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# Response Surface and Machine Learning Modeling for Optimizing Electrical Discharge Machining: A Mechanical Analysis Approach

Ikram Messaoudi[1], Hamdi Hentati[1,2*], Boutheina Ben Fraj[3], Taoufik Kamoun[4], Walid Meslameni[4], Mounir Ben Amar[5], Ali Akrout[1], Mohamed Haddar[1]

[1]*Research Laboratory of Mechanics, Modeling and Manufacturing, National Engineering School of Sfax, University of Sfax, Tunisia*
[2]*High School of Sciences and Technology of Hammam Sousse, University of Sousse, Tunisia.*
[3]*Nanomaterials and Systems for Renewable Energy Laboratory, Research and Technology Center of Energy, TechnopoleBorjCedria, HammamLif, Tunisia*
[4]*Higher Institute of Technological Studies of Sfax, Tunisia*
[5] *Laboratoire des Sciences des Procédés et des Matériaux, CNRS, Université Sorbonne Paris Nord, Villetaneuse, France.*

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**Abstract**

The main challenge in Electrical Discharge Machining (EDM) is to achieve an optimal balance between material removal rate (MRR) and the surface roughness (Ra) of the machined component. The key EDM parameters influencing these outcomes are pulse current (I), pulse on-time (Ton), and pulse off-time (Toff). To enhance the cutting performance, this study analyzes and optimizes the influence of these machining parameters. Experimental results reveal that while a higher pulse current significantly improves MRR, it often compromises surface accuracy and overall machining precision. Furthermore, our study finds an optimum set of input parameters that ensure both high machining efficiency and desirable surface integrity by employing various machine learning (ML) models. An inverse optimization approach is introduced then to validate the predictive capability of the developed models, which constitutes a novel contribution of this work. In addition, microscopic analyses of surface roughness, crater morphology, and three-dimensional surface topography are incorporated to provide a comprehensive evaluation of the EDM process. The proposed framework offers useful guidelines for industrial EDM parameter selection, allowing improved productivity and enhanced surface quality in cutting applications.



**Keywords:** EDM, Material removal rate, Surface roughness, Response surface modeling, Machine learning.

## 1. Introduction

Significant progress in manufacturing engineering has focused on improving the performance and optimizing manufacturing processes [1–3]. In this context, Extensive research has focused on the mechanical and damage properties of obtained components through diverse methods [4–6]. These studies have investigated damage mechanisms such as crater dimensions, crack initiation, and crack propagation paths using experimental techniques, numerical simulations, or combined experimental–numerical approaches [7–8]. Such methods integrated with optimized methods are particularly important for understanding accurately surface integrity in manufactured components. These developments have accelerated the adoption of advanced manufacturing techniques in diverse industrial sectors, enabling higher efficiency, improved precision, and better product reliability [9-10]. Among these techniques, Electrical Discharge Machining (EDM) has attracted significant attention due to its capability to precisely machine complex geometries in hard-to-cut materials. Diverse studies have provided valuable insights into the influence of EDM parameters on material behavior, damage mechanisms, and surface quality [11-13].

Quarto et al. [14] developed and validated a finite element model for micro-drilling EDM, highlighting that discharge energy is the dominant factor, as higher energy increases material removal rate (MRR) but simultaneously degrades surface roughness due to larger craters and an extended HAZ.

Velpula et al. [15] investigated the influence of EDM parameters on material removal and tool wear rates when machining 17-4 PH stainless steel, showing that appropriate parameter optimization is crucial for improving machining efficiency. Then, research on EDM performance has increasingly emphasized advanced optimization methodologies, where experimental data are systematically gathered, mathematical models are established, and process simulations are refined to improve both accuracy and efficiency. Soori et al. [16] presented the advantages and limitations of various optimization approaches for EDM, with a focus on input parameters. They highlighted that methods such as Taguchi design, artificial intelligence,

* Corresponding author e-mail: hamdi.hentati@yahoo.fr.

genetic algorithms, and other advanced techniques can significantly enhance MRR, tool wear, and surface quality, while addressing key challenges in process optimization. Among these approaches, Artificial Neural Networks (ANN) and Response Surface Methodology (RSM) have been widely adopted for modeling and prediction purposes [17-20]. Although RSM has been the most used empirical modeling approach, recent studies have increasingly adopted Artificial Neural Networks (ANNs) due to their superior ability to accurately predict EDM process responses. ANNs are now among the most widely applied AI tools for capturing the complex relationships between EDM input parameters and process outcomes [21].However, studies have shown that ANN models can predict EDM performance with high accuracy, provided they are trained on a sufficiently large set of experimental or simulated data. Pradeepkumar et al. [22] demonstrated that the integration of ANN with genetic algorithms efficiently optimizes EDM parameters for AZ91D alloy, where ANN outperformed RSM in prediction accuracy and enabled the identification of optimum machining settings for best surface quality and cost-efficient manufacturing. In this context, Quarto et al. [23] demonstrated that an integrated ANN–PSO methodology, compared with FEM simulation, provides a faster and more accurate tool for forecasting and optimizing micro-EDM drilling performance. In the same context, Sahu et al. [24] applied an integrated ANN–NSGA-II approach to optimize EDM of A2 steel, balancing the conflicting objectives of MRR and tool wear rate (TWR) by adjusting discharge current and pulse-on and pulse-off times. Anitha et al. [25] demonstrated that using ANN for multi-objective optimization of EDM enables accurate prediction of MRR and surface roughness, providing optimal input parameters that enhance productivity while highlighting the inherent trade-off between high MRR and surface quality.

