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Prediction of optimal wire EDM machining parameters for Inconel grades using machine learning technique

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KEYWORDS

Wire-cut electric discharge
Optimization
Machine learning algorithms
Surface roughness
Material removal rate

ABSTRACT

The prediction of optimal machining parameters for various manufacturing processes with the help of machine learning algorithms has been adopted for improved system efficiency in several machining techniques. Wire Electrical Discharge Machining (WEDM) is one of the advanced machining techniques used widely to produce intricate profiles on hard-to-cut materials. This study predicts the machining parameters of Inconel for WEDM by using ML algorithms, considering the chemical composition of Inconel as one of the input parameters. The prediction of the output parameters is specifically for those Inconel grades that are not machined on WEDM yet. Two major output variables, surface roughness (SR) and material removal rate (MRR) are selected for the prediction model. Major controllable parameters of WEDM including pulse on/off time, current, and voltage are selected as input parameters to the algorithms, along with the chemical composition, which is the novelty of the research. Four ML algorithms are used for prediction, namely Linear Regression (LR), Random Forest (RF), K- Nearest Neighbor (KNN) and Support Vector Machine (SVM), out of which RF is found to provide the best results based on statistical analysis. RF is significantly superior to LR and SVM, with improvements of 63.61% and 70.21%, respectively. For SR, RF shows substantial improvements of 29.68% over KNN, 66.64% over LR, and 66.76% over SVM. The novelty of this research is the approach and the process adopted, the comprehensiveness of evaluated variables.

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1.0 INTRODUCTION

Inconel materials are superalloys belonging to the nickel-chromium-based alloy family, specifically engineered to provide high corrosion and oxidation resistance, along with exceptional strength at elevated temperatures. These characteristics are essential for applications in automotive, aerospace, and oil & gas industries, where components must withstand harsh environments and extreme operating conditions. The chemical composition of Inconel primarily consists of nickel, with additional elements such as chromium, iron, cobalt, molybdenum, titanium, and niobium (Akca & Gürsel, 2015). The different grades of Inconel are formulated by adjusting the percentage composition of these elements, thereby offering varied material properties by the theory of alloy formation (Wang & Li, 2019).

Due to the work-hardening nature of Inconel, conventional machining processes often prove less efficient. As a result, wire electrical discharge machining (WEDM) is widely employed as a highly efficient, non-conventional machining method (Natarajan et al., 2022). WEDM is a non-contact machining process, where material removal occurs through electrical discharges (sparks) generated between the tool (a wire, either consumable or non-consumable) and the workpiece. This process is facilitated by applying a potential difference with high current (Alkahlan et al., 2023; Chaudhari et al., 2019).

In WEDM, the wire acts as a cathode and moves in a controlled manner to cut the work material (anode). The wire is continuously wound and unwound between two rollers, allowing for precise machining of complex contours. The wire's direction is carefully set to achieve the desired shape, as illustrated in Figure 1. Sparks are generated between the cathode and anode, eroding the work material and forming the required contours (Chaudhary et al., 2022). A dielectric medium is used throughout the process to enhance machining efficiency and facilitate debris removal (Muhammad et al., 2021).

A significant advantage of WEDM is that it does not require physical contact between the tool and the workpiece, making it feasible for machining electrically conductive materials irrespective of their hardness. The process primarily relies on thermal energy to erode or remove the workpiece, making it an attractive solution for manufacturing complex geometries such as precision molds and dies. This capability is particularly valuable in high-precision industries including aerospace, automotive, and medical device manufacturing, where extreme accuracy and surface quality are critical (Aggarwal et al., 2020).

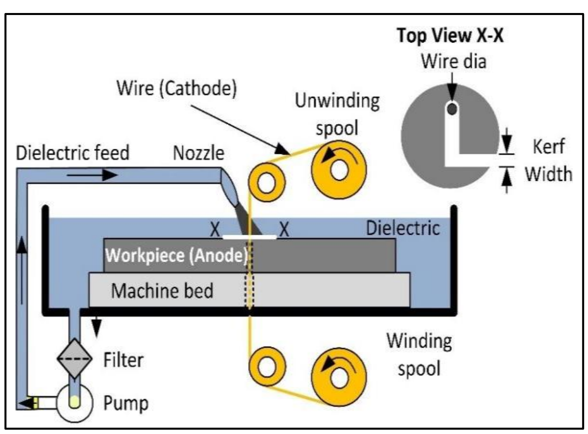

Figure 1: Schematic diagram (Chaudhary et al. 2022).

The controllable parameters of the WEDM process include pulse-on time, pulse-off time, voltage, and current, which primarily govern material erosion through electrical discharges. The resultant process variables include surface roughness (SR), wire consumption, kerf width, and material removal rate (MRR) (Farooq et al., 2020). Among these, SR and MRR are the most critical due to their direct impact on both the quality of the machined workpiece and the efficiency of the machining process. However, these two variables are mutually conflicting, as an increase in MRR often leads to a corresponding increase in SR, creating an optimization challenge. This relationship forms a convex optimization problem, where maximizing MRR results in higher SR, and vice versa (Joshi & Joshi, 2019).

Surface roughness and MRR are also highly influenced by the chemical composition of the material, which can be controlled as an input parameter in WEDM. Since the characteristics of Inconel vary based on its chemical composition, MRR and SR are influenced by the selected process parameters. Optimizing these parameters for a specific Inconel composition is of particular interest. A comprehensive literature review has been conducted to analyze the impact of these parameters across various Inconel compositions. Researchers have incorporated different elements and compounds into the dielectric medium during EDM and WEDM machining to evaluate their effects on process outcomes. Various dielectric additives such as aluminum (Al), titanium (Ti), silicon (Si), copper (Cu), molybdenum (Mo), chromium (Cr), tungsten (W), titanium carbide (TiC), silicon carbide (SiC), and carbon nanotubes (CNT) have been investigated for their influence on machining performance (Abdudeen et al., 2020; Chaudhari et al., 2021).

Kumar et al. (2019) reported better surface roughness and enhanced MRR when different chemicals were added to the dielectric during the EDM machining of Inconel. In another study, Rathod et al. (2022) examined titanium alloys machined using EDM, incorporating various chemical additives in the dielectric and observing overall improvements in MRR. Additionally, Shabgard & Khosrozadeh (2017) reported significant machining stability when carbon nanotubes were introduced into the dielectric during Ti6Al4V machining using EDM. Wasif et al. (2020, 2022) conducted WEDM experiments on steel and titanium-based alloys, varying the dielectric composition and noting substantial differences in machining performance based on the selected dielectric medium.

Machine learning (ML) has emerged as a rapidly developing branch of artificial intelligence (AI) that leverages data analysis and computational learning to create intelligent applications (Sarker et al., 2021). ML enables computers to make decisions without explicit programming. In ML applications, systems are trained using predefined algorithms by processing large datasets, and the trained model is then validated and tested on additional data. Based on this training, the model performs predictions and decision-making (Chatterjee, 2021). Recent research trends emphasize integrating machine learning with manufacturing processes to enhance production efficiency (Naresh et al., 2020). ML makes manufacturing systems more intelligent, allowing them to learn from data and perform real-time predictions without requiring explicit rule-based programming (Bhukya, 2021).

