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Machine Learning-Based Predictive Modelling of Surface Roughness and Overcut in Electro Chemical Discharge Machining

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Abstract: Electrochemical Discharge Machining (ECDM) is an advanced non-conventional machining technique well suited for micro-machining of hard, brittle and non-conducting materials such as glass and ceramics. Because of the intricate, nonlinear interactions between various input parameters, existing modelling techniques are not able to simulate process behaviour accurately. In this work, machine learning approaches are used to construct predictive models for two primary responses of ECDM—surface roughness (Ra) and overcut (OC) based on results of 27 experiments with varying five input parameters such as applied voltage, electrolyte concentration, stand-off distance, pulse frequency and pulse on time. Four regression models such as Linear Regression, Decision Tree, Random Forest and Support Vector Regression have been trained and tested against R^2 value, MAE and RMSE metrics. Results indicated that the Random Forest model provided the highest predictive performance, especially using R^2 values of 0.932 for surface roughness and 0.843 for overcut with its superiority compared to other models. This paper illustrates that machine learning methods based on ensemble offer a robust, data-driven methodology for effective prediction and optimization of ECDM process parameters towards enhanced precision manufacturing results.

Keywords: ECDM, surface roughness, Machine Learning, linear regression, decision tree, Random Forest, SVM.

INTRODUCTION

ECDM is one of the major non-traditional machining methods used for machining hard and brittle materials like glass, ceramics and quartz [1-3]. It works based on a hybrid mechanism using both electrochemical reactions and spark discharges to effectively erode material, thus proving ideal for precision machining and micro-drilling operations. Despite this, the ECDM process is nonlinear and features intricate interactions between various parameters like applied voltage, electrolyte concentration, stand-off distance (SOD), pulse frequency and pulse on time [4-6]. These parameters play a crucial role in affecting machining results like material removal, surface roughness and overcut, which are determinant factors of surface quality and dimensional accuracy. The conventional empirical and statistical modeling methods such as Taguchi methods, ANOVA and Response Surface Methodology (RSM) were extensively employed to explore the ECDM process [7-10]. Wüthrich et al. (2014) discussed ECDM basics and applications [11], Charak et al. (2020) and Ali et al. (2022) investigated the effect of process parameters on machining performance using RSM, whereas Sathisha, N et al. (2014) utilized Artificial Neural Networks to predict material removal rate [12-14]. While these studies have aided process understanding, they tend to lack in describing the nonlinear behaviour and multiple response relationships typical of ECDM. Further, the literature features sparse applications of sophisticated machine learning (ML) methods such as Random Forest, Support Vector Regression (SVR) and Gradient Boosting for predicting multi-response [15-17]. Counter to this background, the current study introduces a new data-driven method for modeling the ECDM process via

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machine learning algorithms to predict surface roughness and overcut simultaneously. The study establishes and compares the performance of various ML models on the basis of important parameters like R^2, MAE and RMSE. Feature importance analysis is also utilized to quantify the contribution of individual input parameters to the output responses. This unified framework not only improves prediction quality but also helps to analyze parameter sensitivity and thus it is a tool of great value in optimizing the ECDM process. The innovation of the present research is its extensive application of machine learning to multi-output prediction in ECDM, filling the shortcomings of previous studies regarding model accuracy, parameter sensitivity and simultaneous optimization of surface finish and dimensional accuracy.

EXPERIMENTAL WORK

ECDM is a hybrid non-conventional machining operation that utilizes the principles of electrochemical machining as well as spark erosion [18]. It is especially suitable for machining hard and brittle materials like glass, ceramics and quartz, which are difficult to machine with conventional methods. The glass was chosen as working material during experimentation. In ECDM, a tool electrode is partially submerged in an electrolyte, an alkaline solution NaOH were used. When an adequate voltage is applied between the tool and a counter electrode, electrochemical reactions on the tool surface result in the generation of a gas film, consisting mainly of hydrogen bubbles. At a voltage beyond a certain critical value, spark discharges happen through this insulating gas layer, producing localized melting and vaporization of material below the tool. The synergy between electrochemical etching and heat erosion by spark discharges enables efficient material removal for micro-scale machining applications.

For the current research, a total of 27 experimental runs was developed by changing five most important input parameters: applied voltage (45 V, 50 V, 55 V), electrolyte concentration (10 wt%, 17.5 wt%, 25 wt%), stand-off distance (SOD) (0.5 mm, 1 mm, 1.5 mm), pulse frequency (200 Hz, 300 Hz, 400 Hz) and pulse on time (45 µs, 50 µs, 55 µs) presented in table 1.