In recent years**,** several advanced frameworks for multi-objective optimization have **been developed,** aiming to identify the most effective combinations of EDM process parameters**. In fact, various Machine Learning (ML) models have** been advanced [26-28], in order to achieve the optimal machining parameters among multiple performance criteria, including material removal rate, surface quality, and tool wear. These models **remain underused** and their potential is not fully assessed.

The main objective of this study is to select the most suitable electrode material for EDM based on wear and machinability, and then to systematically analyze the effects of key machining parameters, which are pulse current (I), pulse on-time (Ton), and pulse off-time (Toff), on material removal rate and surface quality. The methodology involves a comparative study of three different electrode materials, followed by a design of experiments (DOE) to generate data for Response Surface Methodology (RSM). A correlation matrix is used to identify the most influential parameters, and ML models are applied to predict machining performance. Furthermore, an inverse optimization approach is employed to validate the predictions and determine the optimal process parameters, ensuring both high efficiency and desirable surface integrity.

## 2. Methods and materials

### *2.1. Mechanical properties of material parts*

Non-alloy steel C45, a medium-carbon steel, was selected as the workpiece material due to its balance between strength, hardness, and machinability. C45 is frequently used in automotive, aerospace, and tooling industries [17,32]. Table 1 presents the mechanical and chemical properties of the workpiece.

**Table 1.** Mechanical properties and chemical composition (wt %) of workpiece

| Tensile strength ($N/mm^2$) | Yield stress ($N/mm^2$) | Hardness (HB) | Density ($g/cm^3$) |
|---|---|---|---|
| 560 – 620 | 275 – 340 | 170 | 7.85 |
| **C(%)** | **S(%); P(%)** | **Mn(%)** | **Si(%)** |
| 0.50 – 0.52 | ≤ 0.035 | 0.50 – 0.80 | 0.40 max |

In this study, three different electrode materials were selected for comparative analysis: graphite, copper, and steel. Each of these materials possesses distinct mechanical and physical properties that influence their performance during the EDM process. In fact, graphite is lightweight and thermally stable, with excellent resistance to wear and erosion. Copper, known for its high electrical and thermal conductivity, ensures efficient energy transfer and controlled discharge behavior. Steel, although less commonly used as an EDM electrode, was chosen for its mechanical strength and availability, allowing a broader comparison across materials with varying characteristics. Table 2 summarizes the main physical characteristics of the three electrode materials used in this study.

**Table 2.**Physical characteristics of the electrode materials [29-31]

| Property | Graphite | Copper | Steel |
|---|---|---|---|
| **Density($g/cm^3$)** | 2.25 | 8.89 | 7.85 |
| **Thermal Conductivity (W/m·K)** | 125 | 390 | 55 |
| **Melting Point (°C)** | 3000 | 1083 | 1490 |
| **Machinability Ks($N/mm^2$)** | 400 | 20 | 60 |

The experimental investigation was carried out using a structured DOE–based comparative approach to systematically assess the influence of electrode material on EDM performance.

To evaluate their suitability as EDM electrodes, we conducted experiments to compare two key performance indicators, which are the electrode wear ratio (Wr (%)) and the machinability index (Ks). Wr (%) reflects tool durability and Ks measures the efficiency of material removal.

### *2.2. Experimental Setup*

The experiments were carried out on an EROTECH Basic 450 EDM machine, as shown in Figure 1. The machine is equipped with an electrical energy generator that produces high-frequency electrical pulses, a conductive electrode, and a worktable for holding the workpiece. It also includes a control system for regulating the machining process and a dielectric tank that prevents arcing between the electrode and the workpiece. Mineral oil was used as the dielectric fluid in the experiments, which was selected for its essential properties that make it well suited to the EDM process.


**Figure 1**.Experimental set up of EDM machine (EROTECH basic 450)

The experimental flow chart is illustrated in figure 2. This flow chart illustrates the experimental procedure for EDM process. It starts with defining the workpiece (C45 steel) and the tools (copper, graphite, steel).

