DOI: 10.21062/mft.2026.017 http://www.journalmt.com

Machine Learning-Based Predictive Modelling of EDM and EAM-V Processes for Performance Analysis

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The promotion of Electrical Discharge Machining (EDM) and vibration aided Electric Arc Machining (EAM-V) processes is characterized in the study in terms of their capability for precision manufacture, mainly drawing any performance comparisons from a machine learning approach. The present machine learning study aims to predict some important metrics of machining utility, such as Material Removal Rate (MRR), Tool Wear Rate (TWR), and Surface Roughness (SR), against process parameters like current, pulse-on/off time, etc. Some advanced models like Gradient Boosting and Random Forest are used to analyse the efficacy and effectiveness of EDM and EAM-V, comparing the respective influences these parameters have on honing outcomes. The study describes an elaborate methodology: data collection, preprocessing, feature scaling, and application of multiple regression algorithms for machining performance forecasting. The experimental data for model training and testing were partitioned into 80% and 20%, respectively. The results revealed that Gradient Boosting (GB) performed better than Random Forest (RF) for all parameters. In GB, the R^2 values of MRR, TWR, and SR were higher; hence, its degree of accuracy was superior in comparison with RF. For instance, an R^2 value of 0.970, 0.994, and 0.999 was achieved by GB for MRR, TWR, and SR, respectively, thus proving its better predictive ability. Moreover, according to average predicted values, EAM-V performs better for MRR; EDM, comparatively, from TWR and SR, is more suitable for precision applications. The performance validation of GB through RMSE and MAE also confirms its efficacious predictions.

Keywords: EDM, EAM-V, Machine Learning, Material Removal Rate, Tool Wear Rate, Surface Roughness, Gradient Boosting, Random Forest.

1 Introduction

In the advanced manufacturing sector, the demand for environmentally friendly manufacturing is progressively rising. One of the emerging non-conventional machining processes is the Electrical Discharge Machining (EDM), which improves machining characteristics and produces dimensions that are more precise. One area where EDM is gaining popularity is in the manufacturing processes of aerospace, automotive, and medical components because it is contactless, thereby solving one of the most serious problems of mechanical vibration and stress. Thus, this process is very effective for machining hard materials, especially brittle ceramics and heat-resistant super-alloys with an accuracy level and cost-effectiveness that would probably make this process an important solution to machining most complex and difficult materials in the future [1].

Silicon (Si) and silicon carbide (SiC) wafers have been the backbone of the semiconductor industry for almost 50 years. The conventional techniques that are traditionally used to give final shape to electrical circuits in these substrates are sawing with ID saws and wire saws, which, however, suffer from roughness of surface, wastage of material, and formation of cracks. Newer approaches that include Abrasive Water Jet Machining (AWJM), Laser Beam Machining (LBM), and EDM have been developed to counteract these limitations. While AWJM offers quite a good surface finish with little thermal deformation, it is not recommended for very thin components because of the kerf loss. LBM gives very high-speed material removal with less thermal damage of thin semiconductor materials; not suitable for thick materials, EDM still remains the most effective for hard to machine brittle materials but causes thermal damage in terms of recast layers and residual stresses, but these limitations are being countered to give a better solution for the semiconductor machining [2]. The Fig. 1 reveals the major challenges and corresponding solutions in advanced manufacturing techniques. It arranges them into the four quadrants: Environmental Impact, Material Limits, Precision and Accuracy, and Technology Advancements. Environmental issues such as material waste and energy consumption are followed by focus on limitations of materials in terms of brittleness and heat resistance, precision issues are tool wear, surface roughness, and technology advancements such as soft computing models and regression-based modelling that potentially provides solutions to improve the performance of processes regarding efficiency.

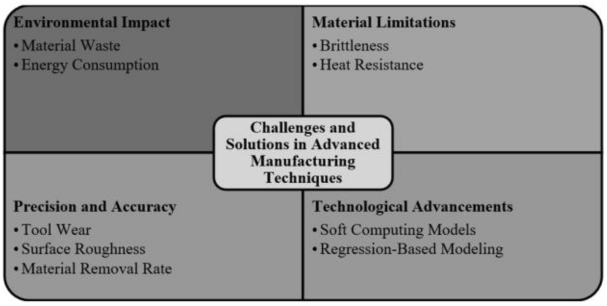

Fig. 1 *Challenges and Solutions in Advanced Manufacturing Techniques*

Carbon fibber reinforced thermosetting composites with excellent mechanical properties and lightweight characteristics are often applied in the aerospace, automobile, and electronic industries. The anisotropic composition of composites needs specialized machining techniques, especially when it comes to precision drilling with small tolerances. Conventional drilling faces several challenges, including tool wear and increasing temperatures, which ultimately lead to degradation of the cutting edges and the final hole diameter. Alternative methods such as cryogenic cooling or use of lubricants can aid in diminishing operational costs, yet at the same time increase the environmental burden [3], [4]. AWJM, LBM, and EDM non-conventional processes are being explored presently to defeat these limitations, with EDM being more popular in research arena for precision drilling due to retained concerns over electrical conductivity and surface finish [5].

Difficult-to-machine materials like high-temperature alloys have progressively found applications in industries such as aerospace, military, and petrochemical. Consequently, there comes the need for good machining techniques [6]. Inconel 718 is a nickel-based superalloy necessary for the fabrication of aerospace components due to its high-temperature strength; it poses significant challenges in machining due to rapid cold work hardening that leads to surface hardening and plastic deformation [7]. Conventional machining techniques, namely turning and milling, are virtually impossible due to excessive cutting forces and heat accumulation that causes chatter and vibration, resulting in quick tool wear and even breakage. In contrast, some non-conventional processes—such as electro-discharge machining (EDM)—can attain tool-workpiece separation under high thermal loads without physical contact, making it more capable of machining these aberrantly hard materials. Yet, its traditionally low machining efficiency coupled with poor material removal rates has minimized its use for manufacturing complex components [8], [9].

