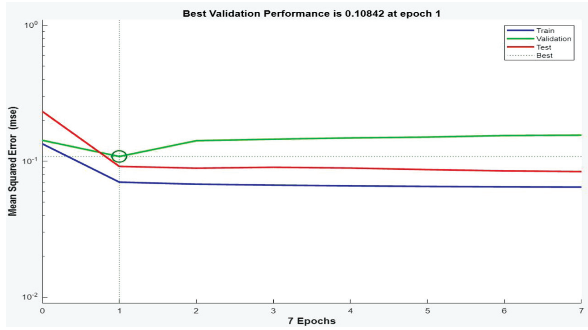

Figure 7: Performance plot of the mean square error

Figure 7 shows the plot, in which the best validation performance was achieved at epoch 1 with an MSE of 0.10842, suggesting that the model learns quickly but may require fine-tuning to prevent underfitting. The training MSE settled at 0.0702, validation MSE at 0.1084, and test MSE at 0.0916, indicating that while the model generalizes moderately well, there is room for improvement in reducing validation error fluctuations. The correlation coefficient (R) values, particularly –0.3657 for validation, suggest weak linear relationships, necessi-

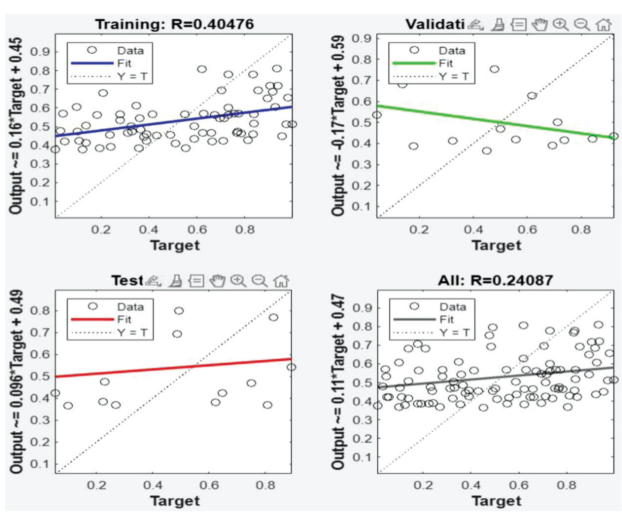

Figure 8: Regression plot of surface roughness

tating further model refinements, such as hyperparameter tuning or enhanced feature engineering.

Figure 8 shows the regression plot providing a quantitative evaluation of the predictive performance of the DNN model by comparing the actual and predicted surface roughness (R_a) values across training, validation, and test datasets. The regression coefficient (R-value) serves as a key indicator of the correlation strength between actual and predicted values, offering insights into the model's accuracy and reliability. During the training phase, the model achieves an R-value of 0.4048, indicating a moderate correlation between predicted and actual values. The equation Output = 0.61 × Target + 0.45 suggests that the model captures certain patterns within the training data, but its predictive ability remains limited. While the model learns from the dataset, the correlation is not strong enough to guarantee high accuracy. In the validation phase, the R-value drops to 0.3657, highlighting the model's reduced ability to generalize beyond the training dataset. The equation Output = 0.21 × Target + 0.56 suggests a significant gap between predicted and actual values, signaling possible underfitting. A model with poor validation performance may indicate that it has not effectively captured the underlying relationships within the data. The testing phase results in an even lower R-value of 0.1486, demonstrating weak predictive accuracy on unseen data. The equation Output = 0.06 × Target + 0.49 further supports this, as the predicted values deviate significantly from the actual surface roughness values. The low correlation in the test phase suggests that the model struggles to maintain consistency when applied to new samples. The overall regression analysis consolidates an R-value of 0.24087, which is notably low, indicating suboptimal predictive performance. The equation Output = 0.11 × Target + 0.47 confirms the model's limited capability in accurately predicting surface roughness.