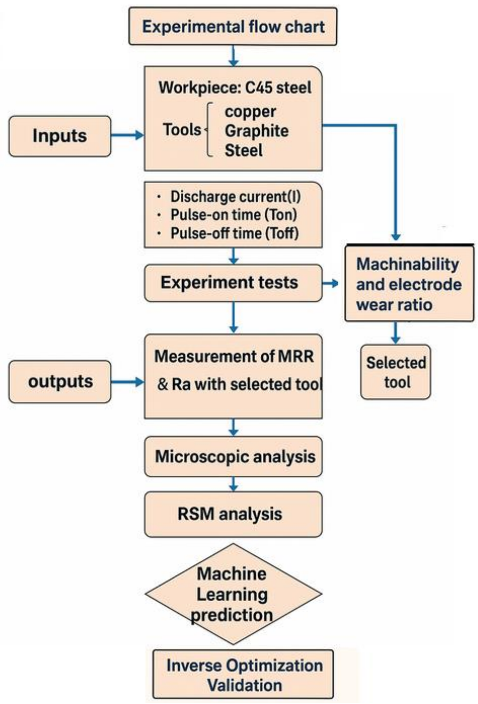



**Figure 2.** Experimental flow chart

The process then moves to experiment tests, where results such as electrode wear ratio and machinability are evaluated. Based on these, a selected tool is chosen. With the selected tool, the measurement of MRR and Ra is carried out. Indeed, various experiments are conducted, and the masses of both the workpieces and the weights of electrodes were measured before and after machining using a digital scale with a precision of ±0.01g to calculate MRR and Wr (%).

After the measurement of MRR and Ra with the selected tool, the process continues with a microscopic analysis to investigate the surface morphology and micro-cracks caused by EDM, providing deeper insight into the quality of the machined surface. Following this, a RSM analysis is carried out to quantify the influence of the input parameters and determine the interactions between them. These models are then enhanced using ML prediction techniques, which allow capturing non-linear relationships and improving the accuracy of performance predictions. Finally, an inverse optimization and validation stage is conducted to identify the optimal machining parameters that balance machinability, surface quality, and tool wear, while validating the predictive models against experimental results to ensure reliability and robustness.

## 3. Results and discussion

### *3.1. Machinability and electrode wear ratio*

The performance of the three electrode materials was evaluated based on two critical criteria: the electrode wear ratio (Wr%) and the machinability index (Ks). These indicators reflect both the durability of the electrode and its efficiency in removing material during the EDM process. The discharge parameters were set at specific values to examine their effect on machining performance. I was tested at two levels: 16 A and 64 A. Similarly, Ton was assigned two values: 25 µs and 100 µs. Toff was kept constant at 50 µs throughout all experiments. This combination of parameters allowed the investigation of machining responses under various energy discharge conditions. These findings are summarized in Figure 3, which clearly illustrate the inverse relationship between electrode wear and machinability for the materials tested.

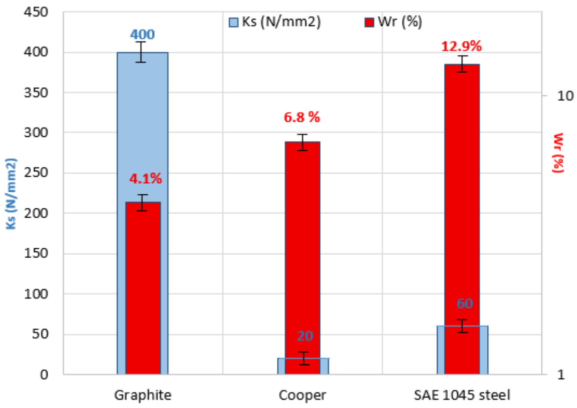



**Figure 3.** Wr% and KS (N/mm$^2$)

We show that the graphite had the lowest wear ratio (Wr% = 4.1%), indicating high resistance to tool degradation, but its very high machinability index (Ks = 400 N/mm²) reflects low material removal efficiency. In contrast, steel exhibited a higher Ks (30 N/mm²) than copper, suggesting better erosion capacity, but also suffered from the highest wear (Wr% = 12.9%), which limits its practical use. Copper, with a moderate wear ratio (6.8%) and the lowest Ks (20 N/mm²), offers the best balance between tool life and machinability, making it the most suitable electrode among the three for the given EDM conditions. Therefore, copper was selected as the manufacturing tool material for the subsequent EDM experiments.

*3.2. Measured roughness*

Multiple EDM machining tests were conducted with varying parameters. Among these tests, one representative trial was selected for an in-depth analysis. This test was performed using the following parameters: I=64A, Ton=8 µs, and Toff=4µs. The resulting surface condition was examined through microscopic imaging and 3D topography measurements obtained using an optical profilometer, as shown in Figure 4.The assessment of surface texture quality was carried out in accordance with ASME B46.1-1995 standards, employing a comprehensive set of roughness parameters to ensure an accurate and detailed evaluation. The average roughness (Ra) provides a general indication of surface smoothness by representing the arithmetic mean of profile height deviations from the mean line.

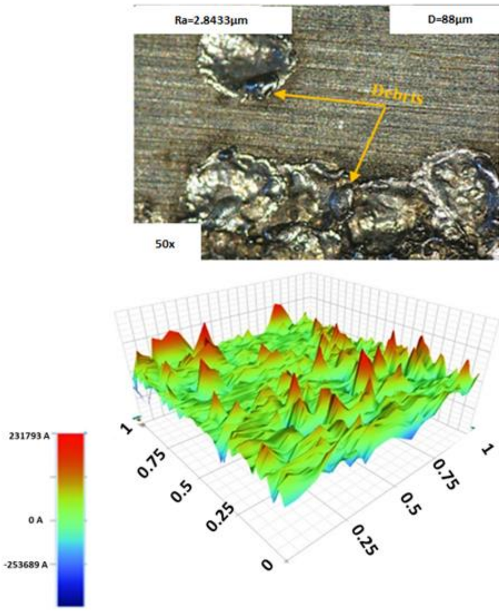



**Figure 4.** Microscopic images of surface roughness and craters, and 3d surface topography for I=64 A, Ton=8µs and Toff =4 µs.