The effectiveness of an ML model depends on the nature, size, and characteristics of the data being used. These factors are essential for constructing a data-driven machine learning model (Sarker et al., 2020). Data can be categorized into three primary types: structured, unstructured, and semi-structured. Structured data is typically well-organized, stored in tables with labeled attributes such as parameter names, ranges, mean values, and standard deviations (Bhukya, 2021). Unstructured data, in contrast, lacks a predefined format, making it difficult to process and analyze (Jadhav et al., 2023). Semi-structured data exists between these two categories, possessing some organizational properties that assist in data analysis. A newly recognized category is metadata, essentially "data about data". Metadata provides contextual information, enhancing the interpretability of raw data for end users (Bhukya, 2021; Sarker, 2021; Java point, 2022).

Various machine learning techniques depend on data type, analytical goals, and real-world applications. ML models are broadly categorized into four types. Supervised Learning: A task-driven approach where models learn from labeled data, with each data point associated with a specific label. Unsupervised Learning: A data-driven approach where models identify patterns and relationships in unlabeled data. Semi-supervised Learning: A hybrid approach that combines both labeled and unlabeled data to enhance model performance. Reinforcement Learning: An environment-driven approach based on trial and error, where models learn from rewards and penalties (Sharma et al., 2020).

The primary objective of this research is to examine the impact of varying chemical compositions in different grades of Inconel during WEDM machining and to predict the machining outcomes for new Inconel grades that have not yet been extensively studied in WEDM. Among the various process variables, material removal rate (MRR) (mm^3/min) and surface roughness (SR) (μm) are selected as key performance metrics, as these are the most significant indicators of machining efficiency and workpiece quality, particularly in intricate machining processes (Mohapatra et al. 2017). Similarly, among the multiple controllable parameters, voltage, current, pulse-on time, and pulse-off time are chosen due to their dominant influence on the machining process (Kar et al. 2023). A novel aspect of this research is the inclusion of chemical composition as an additional input parameter, recognizing the role of alloying elements in influencing WEDM performance. This approach introduces a new dimension to process modeling, allowing for a more comprehensive understanding of how chemical composition affects machinability, MRR, and surface roughness.

2.0 EXPERIMENTAL PROCEDURE

The research strategy has been designed following a project lifecycle approach, as illustrated in Figure 2. The first step involves gathering input data from machining datasets of various Inconel grades, extracted from existing research articles. Studies report that wire EDM process parameters, such as applied current, voltage, and pulse-on/off times, are specifically targeted to study MRR and SR (Bhowmick et al. 2023; Bisaria & Rouniyar, 2023; Kar et al. 2023; Kosaraju et al. 2023; Raj et al. 2023). A brief relationship between these input variables & output parameters is shown in Table 1. Additionally, the chemical composition of the respective Inconel grades is explicitly included as an input parameter, representing a novel approach that could significantly impact the wire EDM process. This aspect is a key focus of the study. A total of 67 research articles were analyzed, yielding a dataset of 944 values, which serves as the foundation for this research.

The dataset is carefully prepared for input into machine learning (ML) models in the second step. The data is formatted under well-defined headers, and incomplete or inconsistent entries are filtered out using interpolation techniques. Additionally, the dataset is divided into two subsets: 80% for training the ML models and 20% for validation (Bisaria & Rouniyar, 2023). The third step involves training four selected machine learning techniques: Linear Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF), The chosen models represent a diverse mix of tree-based, distance-based, kernel-based, and linear approaches, ensuring that our predictions are evaluated across different machine learning paradigms (Singh et al. 2023). These models are fine-tuned to optimize their predictive accuracy. The training process of these ML techniques is further elaborated in Section 4 of this study. The fourth step involves hyperparameter tuning to enhance model efficiency. Specifically, "trees" were tuned for the RF model, while "neighbors" were optimized for the KNN model (Narayana et al. 2022). These details are comprehensively discussed in Section 4. Finally, the ML model with the least prediction error is selected as the most precise for machining parameter estimation. This selected model is then validated using the remaining dataset to assess its prediction accuracy and effectiveness, as discussed in Section 5 of this article.

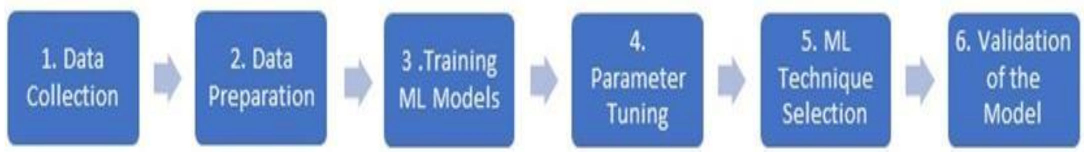

Figure 2: Research strategy.

The data collection process involves gathering machining datasets from previously published research articles on WEDM machining of Inconel alloys. For this purpose, all available research articles published until February 2024 have been included to form a comprehensive dataset for machine learning (ML) models. Since some Inconel grades may not yet have been machined using WEDM, this research aims to predict the optimal process parameters for those “unmachined” Inconel grades, thereby expanding the applicability of WEDM to new material compositions.

After filtering the collected data, a final dataset of 944 entries was created, encompassing all relevant machining parameters and variables for different Inconel grades. While this dataset size may be considered relatively small, previous studies have demonstrated that ML models remain effective even with limited data when appropriate techniques are applied (Zhang & Ling, 2018). The selection of ML algorithms for this study was based on the dataset's size and nature.

A CSV file was prepared to organize the selected dataset for machine learning applications. Notably, the chemical composition of each Inconel grade was included as a novel input parameter for the WEDM process, an approach that has not been previously explored. By integrating chemical composition into the ML framework, this research introduces a new dimension to process optimization, enabling more accurate predictions of machining outcomes for different Inconel grades. Inconel grades exhibit variations in chemical composition, necessitating an analysis of the mean values of their elemental composition. Ranges for pulse-on time, pulse-off time, voltage, and current were generated to predict surface roughness (SR) and material removal rate (MRR) in Inconel grades with unknown WEDM data. A relationship between these parameters is shown in Table 1.

Table 1: Effects of chosen WEDM process parameters on MRR & SR.

Process Parameter	Effect on MRR	Effect on SR	References
Current (I)	Increases MRR (Higher current increases discharge energy, resulting in more material removal).	Increases SR (Higher energy causes deeper craters and rougher surface texture).	
Voltage (V)	Minimal direct effect on MRR (Controls spark gap; minor influence on removal rate).	Increases SR (Extended exposure leads to deeper craters and rougher surfaces).	Kosaraju et al. (2023), Kar et al. (2023), Raj et al. (2023), Bhowmick et al. (2023), Bisaria & Rouniyar (2023), Chaudhari et al (2019), Kumar et al (2019)
Pulse-on Time (T_{on})	Increases MRR (Longer discharge duration enhances material removal per pulse).	Increases SR (Extended exposure leads to deeper craters and rougher surfaces).	
Pulse-on Time (T_{off})	Increases MRR (Longer discharge duration enhances material removal per pulse).	Increases SR (Extended exposure leads to deeper craters and rougher surfaces).	

For Inconel grades with similar chemical compositions, interpolation was applied to determine the controllable parameter ranges (current, voltage, pulse-on time, and pulse-off time) based on actual machining data collected from research articles. Maximum and minimum limits were defined for each parameter in the unknown Inconel grades, where WEDM machining data has not yet been reported. To train the machine learning (ML) model, datasets were generated by considering all possible combinations of pulse-on time, pulse-off time, voltage, and current within the defined ranges. The dataset was then divided into training and testing subsets in an 80:20 ratio. To enhance prediction reliability, the training set was further split into training and validation datasets. The parameter ranges for the unknown grades of Inconel used in this study are presented in Table 2, providing a basis for ML-driven predictions of machining performance in WEDM. A comprehensive compilation of the chemical composition of all Inconel grades is shown in Table 3.