Input Parameters	Unit	Level 1	Level 2	Level 3
Applied Voltage	V	45	50	55
Electrolyte concentration	wt%	10	17.5	25
SOD	mm	0.5	1	1.5
Pulse frequency	Hz	200	300	400
Pulse on time	µs	45	50	55

Table 1. Input parameters and their levels

The experiments were carried out on a lab-scale ECDM system with a stainless-steel tool electrode and NaOH-based electrolyte. The two output responses after each trial of machining were recorded: surface roughness (Ra) by profilometer and overcut (dimensional deviation) by an optical measuring system. Both responses are regarded as key indicators of surface integrity and machining accuracy. The entire dataset, including input parameters and corresponding output responses, was the basis of predictive model building.

MACHINE LEARNING METHODOLOGY

For modeling the correlation between the input parameters and the machining responses, a machine learning framework was established with Python. The dataset was preprocessed by normalizing the input features for uniform scaling [19]. Individual supervised regression models were separately developed for surface roughness and overcut with different algorithms such as Linear Regression, Support Vector Regression (SVR), Decision Tree, Random Forest. The models were then compared based on various performance parameters such as R^2 score, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) using 5-fold cross-validation. Feature importance was also analyzed to determine the most dominant parameters impacting the responses [20]. This data-driven strategy offers a useful instrument for precise prediction of machining result and has the capability to minimize experiment effort considerably by leading in the choice of the best parameters for required surface quality and accuracy in ECDM.

The raw experimental data collected from the ECDM trials was pre-processed in order to make it machine learning ready. The dataset was first checked for consistency, missing values and outliers, but all values were found to be valid because of the controlled experimental setup. The input parameters pulse on time, applied voltage, electrolyte concentration, stand-off distance (SOD) and pulse frequency were normalized through Min-Max scaling to scale all features to a 0–1 range, such that feature-sensitive algorithms like Support Vector Regression would be able to work effectively. The output responses, surface roughness and overcut, were considered as continuous variables and the dataset was divided at random into training (80%) and test (20%) subsets to assess model generalization.

To simulate the process between the process parameters and the machining responses, four supervised machine learning regression models were used: Linear Regression, Decision Tree Regressor, Random Forest Regressor and Support Vector Regressor (SVR). Linear Regression was first employed as a baseline model because it is easy to interpret and simple, although it assumes linearity and independence of variables. The Decision Tree Regressor, a non-parametric model was utilized in order to capture nonlinear relationships by learning data patterns through recursive binary splits based on information gain. Although strong on smaller data sets, decision trees suffer from overfitting, which was countered by using the Random Forest Regressor, an

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ensemble learning approach that builds a multitude of trees and then averages their predictions to enhance stability and decrease variance.

SVR was also used to test its strength in solving nonlinear regression problems with few data points. SVR model relies on kernel functions to map the input space and determine an optimal hyperplane to fit the data within a specified margin of tolerance. All the models were trained with 5-fold cross-validation to avoid overfitting and to stabilize the results. Model performance was measured with R^2 (coefficient of determination), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The top-performing models were also explored in greater detail via feature importance plots to find out which parameters of the input had the greatest impact on surface roughness and overcut. The approach allows for comparative understanding and facilitates the identification of the best algorithm for predicting ECDM response.

RESULTS AND DISCUSSION

The resultant machine learning models were tested on the experimental dataset that consisted of 27 ECDM trials. The data were partitioned into training and test sets in an 80:20 ratio, and models were trained to predict two output responses: surface roughness (Ra) and overcut. Evaluation metrics including the coefficient of determination (R^2), MAE and RMSE were obtained for every model. The compared models were Linear Regression, Decision Tree Regressor, Random Forest Regressor and SVR. Visualization was achieved by creating scatter plots of actual vs predicted values (below) for both responses.

Linear Regression

Linear Regression was employed as the baseline model because of its simplicity. In case of surface roughness prediction, it resulted in 0.7456 R^2, MAE of 0.1376 µm and RMSE of 0.1609 µm, meaning there was moderate correlation between them. The model was quite good even for overcut, with the R^2, MAE and RMSE being 0.6854, 11.75 µm and 13.19 µm respectively. But the linear model makes assumptions of linearity and independence of features, which will certainly cap its predictability in identifying the nonlinear relationship of ECDM.