Within EDM, sinker EDM is the thickest kind where a block electrode with the exact reverse shape of the workpiece cavity has a linear up and down working motion which causes electric discharges to melt portions of the workpiece surface. In contrast to traditional machining fluid, EDM eliminates cutting forces, stresses, chatter, and vibrations. However, precision in die-sinking EDM is restricted, especially for complicated parts, using large custom electrodes and one-axis linear kinematics. Milling EDM (MEDM) solves this by employing smaller electrodes with simple geometries as well as layer-by-layer cutting paths to allow efficient machining of large and complex parts from hard-to-machine materials [10]. The stochastic means that a few variables such as current or pulse timing will affect the response of the process. The precise control of input EDM parameters is required to achieve a high Material Removal Rate (MRR) and a low tool wear rate (TWR) and surface roughness (SR) [11]. Traditional modelling methods fail to predict the results accurately, given the complexity of the process, indicating that soft computing- regression-based modelling is being increasingly used in prediction. The regression models establish correlations between the machining variables and EDM process outputs- MRR, and SR [12]. Therefore, regression-based experimental modelling is predominantly used; this mainly encompasses multiple linear regression to model the above relationships, model performance, and validity by determining measures such as the coefficient of determination (R^2) and furthered with statistical analyses (F-test, t-tests) to evaluate the performance and accuracy of the models [13].

Material removal in EDM occurs at extremely high temperatures whereby workpiece and tool components are melted and vaporized to form debris. The presence of debris will interfere with the machining efficiency if it is not flushed away. Hence, there is a need for continuous flushing of the dielectric medium under which the motion of the tool or workpiece is controlled. The proposal of ultrasonically vibrating the tool, workpiece, or dielectric liquid (USEDM and USμEDM) serves as an effective mechanism for flushing away debris. Additional enhancements include powder-mixed dielectrics, gas-assisted dielectrics, and magnetic field (MF) assistance. These are deployed to enhance process efficiency, material removal rates of the dielectric media, and surface quality with respect to electrode wear rates. Ultrasonic vibration assistance has shown improvements in the above parameters in their favour by reducing tool wear and improving the surface finish of the work surfaces [14]. Furthermore, this extends the EDM process, using CNC machining to manufacture three-dimensional micro/macro features. This form of electrical discharge-milling (ED-Milling) allows for high-precision production of complex shapes. Recent investigations have investigated compromising tool wear, machining performance, and the sustainable use of dielectrics in ED-Milling. Several studies have delved into various micro-fabrication technologies and mechanisms that enhance machining performance, thereby contributing to the advancement of the field [15]. As already said, ultrasonic vibration-assisted short electric arc processing has also been developed to suppress some discharge irregularities like short circuits and secondary discharges in conventional processing. The new method with ultrasonic application, in fact, refines the machining process, lowering surface roughness values by more than 16%, and improving some material properties. Likewise, working on electro-discharge machining of shape memory alloys (SMAs) has been extensively researched, with special emphasis on NiTi-based alloys [16]. Legitimately selected process variables and tool electrodes can ensure a greater process efficiency, followed by wire-cut EDM as a processing method for SMAs. Most of the challenges pertaining to machining operations with SMAs have, thus, encouraged much research into better optimization of ED machining processes for these materials [17].

The EDM-milling (EDMM) technology is, lastly, a method used for producing complex 3D geometries, especially in hard materials. EDM is a very versatile tool, but some limitations such as tool wear and material removal rates have restricted its acceptance [18]. Thus, came into the picture the addition of vibrations into the EDM process known as vibration-assisted EDM (V-EDM) to increase material removal rates, decrease machining time, and enhance surface quality. Increased frequencies of vibration enhance the efficiency of the machining operation hence increasing both material removal rates and surface finishes [19]. Eco-friendly practices are used to minimize the effect of the EDM process on the environment, incorporating bio-dielectrics and optimized electrical parameter control20 13]. Using hybrid EDM processes alongside recent advancements in mathematical modelling is key to optimizing these methods and promoting their sustainability [21]. Table 1 provides an examination of different electrical discharge machining (EDM) variants such as ultrasonic-assisted EDM, ED-milling, and vibration-assisted EDM in the context of processing parameters, materials, and merits viz improved material removal rate (MRR), reduction of tool wears, and surface quality improvement.

Recently, the EDM system has been modernized to curb problems like high electrode wear rate (EWR) and more importantly the dimensional inaccuracy (overcut). Among other things, the mixed nano-powder EDM (NPMEDM) application can infinitely improve the removal rate due to its advanced dielectric property. Furthermore, the addition of cryogenically treated (CT) brass electrodes have provided massive improvements in EDM operations when experiments gave 65.02% and 59.73% EWR reductions and overcut for NT brass electrodes using deionized water, respectively. The remarkable EWR reduction of 78.41% and dimensional accuracy enhancement of 67.79% by CT brass electrodes compared to the traditional method of kerosene oil [22]. By these advancements, the multiparametric optimization techniques, like Grey Relational Analysis (GRA) and Analysis of Variance (ANOVA), have been employed to also enhance surface roughness (SR) and material removal rate (MRR) in the EDM of tool steels. The optimization of process parameters such as peak current and pulse on-time resulted in achieving an SR value of 1.50 μm and an MRR of 12.50 mm^3/min [23].

Artificial Intelligence frameworks have surfaced as another important tool in EDM improvement. For example, an application of the AI-based model used by Artificial Neural Networks (ANN) was based on the machining of Inconel 617 which optimized the key process parameters, such as powder concentration and surfactant concentration. This brought a phenomenal improvement in MRR by 93.75% and 58.90% enhancement in SR [24]. Multi-objective optimization in GAs has been applied to the EDM processes of Al-SiC composites. The effects of the discharge current and gap voltage on MRR and surface roughness were studied [25]. Machine learning models such as Random Forest, Polynomial Regression, and Gradient Boosted Trees were used in EDM of D2 steel to predict tool wear and surface roughness. These models identified strong predictive power and became an important part of machining parameter optimization [26]. Tests have also been conducted to include MF-EDM and perform machining on SiCp/Al composites. The outcome indicated a good process parameter optimization achieved at 95.83% improvement of machining performance [27].