After screening and selecting the controllable parameters and machining variables for the WEDM process, a correlation matrix was developed to visualize the relationships between the alloying elements of Inconel and the selected controllable parameters in wire EDM. The correlation matrix, presented in Figure 3, provides insight into these relationships by using a color gradient. Darker red shades indicate a strong positive correlation (a direct linear relationship). Brighter blue shades indicate a strong negative correlation (an inverse relationship). The matrix reveals several key correlations: Titanium (Ti) exhibits a positive correlation of 0.4 with pulse-off time (Toff) and surface roughness and a positive correlation of 0.3 with applied voltage. Nickel (Ni) has a positive correlation of 0.3 with MRR. Iron (Fe) shows a positive correlation of 0.3 with applied voltage. Carbon (C) demonstrates a negative correlation of 0.3 with MRR. Sulfur (S) exhibits a negative correlation of 0.3 with applied voltage. Additionally, the correlation matrix highlights interdependencies between different alloying elements as well as inter-correlations between machining parameters, offering valuable insights for optimizing the WEDM process based on the chemical composition of Inconel alloys.

Table 2: Interpolated ranges for the grades of Inconel with an unknown data set as input to the ML algorithms.

Targeted Grades	**Available Grades with data**	**Max IP (Amp)**	**Min IP (Amp)**	**Max Ton (µS)**	**Min Ton (µS)**	**Max Toff (µS)**	**Min Toff (µS)**	**Max Voltage (Volts)**	**Min Voltage (Volts)**
Inconel 188	Inconel 800	220	100	1.25	0.35	27	7	80	20
Inconel 230	Inconel 625	120	5	500	10	100	30	90	5
Inconel 713 C	Inconel 625	120	5	500	10	100	30	90	5
Inconel 751	Inconel X-750	170	8	500	100	2000	37	100	20
Inconel 792	Inconel 800	220	100	1.25	0.35	27	7	80	20
Inconel 907	Inconel 800	220	100	1.25	0.35	27	7	80	20
Inconel 909	Inconel 800	220	100	1.25	0.35	27	7	80	20
Inconel 925	Inconel 800	220	100	1.25	0.35	27	7	80	20

TABLE 3: Chemical composition of the training dataset of the Inconel grades.

Inconel Grade	Ni	Cr	Fe	Co	Mn	Si	C	S	P	B	W	La	Mo	Cu	Al	Ti	Nb & Ta	Zr
Inconel 188	20.0-24.0	20.0-24.0	≤3.0	35.0-40.0	≤1.25	0.2-0.5	0.05-0.15	≤0.01 5	≤0.02	≤0.015	13.0-16.0	0.02-0.12	---	---	---	---	---	---
Inconel 230	47.0-65.0	20.0-24.0	≤3.0	≤5.0	0.3-1.0	0.25-0.75	0.05-0.15	≤0.015	≤0.03	≤0.015	13.0-15.0	0.02-0.12	1.0-3.0	≤0.5	0.20-0.50	≤0.1	---	---
Inconel 600	72.0-78.0	14.0–17.0	6.0–10.0	---	≤1.0	≤0.5	≤0.8	≤0.015	---	---	---	---	---	≤0.5	---	≤0.5	---	---
Inconel 601	58.0-63.0	21.0-25.0	Bal	---	≤1.0	≤0.5	≤0.1	≤0.5	---	---	---	---	---	≤1.0	1.0-1.7	---	---	---
Inconel 617	44.2–61.0	20.0-24.0	≤3.0	10.0–15.0	≤0.5	≤0.5	0.05-0.15	≤0.015	≤0.015	≤0.006	---	---	8.0–10.0	≤0.5	0.8–1.5	≤0.6	---	---
Inconel 625	≥58.0	20.0–23.0	≤5.0	≤1.0	≤0.5	≤0.5	≤0.1	≤0.015	≤0.015	---	---	---	8.0–10.0	≤0.5	≤0.4	≤0.4	3.15–4.15	---
Inconel 686	52.0-63.0	19.0-23.0	≤5.0	---	≤0.75	≤0.08	≤0.01	≤0.02	≤0.04	---	3.0-4.4	---	15.0-17.0	---	---	0.02-0.25	---	---
Inconel 690	≥58.0	27.0–31.0	7.0-11.0	---	≤0.5	≤0.5	≤0.05	≤0.015	---	---	---	---	---	≤0.5	---	≤0.4	---	---
Inconel 706	39.0-44.0	14.5-17.5	Bal	---	≤0.35	≤0.35	≤0.06	≤0.015	≤0.02	≤0.006	---	---	---	≤0.3	≤0.4	1.5-2.0	---	---
Inconel 713	Bal	12.0-14.0	≤2.50	---	≤0.25	≤0.5	0.08-0.20	---	---	0.005-0.015	---	---	3.80-5.20	≤0.5	5.5-6.5	0.5-1.0	1.8-2.8	---
Inconel 718	50.0-55.0	17.0-21.0	Bal	≤1.0	≤0.35	≤0.35	≤0.08	≤0.015	≤0.015	≤0.006	---	---	2.8–3.3	≤0.3	0.2-0.8	0.65-1.15	4.7–5.5	---
Inconel X-750	≥70.0	14.0–17.0	5.0–9.0	≤1.0	≤1.0	≤0.5	≤0.08	≤0.01	---	---	---	---	---	≤0.5	0.4–1.0	2.25–2.75	0.7–1.2	---
Inconel 751	≥70.0	14.0-17.0	5.0–9.0	---	≤1.0	≤0.5	≤0.08	≤0.01	---	---	---	---	---	≤0.5	1.0-1.5	2.0-2.7	0.7–1.2	---
Inconel 792	60.0-69.0	11.0-13.0	Bal	8.0-10.0	---	---	≤0.21	---	---	≤0.02	3.5-4.5	---	1.6-2.4	---	≤3.2	3.5-4.5	3.5-4.5	≤0.1

Inconel 907	35.0-40.0	≤1.0	36.5-47.1	12.0-16.0	≤1.0	0.07-0.35	≤0.06	---	---	---	---	---	---	≤0.5	≤0.2	1.3-1.8	4.3-5.2	---
Inconel 909	35.0-40.0	≤1.0	36.3-46.9	12.0-16.0	≤1.0	0.25-0.50	≤0.06	≤0.015	≤0.015	≤0.012	---	---	---	≤0.5	≤0.15	1.3-1.8	4.3-5.2	---
Inconel 925	42.0-46.0	19.5-22.5	≥22.0	---	≤1.0	---	≤0.03	≤0.03	≤0.03	---	---	---	2.50-3.50	1.5-3.0	0.1-0.5	1.9-2.4	≤0.5	---
Inconel 939	46.4-56.3	21.4-23.4	≤5.0	16.0-20.0	≤0.5	≤0.5	≤0.1	≤0.01 5	≤0.01 5	---	---	---	8.0-10.0	---	0.1-0.5	3.2-4.3	0.9-1.9	---

