Diyala Journal of Engineering Sciences

Journal homepage: https://djes.info/index.php/djes

ISSN: 1999-8716 (Print); 2616-6909 (Online)

Performance Prediction in Wire EDM Using Statistical and ML Techniques

Mohd Rafeeq*, Saad Parvez

Department of Mechanical Engineering, National Institute of Technology, Srinagar, Jammu and Kashmir, India

ARTICLE INFO

Article history:
Received June 16, 2025
Revised August 24, 2025
Accepted August 27, 2025
Available online September 01,2025

Keywords:
Wire EDM
Surface roughness
Taguchi method
Machine learning
Predictive modelling

ABSTRACT

Wire EDM plays a vital role in the precision machining of hard-to-cut materials, but its efficiency depends on the optimal selection of parameters. The influence of machining parameters on WEDM quality for Stainless Steel 202. This study integrates Taguchi's L9 orthogonal design with machine learning (ML) to optimise and predict surface roughness (SR) outcomes. ANOVA revealed peak current as having a significant impact on machining quality, with a moderate non-significant effect from pulse on time; wire speed and pulse off time had minimal effect. Increased peak current and pulse on time result in higher discharge energy, which generates deeper craters on the workpiece surface, thereby leading to increased surface roughness. To boost predictive accuracy, three ML models—Random Forest (RF), Artificial Neural Network (ANN), and Support Vector Machine (SVM)— were evaluated by using k-fold cross-validation in addition to the conventional 80/20 train-test split. RF achieved the highest prediction accuracy (R^2 = 0.931), followed by ANN (R^2 = 0.918) and SVM (R^2 = 0.810). This approach minimises experimental efforts and enhances machining precision. The findings suggest that combining statistical tools with ML can streamline WEDM processes, improve surface quality, and reduce defects. Future work may focus on real-time control systems, hybrid optimisation, and deep learning models for further improvement

1. Introduction

As a present-day non-conventional machining method, wire repeatable electric-discharge machining (WEDM) has been extensively utilised, thus the complex shape of modern materials such as super alloys, composite materials, HSS, and conductive ceramics. This is essential for the manufacture of components with high-density materials in aerospace, automotive, mould-making and surgical tools industries, where the precise processing of electrically conductive materials by thermal energy is a must. WEDM workpieces submerge within a dielectric fluid pattern, where controlled electrical discharge or sparks occur between a wire electrode and the work material itself. This technique allows for high-precision erosion of material, allowing for detailed and complex cuts that would otherwise be difficult to achieve with traditional machining processes. WEDM has become a CNC-based technology; however, the cutting mechanism is highly complex and non-linear, and establishing and settling optimal parameters is hard. Finding the right machining conditions usually takes lots of time and trial and error.

Moreover, several factors affect material removal rate (MRR) and surface roughness (SR) in WEDM, making it difficult to accurately

* Corresponding author.
E-mail address: rafeeq7054@gmail.com
DOI: 10.24237/djes.2025.18304

perform the modelling of the effect of process parameters on machining performance. Improving process efficiency and precision is a significant goal as WEDM technology continues to evolve. Implementing state–of–the–art computational modelling and optimisation methods is essential for alleviating current limitations and enhancing the accuracy and performance of this important machining process [1]. Process parameters like pulse-on time, pulse-off time, corner servo voltage, wire feed, and wire tension affect WEDM performance by directly affecting MRR, spark gap, and SR. The best choice of parameter settings is critical to improving the efficiency and accuracy of WEDM [2].

It is an unconventional machining process in which controlled electrical discharges are used to remove material. It uses a soft tool electrode to wear away harder materials, gradually vaporising the workpiece [3]. A dielectric fluid removes the debris created from the process, providing a stable machining environment. Since Electric Discharge Machining(EDM) technology is widely used for machining complex geometries and hard metals, it is also particularly effective for applications requiring small, high-aspect-ratio holes [4]. EDM, specifically die-sinking EDM, is commonly used to manufacture tooling, dies and complex cavities. The performance of both EDM and WEDM is highly dependent on accurate control of process parameters for precision, productivity, and superior machining quality [5]. With the advancement of technology and the requirement for materials that can function reliably in intense conditions, the demand for stainless steel has increased rapidly. As industries demand a more excellent range of performance, effective machining of these materials becomes critical. Conventional traditional machining techniques, however, usually fail to reach the desired goals regarding performance, tool wear, finish, and productivity. The advent of unconventional machining processes like WEDM can address this problem [6]. Has come out to be a suitable replacement for machining stainless steels, as these parts need to meet high dimensional tolerances and complex geometries that are sometimes seen in aerospace applications. Utilising electrical discharges, this innovative machining method removes material from the workpiece, enabling precision machining of tough materials without the need for direct contact, which leads to tool wear [7].

The present work researches the influence of machining parameters on WEDM quality for annealed SS 202. The main factors studied include pulse on time, pulse off time, peak current, and wire speed, with an emphasis on the surface roughness of cut specimens. Empirical models to characterise surface roughness concerning process parameters are developed through ANOVA and regression analysis, which reveal the dominance of peak current as a significant factor for SR. Compared to traditional machining processes, only a few studies have investigated the impact of parameters on complex parts with different cutting speeds, which might have an impact on the efficiency of manufacturing on SS 202 in the automotive industry and the high-performance area of the industry. While WEDM offers several recognised advantages, a gap still exists in the current literature, especially when it comes to the machinability of superalloys and the influence of the different machining parameters on responses like MRR and surface integrity. The review explored machining superalloys compared to the wealth of literature surrounding more general materials [8]. As a result, mechanisms for optimising machining processes and practical approaches toward utilising these materials are limited. Hence, the WEDM of superalloys can be better understood through detailed investigations to benefit the field engineers.

Modern engineering endeavours must achieve stainless steel components that provide more excellent machining performance using advanced techniques like WEDM. With growing innovations, material applications contemplate high performance and reliability, which are key factors in material selection. Henceforth, it is essential to understand how to process components of this nature, ensuring the right machining parameters [9]. The current study aims to establish a fundamental understanding of WEDM parameters that affect the SR and surface integrity of stainless steel202 alloys during machining and further advance this knowledge to utilise high-performance materials effectively. The research understanding would expand and serve as a practical aspect of machining stainless steel in high-performance environments, thus contributing to the realm of applied research and industrial applications [10]. Various modelling techniques and analytical techniques (e.g., Response Surface Methodology (RSM), Particle Swarm Optimisation (PSO), Support Vector Machine (SVM), regression analysis, and sensitivity analysis) have been widely used for evaluating the performance of EDM and WEDM for machining advanced materials [11]. They provide useful information on how to adjust machining parameters, what might enhance the quality of surface finish, etc. Different modelling approaches have been used to describe and predict machining behaviour across different research fields.

The novelty of this study is in creating a hybrid modelling framework that combines the Taguchi L9 experimental design with machine learning algorithms, including Random Forest, Artificial Neural Network, and Support Vector Machine. This framework predicts surface roughness during WEDM of stainless steel SS-202—a material for which very limited predictive modelling studies exist. In using k-fold cross-validation for robust model assessment, we address this knowledge gap and show that there is a powerful synergy in combining statistical design with computational tools to improve prediction performance, reduce experimentation complexity, and assist in intelligent machining, adaptive process control, and cost-effective manufacture of difficult-to-cut materials.

2. Literature review

A comprehensive review of prior research in the field has been conducted to understand the advancements and methodologies related to this study. The optimised WEDM parameters increase the machinability of SS304, which is a non-magnetic stainless steel known for its corrosion resistance. The MMR for brass wire is superior to that of zinc-coated wire. Pulse on time and pulse off time identified the optimal parameters for MRR and kerf reduction [12]. The capability of WEDM to the machine is to produce the complex shapes of parts with changing hardness. Titanium alloys are complex to work with using traditional methods. Less pulse-on time and lower pressure ultimately grant a remarkable surface finish. Higher current improves surface smoothness and material outlet rate. WEDM process variables could be adjusted at the response surface level [13]. The influence of WEDM variables on surface texture and kerf width is explored in this investigation. Additionally, Grey relational analysis is employed to determine the optimal WEDM setting. Results of ANOVA show that the parameter pulse on time greatly influences surface roughness and kerf width [14]. Studies mainly focus on SR and MRR. WEDM is less utilised due to its complex nature. One of the best methods for optimising machining parameters is the Taguchi methodology. AISI D3 steel is widely used in industries. Improving surface finish and reducing roughness with optimal machining parameters for lowering the pulse off time, increasing surface craters and micro-damage [15].The optimisation of WEDM parameters for SS304. Coated brass wire showed higher MRR than uncoated. Coated brass wire improves the MRR significantly. Increasing pulse on time and current enhances MRR during WEDM [16]. Higher pulse off time and voltage reduce MRR.