EDM has found its way into a variety of advanced materials and multicultural setups. In addition to the example of WE43 magnesium alloys, EDM was optimized through ANN, Random Forest, and Decision Tree machine learning methods so that an accuracy of 96.7% was reached in predicting MRR [28]. The growing concern for sustainable EDM practices has also bore fruit. Results of research indicate that using copper electrodes will result in a superior MRR and surface finish at a lesser energy consumption compared to using brass electrodes [29]. The more recent example of optimization in multi-material systems like SS304 and SS316 used the machine learning models SOML and MOML, in combination with TOPSIS, to achieve less than 10% error in achieving right optimizations of process parameters [30]. Moreover, such industrial applicative importance of EDM has been through machining AMCs and developing high-precision grinding wheel dressing technology, all of which have ultimately improved the tool-wear, machining quality, and sustainability in the overall manufacturing process [31], [32], [33]. Table 2 summarizes state-of-the-art EDM processes and optimization technologies by way of machine learning or optimization algorithms, illustrating the improvement in machining performance and prediction precision obtained from AI-based models, such as the trees, neural networks, random forests, etc., multi-objective optimization technique.

Tab. 1 *Comparative Overview of Electrical Discharge Machining (EDM) Variants and Their Performance Metrics*

Ref. No.	Process Used	Metal Used	Parameters	Key Findings	Results
[14]	USEDM and USμEDM	Various materials	US vibration, Powder mixed dielectric, Gas, Magnetic field assistance	Enhanced material removal rate (MRR), improved surface quality, and reduced electrode wear rate.	Significant improvement in EDM and micro-EDM performance, especially in material removal and surface finish.
[15]	ED-Milling	Various materials	Tool type, Dielectrics, Machining methods	ED-Milling achieves 3D machining with high precision and advanced techniques for complex fabrication.	Successful application in complex 3D machining with sustainable dielectrics and tool wear reduction.
[16]	Ultrasonic Vibration-Assisted Short Electric Arc Machining	Workpiece materials	Short Electric Arc, Ultrasonic vibration	Ultrasonic vibration significantly improves machining quality, reduces electrical corrosion pits, and decreases surface roughness.	Introduction of ultrasonic vibration improves processing quality with reduced recast layer thickness and surface defects.
[17]	EDM of SMAs	Shape Memory Alloys (NiTi-based SMAs)	Process variables, Tool electrode, Dielectrics	Wire-EDM is most explored for cutting SMAs; proper selection of process variables improves overall effectiveness.	Wire-EDM proved effective for SMA processing; the right choice of electrode and dielectric improved results.
[18]	EDMM	Various materials	Tools, Dielectrics, Classification	EDMM achieves high precision for micro/macro features, with adaptive control methods used for tool wear and surface quality.	EDMM shows improvement in machining performance with enhanced tool wear control and sustainable techniques.
[19]	V-EDM	Bohler K110 Steel	Vibration frequency, Dielectric fluid, Workpiece	V-EDM improves MRR and surface roughness, especially with elevated vibration frequency.	V-EDM enhances machining efficiency, achieving significant improvements in MRR and reduced machining time.
[20]	EDM	Various materials	Process parameters, Erosion, Surface quality	EDM's versatility lies in fabricating 3D geometries in hard materials with improved erosion and surface quality.	EDM provides high precision in manufacturing, with improvements in material removal and surface finish.
[21]	EDM	Hybrid Metal Matrix Composites (MMCs), Ceramics, Nanomaterials	Bio-dielectrics, Energy consumption, Process optimization	The use of bio-dielectrics and energy optimization methods contribute to sustainability and environmental friendliness in EDM.	Bio-dielectrics and optimization of parameters reduce environmental impact and improve EDM sustainability.

Tab. 2 *Comparative Overview of Advanced EDM Processes and Optimization Techniques*

Ref. No.	Metal Used	Process Used	Model/ Algorithm Used	Process Parameters	Tools Used	Key Findings	Results
[22]	Aluminium 6061	Nano Powder Mixed EDM (NPMEDM)	ANN, MOGA	Peak current, spark voltage, pulse on time, powder concentration	NT brass electrode, CT brass electrode	EWR and OC improvement with CT brass electrode using deionized water	65.02% reduction in EWR and 59.73% in OC for NT brass; 78.41% reduction in EWR for CT brass
[23]	Tool steels	WEDM	MRM	Peak current, pulse on-time, discharge voltage, pulse off-time	Various EDM tools	Optimized SR and MRR for tool steels with low peak current and low pulse on-time	SR of 1.50 μm and MRR of 12.50 mm^3/min achieved
[24]	Inconel 617	EDM	ANN	Powder concentration, treatment, surfactant concentration	Various EDM tools	Identified key parameters affecting MRR and SR; optimized MRR and SR using AI framework	MRR improved by 93.75% and SR by 58.90%
[25]	Al-SiC MMC	EDM	ANN, RSM, GA	Discharge current, gap voltage, pulse-on-time, pulse-off-time, flushing pressure	Brass electrode	Multi-objective optimization for EDM using RSM, GA, with a focus on environmental impact	Significant contributions of discharge current to MRR and Ra
[26]	D2 Steel	EDM	Random Forest, Polynomial regression, Gradient Boosted Trees	Input current, gap voltage, pulse on-time, pulse off-time, dielectric flushing pressure	Composite tool tip (80% Cu, 20% SiC)	Identified significant parameters affecting tool wear and surface roughness; developed ML models	Best surrogate model for optimization based on R^2 and MSE comparisons
[27]	SiCp/Al composites	MF-EDM	BPNN, MOMS	Peak current, magnetic field, pulse width, pulse interval	SiCp/Al composites, BPNN	BPNN model provides the best accuracy; MOMS optimization achieves 95.83% improvement	Verified optimized parameter results dominating 95.83% of original experiments
[28]	Magnesium Alloy (WE43)	WEDM	ANN, RF, DT	Current, pulse on-time, pulse off-time	Various WEDM tools	Optimized MRR for Mg alloy with ANN; key parameters affecting material removal rate	96.7% accuracy with ANN for MRR prediction
[29]	SS310 Alloy	EDM	Multi-criteria decision-making (MCDM) approach	Discharge current, spark gap, pulse duration, duty cycle	Copper and Brass electrodes	Sustainability analysis considering environmental impact and energy consumption	Copper electrode outperforms brass in terms of MRR, Ra, and carbon emissions
[30]	SS304 & SS316	EDM	SOML, MOML, TOPSIS	Process variables, compositional variables	Various EDM tools	SOML models offer better accuracy than MOML; optimized responses with TOPSIS method	Validation with less than 10% error in response predictions
[31]	Al-SiC composite	EDM	ANN	Current, pulse-on-time, pulse-off-time	Brass electrode	ANN model successfully predicted complex EDM processes for Al-SiC composites	High prediction accuracy with coefficient of correlation of 0.99072
[32]	Silicon carbide ceramic	EDAG	Various experimental techniques	Process parameters for coarse-grained grinding wheels	Diamond grinding wheel	High-precision dressing technology; improved radius size errors and surface roughness	Radius errors reduced to 0.17% and 0.053% for concave and convex arcs, respectively
[33]	Steel and Copper electrodes	EDM	Mathematical model, Matlab simulation	Pulse on-time, peak gap current	Copper, graphite electrodes	Simulation of dynamic EDM behavior with error comparison to experimental data	MRR prediction accuracy with an average error of 8.27% for steel and copper