For the selected EDM condition, the machined surface exhibits relatively large and deep craters, characteristic of the high-energy discharges generated under these parameters. The measured average crater diameter (D) is approximately 88 µm, indicating an intense spark action that significantly alters the surface morphology. The corresponding crater depth reaches about 25.37 µm, reflecting substantial material melting and ejection during each discharge. This pronounced surface topography is consistent with the measured surface roughness (Ra) for this test, confirming that the selected parameters lead to a highly textured surface with prominent micro-features typical of high-energy EDM machining.

However, since Ra does not capture extreme surface features, the root mean square roughness (Rq) was also measured to provide greater sensitivity to significant deviations. Additionally, the maximum profile peak height (Rp) is considered, as it highlights the highest peak within the measured profile. The maximum height (Rz) is used to capture the average height difference between the highest peaks and lowest valleys across multiple sampling lengths, providing a more robust characterization of surface irregularities. The combination of these parameters ensures a comprehensive analysis the surface texture. The different measures are summarized in Table 3.

**Table 3.** Surface roughness parameters

| *I* (A) | *Ra* (Å) | *Rq* (Å) | *Rp* (Å) | *Rz* (Å) |
|---|---|---|---|---|
| 64 | 28433.84 | 40998.45 | 231953 | 485864.96 |

Finally, the five-point average maximum height (Rz) was used to characterize the average height difference between the highest peaks and lowest valleys across multiple sampling lengths, offering a more comprehensive evaluation of surface irregularities.

*3.3. Response Surface Methodology (RSM)*

RSM is a powerful statistical approach used to study how multiple input variables influence one or more outcomes. Its main purpose is to identify the best set of EDM conditions through carefully designed experiments while minimizing the number of trials required. RSM relies on a second-order (quadratic) polynomial regression model to capture both the main effects and the interactions among process parameters, ensuring reliable representation of the system. In this study, RSM is applied to systematically investigate the effect of discharge current, pulse-on time, and pulse-off time on the output responses of EDM. By generating three-dimensional surface plots and two-dimensional contour grids, RSM provides a clear visualization of how variations in input parameters affect key performance measures. In this context, Figures 5 and 6 illustrate the response surface diagrams obtained from the RSM analysis, which provide a graphical representation of the influence of EDM process parameters on the output responses.

Figure 5 presents the response surface plots for MRR under different conditions. These plots reveal how variations in the other two parameters influence MRR and help in identifying the conditions that promote higher material removal efficiency.

As shown in Figure 5 when the current (I) is held constant, MRR increases with Ton and Toff, reaching a stable value, suggesting a saturation point. Increasing Ton improves the MRR, but once a threshold is reached, no significant improvement occurs. Similarly, increasing Toff promotes MRR up to an optimal value, after which the gains become marginal. Finally, the relationship between Ton and Toff with MRR, for a constant current, shows a parabolic curve, indicating that a balanced combination of these parameters is necessary to optimize MRR. These results highlight the importance of precise parameter adjustment to maximize the efficiency of the EDM process.

Similarly, Figure 6 shows the response surface plots for surface roughness (Ra) under the same set of conditions. These diagrams demonstrate how the interaction between process variables affects the surface quality, highlighting the trade-off between high material removal rates and acceptable surface finish.