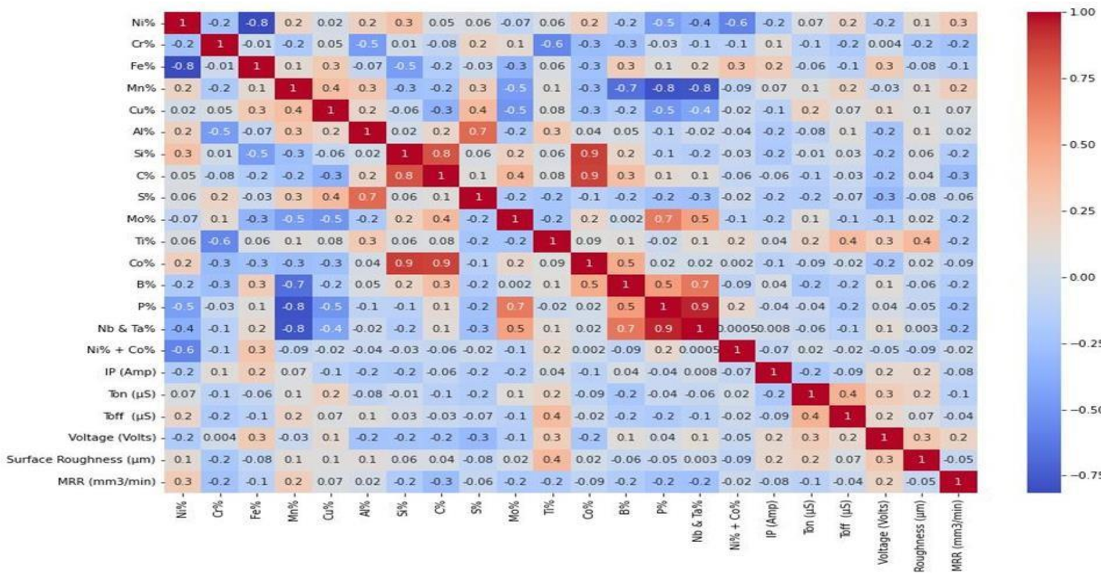

Figure 3: Correlation matrix between alloying elements and the Wire EDM Parameters.

An open-source programming language, Python is used for the application of ML learning in this research due to its versatility, powerful libraries, simplicity, and robust and user-friendly environment. This research used the following Python libraries:

i) Pandas: For Data manipulation and/or analysis
ii) NumPy: For numerical computations and/or array operations
iii) Scikit-learn: For Machine learning algorithms and tools.
iv) Matplotlib: The general-purpose plotting library
v) Seaborn: Statistical data visualization with aesthetics.

Data scaling is a crucial pre-processing step to improve the performance and accuracy of machine learning models. It transforms the data into a more adaptable form, ensuring that values from different ranges are brought closer together, thereby enhancing the effectiveness and efficiency of the algorithm (V. Sharma, 2022). There are three primary types of data scaling techniques: the Standard Scaler method, the Min-max method, Robust method (Sharma, 2022). Among these, standardization is one of the most commonly used techniques. It ensures that the data is scale-free, transforming it into a standardized distribution with a mean of zero and a standard deviation of one. This method addresses the issue where different variables in the dataset exist in varying numerical ranges, preventing them from contributing equally to the model's training process and predictive accuracy. Such variations can introduce bias in predictions. The standard scaler method enhances the stability of the algorithm, making it less sensitive to outliers while preventing model bias (Sharma, 2022).

For this study, the standard scaler method was applied to normalize the machine-controllable input parameters (pulse-on time, pulse-off time, voltage, and current) as practiced by (Sharma, 2022) in eq (1) presented mathematically expressed as:

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

Where x is the original value of the variable, μ is the mean of the variable, and σ is the standard deviation. The gathered data is labeled and categorized, and supervised machine learning techniques were selected for modeling. Among various supervised ML methods, Linear Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN) were considered due to their compatibility with the dataset (Kumar et al. 2024).

3.0 RESULTS AND DISCUSSION

3.1 Evaluation of Algorithms

The selected machine learning algorithms were tested on the training dataset and evaluated using the Root Mean Square Error (RMSE) method. RMSE is a widely used statistical metric for assessing the accuracy of a predictive model, providing a measure of the average deviation between the predicted values and the actual observed values. RMSE quantifies the differences between predicted values (y1) generated by the model and the actual (y2) observed values from the dataset. The formula for RMSE is expressed in eq (2) as practiced by (Karunasingha, 2022).

$$R.M.S = \sqrt{\frac{1}{N}(y_2 - y_1)} \tag{2}$$

A lower RMSE value indicates that the model's predictions are closer to actual values, signifying higher accuracy and better model performance. By minimizing RMSE, the model is optimized to reduce errors, thereby improving its predictive reliability for unseen data. After testing the dataset on the four selected machine learning algorithms, Random Forest (RF) yielded the lowest RMSE among all models for both Material Removal Rate (MRR) and Surface Roughness (SR), as illustrated in Figure 4. K-Nearest Neighbor (KNN) provided the second-best results, indicating its potential as a suitable alternative. The initial RMSE values suggest that RF and KNN are the most promising algorithms for this dataset. However, to ensure the robustness and generalizability of the model, this finding is further verified through cross-validation before proceeding with the final model selection. This additional validation step enhances the reliability of the selected algorithm, ensuring it performs consistently across different subsets of the data.

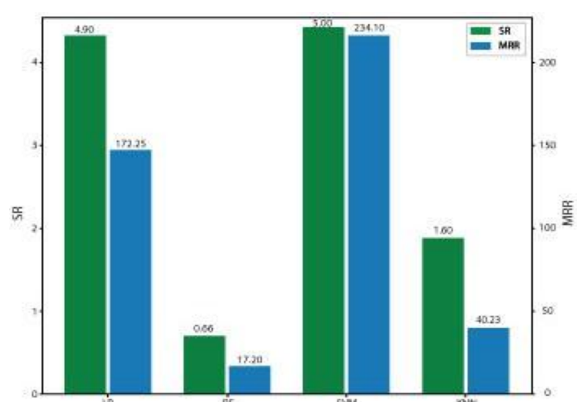

Figure 4: Initial RSME scores for algorithms.

3.2 Cross-Validation of the Algorithms

All four machine learning algorithms were then subjected to cross-validation to ensure better accuracy and reliability. Cross-validation is a technique used to assess the generalization ability of an ML model by evaluating its performance on unseen data (Ramezan et al., 2019). This method helps determine how well a model performs beyond the training dataset by training it on different subsets of the input data (King et al., 2021). Among the seven major cross-validation techniques—Holdout, K-Fold, Stratified K-Fold, Monte Carlo, Rolling, Leave-One-Out, and Leave-P-Out, K-Fold Cross-Validation was selected for this study. This method was chosen because it requires less computational power, is insensitive to outliers, and effectively reduces variability in model performance (Ramezan et al., 2019).

In K-Fold Cross-Validation, the dataset is divided into k equal subsets (folds). The model is trained iteratively on k-1 folds, while the remaining fold is used for validation. This process repeats k times, ensuring that each data point is used once in the validation set and k-1 times in the training set (Nti et al., 2021). The final model performance is determined by averaging the errors across all k iterations, providing a more robust evaluation of its predictive accuracy.

To visualize the effectiveness of each ML model, a boxplot of RMSE values was generated. The boxplot highlights both the median RMSE value and the variability of each model. A lower median RMSE and a narrower box indicate a more consistent and reliable model. Figure 5 presents the boxplot of mean RMSE values for Material Removal Rate (MRR).

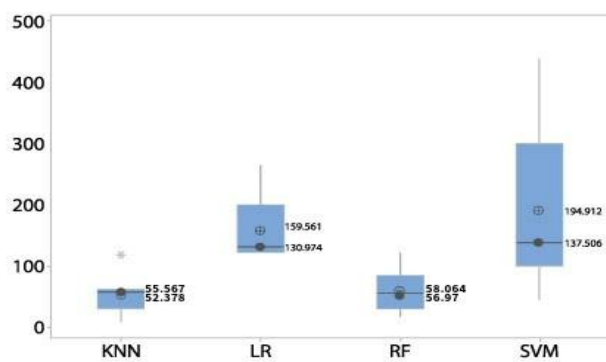

Figure 5: Boxplot for MRR.