There exists a research gap in machining hard-to-cut materials, enhancing surface quality, and minimizing EWR and OC in EDM due to complexity and inefficiency of other processes. Though some methods like ultrasonic vibrations, powder mixing, and magnetic field assistance have shown future promise in improving the EDM process, they remain impractical due to the absence of proper optimization models and real-time monitoring. Other studies have focused on optimizing parameters such as pulse-on-time, current, and dielectric fluid, but reaching a compromise between MRR, SR, and tool wear is a challenge that persists. Different studies on EDM have begun to apply ML models to predict EDM behaviours. Yet, the consideration of integrating these with process modeling to predict all phases of the discharge process has gained insufficient attention, nor has there been any considerable depth of research into sustainable and eco-friendly alternatives of dielectric fluids and optimization for energy consumption. These gaps point towards the need for more robust real-time adaptive control systems, more accurate modeling of EDM's dynamic behavior, and putting into action effective sustainable practices in EDM processes. The previous studies and the research gap found from them leads us to go further with our study and decide what must be our objectives which can be defined as the comparison of machine learning models-of EDM and EAM-V performances in terms of process parameters like current and pulse-on/off time regarding their influence on MRR, TWR, and SR using gradient boosting and random forest models for prediction is finally assessed based on R^2, RMSE, and MAE for determining the best-performing machining process depending on priorities.

2 Methodology

The research methodology specifies using machine learning techniques for prediction and analysis of significant performance metrics for the processes of Electrical Discharge Machining (EDM) and vibration aided Electric Arc Machining (EAM-V). These processes are influenced by several controlling parameters, and material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR) should be modelled based on the EDM and EAM-V derived database.

2.1 Data Collection and Pre-processing

In this research, the dataset that will be used comprises experimental data obtained from Electrical Discharge Machining (EDM) and vibration aided Electric Arc Machining (EAM-V) processes. In addition, several control parameters that affect these machining processes are present. They comprised Current (A), which is the electrical current used during the machining processes that play critical roles in material removal and tool wears; Pulse-On Time (μs) in EDM, duration during which an electrical pulse is applied and value by which amount of energy delivered to the workpiece is varied; and Pulse-Off Time (μs), which determines the time between pulses and thus impacts cooling and re-solidification. Among the output parameters, or dependent variables, from this dataset are Material Removal Rate (MRR), which measures the volume of material removed per unit time and is thus a key indicator of machining efficiency; Tool Wear Rate (TWR), denoting the rate of wear of the tool in the process; and Surface Roughness (SR), which refers to the texture or finish of report surfaces and is a critical factor in determining the quality of the workpiece.

The data pre-processing process included paramount steps that prepared the dataset for machine learning analysis. It started with compilation of the dataset from different experimental sources and data cleaning to facilitate making data consistent. This included handling any missing values, removing duplicates, and addressing any outlying observations that could adversely affect the performance of the model. In addition, the dataset had a categorical column, 'Process,' that distinguished between the EDM and EAM-V processes. Label encoding was used to convert this column into a numerical format acceptable by a machine learning algorithm, thereby converting categorical data into a numerical model training format.

2.2 Feature Scaling

The data for this study comprise input features consisting of current, pulse-on time, and pulse-off time in different units and ranges. On an unscaled basis, these features would not be expected to contribute to the learning evenly, particularly for scale-sensitive models such as distance-based algorithms like K-Nearest Neighbours (KNN) or gradient-based algorithms. For instance, if one feature has a considerably larger range relative to others, it could dominate the learning process and yield a biased model. To remedy this situation and guarantee that each feature equally contributes to a given learning algorithm, the authors normalized numeric input features using Standard Scaler. The Standard Scaler removes the mean and then scales to unit variance, thus ensuring that each feature has a mean of 0 and a standard deviation of 1. Therefore, these features are comparable and, accordingly, the machine learning models can learn from every feature equally, regardless of its original scale.