Grey relational analysis optimises WEDM process parameters effectively [12]. Investigate the hydrogen embrittlement in superalloys. It focuses on nickel, cobalt, and iron-based superalloys. It highlights dislocation movements and fracture surface analysis. Common themes include void and micro-crack formations. Nickel content influences hydrogen embrittlement in Fe-Ni-Cr superalloys—high-pressure and temperature impact superalloy properties. Material factors affect hydrogen embrittlement severity [17]. The WEDM procedure on AISI 1045 steel involves using an ANN to forecast the MRR and SR. Key factors to consider are the pulse on time and pulse off time. The most effective parameters for achieving the highest MRR have been determined. The pulse on time plays a vital role in the performance of SR and MRR metrics [18].

Optimisation of surface integrity WEDM parameters was conducted using the Taguchi method. Increasing the pulse on time leads to higher SR, while decreasing the pulse off-time results in lower micro-hardness. The current influences both roughness and hardness. Notably, pulse off time has a significant impact on both SR and microhardness. During parameter optimisation, SR is minimised to achieve the target microhardness [19]. Various techniques, such as ANN, SVM, and Genetic Algorithm(GA), were employed to predict SR through WEDM parameter optimisation. The SVM model demonstrated an impressive 99.9985% R-value performance, while GA optimisation yielded a superior result of 61.31% for surface roughness. Peak current plays a crucial role, contributing 60.21% to surface roughness. Key parameters leading to minimal SR were identified, with the best fitness objective value reaching 0.2685 [20].

Using SVM models to predict electrochemical machining parameters such as MRR, SR, and the radial overcut. SVM outperforms both linear and quadratic regression models for prediction accuracy. In particular, the feed rate of the tool plays an essential role in determining machining responses, while MRR and SR in ECM operations are predicted well using SVM models. Regression models are used to study the relationship between input parameters and response, and the Gaussian radial basis kernel function plays a vital role in improving SVM prediction accuracy. The prediction performance of SVM is consistently superior to both linear and quadratic regression models, thereby ensuring proximity of predicted values, i.e., provided by the SVM model, to actual response values. The study also compared fuzzy logic and BP-ANN models concerning WEDM outcomes, revealing the superiority of BP-ANN over fuzzy logic in surface roughness evaluation [21]. Pulse-on time and spark gap voltage are identified as the primary parameters affecting surface roughness, while both pulse-on time, pulse-off time, and spark gap voltage collectively influence waviness. The Taguchi method was applied for experiment design and analysis, determining that the BP-ANN model is more accurate and dependable than the fuzzy model. Notably, surface roughness and waviness experience significant effects from pulse-on time, highlighting the impact of WEDM parameters on titanium alloy machining. Furthermore, an Adaptive Network-Based Fuzzy Inference System (ANFIS) model was created to effectively predict surface roughness and material removal rate (MRR) during the WEDM process [22]. The research focused on optimising crucial machining parameters like taper angle, peak current, pulse-on time, and pulse-off time to enhance machining efficiency and surface quality. Comparative analysis revealed that the ANFIS model surpassed traditional regression models in predictive accuracy. Moreover, a multi-parametric optimisation strategy incorporating Grey Relational Analysis (GRA) was employed to reach optimal machining conditions, identifying the most beneficial combination of process parameters for enhanced WEDM performance. The results indicate that peak current and pulse-off time play critical roles in determining MRR, with higher peak current values leading to a significant increase in material removal. Conversely, surface roughness tends to improve with increasing peak current, while the dielectric flow rate has minimal impact on both surface roughness and MRR [23].

Investigate B4C-reinforced composites despite their superior stiffness and hardness. It also identifies fly ash as a cost-effective reinforcement, offering good wear resistance and other beneficial properties. The literature review explores various mathematical approaches for optimising machining parameters, focusing on the Grasshopper Optimisation (GHO) algorithm, which is compared against Particle Swarm Optimisation (PSO) and Moth-Flame Optimisation. The study utilises an L_{27} orthogonal array to analyse machinability by evaluating key output responses, including volume removal rate (VRR) and SR. Additionally, ANOVA is applied to determine the statistical significance of the process parameters, ensuring a comprehensive assessment of their impact on machining performance. Results show that the GHO algorithm surpasses other methods in maximising VRR and minimising SR, demonstrating the potential of evolutionary algorithms for optimising WEDM processes [24].

This research combines Taguchi's method with machine learning algorithms to optimise and forecast the performance of WEDM processes. The primary objectives include optimising WEDM parameters and identifying key machining parameters affecting SR using the Taguchi methodology. Development of Predictive Models: Employ ANN, Random Forest (RF), and Support Vector Machine (SVM) to forecast machining outcomes. Assessing ML Model Accuracy: Evaluate and compare the predictive accuracy of ML models based on metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 (Coefficient of Determination).

Current research has increasingly used machine learning in WEDM for the prediction of machining responses like surface roughness, with superior accuracy compared to traditional statistical models. Such predictive information not only holds significant value towards increasing model reliability but also towards real-world industrial applications. Through the estimation of surface roughness before machining, ML models assist in minimising material loss and ensuring first-pass quality. Parametric optimisation prolongs tool and wire life, reduces consumable expenses, and minimises downtime. Moreover, minimising trial-and-error experimentation reduces setup times and speeds up production cycles. These benefits are especially paramount in precision industries such as aerospace, biomedical, and automotive manufacturing, where better surface finish, close dimensional tolerances, and cost-effectiveness directly determine competitiveness and sustainability.

3. Methodology

The experimental design in this study has been structured using the Taguchi method, a systematic technique for enhancing machining parameters while reducing the need for numerous experimental trials. The Design of Experiments (DOE) framework requires careful planning and precise mechanical configuration, and the Taguchi methodology provides similar structured measures at each DOE stage. By using this approach, the number of tests needed is significantly reduced while maintaining reliable results. Accordingly, to focus was solely on the actual response variable—surface roughness. The experimental setup followed an orthogonal array design, specifically the L_9 orthogonal array, which allows for a balanced evaluation of multiple parameters. The four primary process parameters selected for investigation were pulse on time (POT), pulse off time (PFT), peak current (IP), and wire speed, each tested at three different levels, as shown in Table 1. The experimental results, collected based on the Taguchi-designed layout, were further utilised as a dataset for machine learning applications. Regression-based machine learning models were utilised for surface roughness prediction, improving the accuracy and dependability of machining performance evaluation.

Table 1: Controlled input parameters and levels

Factor	Process Parameter	Level-1	Level-2	Level-3
A	Pulse on Time (POT)µs	32	35	38
B	Pulse off Time (PFT)µs	9	10	11
C	Peak Current (IP)A	2	4	6
D	Wire Speed (WS)m/min	92	94	96

3.1 Experimental setup

As per DOE, machining trials were performed using an Ezeewin CNC WEDM , as shown in Figure 1. A 100×100×10 mm plate of Stainless Steel 202 (SS 202) was used as the workpiece for the experiments. SS-202 comprises the following elements: (0.15%) of carbon, 17–19% (of) chromium, 4-6% (of) nickel, 75%10% of manganese, as well as 0.25% (of) nitrogen as indicated in Table 1. SS 202 is a good, cost-effective option due to its nickel-reduced grade; replacing some nickel helps with the strength of the final product, nitrogen, and manganese, making SS 202 cheaper than SS 304. A molybdenum wire electrode measuring 0.25 mm in diameter was utilised for the experiments. The positive and negative polarities were applied to the workpiece and wire electrode, respectively, from the DC power source. Deionised water has been used as the dielectric material so that a stable machining environment is provided during machining. Deionised water was used as the dielectric fluid during machining, which was supplied at a pressure of 0.5 kg/cm² and a flow rate of around 4 L/min.The flushing was carried out continuously through the top and bottom nozzles, ensuring effective debris removal.

The essential variable parameters considered in the study were pulse-on time (μs), pulse-off time (μs), peak current, and wire speed. Experiments were designed using the Taguchi L_9 orthogonal array to facilitate the study of nine combinations of the parameters. To investigate machining performance, three points were measured for SR along the length of the cutting channel after each test [25].