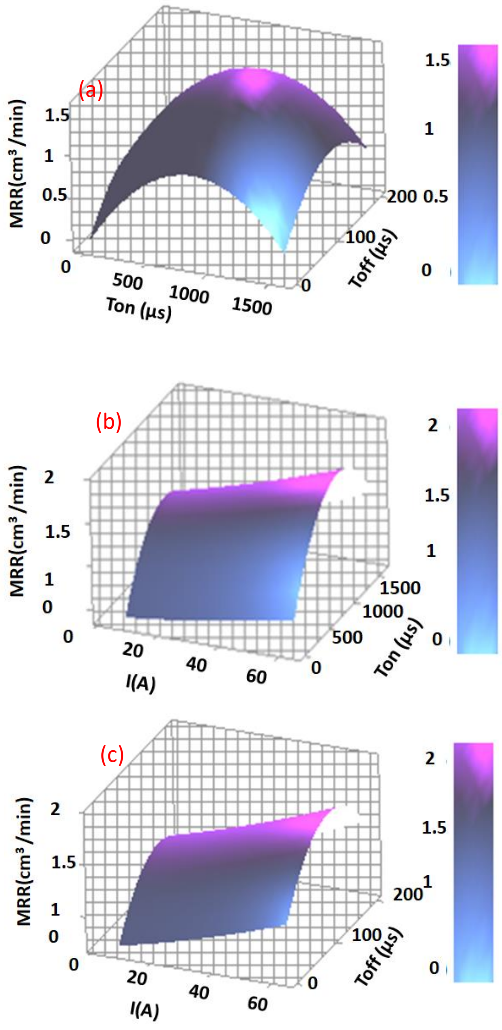
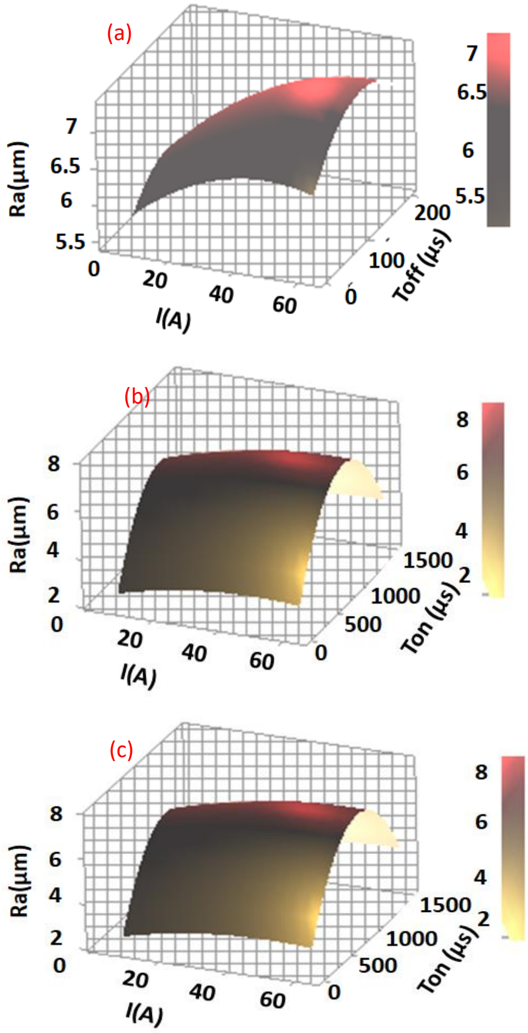



**Figure 5**. Response Surface diagram of Material Removal Rate (MRR) (a) I=36 A (b) Ton=804µs and (c) Toff=102µs A Shaded regions represent the 97% confidence interval associated with RSM prediction

As shown in Figure 6, the discharge current (I) and pulse-on time (Ton) have a positive effect on Ra, due to the increase in discharge energy, which results in deeper craters on the workpiece surface. In contrast, the pulse-off time (Toff) has an inverse effect, helping to reduce Ra by allowing better cooling of the machining zone and more effective debris removal. The interaction effects suggest that a proper balance between sufficient pulse duration to ensure material removal and adequate pause time is essential for optimizing surface quality. The correlation analysis (Figure 7) highlights the influence of EDM parameters on machining performance.

A strong positive correlation was observed between the discharge current (I) and the material removal rate (MRR) (r = 0.66), confirming that increasing current significantly enhances erosion efficiency. The pulse on-time (Ton) showed a moderate positive correlation with surface roughness (Ra) (r = 0.52), suggesting that longer pulses tend to deteriorate surface finish due to prolonged thermal impact. The pulse off-time (Toff) exhibited weak correlations with both MRR (r = 0.06) and Ra (r = 0.23), indicating a limited but stabilizing role by allowing better spark recovery and cooling. Among all parameters, current (I) appeared as the most influential factor, particularly in enhancing material removal.

These correlations helped us choose the most relevant input variables for both the RSM and ML models, highlighting the current (I) as the key factor in predicting and optimizing the EDM process.




*Shaded regions represent the 97% confidence interval associated with RSM prediction*

**Figure 6.** Response Surface diagram of surface roughness for (a) Ton=804µs, (b) Toff=102µs A and (c) I=36 A

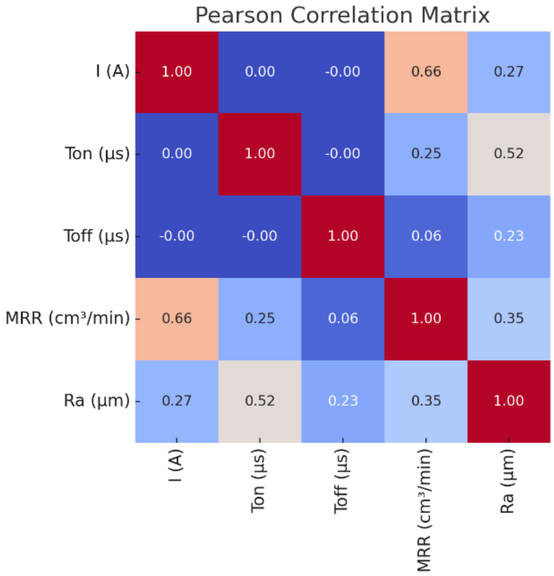



**Figure 7.** Pearson Correlation Matrix

## 4. Predictive modeling for the EDM process

In predictive modeling for the EDM process, various nonlinear regression methods were investigated to accurately predict the target variables, MRR and Ra. The evaluated techniques include Support Vector Regression (SVR), Random Forest Regressor (RFR), Artificial Neural Networks (ANN), ANN with backpropagation (BackANN), and Extreme Gradient Boosting (XGBoost). By training these models on experimental EDM data, precise predictions can be made under several machining conditions. A total of 90 experimental trials were conducted. The data were split into 70 % for ML training (63 trials) and 30 % for testing (27 trials). This approach not only enhances process optimization but also provides valuable insights into improving surface quality and machining efficiency. To assess the accuracy of the predictive models used in this study, two key performance metrics were considered: Mean Squared Error (MSE) and the coefficient of determination ($R^2$). The MSE quantifies the average squared difference between the actual and predicted values. It is expressed as (Eq. 1):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