The RMSE values for the four ML techniques are as follows:

i) K-Nearest Neighbor (KNN): 52.37
ii) Linear Regression (LR): 159.96
iii) Random Forest (RF): 58.06
iv) Support Vector Machine (SVM): 194.91

Among these, KNN achieved the lowest RMSE value (52.37), indicating superior prediction accuracy for MRR. Hence, the cross-validation results recommend the use of KNN as the most suitable algorithm for predicting material removal rate (MRR) in WEDM machining. Similarly, Figure 6 presents the boxplot of mean RMSE values for Surface Roughness (SR), illustrating the variability and performance of each ML model. The RMSE values computed for the four ML techniques are as follows:

i) K-Nearest Neighbor (KNN): 2.282
ii) Linear Regression (LR): 4.48
iii) Random Forest (RF): 1.49
iv) Support Vector Machine (SVM): 4.49

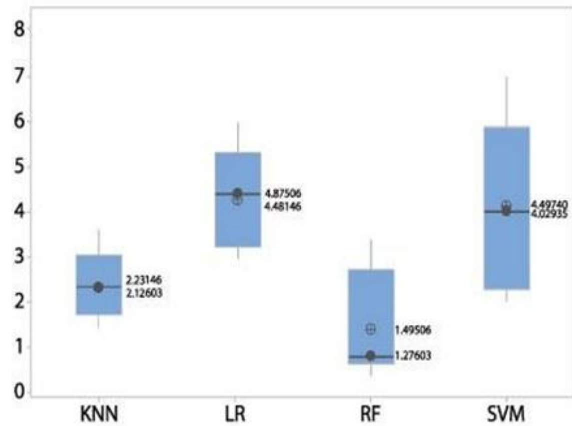

Figure 6: Boxplot for SR.

Among these, Random Forest (RF) achieved the lowest RMSE value (1.49), indicating superior prediction accuracy and better model stability for surface roughness (SR). Based on cross-validation results, Random Forest (RF) is recommended as the most suitable ML algorithm for the prediction of surface roughness (SR) in WEDM machining. The mean RMSE values and standard deviations for Material Removal Rate (MRR) and Surface Roughness (SR) are presented in Table 4. The results indicate that the K-Nearest Neighbor (KNN) technique achieves the lowest mean RMSE and standard deviation for MRR, while the Random Forest (RF) method exhibits the lowest mean RMSE and standard deviation for SR. As a result, both KNN and RF are selected for further tuning and model verification, ensuring enhanced prediction accuracy and robustness in the final model selection process.

Table 4: RMSE Results of the four ML techniques.

Model	Mean RMSE for MRR	Standard Deviation of MRR	Mean RMSE for SR	Standard Deviation of SR
KNN	52.378	30.080	2.126	0.914
LR	159.561	53.258	4.481	1.207
RF	58.064	36.062	1.495	0.908
SVM	194.912	130.571	4.497	1.783

3.3 Parameter Tuning

A model's performance is optimized through parameter tuning, a process that aims to maximize prediction accuracy while minimizing overfitting and variance (Trivedi et al., 2021). Parameter tuning involves adjusting hyperparameters, which are pre-defined settings within an algorithm that influence the learning process. Unlike standard model parameters, hyperparameters are explicitly set by the user and require experience to fine-tune for optimal performance (Manikandan et al., 2021).

In Random Forest (RF) and K-Nearest Neighbor (KNN), the key hyperparameters are: "Trees" in RF, which determines the number of decision trees in the ensemble model. "Neighbors" in KNN, which specifies the number of nearest neighbors considered for classification or regression.

In this study, the number of trees in RF was tested within a range of 1 to 20 to evaluate its impact on Material Removal Rate (MRR) and Surface Roughness (SR) predictions. Since the dataset size is relatively small, using a lower k-value helps prevent overfitting. A significant decrease in RMSE was observed for both MRR and SR at 20 trees, indicating the best performance with the least prediction error, as illustrated in Figure 7.

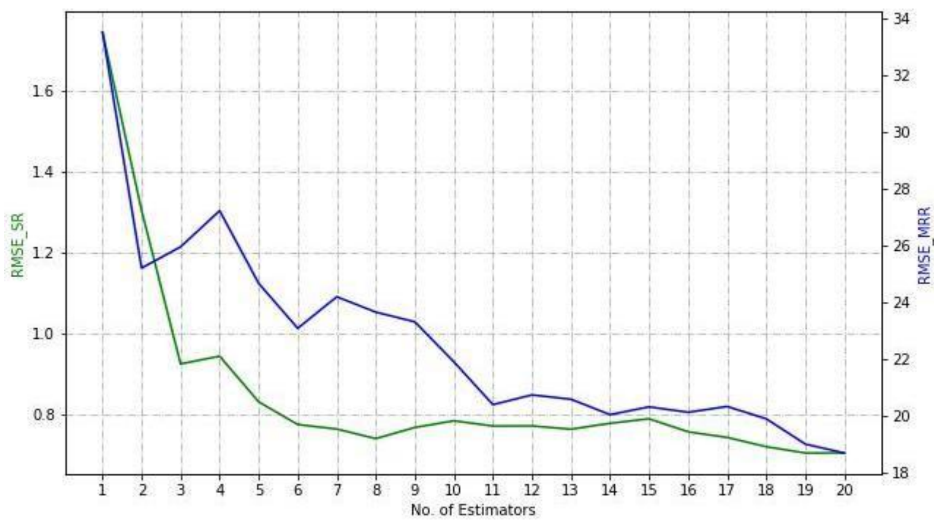

Figure 7: Tuning of RF parameters (trees) for the least RMSEs of SR and MRR.

The number of neighbors in the K-Nearest Neighbor (KNN) algorithm was tested within a range of 1 to 20 in this study. While 20 trees were found optimal for Random Forest (RF), too many trees can increase training time and raise the risk of overfitting. The results indicate that only the first neighbor (k=1) yielded the lowest RMSE (see Figure 8). However, this result highlights a lack of generalizability in KNN, as relying on just one neighbor makes the model highly sensitive to individual data points, leading to high variance and instability. Due to KNN's inability to generalize well with the provided dataset, it is deemed unsuitable for predicting Material Removal Rate (MRR) and is thus excluded from the final model selection list. Consequently, Random Forest (RF) is retained as the most suitable model for further analysis and optimization.