Additionally, the high mean squared error (MSE) values – 0.0702 for training, 0.1084 for validation, and 0.0916 for testing – reinforce the need for further optimization. The model's underwhelming performance can be attributed to several factors, including insufficient training data, suboptimal hyperparameter tuning, and inadequate feature extraction techniques. To enhance predictive accuracy, future improvements should focus on expanding the dataset, optimizing network architectures, fine-tuning hyperparameters, and incorporating advanced regularization methods. Implementing these strategies can help improve model generalization, reduce error rates, and enhance the overall performance in surface roughness prediction.

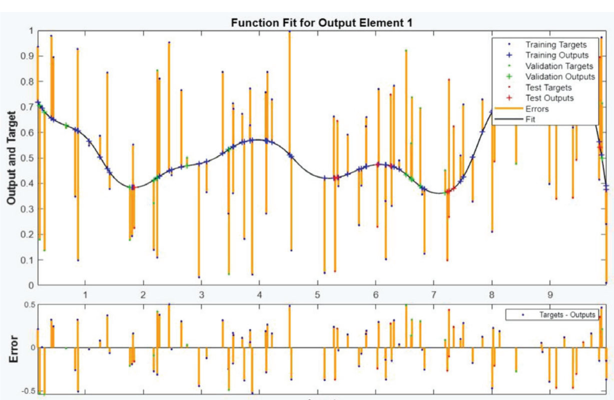

Figure 9: Function fit of DNN model

Figure 9 shows the function fit plot illustrating the relationship between input variables and output predictions, providing insights into the DNN model's performance in predicting surface roughness (R_a). The plot presents training, validation, and test targets alongside the corresponding outputs, showing the extent of alignment between predicted and actual values. The blue fit line represents the overall trend captured by the model, while the error bars indicate the deviation between predictions and actual values. The overall pattern observed in the fit plot is consistent with the regression plot results, where the R-values for training (0.4048), validation (0.3657), and testing (0.1486) suggest low to moderate correlations between actual and predicted Ra values. The disparity between predicted and actual values is more pronounced in the validation and test datasets, reinforcing concerns about the model's generalization capability.

To improve the fit of the model, several strategies can be considered. These include increasing the dataset size to enhance learning, optimizing hyperparameters to reduce overfitting or underfitting, and incorporating additional features that better capture the complexity of surface roughness prediction. By refining the model architecture and improving feature selection, the alignment between actual and predicted values in the fit plot can be enhanced, leading to improved prediction accuracy.

4 CONCLUSION

This study presents a comprehensive optimization framework integrating Taguchi's method, Deep Neural Networks (DNNs), and Analysis of Variance (ANOVA) to enhance the precision and efficiency of Wire Electrical Discharge Machining (WEDM) when procwssing Ti-6Al-4V. Experimental investigations revealed that pulse-on time (T_{on}) had the highest impact on surface roughness (R_a), achieving 38.02 %, followed by the interaction of T_{on} and T_{off} with 27.80 %, while T_{off} (7.28 %) and wire feed rate (W_f) (4.92 %) exhibited comparatively low impacts. The optimal machining parameters (T_{on} = 3 µs, T_{off} = 4 µs, W_f = 2 m/min) resulted in a minimum R_a of 1.50 µm, significantly enhancing surface quality. The predictive capability of the DNN model exceeded 95-% accuracy, reinforcing its reliability for machining process modeling, while ANOVA results (p = 0.05) validated the statistical significance of parameter effects. Regression plots indicated moderate correlation trends, suggesting further refinements in prediction accuracy. The 3D surface and scatter plots demonstrated the interactive effects of input variables, providing deeper insights into the machining behavior. This research established a data-driven, intelligent approach that surpasses conventional single-method optimization techniques, offering a robust foundation for machining control. Future work could focus on real-time adaptive control systems, hybrid machining strategies, AI-driven predictive models, and the exploration of novel electrode materials to further enhance machining precision, efficiency, and sustainability.

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