Where $y_i$ represents the actual value, $\hat{y}_i$ is the predicted value, and n is the total number of observations. A lower MSE indicates a more accurate model, as it penalizes large deviations more heavily.The $R^2$ coefficient measures the proportion of variance in the target variable. It is defined as (Eq. 2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (2)$$

Where $\bar{y}$ is the mean of the actual values.

After performing the predictions using the regression models, the following Figure 8 presents the curves of the predicted and experimental MRR values and Figure 9 illustrates the comparison between the predicted and experimental Ra values obtained from the regression models.

After a thorough evaluation of model performance of MRR evolution, XGBoost and the ANN model demonstrated a clear superiority in terms of accuracy and robustness. For these two models, the majority of the predicted points closely matched the experimental results, indicating their strong ability to capture the underlying relationships between process parameters and output responses. This high compatibility suggests that both models have good generalization capability and low prediction error across the tested dataset. In addition, for of Ra evolution, SVR model performs poorly, with predicted values significantly deviating from experimental results. This indicates that SVR fails to accurately capture the underlying relationship between variables in this study. By analyzing both MSE and $R^2$ (Table 4), we can effectively evaluate the predictive performance of the ML models applied to the EDM process.

**Table 4.** Metrics for the considered ML models

| ML Model | $R^2$ (%) | | MSE (value) | |
|---|---|---|---|---|
| | MRR | Ra | MRR | Ra |
| XGBoost | 99 | 99.44 | 0.08 | 0.17 |
| SVR | 93.20 | 70.51 | 0.54 | 8.99 |
| RFR | 96.38 | 92.79 | 0.32 | 4.05 |
| BackANN | 93.65 | 87.07 | 0.51 | 4.96 |
| ANN | 98.64 | 98.15 | 0.16 | 0.51 |

Indeed, XGBoost and ANN achieved predictions with a low MSE and a high $R^2$, demonstrating its ability to effectively model the nonlinear and interactive phenomena present in the data. Consequently, XGBoost is selected as the optimal predictive model for this study, providing a robust and reliable solution for predicting EDM process outcomes.

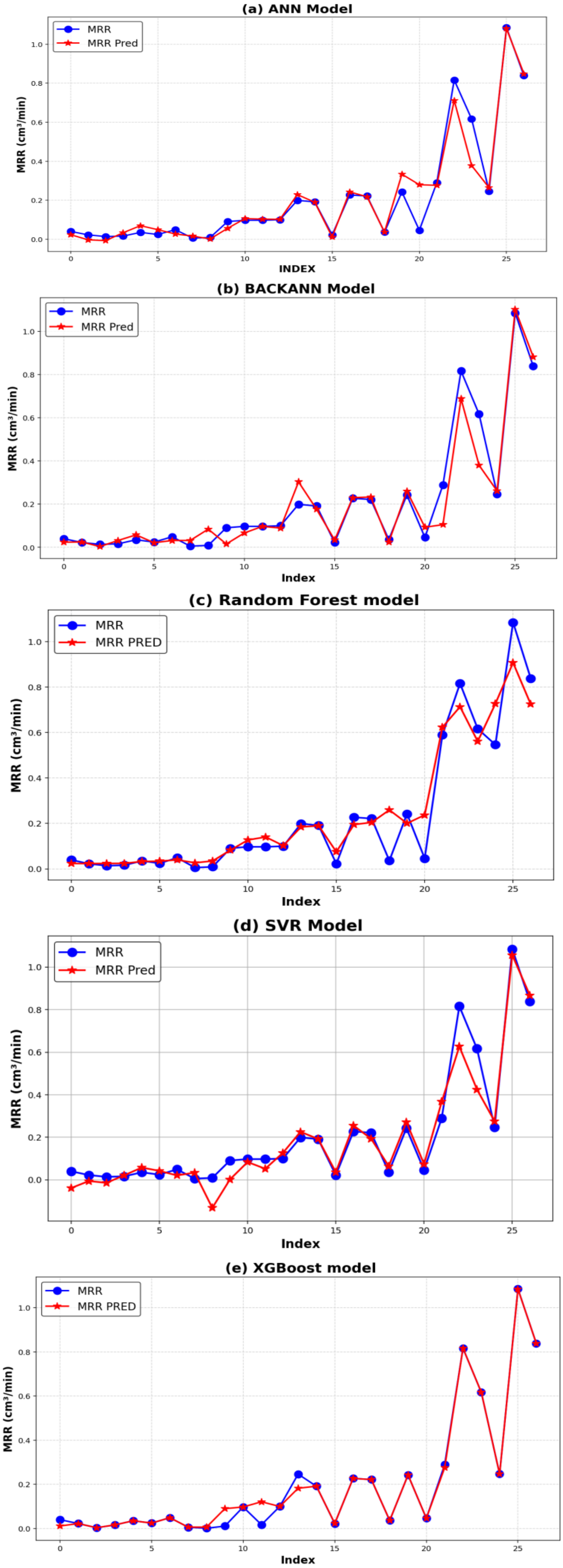



**Figure 8.** Experimental vs predicted MRR using various ML models: (a) ANN, (b) BackANN, (c) RFR, (d) SVR and (e) XGBOOST