Figure 1. Experimental Set-up of Ezeewin CNC WEDM

The Stainless steel, specifically 202 grades, was utilised in the shape of a thick rectangular plate. The chemical composition of 202 Stainless steel consists of iron alloyed with chromium, nickel, and manganese. It has similar properties such as 202 stainless steel. The 202 classification is highly durable in cold environments. This non-magnetic, chromium-nickel–manganese alloy has superior corrosion-resistant levels, making it the most used precipitation hardening grade, with high hardness and strength. There are also prominent characteristics located under this grade. The SS 202 can be used in various applications, including cooking utensils, railway vehicles, and types of stainless steel 202 are used daily in kitchen utensils, automotive components, and some architectural applications where cost might be a concern [26]. The atmosphere is not particularly corrosive, etc. A Mitutoyo surf-test surface roughness tester assessed the machined samples' surface roughness. Each sample underwent evaluation three times, and the resulting mean values were computed. The surface roughness was evaluated using the equation shown in Equation 1.

$$Surface\ roughness\ = \frac{1}{L}\int_0^L \text{Zx}\ \langle \text{dx} \rangle\ (\mu\text{m}) \qquad (1)$$

Where Surface roughness (SR), measured in micrometres (µm), is determined based on the evaluation length (**L**) and the profile height function (**Z(x)**). The parameter **L** represents the length over which the surface roughness is assessed, while **Z(x)** defines the variations in surface profile height. Figure 2 shows that the Taylor Hobson Surtronic 3+ is used to measure surface roughness (Ra, Rz, Rt, Rp, Rv) as described in ISO 4287. The instrument's high accuracy and consistency are a diamond-tipped stylus with motorised traverse that displays repeatable readings on a 2.4-inch colour LCD. The output delivers ± 5 % accuracy, ± 2 % repeatability and has automatic calibration that is traceable to certified standards that measure the effects of process parameters on the surface roughness tester [27].

In this study, three supervised machine learning models, including ANN, RF and SVM models, were used to predict the surface roughness generated from WEDM parameters. Next, normalisation for uniform scaling is applied to the training data, and further tuning of model-specific parameters is performed. In order to reduce the bias in assessing the performance of models, a K-Fold cross-validation approach was used.

4. Analysis of experimental data

4 .1 S/N Ratio analysis for process optimisation

The signal in Taguchi methodology represents an ideally desired response parameter (mean), and noise represents the non–ideally desired response parameter (standard deviation). In this context, the signal-to-noise (S/N) ratio is used to study quality characteristics relative to the target value. The S/N ratios utilised include those designed for small, induced, and larger dimensions. Table 2 shows the experimental results of surface roughness. The S/N ratio in equation 2 represents surface roughness, a quality attribute in a specific type of machining where 'smaller is better'.

$$S/N = -10\log\left[\frac{1}{n}(y_1^2 + y_2^2 + \dots\dots + y_n^2)\right] \qquad (2)$$

The responses of the machining characteristic of a specific trial condition repeated n times can be denoted as $y_1, y_2, \dots, y_n$. The S/N ratio is calculated using equation (2) for all nine trials. The calculation results and raw data values are represented in Table 2.

Figure 2. SR measuring equipment (Taylor Hobson)

Table 2: Experiment plan with performance measured value.

Trial no.	Pulse on time (μs)	Pulse off time (μs)	Peak Current (Amp)	Wire Speed (m/min)	Surface Roughness (μm)	S/N ratio (db)
1	32	9	2	92	3.66	-11.26
2	32	10	4	94	3.78	-11.54
3	32	11	6	96	4.40	- 12.86
4	35	9	4	96	4.04	-12.12
5	35	10	6	92	4.08	-12.21
6	35	11	2	94	3.58	-11.07
7	38	9	6	94	5.06	-14.08
8	38	10	2	96	3.84	-11.68
9	38	11	4	92	4.46	-12.98

4.2. Effect of process factors on the response variable

The effects of process variables on the responses can be comprehended through the main effect graph, as shown in Figure 3. The effect of cutting parameters on the SR of SS 202 reveals various characteristics post-WEDM, outlined as follows:

When the current intensity remains constant, surface roughness increases with longer pulse durations as the current strength rises, leading to a more significant energy discharge. Which leads to a greater number of chips being dislodged and greater surface roughness. The surface structure is almost unaffected by using appropriate liquid circulation at high pressure. Surface roughness increases and decreases with an increase in the current and pulse duration to prevent the wire from breaking [10]. The wire speed used has a minimal impact on the surface roughness. In WEDM, however, the heat produced by the discharge energy melts and vaporises small surface pieces at the points of impact of the spark, thereby affecting the surface roughness. The peak current and pulse duration affect the surface profile, with current and pulse duration being the major contributing factors for the surface profile. A lesser current would generate fewer accretionary sparks, thus rendering the surface smoother because of an improved erosion effect.

The average value of performance characteristics for each parameter at levels 1, 2 and 3 is compiled as the mean response in Table 3. The tables also include ranks using delta statistics, enabling comparisons of the effects' relative magnitude. The delta statistic is the difference between each factor's high and low average. The surface roughness of the specimens shows a general trend of decrease in its value according to the reduction in cutting parameters. Table 4 presents the computed average S/N (signal-to-noise) ratio for different parameters at various levels. The optimal level for each factor is identified as the one with the highest S/N ratio, which indicates the best conditions for the measured responses[28,29]. Based on the S/N ratio analysis shown in Figure 4, the ideal machining parameters for minimising surface roughness are: a pulse on time of 35 μs (level 2), a pulse off time of 10 μs (level 2), a peak current of 2A (level 1), and a wire speed of 92 (level 1).

Table 3: Average Values (Raw Data: Surface Roughness)

Process parameter Designation	Average values of Surface Roughness			Delta	Rank
	L1	**L2**	**L3**		
A	3.947	3.900	4.453	0.553	2
B	4.253	3.900	4.147	0.353	3
C	3.693	4.093	4.513	0.820	1
D	4.067	4.140	4.093	0.073	4

Table 4: S/N Ratio Average Values (Raw Data: Surface Roughness)

Process parameter Designation	Average values of Surface Roughness			Delta	Rank
	L1	**L2**	**L3**		
A	-11.90	-11.81	-12.92	1.11	2
B	-12.49	-11.82	-12.31	0.68	3
C	-11.34	-12.22	-13.06	1.71	1
D	-12.16	-12.24	-12.23	0.08	4

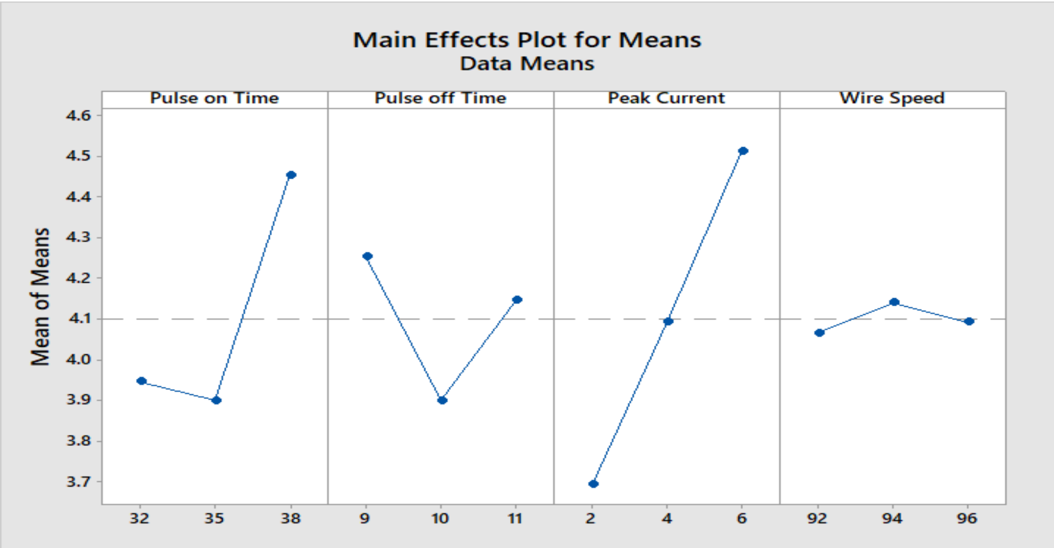

Figure 3. Main effect analysis of means for SR (Raw Data)