2.3 Train-Test Splitting

The performance and generalization ability of the machine learning models were assessed by splitting the dataset into two subsets: a training set and a testing set. 80% of the data was used for building the models and taught to find relationships between input features (like current, pulse-on time, and pulse-off time) and output parameters (like MRR, TWR, and SR). The remaining 20% of the data was held back for testing the ability of trained models on fresh, unseen data to guarantee that it was not overfitted to the training data. This split is a widely accepted rule of thumb in machine learning: it tries to ensure enough data to train a model well while retaining sufficient data to evaluate the model's abilities to generalize.

2.4 Model Training

The final step was to run different machine learning models on the training data to obtain prediction results on the outcome variables (MRR, TWR, and SR). Three distinct models were applied to accomplish this. The first was the Random Forest Regressor (RF), used as a baseline model. Random Forest is an ensemble learning method that builds multiple decision trees, where each tree is trained on a random subset of the data. The final prediction is made by averaging the predictions of all trees, which stabilizes the overall accuracy and reduces generalization error. After that baseline model, Gradient Boosting Regressor (GB) was also applied in pursuit of higher precision. Another kind of tree modeling is the Gradient Boosting approach, which builds the trees sequentially, whereby each new one learns from the mistakes of the previous one, so it tends to be more predictive with its output. Finally, Multioutput Regressor wrapper was employed considering that the task was to predict multiple output parameters. Here are the models: Random Forest, Gradient Boosting; hence, they can predict multiple outputs (MRR, TWR, SR) while training a single model to be trained for each output while using the same input features.

2.5 Model Evaluation

These performance metrics were obtained after training the different models. R2 score or coefficient of determination explains how much variance in dependent variables (MRR, TWR, SR) can be explained with the help of input parameters by a model. As the R2 value approaches 1, the better the model fits the data and accounts for a larger part of the variance in the data. The Root Mean Squared Error (RMSE) assessed actual versus predicted error magnitudes, lowering RMSE signifying better performance. The last one is the Mean Absolute Error (MAE), which is an average of absolute differences between both the actual and predicted value just for understanding how loss is happening through predictions, lower MAE signifying predictions within actual values.

2.6 Model Comparison

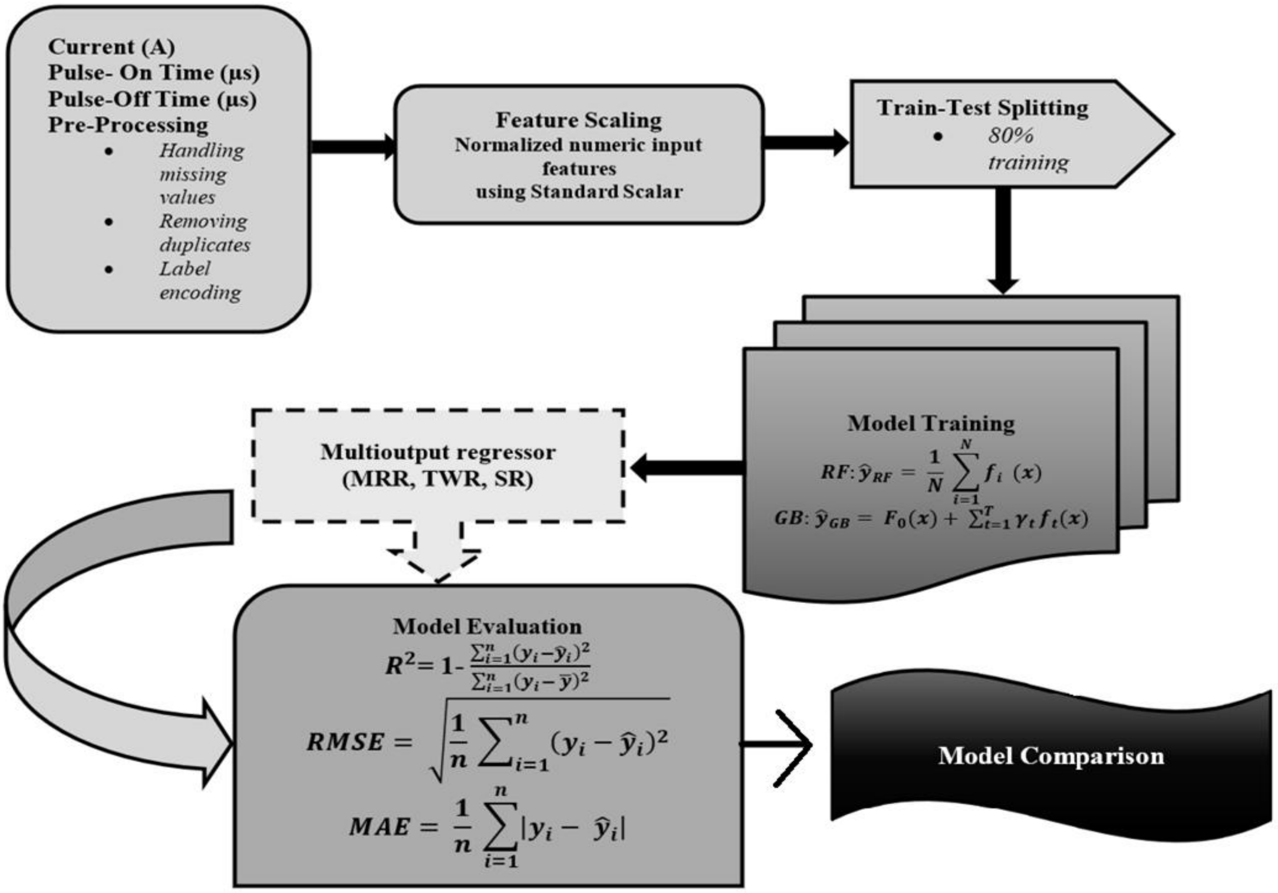

Fig. 2 *Machine Learning-Based Predictive Modeling Pipeline for EDM and EAM-V Performance Metrics*

The performance of the Random Forest Regressor and Gradient Boosting Regressor, as indicated by the evaluation metrics of R², RMSE, and MAE, was then compared. The model that had generalized better onto the unseen testing data and had predicted MRR, TWR, and SR more accurately was then selected as the best performing. The comparison of the two is therefore essential in identifying which model offers more reliable predictions for the machining processes being examined.