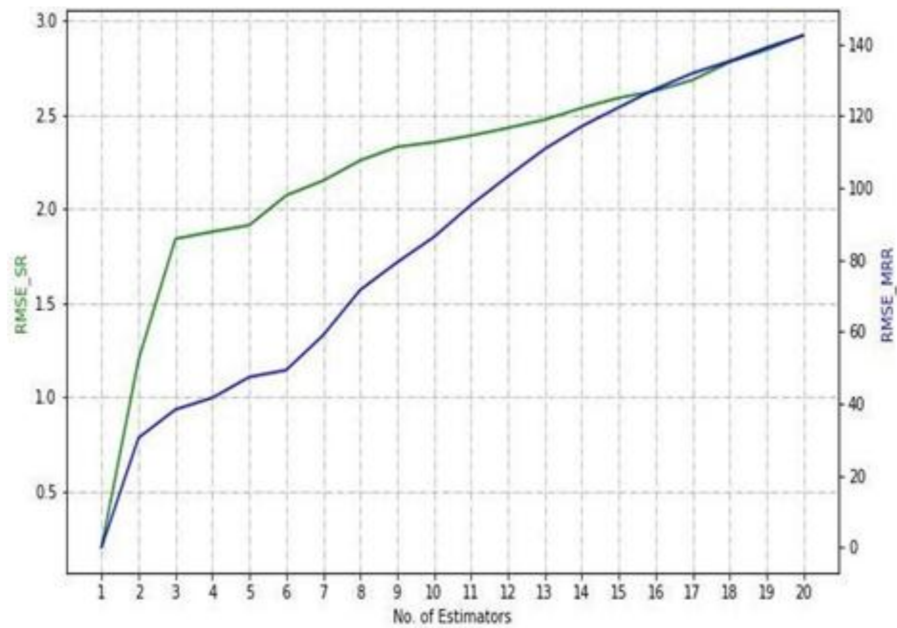

Figure 8: Tuning of KNN parameters (neighbor) for the least RMSEs of SR and MRR.

3.4 Selection of Suitable ML Technique

Since Random Forest (RF) has been identified as the most suitable machine learning technique for the Inconel WEDM dataset, it is selected for further validation. To ensure the robustness and reliability of the model, K-Fold Cross-Validation is performed while maintaining 20 trees in the RF model.

The selection of 20 trees is well justified, as it provides an optimal balance between computational efficiency and prediction accuracy. Increasing the number of trees beyond this point would increase training time and computational cost without significant improvements in model performance. By keeping the number of trees at 20, the model achieves high accuracy, low variance, and efficient computation, making it the best choice for predicting machining outcomes in the Inconel WEDM process. Table 5 summarizes the estimated and expected performance of the Random Forest (RF) model for the given dataset. The results indicate that the model, on average, predicts Surface Roughness (SR) with an error of 1.49 ± 0.92 and Material Removal Rate (MRR) with an error of 58.06 ± 36.12.

Table 5: Cross Validation for the RF model.

Model	**Mean RMSE for SR**	**Standard Deviation of SR**	**Mean RMSE for MRR**	**Standard Deviation of MRR**
RF	1.49	0.92	58.06	36.12

Figures 9 and 10 illustrate the predicted range of unknown Material Removal Rate (MRR) and Surface Roughness (SR) for different grades of Inconel, providing insights into their expected machinability under Wire Electrical Discharge Machining (WEDM) conditions. The distribution of MRR across the Inconel grades in Figure 9 reveals substantial variation, with certain grades such as Inconel 713C, 751, and 792 exhibiting higher MRR values, suggesting that these materials may experience faster material removal rates. In contrast, Inconel 909 and 925 demonstrate lower MRR values, indicating a potentially slower machining process, likely due to differences in hardness or resistance to thermal erosion. The scatter pattern observed across the grades suggests variability in the predicted MRR, which could be influenced by differences in chemical composition, electrical conductivity, and thermal response. These variations highlight the necessity of optimizing machining parameters to achieve efficient material removal rates tailored to each alloy's characteristics.

The predicted SR values in Figure 10 also indicate notable differences across the various Inconel grades, reflecting variations in the resulting surface finish. Inconel 188 and 230 exhibit lower SR values, suggesting that these materials may produce a smoother machined surface, which is advantageous in applications requiring high precision and minimal post-processing. Conversely, Inconel 713C, 751, and 792 display moderately higher SR values, likely due to their thermal conductivity influencing material erosion during the machining process. Inconel 909 and 925 present the highest SR values, implying that these materials may require additional optimization of WEDM parameters, such as reducing pulse-on time or enhancing flushing techniques, to improve the surface finish. The correlation between chemical composition and surface quality further emphasizes the need for parameter adjustments specific to each Inconel grade to achieve desirable machining outcomes.

The findings underscore the significance of predictive modeling in optimizing machining processes for previously untested Inconel grades. The variability in both MRR and SR predictions suggests that each grade requires a unique set of machining conditions to balance material removal efficiency and surface finish quality. The effectiveness of the Random Forest-based prediction model in capturing machinability trends for different Inconel alloys further reinforces its potential as a robust tool for WEDM process optimization. By leveraging these insights, researchers and manufacturers can make informed decisions regarding WEDM parameter selection, ultimately improving machining efficiency and the overall quality of finished components.

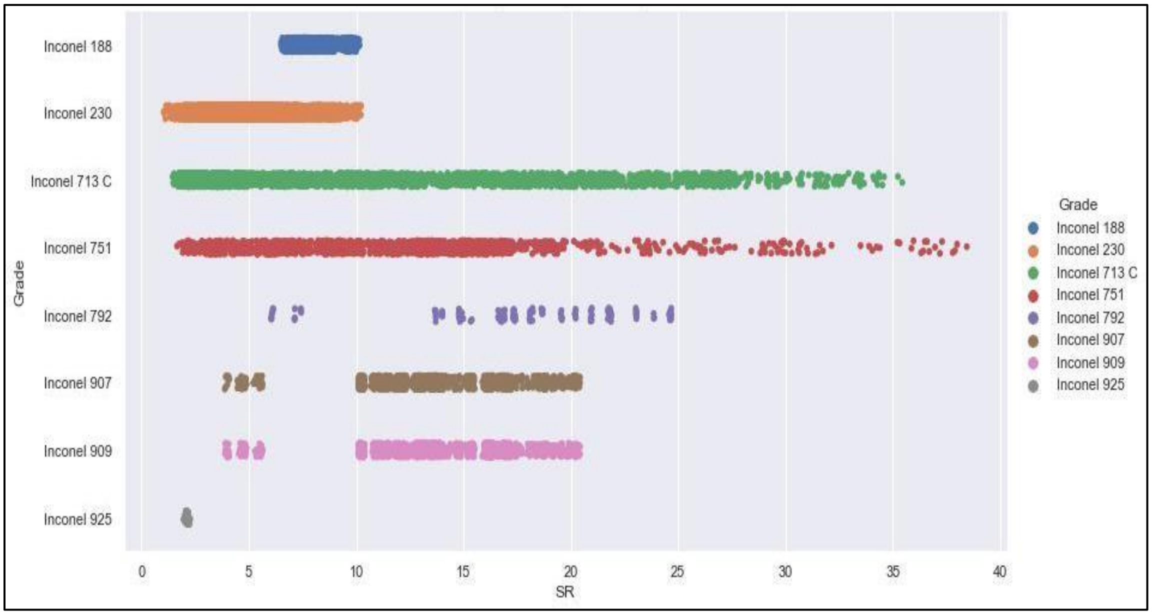

Figure 9: Predicted range of unknown SR (in μm).