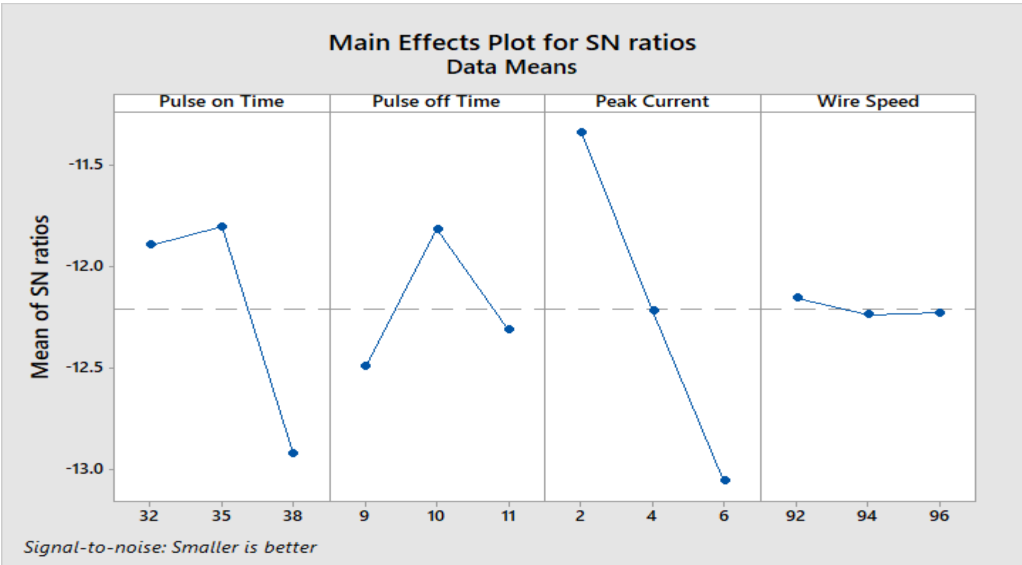

Figure 4. Main effect analysis of S/N Ratio for SR (S/N Data)

4.3 Statistical analysis of the experimental results

In this study, variance analysis (ANOVA) is a statistical tool that objectively analyses differences in the mean performance of various test groups. Statistical analysis was performed using the ANOVA method to discuss how the machining parameters affect operational performance[18]. The study employed ANOVA to analyse the impact of machining parameters on cutting quality in WEDM. Table 5 displays the ANOVA results for SR and WEDM, highlighting the influence of different parameters on cutting quality. Notably, peak current intensity emerged as the most significant factor affecting surface roughness. This analysis involves comparing the mean square to experimental errors at a specified confidence level to assess the importance of main factors and their interactions. The total sum of squared deviations (SS_T)as shown in equation 3 from the overall mean Signal-to-Noise (S/N) ratio is computed, where *n* denotes the number of experiments in the orthogonal array, and n_i represents the mean S/N ratio for the i^{th} experiment. The P-value is calculated as shown in equation 4.

$$SS_T = \sum_{i=1}^{n} (n_i - n_m)\,.^2 \tag{3}$$

Here, *n* represents the total number of experiments in the orthogonal array, while n_i denotes the mean Signal-to-Noise (S/N) ratio for the i^{th} experiment.

$$P = \frac{SS_d}{SS_T} \tag{4}$$

Table 5: ANOVA of surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Percentage Contribution
Pulse on Time	1	0.38507	0.38507	4.26	0.108	21.64%
Pulse off Time	1	0.01707	0.01707	0.19	0.686	0.96%
Peak Current	1	1.00860	1.00860	11.16	0.029	56.68%
Wire Speed	1	0.00686	0.00686	0.08	0.797	0.39%
Error	4	0.36161	0.09040			20.32%
Total	8	1.77920				100%

The F-test [30], named after Fisher, is a statistical method utilized to assess the design parameters that have a significant impact on the quality characteristic. It assesses significance by comparing the mean square error with the residual error. Peak current was identified as the most influential factor in this analysis, contributing to 56.68% of the variation in Surface Roughness (SR), with a p-value of 0.029, indicating statistical significance. Pulse on time has a moderate effect (21.64%) but is not statistically significant (p = 0.108). Pulse off time and wire speed have negligible impacts on SR. Figure 5 shows the Pareto Chart, which displays each process parameter's contribution to the WEDM process. Peak current has the highest impact on SR. Pulse on time also contributes significantly. Pulse off time and wire speed have minimal effects.

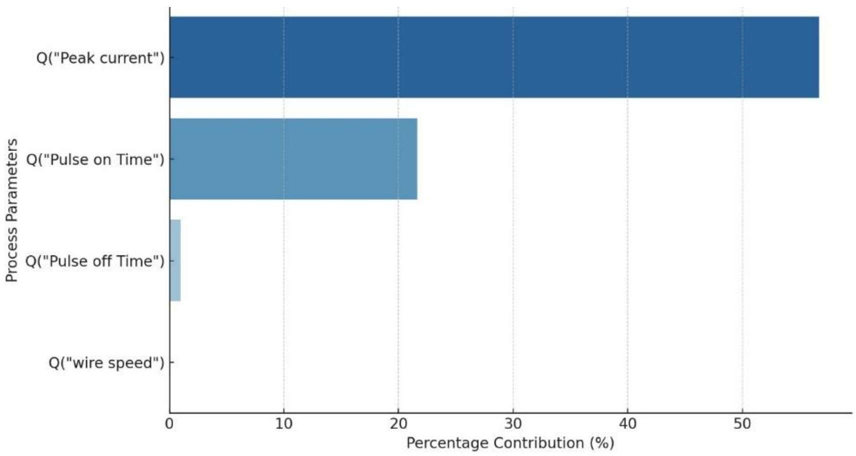

Figure 5. Pareto chart process parameter's contribution

5. Discussion

5.1 Statistical and ML-Based Predictive Models

Multiple regression analysis was conducted in SPSS 16 to examine the relationship between surface roughness (SR) and independent variables. Moreover, an SPSS artificial neural network (ANN) was used to evaluate prediction accuracy. In addition, the study uses three supervised regression-based algorithms for surface roughness prediction. Models, such as ANN, Random Forests, and Support Vector Machines, were trained using R programming to validate their results. The dataset was split into two subsets: 80% for training and 20% for testing, along with k-fold cross-validation [31]. The feature importance analysis shown in Figure 5 above indicates that peak current was identified as the most significant factor influencing surface roughness, and the pulse on time had a reasonable effect. In contrast, pulse-off time and wire speed had a minimal effect on the output. This insight helps to refine the prediction model by focusing on the most relevant machining parameters.

5.1.2 Analysis of Residual Normality Using a P-P Plot

This analysis employed residual regression and a mathematical model to evaluate the model's reliability. Figure 6 shows the Normal P-P plot, which evaluates the standardised residuals of the regression model, adhering to a normal distribution[11,33]. This conformity is a vital assumption in regression analysis.

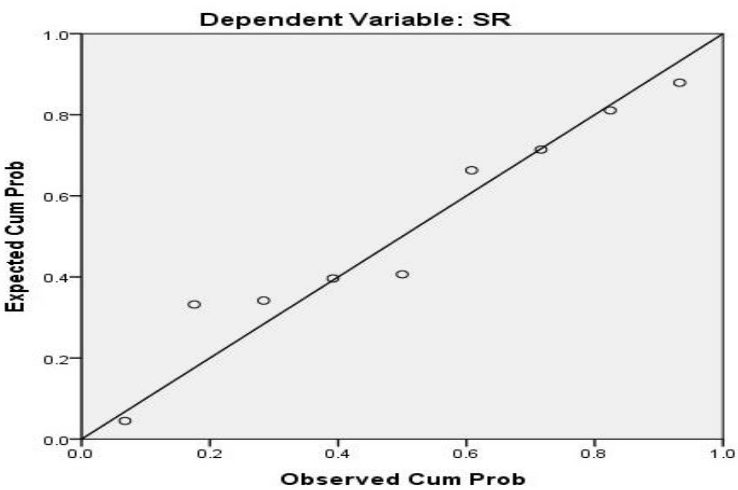

Figure 6. Normal P-P plot of regression standardised residual

The P-P plot examines the accumulated probability of the standardised residuals seen against the cumulative probability expected based on a normal distribution. Residuals are aligned well on the reference line, and the regression model is acceptable.

5.1.3 Mathematical model for the experimental data

In this work, a mathematical model was used to validate the experimental results from investigating the surface roughness (SR) obtained from the WEDM cutting experiments. The process and cutting parameters served as inputs to obtain experiment results, with the SR values as the output [33]. A regression equation was created for each desired output using Minitab 17.

SR = 0.93 + 0.0844 pulse on time - 0.053 pulse off time + 0.2050 peak current - 0.00097 wire speed(5).

Furthermore, the heatmap plot of the experimental dataset was built, as shown in Figure 7. Peak current shows some influence on SR, suggesting a direct relationship between discharge energy and surface characteristics. Pulse on time and surface roughness show a moderate positive correlation, meaning that higher pulse on time may lead to increased surface roughness. Pulse off time appears to have a weaker correlation with SR, indicating that it may have a less direct impact. Wire speed has a relatively lower correlation with SR, indicating that its effect might be minimal compared to other factors.