The flowchart in Fig. 2 describes the methodology for predicting performance metrics (MRR, TWR, and SR) of EDM and EAM-V processes using machine learning models. It elaborates on the data pre-processing, feature scaling, and train-test splitting, training the models using Random Forest and Gradient Boosting, and evaluating them using R², RMSE, and MAE metrics, followed by the comparison of models to select the best predictive model. Such a method is well-adapted for applications in precision manufacturing.

This method lays down a proper setting for developing and accessing machine learning models for the prediction of crucial performance metrics such as MRR, TWR, and SR for EDM and EAM-V processes. Processes include crucial steps such as data preprocessing, feature scaling, and splitting the data into training and testing data sets to ensure accurate evaluation of the designed model. Multiple machine learning models such as Random Forest and Gradient Boosting can be trained and compared for selection of the best model that accurately predicts and optimizes the pertinent processes.

3 Results and discussion

While comparing the performance of Electrical Discharge Machining (EDM) against Vibration aided Electric Arc Machining (EAM-V), machine learning models were employed to present the results and discussions. Such models are Gradient Boosting (GB) and Random Forest (RF).

The Table 3 shows R² scores of both machines for three different output parameters: Material Removal Rate (MRR), Tool Wear Rate (TWR), and Surface Roughness (SR). The score clearly indicates Gradient Boosting outperforms Random Forest by presenting higher R² scores in all three. The R² Value of MRR=0.970, TWR=0.994 and SR=0.999 demonstrates that Gradient Boosting gives Better Predictions Compared to Random Forest, which scored a little lower with R² readings of 0.957, 0.975 and 0.989.

Tab. 3 *R² Comparison Between Models*

Metric	MRR	TWR	SR
R² (GB)	0.970	0.994	0.999
R² (RF)	0.957	0.975	0.989

The Table 4 showing the predicted output averages includes both EDM and EAM-V processes. The EAM-V recorded MRR at 1446.0 mm³/min; thus, high speed for material removal indicates applications for high-speed machining. The EDM, in comparison, has better TWR at 3.19 mm³/min and SR at 12.73 μm, meaning the process has less tool wear and a smoother surface, which is good for precision applications.

Tab. 4 *Predicted Output Averages by Process*

Process	MRR (↑)	TWR (↓)	SR (↓)
EDM	20.2	3.19	12.73
EAM-V	1446.0	18.94	197.37

Further evaluation of Gradient Boosting models is provided in Table 5, accompanied by R² values, RMSE and MAE. These measurements give a further understanding of the model performance. Our prediction for the material removal rate indicates a reasonable error margin, with an R² score of 0.970, RMSE of about 146.11, and MAE of about 72.82, when determining the MRR. The exceptionally high R² value (0.994) is connected to very low RMSE (1.22) and MAE (0.93) values; it indicates that tool wear rate (TWR) is very accurately predicted by the model. The model has an almost perfect R2 score (0.999) for SR, while the RMSE and MAE scored 9.73 and 6.42 respectively, which indicates very high predictive accuracy.

Tab. 5 *Performance Metrics for Gradient Boosting Model*

Output	R² Score	RMSE	MAE
MRR	0.970	146.11	72.82
TWR	0.994	1.22	0.93
SR	0.999	9.73	6.42

3.1 Visual representation of model results

The visuals show that the model has been able to isolate certain significant relationships between the process parameters and the quality indicators. This serves as a reasonable basis for extrapolating and optimizing the process in the future.

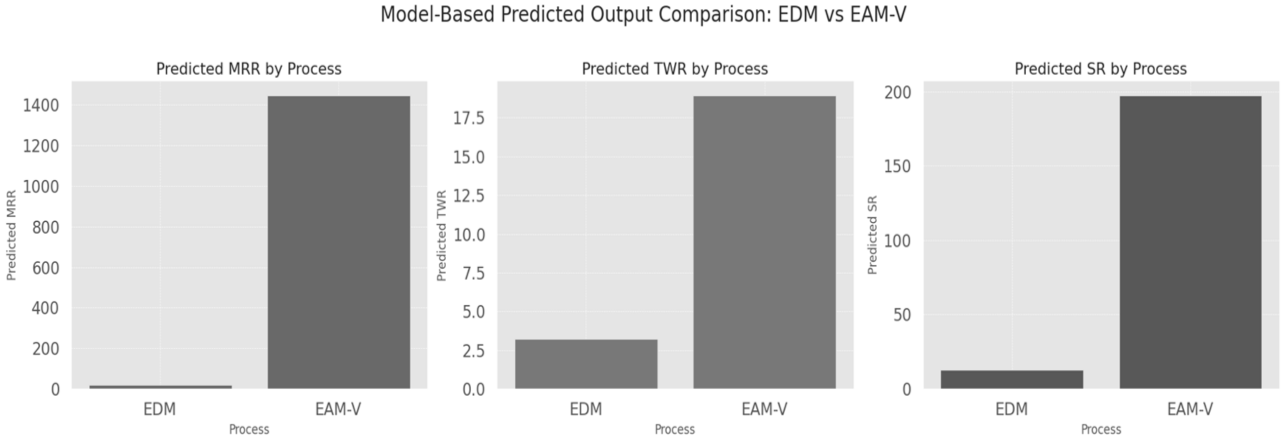

Fig. 3 *Predicted Machining Performance by ML GB Model, (EDM vs EAM-V)*

These findings are visualized in several diagrams. Fig. 3 compares the predicted machining performances for both EDM and EAM-V, which offers perspectives on the benefits of using EAM-V relative to EDM regarding the amount of material removed but shows that if one's aim is to minimize tool wear and surface roughness, the EDM transaction could be the preferred option.

Fig. 4 shows the R² values obtained in the two models, by which the superiority of Gradient Boosting is revealed as far as predictive power is concerned.