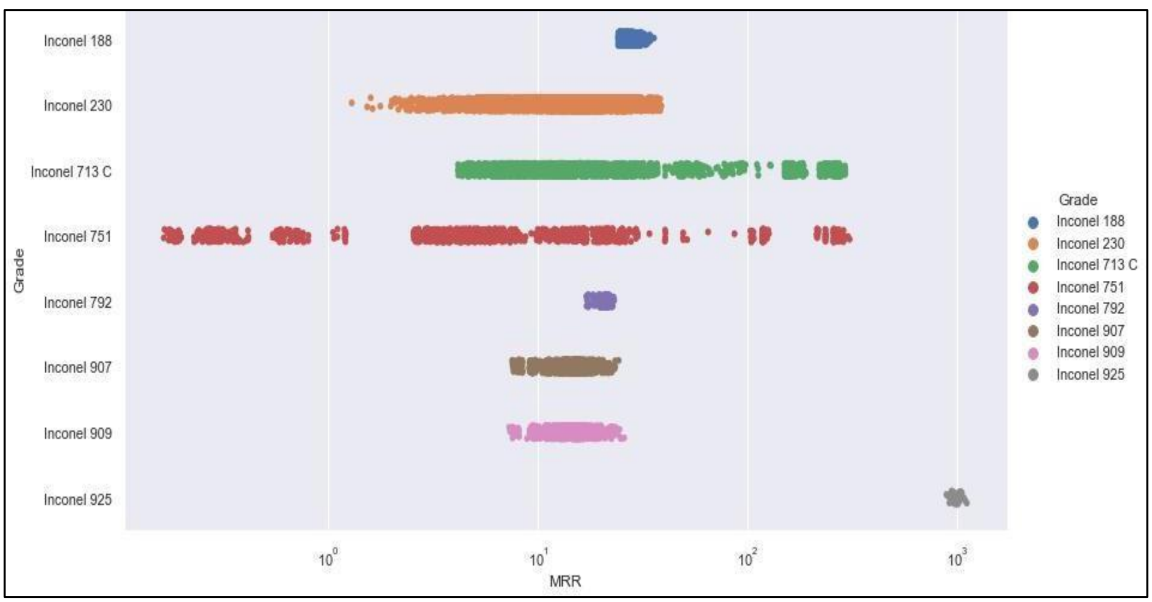

Figure 10: Predicted range of unknown MRR (in mm^3/min.).

CONCLUSIONS

This research introduces a novel methodology for predicting the machining performance of Inconel alloys in Wire Electrical Discharge Machining (WEDM) by incorporating the chemical composition of the alloy as a key input parameter in machine learning (ML) algorithms. This approach was implemented by systematically collecting, filtering, and interpolating actual machining data from existing studies to ensure compatibility with ML models. A correlation matrix was developed to examine the relationships between the alloying elements of different Inconel grades and the selected machining input parameters and output process variables. The analysis identified titanium as the most influential element affecting the machining process in WEDM, underscoring its significance in determining machining efficiency. Furthermore, the correlation matrix provided valuable insights into the interdependencies between various alloying elements, illustrating their collective impact on machinability.

Among the four supervised ML techniques tested, the Random Forest (RF) algorithm demonstrated the highest prediction accuracy for estimating the machining parameters of new Inconel grades. The predictive capability of RF presents a practical tool for the manufacturing industry by enabling data-driven performance predictions for WEDM machining processes across a range of alloys and materials. This approach has the potential to enhance process optimization, reduce trial-and-error experimentation, and improve overall machining efficiency.

In terms of future research, this methodology can be extended to other manufacturing processes, particularly those involving high-alloy materials where chemical composition plays a crucial role in machinability. Additionally, this approach can be further generalized for WEDM applications across different alloying materials, broadening its applicability in precision machining. Incorporating additional machining parameters could enhance the model's robustness, allowing for more comprehensive process optimization. Expanding the dataset with additional experimental machining data would further improve the accuracy and reliability of the proposed ML model, ensuring its effectiveness in real-world industrial applications.

The research has the following limitations:

(a) A larger dataset could potentially improve the model's robustness and generalizability.
(b) The data used in this research is gathered from previously published research articles. This introduces a potential limitation, as the accuracy and consistency of the data depend on the quality of the original studies.
(c) The findings are specific to Inconel alloys and WEDM. The applicability of the proposed methodology to other materials and machining processes may be limited.

REFERENCES

Abdudeen, A., Abu Qudeiri, J. E., Kareem, A., Ahammed, T., & Ziout, A. (2020). Recent Advances and Perceptive Insights into Powder-Mixed Dielectric Fluid of EDM. Micromachines, 11(8), 754. https://doi.org/10.3390/mi11080754

Aggarwal, V., Singh, J., Sharma, S., Sharma, A., Singh, G., & Parshad, J. (2020). Empirical modeling of machining parameters during WEDM of Inconel 690 using response surface methodology. 020032. https://doi.org/10.1063/5.0027284

Akca, E., & Gürsel, A. (2015). A review on superalloys and IN718 nickel-based INCONEL superalloy. Periodicals of Engineering and Natural Sciences (PEN), 3(1), Article 1. https://doi.org/10.21533/pen.v3i1.43

Alkahlan, B., Tabbakh, T., Kurdi, A., Pramanik, A., & Basak, A. K. (2023). Formation and Characterization of the Recast Layer Formed on Inconel 718 during Wire Electro Discharge Machining. Materials, 16(3), Article 3. https://doi.org/10.3390/ma16030930

Bhowmick, S., Mondal, R., Sarkar, S., Biswas, N., De, J., & Majumdar, G. (2023). Parametric optimization and prediction of MRR and surface roughness of titanium mixed EDM for Inconel

718 using RSM and fuzzy logic. CIRP Journal of Manufacturing Science and Technology, 40, 10–28. https://doi.org/10.1016/j.cirpj.2022.11.002

Bhukya, D. R. (2021). Exploring Machine Learning: A Beginners Perspective. Horizon Books (A Division of Ignited Minds Edutech P Ltd).

Bisaria, H., & Rouniyar, A. K. (2023). Processing of Triangular Profile on Inconel-825 Superalloy by Wire Electrical Discharge Machining and Corner Error Optimization Using Teaching Learning-Based Optimization Technique. Journal of Materials Engineering and Performance, 32(20), 9405–9417. https://doi.org/10.1007/s11665-022-07797-y

Chatterjee, I. (2021). Machine Learning and Its Application: A Quick Guide for Beginners. Bentham Science Publishers.

Chaudhari, R., Vora, J. J., Mani Prabu, S. S., Palani, I. A., Patel, V. K., Parikh, D. M., & de Lacalle, L. N. L. (2019). Multi-Response Optimization of WEDM Process Parameters for Machining of Superelastic Nitinol Shape-Memory Alloy Using a Heat-Transfer Search Algorithm. Materials, 12(8), 1277. https://doi.org/10.3390/ma12081277

Chaudhari, R., Vora, J., López de Lacalle, L. N., Khanna, S., Patel, V. K., & Ayesta, I. (2021). Parametric Optimization and Effect of Nano-Graphene Mixed Dielectric Fluid on Performance of Wire Electrical Discharge Machining Process of Ni55.8Ti Shape Memory Alloy. Materials (Basel, Switzerland), 14(10), 2533. https://doi.org/10.3390/ma14102533

Chaudhary, A., Sharma, S., & Verma, A. (2022). WEDM machining of heat treated ASSAB ’88 tool steel: A comprehensive experimental analysis. Materials Today: Proceedings, 50, 946–951. https://doi.org/10.1016/j.matpr.2021.06.354

Farooq, M. U., Ali, M. A., He, Y., Khan, A. M., Pruncu, C. I., Kashif, M., Ahmed, N., & Asif, N. (2020). Curved profiles machining of Ti6Al4V alloy through WEDM: Investigations on geometrical errors. Journal of Materials Research and Technology, 9(6), 16186–16201. https://doi.org/10.1016/j.jmrt.2020.11.067

Jadhav, A., Dhaulakhandi, D., Shandilya, S. K., Malviya, L., & Mewada, A. (2023). Data transformation: A preprocessing stage in machine learning regression problems. In Artificial Intelligence Techniques in Power Systems Operations and Analysis (pp. 183-194). Auerbach Publications.