Decision Tree Regressor

The Decision Tree model was far better for surface roughness, predicting an R^2 of 0.9064, MAE of 0.0691 µm and RMSE of 0.0976 µm showcasing its performance in identifying nonlinear relationships. Yet, its performance fell for overcut prediction at R^2 0.4242, indicating overfitting or generalization weakness for this response. This inconsistency indicates that while the Decision Tree performs well in identifying localized behavior, its absence of averaging across branches may diminish robustness for intricate responses such as overcut.

Random Forest Regressor

Random Forest was the most accurate model for surface roughness as well as for overcut. For Ra prediction, it gave R^2 of 0.9321, MAE of 0.0669 µm and RMSE of 0.0831 µm the highest among all models. For Overcut, Random Forest gave R^2 of 0.8430, MAE of 7.65 µm and RMSE of 9.32 µm. Ensemble averaging in Random Forest prevents overfitting while modeling complex patterns efficiently. The predicted vs. actual plots also indicated close bunching near the ideal line, establishing good model reliability.

Support Vector Regression (SVR)

SVR yielded a fair performance for surface roughness with R^2 of 0.7795, MAE of 0.1193 µm and RMSE of 0.1498 µm, better than Linear Regression but worse than Decision Tree and Random Forest. For Overcut prediction, SVR was not good, with a R^2 score of -0.3458, meaning it did not generalize or identify the output patterns. The forecasts were almost horizontal over test samples, implying the model was unable to learn from the data due to kernel limitations or poor parameter tuning.

Scatter Plots for Surface Roughness

The figure 1 shows scatter plots of actual versus predicted values of surface roughness (Ra) for four machine learning models: Linear Regression, Decision Tree, Random Forest and Support Vector Regression (SVR). The individual experimental observations are indicated by blue crosses in each subplot, while the red dashed line represents the ideal prediction line where predicted values are the same as actual measurements ($y = x$). For Linear Regression, scatter points are relatively reasonable but somewhat scattered along the red line and reveal moderate prediction accuracy with some variation in estimates. The Decision Tree model depicts a more compact collection of points closer to the diagonal and implies higher predictive power with lower errors than Linear Regression, particularly at mid-range values of Ra. The Random Forest model further enhances the accuracy of prediction with points closely following the ideal line, showing that its ensemble method accurately identifies the non-linear relationships that affect surface roughness. Likewise, the SVR model is also seen to have strong prediction with low scatter away from the line, affirming that it is fit for regression processes in modeling surface roughness. As a whole, these plots give a visual assessment of how well each model predicts surface roughness in the ECDM process with Random Forest and SVR performing best, then Decision Tree, and finally Linear Regression being relatively less accurate. This relative evaluation supports the choice of more sophisticated ensemble and kernel-based techniques for better prediction of surface roughness in machining parameter optimization research.

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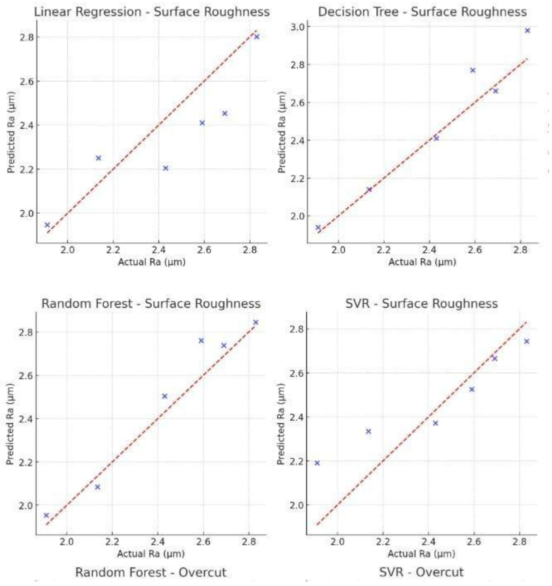

Figure 1: Predicted verses Actual surface roughness of machine learning model.

The Decision Tree model shows considerable variability for large overcut values, particularly with over-prediction at the higher end, indicating overfitting and poor generalization. The Random Forest model does better comparatively, with most of the points tightly following the ideal line, indicating better accuracy because it is an ensemble model and can reduce the variance. Nonetheless, some under-prediction still occurs for mid-level overcut values. The SVR model has more dispersed predictions, particularly for lower and mid-level actual values, indicating that the SVR model may need improved hyper parameter adjustment or kernel selection to enhance generalization for overcut data. In general, of the four models, Random Forest seems to provide the most stable performance in predicting overcut, followed by Linear Regression, while Decision Tree and SVR have larger variances. These plots emphasize the importance of model selection and tuning in obtaining good predictions in ECDM process optimization.