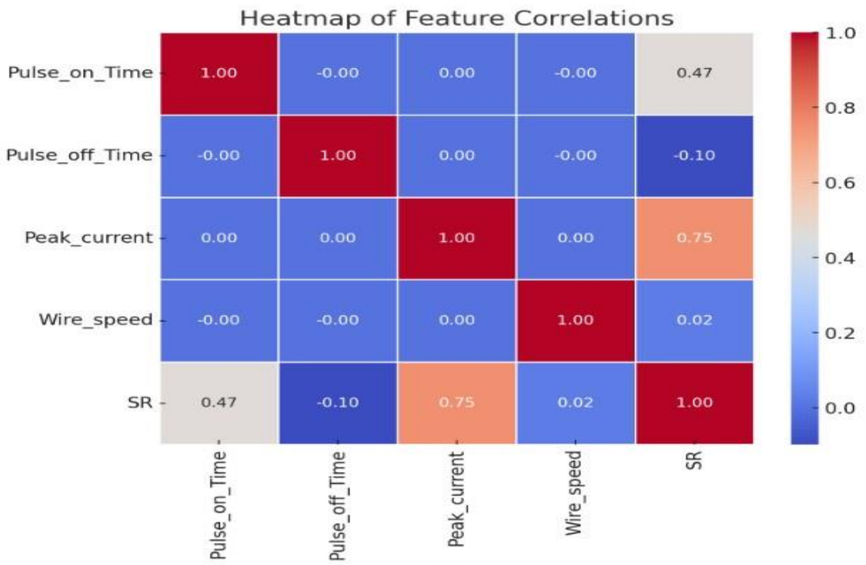

Figure 7. Heatmap representation

5.1.4. Model evaluation using K-Fold cross-validation

Cross-validation (CV) is a strong and accepted technique for estimating machine learning model performance, and k-fold cross-validation was used in this study to give an indication of the performance that we can rely on and that is unbiased [34]. In k-fold cross-validation, we partition the dataset into k equal (or close to equal) subsets called folds. In each iteration, one fold is taken as the test fold (the validation set), and the remaining k- folds are taken as the training set. The model will be trained on the training folds and validated on the test fold. This will be repeated k times, meaning that in total each fold will perform the function of a validation set exactly once. The final performance was obtained by averaging the metrics over the k folds, weighted by the number of samples in each test fold [35].

Increasing the number of folds helps ensure that more data is available for training in each iteration, usually resulting in more accurate performance estimates, and increasing the number of folds could potentially lead to greater computational complexity. Modelling and evaluation took place within an organised framework that maximised the potential for accurate and independent performance estimation [34]. Starting with preprocessing of the dataset—including second-degree polynomial feature generation and SelectKBest feature selection for non-linear interactions and the selection of only the predictors deemed important—three machine learning models were then developed and tuned around pre-defined hyper-parameters (to maximise predictive power): Random Forest (n_estimators = 100, max_depth = 3), Support Vector Machine with radial basis function kernel (kernel='rbf'), and an Artificial Neural Network in the form of an MLP Regressor with one hidden layer of 100 neurons (max_iter = 1000). The performance of the models was assessed using a 5-fold cross-validation procedure, where the total data set was split equally into 5 folds. Each model was trained and tested once at each fold, so that for each iteration, four of the five folds were used for training the model, and onewas used for testing the model, which ensured each fold was tested at least once across the repeated training–testing sequences. This process not only provided unbiased performance estimates but also reduced bias from overfitting [35,36].

Table 6: Feature metrics of the cross-validation

Metric	Random Forest	Support Vector Machine	Artificial Neural Network
MAE	0.304	0.389	1.099
RMSE	0.372	0.476	1.284
MSE	0.139	0.227	1.648
R^2	0.300	-0.146	-7.344

Table 6 and Figure 8 provide the comparative results from the model performance test, which also includes MAE, RMSE, MSE, and R^2, which all show the RF model produced the best predictive accuracy, as it had the smallest MAE (0.304), RMSE (0.372) and MSE (0.139) values, and a positive R^2 of 0.300, which indicates that the RF model explained approximately ~30% of the variance. Meanwhile, SVM and ANN models had negative R^2 values (−0.146 and −7.344, respectively), which means they produced predictions that performed worse than simply predicting the mean, and the highest amount of error belonged to the ANN model. These findings also confirm the advantage of the RF in capturing the underlying characteristics of the data over the SVM and ANN.

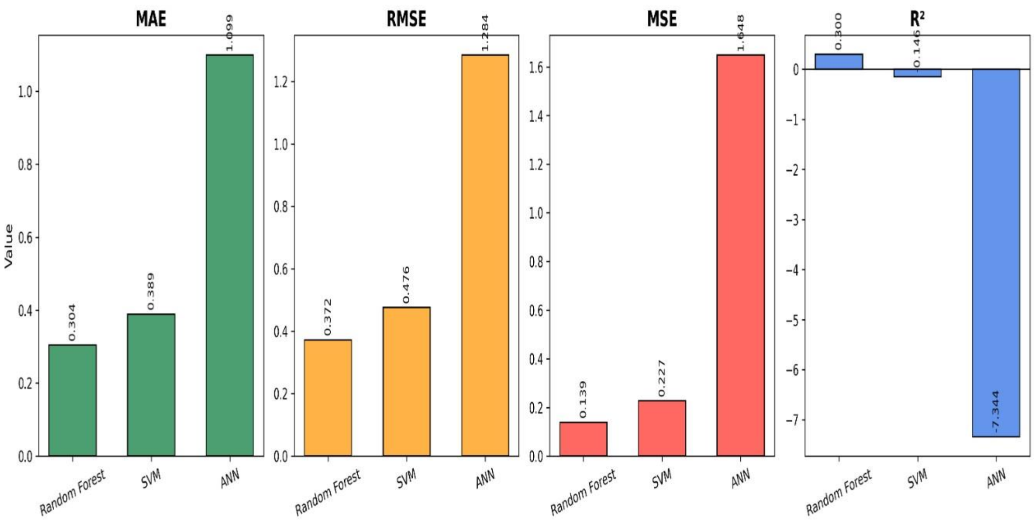

Figure 8. Comparative performance of RF, SVM, and ANN models (5-fold cross-validation)

5.2 Construct the ANN-Based Predictive Model

Artificial Neural Networks (ANN) imitate the human brain, which comprises a network of neurons for information processing and storage. If the learning data is not sufficient, ANNs can produce incorrect output. ANN needs to convert inputs and outputs into the form of numbers, and its performance is greatly affected by the network structure, the different activation functions, and the learning algorithms [15,37].In this study, a rescaling method, normalised adjustments, and hyperbolic tangent activation functions were used to find patterns in data during the ANN training process, as shown in Figure 9. The input variables were standardised through rescaling of covariates. Custom architecture with two hidden layers was employed. Both hidden and output layers used the *hyperbolic tangent* activation function. Training was performed using an initial learning rate parameter (λ) of 0.0000005, an initial sigma of 0.00005, and a minimum relative change in training error of 0.0001. The weights were randomly initialised and biases after updating them iteratively using the trial and error method by a defined learning rate ranging from 0.1 to 0.001. If the learning rate is too low, gradual optimisation is enabled, and in case the rate is too high, it may lead to instability. The regression plot for SR prediction using the ANN model is displayed in Figure 10, where R^2 is found to be a higher value, as indicated by 0.918, signifying a very high standard linear relationship between the predicted and actual SR values. Plotted is the correct prediction of SR after optimisation of the network [18].A predictive model and mathematical equations representing relationships between process parameters and outcomes were created using SPSS Statistics 21.