Joshi, A. Y., & Joshi, A. Y. (2019). A systematic review on powder mixed electrical discharge machining. Heliyon, 5(12), Article 12. https://doi.org/10.1016/j.heliyon.2019.e02963

Kar, S. K., Mishra, P. K., Sahu, A. K., Mahapatra, S. S., & Thomas, J. (2023). Multi-objective optimization of wire-EDM of Inconel 625 by using desirability function approach. International Journal on Interactive Design and Manufacturing (IJIDeM), 17(2), 931–938. https://doi.org/10.1007/s12008-022-01184-6

Karunasingha, D. S. K. (2022). Root mean square error or mean absolute error? Use their ratio as well. Information Sciences, 585, 609-629.

Kosaraju, S., Babu Bobba, P., & Salkuti, S. R. (2023). Optimization and Microstructural Studies on the Machining of Inconel 600 in WEDM Using Untreated and Cryogenically Treated Zinc Electrodes. Materials, 16(8), Article 8. https://doi.org/10.3390/ma16083181

Kumar, A., Mandal, A., Dixit, A. R., Das, A. K., Kumar, S., & Ranjan, R. (2019). Comparison in the performance of EDM and NPMEDM using Al2O3 nanopowder as an impurity in DI water dielectric. The International Journal of Advanced Manufacturing Technology, 100(5), 1327–1339. https://doi.org/10.1007/s00170-018-3126-z

Manikandan, N., Binoj, J. S., Thejasree, P., Sasikala, P., & Anusha, P. (2021). Application of Taguchi method on Wire Electrical Discharge Machining of Inconel 625. Materials Today: Proceedings, 39, 121–125. https://doi.org/10.1016/j.matpr.2020.06.394
Mohapatra, K. D., Satpathy, M. P., & Sahoo, S. K. (2017). Comparison of optimization techniques for MRR and surface roughness in wire EDM process for gear cutting. International Journal of Industrial Engineering Computations, 251–262. https://doi.org/10.5267/j.ijiec.2016.9.002
Muhammad, W., Iqbal, S. A., Khan, Y. A., & Muhammad, T. (2021). Analysis and Multi-Objective Optimization of Wire Cut Process Parameters for Efficient Cutting of Tapered Carbon Steels Using Wire EDM. Journal of Engineering Research. https://doi.org/10.36909/jer.11965
Narayana Moorthy, N., & Kanish, T. C. (2022). Fault detection and identification in friction drilling process. Jurnal Tribologi, 34, 119-138.
Naresh, C., Bose, P. S. C., & Rao, C. S. P. (2020). Artificial neural networks and adaptive neuro-fuzzy models for predicting WEDM machining responses of Nitinol alloy: Comparative study. SN Applied Sciences, 2(2), 314. https://doi.org/10.1007/s42452-020-2083-y
Natarajan, K., Ramakrishnan, H., Gacem, A., Vijayan, V., Karthiga, K., Ali, H. E., Prakash, B., & Mekonnen, A. (2022). Study on Optimization of WEDM Process Parameters on Stainless Steel. Journal of Nanomaterials, 2022, e6765721. https://doi.org/10.1155/2022/6765721
Nti, I., Nyarko-Boateng, O., & Aning, J. (2021). Performance of Machine Learning Algorithms with Different K Values in K-fold Cross-Validation. International Journal of Information Technology and Computer Science, 6, 61–71. https://doi.org/10.5815/ijitcs.2021.06.05
Raj, A., Yadav, L. K., Misra, J. P., & Upadhyay, V. (2023). Empirical Modeling of Material Removal Rate during the WEDM of Inconel 690.
Ramezan, C., A. Warner, T., & E. Maxwell, A. (2019). Evaluation of Sampling and Cross-Validation Tuning Strategies for Regional-Scale Machine Learning Classification. Remote Sensing, 11(2), 185. https://doi.org/10.3390/rs11020185
Rathod, R., Kamble, D., & Ambhore, N. (2022). Performance evaluation of electric discharge machining of titanium alloy-a review. Journal of Engineering and Applied Science, 69(1), 64. https://doi.org/10.1186/s44147-022-00118-z
Sarker, I. H. (2021). Machine Learning: Algorithms, Real-World Applications and Research Directions. Sn Computer Science, 2(3), 160. https://doi.org/10.1007/s42979-021-00592-x
Sarker, I. H., Furhad, M. H., & Nowrozy, R. (2021). AI-Driven Cybersecurity: An Overview, Security Intelligence Modeling and Research Directions. SN Computer Science, 2(3), 173. https://doi.org/10.1007/s42979-021-00557-0
Sarker, I. H., Kayes, A. S. M., Badsha, S., Alqahtani, H., Watters, P., & Ng, A. (2020). Cybersecurity data science: An overview from machine learning perspective. Journal of Big Data, 7(1), 41. https://doi.org/10.1186/s40537-020-00318-5
Shabgard, M., & Khosrozadeh, B. (2017). Investigation of carbon nanotube added dielectric on the surface characteristics and machining performance of Ti–6Al–4V alloy in EDM process. Journal of Manufacturing Processes, 25, 212–219. https://doi.org/10.1016/j.jmapro.2016.11.016
Sharma, R., Kamble, S. S., Gunasekaran, A., Kumar, V., & Kumar, A. (2020). A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. Computers & Operations Research, 119, 104926. https://doi.org/10.1016/j.cor.2020.104926
Sharma, V. (2022). A Study on Data Scaling Methods for Machine Learning. International Journal for Global Academic & Scientific Research, 1(1). https://doi.org/10.55938/ijgasr.v1i1.4

Singh, J., Kumar, S., & Kumar, R. (2023). Support vector machine-based prediction of wear in Ni-20Cr2O3 thermal spray coating under bottom ash slurry conditions. Jurnal Tribologi, 39, 84-105.
Trivedi, U. B., Bhatt, M., & Srivastava, P. (2021). Prevent Overfitting Problem in Machine Learning: A Case Focus on Linear Regression and Logistic Regression. In P. K. Singh, Z. Polkowski, S. Tanwar, S. K. Pandey, G. Matei, & D. Pirvu (Eds.), Innovations in Information and Communication Technologies (IICT-2020) (pp. 345–349). Springer International Publishing. https://doi.org/10.1007/978-3-030-66218-9_40
Wang, G., & Li, Y. (2019). Effects of alloying elements and temperature on thermal conductivity of ferrite. Journal of Applied Physics, 126(12), 125118. https://doi.org/10.1063/1.5115441
Wasif, M., Ahmed Khan, Y., Zulqarnain, A., & Amir Iqbal, S. (2022). Analysis and optimization of wire Electro-Discharge Machining process parameters for the efficient cutting of Aluminum 5454 alloy. Alexandria Engineering Journal, 61(8), 6191–6203. https://doi.org/10.1016/j.aej.2021.11.048
Wasif, M., Iqbal, S. A., Fatima, A., Yaqoob, S., & Tufail, M. (2020). Experimental investigation for the effects of wire EDM process parameters over the tapered cross-sectional workpieces of titanium alloys (Ti6Al-4V). Mechanical Sciences, 11, 221–232. https://doi.org/10.5194/ms-11-221-2020
What is Meta Data—JavaPoint? (2022, November 23). https://www.javatpoint.com/what-is-meta-data
Zhang, Y., & Ling, C. (2018). A strategy to apply machine learning to small datasets in materials science. Npj Computational Materials, 4(1), 25. https://doi.org/10.1038/s41524-018-0081-z