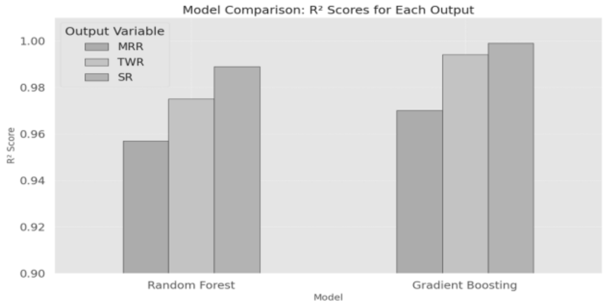

Fig. 4 *Model Comparison - R² Scores for Each Output (Random Forest vs Gradient Boosting)*

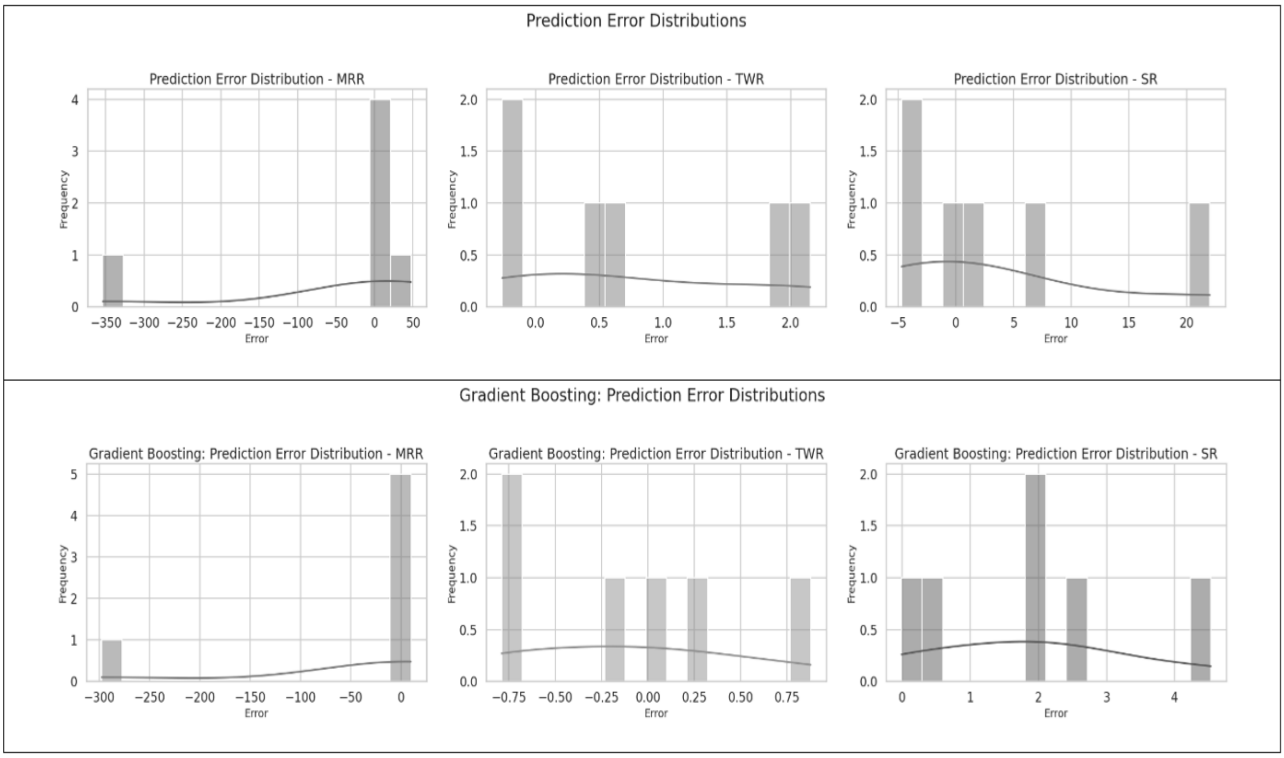

Fig. 5 *Prediction Error Distributions for MRR, TWR, and SR (RF and GB)*

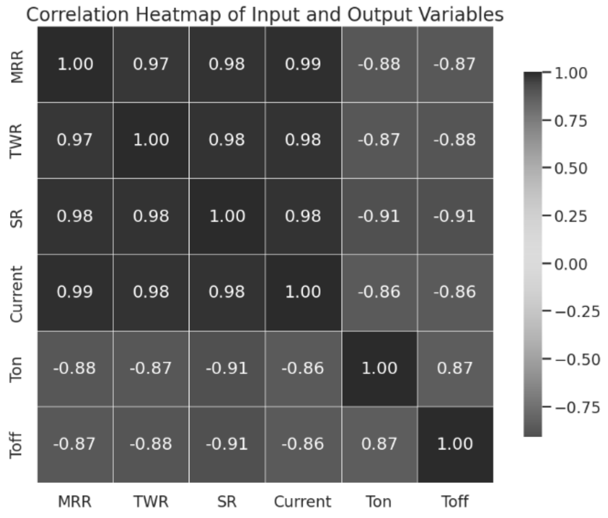

Fig. 6 *Actual vs Predicted Values with Correlation Heatmap*

Error distributions and correlations between predicted and experimental values for MRR, TWR, and SR are displayed in Fig. 5 and 6; such figures further depict the model's stability and share with the reader some of the intricate relationships between the various process parameters.

The randomized forests and the gradient-boosting algorithms, as exemplified in Fig. 7 and 8, predict the material removal rate, tool wear rate, and surface roughness measurements against real ones. In Random Forest, the predicted values of MRR show some closeness with actuals with some slight overestimation in extreme points of the data. TWR predictions also correlate strongly with actuals, but there are some outliers suggesting difficulty with predictions of tool wear for some specific points. For their part, SR predictions are very much in line with the idealized line, with minimal deviations. For Gradient Boosting, the predictions for MRR, TWR, and SR were again lying much closer to actuals, with Hexbin plots further elaborating on model precision and minimal prediction errors. Gradient Boosting is showing superiority over Random Forest for all three metrics and has better accuracy in its predictions for MRR, TWR, and SR, thereby being the most suitable model for the given dataset and working conditions.