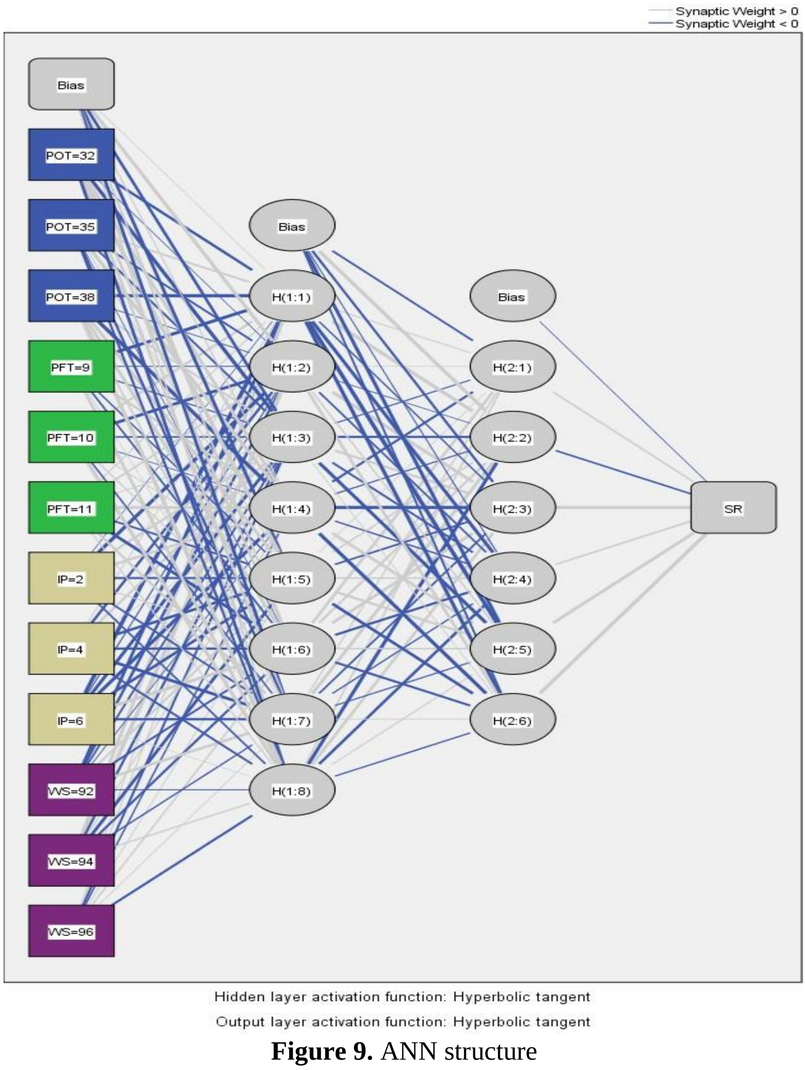

Figure 9. ANN structure

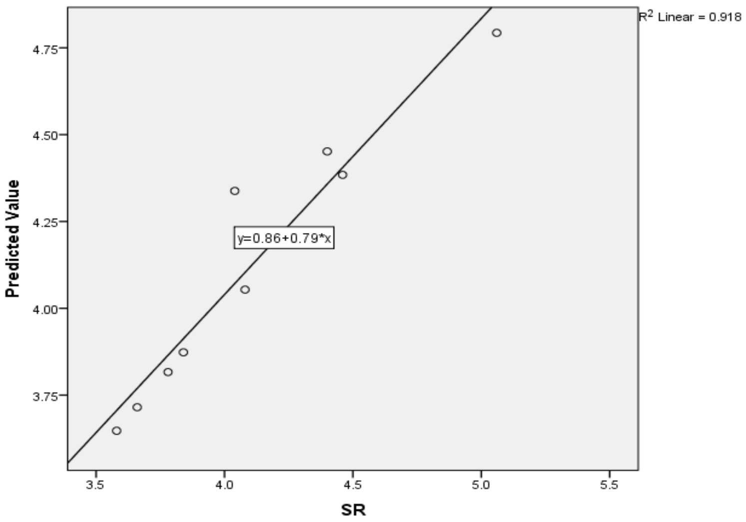

Figure 10. Regression graphs of the ANN model for SR

5.3 Construct the Random Forest-based prediction model

Random Forest employs ensemble learning through the utilisation of the bagging technique, in which numerous decision trees are constructed using distinct subsets of data [38]. Once the maximum number of trees is generated, their results are combined to enhance prediction accuracy while minimising variance and reducing the risk of overfitting. Unlike a single decision tree, which relies on one set of rules, Random Forest aggregates multiple trees, making it a more robust and reliable model [39]. However, this approach requires greater computational power and resources to process effectively. In contrast, the decision tree is simple and doesn't require much computing power. The best tuning parameters obtained for the RF model were: n_estimators = 200, max_depth = 15, min_samples_split = 2, min_samples_leaf = 1 nand max_features = 'sqrt'.Random Forest requires much longer training time than decision trees because it builds many trees (rather than a single tree), and most of the votes will make decisions. Figure 11 shows Regression graphs of the random forest model for SR.

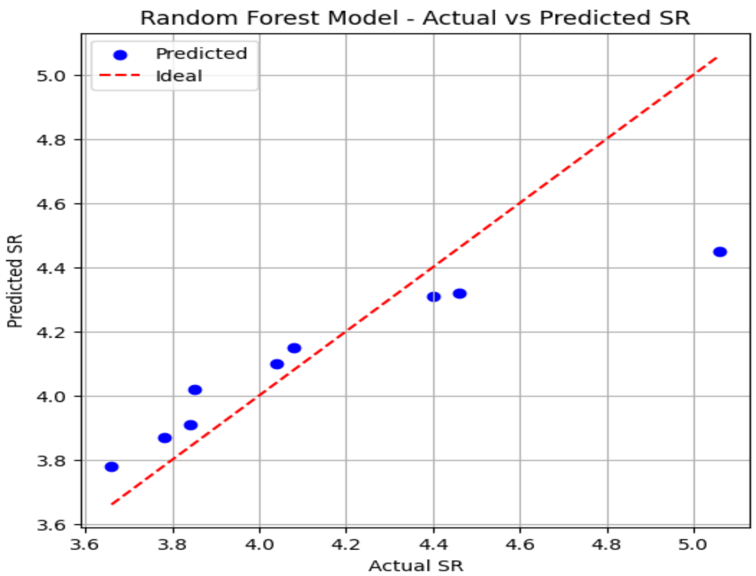

Figure 11. Regression graphs of the random forest model for SR

5.4 Construct the support vector machine-based prediction model

Support Vector Machine (SVM) is a powerful and flexible soft computing approach rooted in statistical learning theory. It finds extensive application in classification, regression, pattern recognition, dependency estimation, and forecasting, establishing itself as a fundamental resource for crafting intelligent systems [38]. Among these models, SVM-based forecasts closely match the observed values with minimal deviations, underscoring the model's precision and dependability in capturing intricate data patterns. The SVM has gained recognition as an effective predictive model in data mining, as it identifies underlying probabilistic structures within datasets to forecast potential outcomes based on input variables. The SVM model has been widely acknowledged and demonstrated to be an effective predictive model in data mining, as it aims to uncover the underlying probabilistic structure of the data to forecast potential outcomes using a specified set of input variables. Each model in SVM has several predictors, which are variables affecting the results [39]. This is an effective method to model multidimensional problems where traditional analytical/statistical methods do not give good results. Unlike conventional statistical methods, which often struggle with multidimensional problems and the risk of overfitting. In this study, SVM-based models were developed to predict SR in the WEDM process. The optimal tuning was: `kernel = radial basis function`, `C = 10`, `gamma = 0.01`, and `epsilon = 0.1`. These models provide valuable insights for process and Industry engineers to maintain high-quality machining outcomes. As illustrated in Figure 12, the regression graph for SR further reinforces SVM's robustness and precision in modelling complex machining processes.

These regressions were constructed using the R programming language. Performance measurement of the supervised machine learning algorithms was conducted using the metric features of the Mean Squared Error (MSE), Mean Absolute Error (MAE) and the coefficient of determination (R^2) as shown in Table 7.

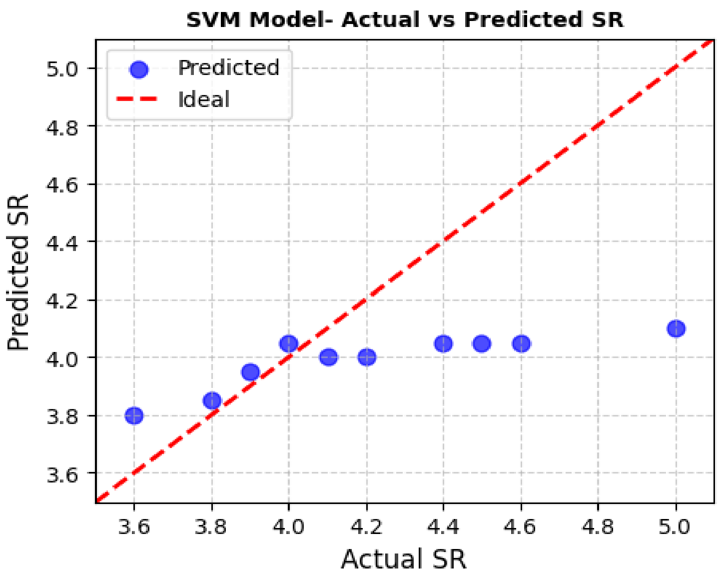

Figure 12. Regression graphs of the Support Vector Machine model for SR

Table 7: Metric feature of the regression-based algorithm

Metric	Artificial Neural Network	Random Forest	Support Vector Machine
MSE	0.080	0.159	0.020
MAE	0.280	0.398	0.140
RMSE	0.283	0.399	0.141
R^2	0.918	0.931	0.810

5.5 Comparison of regression-based algorithm performance

The effectiveness of the predictive models developed in this study is evaluated using three key statistical metrics: MSE, MAE, and the Coefficient of Determination (R^2). These indicators help assess the models' accuracy and reliability in predicting WEDM performance[40]. A comparative analysis of three regression-based machine learning algorithms—ANN, RF, and SVM—is shown in Table 7. By analysing these metrics, the study determines the strengths and limitations of each model, identifying which algorithm provides the most precise and reliable predictions for WEDM outcomes.