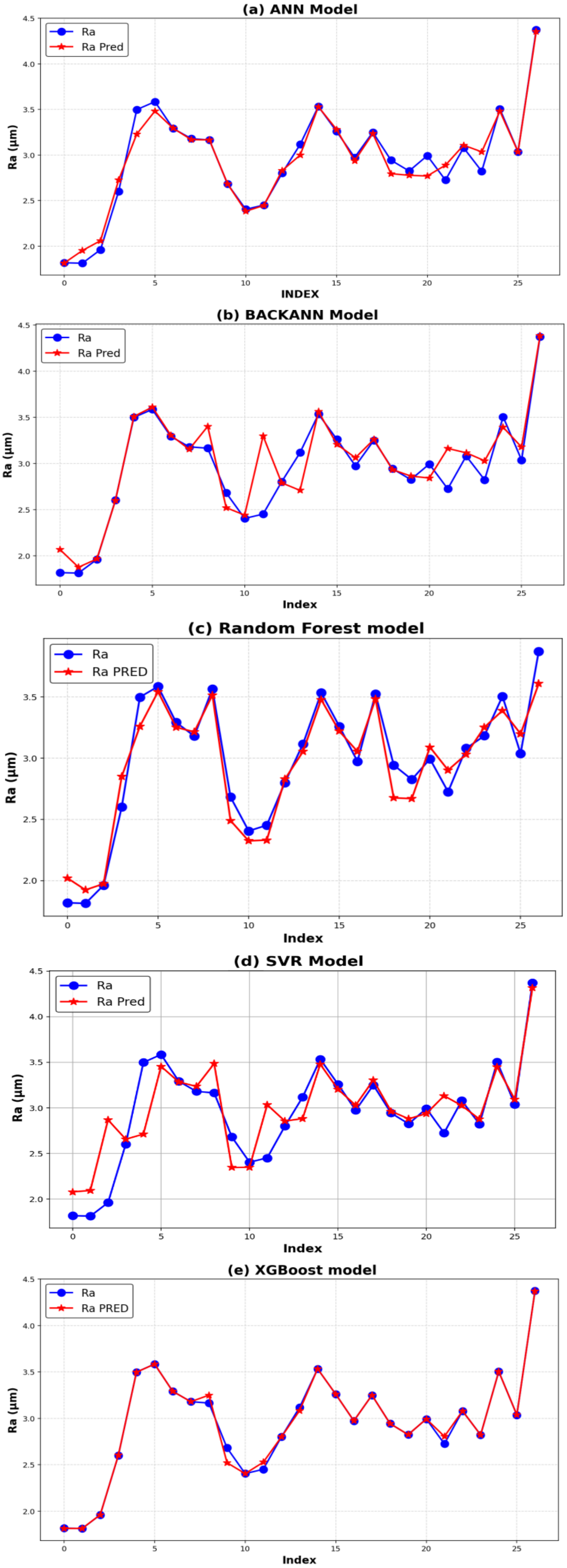



**Figure 9.** Experimental vs predicted Ra using various ML models: (a) ANN, (b) BackANN, (c) RFR, (d) SVR and (e) XGBOOST

## 5. Inverse optimization of EDM process

Inverse optimization is a powerful data-driven approach that seeks to determine the set of input variables required to achieve specific desired outcomes. Unlike traditional (forward) modeling, where outputs are predicted based on known inputs, inverse optimization reverses the process: starting from target outputs, it searches for the optimal input parameters that could produce those results. This technique is particularly useful in complex manufacturing processes, such as EDM, where multiple conflicting objectives must be balanced simultaneously.

In the present study, inverse optimization is developed to identify the optimal machining conditions that maximize the material removal rate (MRR) and minimize the surface roughness (Ra). Indeed, the primary goal of this inverse optimization procedure is to evaluate the reliability and predictive power of the XGBoost regression model, which was identified as the most accurate model based on its high coefficient of determination ($R^2$=99%). Inverse optimization was applied to identify sets of input parameters that achieve target values for material removal rate (MRR) and surface roughness (Ra). This approach reverses the relationship predicted by the XGBoost model, exploring various combinations of discharge current (I), pulse-on time (Ton), and pulse-off time (Toff) that meet the specified objectives.

The results obtained from this inverse optimization are presented in Figure 10.