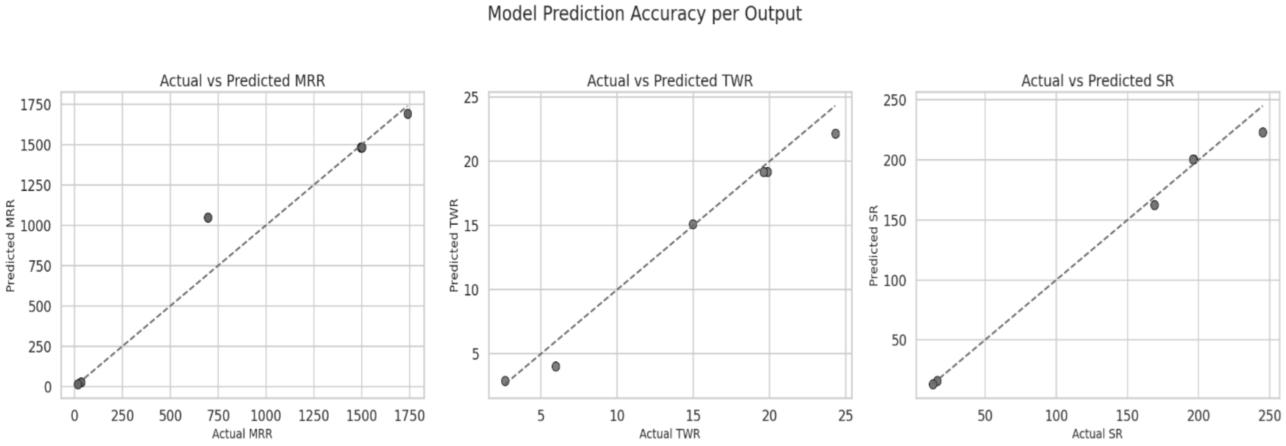

Fig. 7 *Actual vs Predicted Plots (Random Forest)*

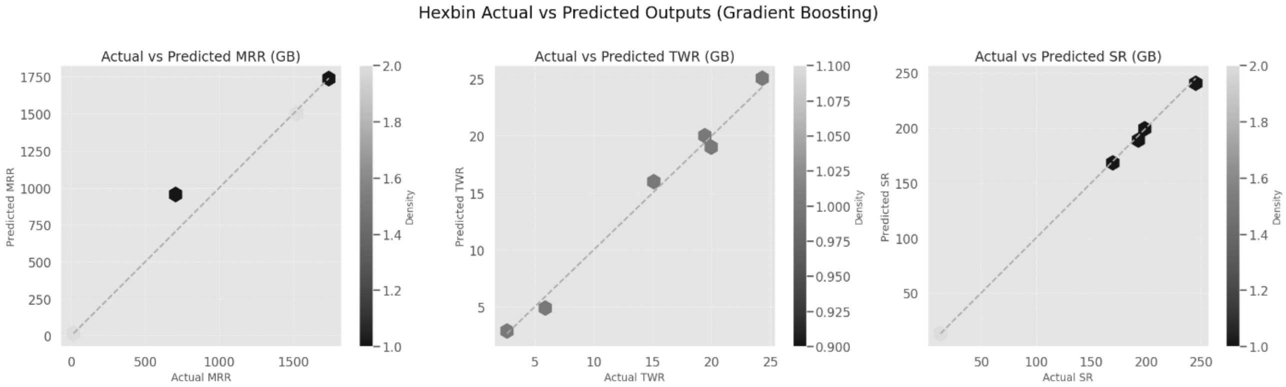

Fig. 8 *Actual vs Predicted Plots (Gradient Boosting)*

The results show that Gradient Boosting is the more efficient model in predicting machining performance outcomes, and considering both EDM and EAM, EAM would be more favourable in high material removal rate applications while EDM would be more applicable for precision works.

4 Conclusions

In the present study, a machine learning–based predictive modelling framework was proposed to analyze performance of Electric Discharge Machining (EDM) and Vibration-Assisted Electric Arc Machining (EAM-V) processes exploiting key process parameters, current, pulse-on time, and pulse-off time. Proposed methodology incorporated: data pre-processing, feature scaling, train-test splitting, Random Forest model(s), and Gradient Boosting model. For model evaluation, various statistical metrics, such as R^2, RMSE, and MAE, have been utilized.

With a degree of optimistic reservation, the experiments concluded that the GB model had better prediction power to work with, compared to the RF model-the R^2 values were 0.970, 0.994, and 0.999, respectively, for MRR, TWR, and SR. In other words, GB model outstood in the capture of nonlinear relations between the machining parameters and the performance metric. By further validation, it could be shown that EAM-V certainly presents a more efficient practice in the MRR, although the EDM provided the lowest TWR and presented the best outcome on the polished surface. This sighting represents the broader application of the process in precision engineering applications.

The results support the supposition that the designed machine learning methodology properly models the processes of EDM and EAM-V, offering reliable estimates of machining performance. Integration of machine learning techniques with machining process analysis can be employed for intelligent retrieval of solutions and parameter optimization in the area of advanced manufacturing. Future work could focus on the inclusion of real-time monitoring data with advanced learning types so as to provide additional enhancing predictive accuracy and adaptive process control.

Acknowledgement

The authors extend their acknowledgement to the financial support of the European Union under the REFRESH-Research Excellence For REgion Sustainability and High-tech Industries project number CZ.10.03.01/00/22_003/0000048 via the Operational Programme Just Transition and has been done in connection with project Students Grant Competition SP2026/061 "Sustainable manufacturing technologies" and SP2026/060 "Research of innovative manufacturing technologies" financed by the Ministry of Education, Youth and Sports and Faculty of Mechanical Engineering VŠB-TUO.

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