Random Forest (RF) demonstrates the best performance, achieving an R^2 score of 93.1% . However, its MSE value (0.159) and MAE value (0.398) are the highest, suggesting some prediction discrepancies. The benefit of the RF model is that it can handle complex relationships. However, it may lead to slight overfitting. ANN yields a competitive R^2 score of 0.918, ranking just behind RF as shown in Figure 13. This model has an MSE value of 0.080 and an MAE value of 0.280, which indicates that it has achieved a better balance between accuracy and minimising error.

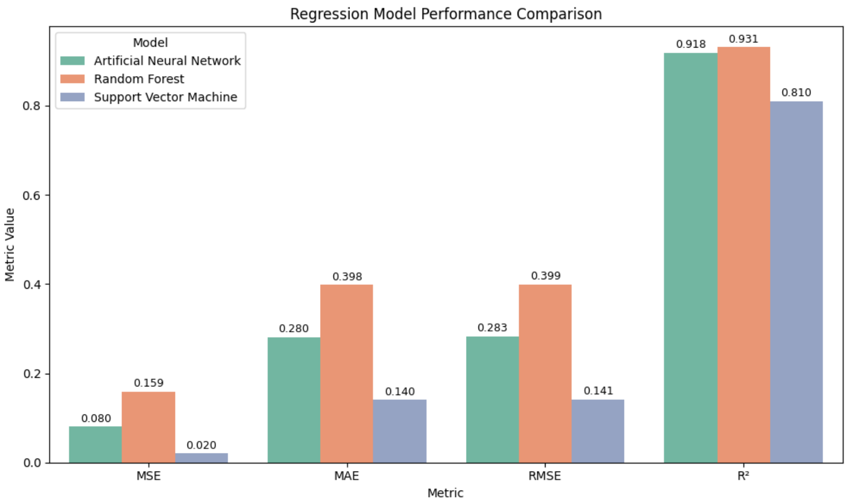

Figure 13. Comparative performance of RF, SVM, and ANN models

The SVM is the model with the minimum value for the MSE=0.020 and MAE=0.140, indicating that the prediction error is minimised. But its R^2 value (0.810) is the lowest, with RF and ANN capturing more variance in the data. Although RF is the most accurate model across the board (best R^2), the lowest error in absolute terms (lowest MSE and MAE) is through the SVM model. The Artificial Neural Network (ANN) offers a good trade-off regarding accuracy and error. Thus, Random Forest is best suited to model the WEDM process as it exhibits the highest predictive ability, followed by ANN due to its stable performance. SVM provides good accuracy but might need to bootstrap predictive power.

6. Conclusion

The following conclusions were drawn after initial investigations and extensive analysis of the WEDM cutting process of Stainless Steel 202.

1. This study applies Taguchi optimisation to improve the WEDM process, focusing on minimising Surface Roughness by identifying optimal machining parameters.
2. ANOVA results highlight that peak current significantly influences machining performance pulse on time showed a moderate yet non-significant influence. Pulse-off time and wire speed show minimal impact.
3. Developed linear regression models demonstrate high accuracy and are supported by strong correlation coefficients and acceptable error margins, confirming their reliability for WEDM process modelling. Cross-validation analysis validated that across all models tested, RF outperformed SVM and ANN, and provides better predictive reliability for surface roughness in WEDM.
4. Machine learning models used for performance prediction include Artificial Neural Networks, Random Forest, and Support Vector Machines. RF outperformed other models, achieved $R^2 = 0.931$, had lower error rates than ANN achieved $R^2 = 0.918$, and SVM achieved $R^2 = 0.810$, and had a strong ability to capture complex data relationships.
5. This combined approach of Taguchi optimisation and ML models effectively enhances, WEDM efficiency, reducing dependency on traditional trial-and-error methods. The findings support using data-driven techniques for more accurate and efficient manufacturing processes.

References

[1] G. Rajyalakshmi, “Optimization of WEDM Process Using Taguchi Utility Analysis,” *Indian J. Sci. Technol.*, vol. 11, no. 23, pp. 1–19, 2018, doi: 10.17485/ijst/2018/v11i23/114377.

[2] P. Shandilya and A. K. Rouniyar, “Multi-objective parametric optimization on machining of Inconel-825 using wire electrical discharge machining,” vol. 0, no. 0, pp. 1–13, 2020, doi: 10.1177/0954406220917706.

[3] A. Equbal and A. K. Sood, “Electrical Discharge Machining: An Overview on Various Areas of Research,” *Manuf. Ind. Eng.*, vol. 13, no. 1–2, 2014, doi: 10.12776/mie.v13i1-2.339.

[4] A. Equbal, M. I. Equbal, and A. K. Sood, “An investigation on the feasibility of fused deposition modelling process in EDM electrode manufacturing,” *CIRP J. Manuf. Sci. Technol.*, vol. 26, pp. 10–25, 2019, doi: 10.1016/j.cirpj.2019.07.001.

[5] P. Sharma, K. Kishore, V. Singh, and M. K. Sinha, “Surface Morphology Analysis of Inconel 625 through Multi-walled Carbon Nanotubes-Based Electric Discharge Machining,” *J. Mater. Eng. Perform.*, no. Ref 9, 2024, doi: 10.1007/s11665-024-09849-x.

[6] B. Tejas Ajay, P. Mayur Vitthal, and G. Rajyalakshmi, “WEDM machining on Aerospace Materials for improving Material Properties,” *Mater. Today Proc.*, vol. 4, no. 8, pp. 9107–9116, 2017, doi: 10.1016/j.matpr.2017.07.266.

[7] L. Slătineanu, O. Dodun, M. Coteaţă, G. Nagîţ, I. B. Băncescu, and A. Hriţuc, “Wire electrical discharge machining—a review,” *Machines*, vol. 8, no. 4, pp. 1–28, 2020, doi: 10.3390/machines8040069.

[8] A. Equbal, M. Israr Equbal, I. A. Badruddin, and A. Algahtani, “A critical insight into the use of FDM for production of EDM electrode,” *Alexandria Eng. J.*, vol. 61, no. 5, pp. 4057–4066, 2022, doi: 10.1016/j.aej.2021.09.033.

[9] D. Dwaipayan, N. Titas, and B. Asish, “Parametric study for wire cut electrical discharge machining of sintered titanium,” *Stroj. Cas.*, vol. 69, no. 1, pp. 17–38, 2019, doi: 10.2478/scjme-2019-0002.

[10] S. Seshaiah *et al.*, “Optimization on Material Removal Rate and Surface Roughness of Stainless Steel 304 Wire Cut EDM by Response Surface Methodology,” *Adv. Mater. Sci. Eng.*, vol. 2022, 2022, doi: 10.1155/2022/6022550.

[11] M. M. Shehata, S. El-hadad, and H. Attia, “Wire Electrical Discharge Machining Process : Challenges and Future Prospects,” *Int. J. Technol. Innov.*, vol. vol.2, no. 2, pp. 31–37, 2022, doi: 10.21608/ijmti.2022.165776.1061.

[12] K. Jayakumar and T. Suresh, “Materials Today : Proceedings Effect of wire materials on performance during WEDM of SS304,” *Mater. Today Proc.*, no. xxxx, 2022, doi: 10.1016/j.matpr.2022.03.617.

[13] C. Sarala Rubi *et al.*, “Comprehensive review on wire electrical discharge machining: a non-

traditional material removal process," *Front. Mech. Eng.*, vol. 10, no. January, pp. 1–16, 2024, doi: 10.3389/fmech.2024.1322605.