**Inverse Optimization**

MRR Min: 0.5 MRR Max: 0.7
Ra Min: 2.5 Ra Max: 3.9

play

| I (A) | Ton (µs) | Toff (µs) | MRR | Ra |
|---|---|---|---|---|
| 64.0 | 100.0 | 200.0 | 0.6165 | 2.8217 |
| 96.0 | 1600.0 | 4.0 | 0.5496 | 3.1167 |
| 64 | 100 | 200 | 0.6168 | 2.8280 |
| 96 | 100 | 4 | 0.5273 | 3.4348 |
| 96 | 1600 | 4 | 0.5496 | 3.1167 |
| 96 | 1600 | 4 | 0.5496 | 3.1167 |

**Inverse Optimization**

MRR Min: 0.002 MRR Max: 0.04
Ra Min: 1.2 Ra Max: 1.9

play

| I (A) | Ton (µs) | Toff (µs) | MRR | Ra |
|---|---|---|---|---|
| 6.0 | 8.0 | 4.0 | 0.0200 | 1.2050 |
| 6.0 | 8.0 | 200.0 | 0.0025 | 1.7080 |
| 8.0 | 8.0 | 25.0 | 0.0225 | 1.8134 |
| 6 | 8 | 4 | 0.0198 | 1.2063 |
| 6 | 8 | 25 | 0.0223 | 1.7073 |
| 6 | 8 | 200 | 0.0024 | 1.7081 |

**Figure 10.** Inverse optimization of EDM process

From these results, one representative combination was selected for experimental validation: I= 6 A, Ton= 8 µs, and Toff=4 µs. Under these conditions, the experimental machining test was conducted using the EDM process. The measured performance metrics were then compared with the values predicted by the XGBoost model. The obtained results can be observed in Figure 11, which presents a microscopic image illustrating the validation of our model.

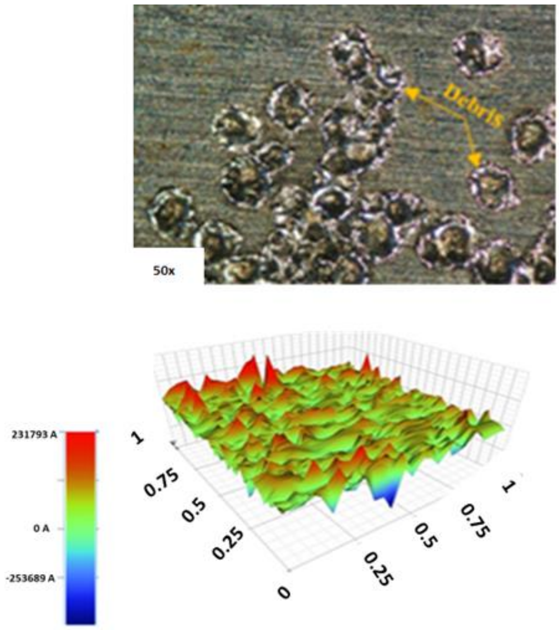



**Figure 11.** Microscopic images of surface roughness and craters, and 3d surface topography for I=6 A, Ton=8µs and Toff =4 µs.

This micrograph illustrates the actual surface condition obtained under the predicted optimal settings. The comparison revealed a very close match between predicted and experimental results:

- MRR: 0.0205 $cm^3$/min (experimental) vs. 0.0200 $cm^3$/min (predicted), with a relative error of 2.44%.
- Ra: 1.2067 µm (experimental) vs. 1.205 µm (predicted), with a relative error of 0.14%.

These small error values highlight the predictive accuracy and reliability of the XGBoost model, not only in approximating machining behavior but also in identifying optimal process settings. The observed result is in very close agreement with the experimental values, thereby providing additional visual confirmation of the accuracy and reliability of the XGBoost-based inverse optimization approach. The results confirm that the XGBoost model can be used as a decision-support tool in EDM applications.

## 6. Conclusion

This study demonstrates that optimizing the Electrical Discharge Machining process requires carefully balancing material removal rate (MRR) and surface quality (Ra). By experimentally analyzing the influence of key machining parameters, which are the pulse current (I), the pulse on-time (Ton), and the pulse off-time (Toff) and applying advanced machine learning techniques, the optimum parameter sets were successfully identified to achieve both high efficiency and desirable surface integrity. The predictive capability of the developed XGBoost model was validated through an inverse optimization approach and confirmed experimentally. The comparison between predicted and measured results showed excellent agreement, with relative errors of only 2.44% for MRR (0.0200 vs. 0.0205 cm³/min) and 0.14% for surface roughness Ra (1.205 vs. 1.2067 µm). These minimal deviations confirm the robustness and accuracy of the proposed model in capturing EDM behavior. Microscopic examinations and 3D surface topography analysis further validated the predicted surface conditions, providing visual evidence of the model's reliability.

Overall, the findings highlight that machine learning-based optimization, mainly using the XGBoost model, offers a powerful and consistent tool for enhancing EDM performance. It supports industrial decision-making through the application of an inverse optimization method, allowing the selection of optimal process settings for specific manufacturing requirements. This approach contributes to improved machining precision while maintaining high process efficiency, making it highly suitable for practical industrial EDM applications.

Future research should extend this framework toward deep learning by integrating an efficient numerical model of the EDM process, along with reinforcement learning approaches, to enable adaptive and intelligent EDM control for advanced manufacturing applications.

## Authorcontribution

Allauthorscontributedtotheresearch,writing,and reviewing of the paper.

## Declarations

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