[14] Z. A. Khan, A. N. Siddiquee, N. Z. Khan, U. Khan, and G. A. Quadir, "Multi Response Optimization of Wire Electrical Discharge Machining Process Parameters Using Taguchi based Grey Relational Analysis," *Procedia Mater. Sci.*, vol. 6, no. Icmpc, pp. 1683–1695, 2014, doi: 10.1016/j.mspro.2014.07.154.

[15] B. K. Lodhi and S. Agarwal, "Optimization of machining parameters in WEDM of AISI D3 steel using taguchi technique," *Procedia CIRP*, vol. 14, no. September 2015, pp. 194–199, 2014, doi: 10.1016/j.procir.2014.03.080.

[16] S. A. Khan, M. Usman, S. Pervaiz, M. Q. Saleem, and R. Naveed, "Exploring the feasibility of novel coated wires in wire EDM of Ti-6Al-4 V aerospace alloy: a case of multi-pass strategy," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 43, no. 5, pp. 1–9, 2021, doi: 10.1007/s40430-021-02994-7.

[17] LEE, "Hydrogen embrittlement of nickel, cobalt and iron-based superalloys," *Natl. Aeronaut. Sp. Adm.*, 2012, doi: 10.1533/9780857093899.3.624.

[18] A. A. A. Alduroobi, A. M. Ubaid, M. A. Tawfiq, and R. R. Elias, "Wire EDM process optimization for machining AISI 1045 steel by use of Taguchi method, artificial neural network and analysis of variances," *Int. J. Syst. Assur. Eng. Manag.*, vol. 11, no. 6, pp. 1314–1338, 2020, doi: 10.1007/s13198-020-00990-z.

[19] N. Z. Khan, Z. A. Khan, A. N. Siddiquee, and K. Arindam, "Investigations on the effect of wire EDM process parameters on surface integrity of HSLA : a multi- performance characteristics optimization," *Prod. Manuf. Res.*, vol. 2, no. 1, pp. 1–18, 2014, doi: 10.1080/21693277.2014.931261.

[20] U. M. R. Paturi, S. Cheruku, V. P. K. Pasunuri, S. Salike, N. S. Reddy, and S. Cheruku, "Machine learning and statistical approach in modeling and optimization of surface roughness in wire electrical discharge machining," *Mach. Learn. with Appl.*, vol. 6, no. May, p. 100099, 2021, doi: 10.1016/j.mlwa.2021.100099.

[21] S. S. Nain, P. Sihag, and S. Luthra, "Performance evaluation of fuzzy-logic and BP-ANN methods for WEDM of aeronautics super alloy," *MethodsX*, vol. 5, pp. 890–908, 2018, doi: 10.1016/j.mex.2018.04.006.

[22] U. Çaydaş, A. Hasçalik, and S. Ekici, "An adaptive neuro-fuzzy inference system (ANFIS) model for wire-EDM," *Expert Syst. Appl.*, vol. 36, no. 3 PART 2, pp. 6135–6139, 2009, doi: 10.1016/j.eswa.2008.07.019.

[23] S. Kumar and S. D. C. S. Narayanan, "Application of ANFIS and GRA for multi - objective optimization of optimal wire - EDM parameters while machining Ti – 6Al – 4V alloy," *SN Appl. Sci.*, vol. 1, no. 4, pp. 1–12, 2019, doi: 10.1007/s42452-019-0195-z.

[24] N. Lenin, M. Sivakumar, G. Selvakumar, and D. Rajamani, "Optimization of Process Control Parameters for WEDM of Al-LM25/Fly Ash/B4C Hybrid Composites Using Evolutionary Algorithms: A Comparative Study Nagarajan," *Metals (Basel).*, vol. 11, no. 1105, 2021, doi: org/10.3390/met11071105.

[25] M. T. Antar, S. L. Soo, D. K. Aspinwall, D. Jones, and R. Perez, "Productivity and workpiece surface integrity when WEDM aerospace alloys using coated wires," *Procedia Eng.*, vol. 19, pp. 3–8, 2011, doi: 10.1016/j.proeng.2011.11.071.

[26] V. Vakharia *et al.*, "Experimental investigations and prediction of WEDMed surface of nitinol SMA using SinGAN and DenseNet deep learning model," *J. Mater. Res. Technol.*, vol. 18, pp. 325–337, 2022, doi: 10.1016/j.jmrt.2022.02.093.

[27] H. Zisov *et al.*, "Effect of Longitudinal and Cross Feed on Flatness and Surface Roughness in Flat Grinding," *Adv. Eng. Lett.*, vol. 4, no. 1, pp. 14–20, 2025, doi: 10.46793/adeletters.2025.4.1.2.

[28] M. Diviya *et al.*, "Parametric investigation of W - EDM factors for machining AM60B conductive biomaterial," *Sci. Rep.*, pp. 1–17, 2024, doi: 10.1038/s41598-023-50777-y.

[29] A. Goyal, "Investigation of material removal rate and surface roughness during wire electrical discharge machining (WEDM) of Inconel 625 super alloy by cryogenic treated tool electrode," *J. King Saud Univ. - Sci.*, vol. 29, no. 4, pp. 528–535, 2017, doi: 10.1016/j.jksus.2017.06.005.

[30] S. S. Kumar, F. Erdemir, T. Varol, S. T. Kumaran, M. Uthayakumar, and A. Canakci, "Investigation of WEDM process parameters of Al e SiC e B 4 C composites using response surface methodology," *Int. J. Light. Mater. Manuf.*, vol. 3, no. 2, pp. 127–135, 2020, doi: 10.1016/j.ijlmm.2019.09.003.

[31] J. M. Gorriz, R. M. Clemente, F. Segovia, J. Ramirez, A. Ortiz, and J. Suckling, "Is K-fold cross validation the best model selection method for Machine Learning?," 2024, [Online]. Available: http://arxiv.org/abs/2401.16407

[32] M. Sheth *et al.*, "Optimization of WEDM parameters for Mg-Zn-RE-Zr alloy using Passing Vehicle Search algorithm," *Mater. Res. Express*, vol. 6, no. 12, p. 1265k6, 2019, doi: 10.1088/2053-1591/ab66f9.

[33] M. Seidi, S. Yaghoubi, and F. Rabiei, "Multi - objective optimization of wire electrical discharge machining process using multi - attribute decision making techniques and regression analysis," *Sci. Rep.*, pp. 1–12, 2024, doi: 10.1038/s41598-024-60825-w.

[34] M. Asrol, P. Papilo, and F. E. Gunawan, "Support Vector Machine with K-fold Validation to Improve the Industry's Sustainability Performance Classification," *Procedia Comput. Sci.*, vol. 179, no. 2020, pp. 854–862, 2021, doi:

10.1016/j.procs.2021.01.074.

[35] L. Sweet, C. Müller, M. Anand, and J. Zscheischler, "Cross-Validation Strategy Impacts the Performance and Interpretation of Machine Learning Models," *Artif. Intell. Earth Syst.*, vol. 2, no. 4, pp. 1–14, 2023, doi: 10.1175/aies-d-23-0026.1.

[36] O. Chamorro-Atalaya *et al.*, "K-Fold Cross-Validation through Identification of the Opinion Classification Algorithm for the Satisfaction of University Students," *Int. J. online Biomed. Eng.*, vol. 19, no. 11, pp. 140–158, 2023, doi: 10.3991/ijoe.v19i11.39887.

[37] M. Quarto, G. D'Urso, and C. Giardini, "Micro-EDM optimization through particle swarm algorithm and artificial neural network," *Precis. Eng.*, vol. 73, no. October 2020, pp. 63–70, 2022, doi: 10.1016/j.precisioneng.2021.08.018.

[38] R. Chalisgaonkar, S. Sirohi, J. Kumar, and S. Rathore, "Investigation and prediction of machining characteristics of aerospace material through WEDM process using machine learning," *Int. J. Interact. Des. Manuf.*, vol. 18, no. 8, pp. 5561–5581, 2024, doi: 10.1007/s12008-024-01923-x.

[39] S. Agarwal, S. S. Dandge, and S. Chakraborty, "A support vector machine-based prediction model for electrochemical machining process," *Karbala Int. J. Mod. Sci.*, vol. 6, no. 2, pp. 164–174, 2020, doi: 10.33640/2405-609X.1508.

[40] B. Sarker, S. Chakraborty, R. Čep, and K. Kalita, "Development of optimized ensemble machine learning- based prediction models for wire electrical discharge machining processes," *Sci. Rep.*, vol. 14, pp. 1–18, 2024, doi: org/10.1038/s41598-024-74291-x 1.