Scatter Plots for Overcut

The scatter plots in the second figure depict the actual versus predicted values of overcut (in µm) using four machine learning models Linear Regression, Decision Tree, Random Forest and Support Vector Regression (SVR). The plots are a comparison of the model performance in the prediction of overcut, which is a significant measure of quality in ECDM. The red dashed line is the ideal fit line whose predicted values exactly fit actual values. In the case of Linear Regression, moderate deviance of data points from the diagonal line signifies low predictive capability and potential lack of ability to capture non-linear trends in the overcut data.

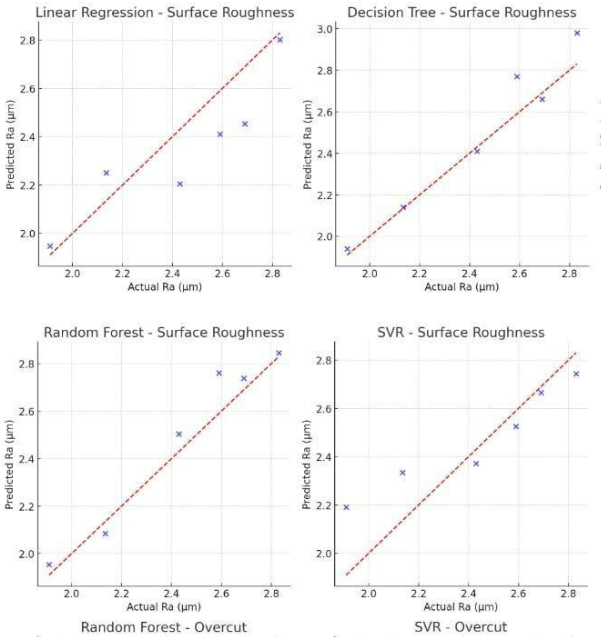

Figure 2: Predicated verses Actual overcut of machine learning model.

Correlation Heatmap

The heatmap used in this research provides thorough visual examination of the performances of four machine learning models Linear Regression, Decision Tree Regressor, Random Forest Regressor and Support Vector Regression (SVR) for prediction of two important ECDM responses: surface roughness (Ra) and overcut. Six performance measures are displayed: R^2, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) for each response. To make values uniform across metrics where always better is higher MAE and RMSE were inverted (1/MAE and 1/RMSE) since lower error represents improved model performance. Darker color represents better performance. From the plot (Fig. 3), Random Forest is uniformly emphasized in all the metrics using the deepest shades, signifying its better predictive ability and resilience for both overcut and surface roughness. The model performs best in all six metrics as compared to other models because of its ability to do ensemble averaging, which lowers variance and also deals with nonlinearities well. Decision Tree Regressor displays a heavy shade for surface roughness (Ra R^2), but considerably lighter for overcut R^2 and error measures, indicating high variance and low generalization, probably due to overfitting.

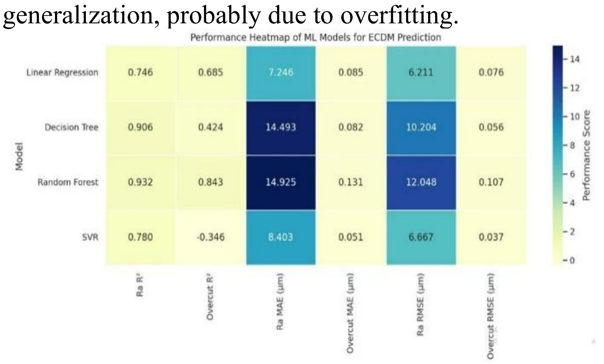

Figure 3: Heatmap of machine learning models.

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Linear Regression, although more even, displays only a moderate amount of shading, indicative of its poor ability to handle nonlinear relationships even though it delivers acceptable output for both of them. SVR shows a mixed result: moderate to excellent for Ra prediction, but the lightest colors for overcut metrics, especially a negative R^2, which means that the model did not generalize for overcut. This might be because there was not enough kernel selection or hyperparameter tuning for complicated data. In short, the heatmap serves to intensely illustrate the performance of every model in every metric. It easily singles out Random Forest as the most accurate and consistent performer for ECDM response prediction and visualizes the relative disadvantages of Decision Tree and SVR, particularly for multi-response issues such as overcut. This graphical comparison then further emphasizes the advantage of employing ensemble-based approaches to machining process modeling and optimization.

Model Comparison Summary

A consolidated comparison indicates Random Forest always produced the best performance in both responses. Decision Tree was good for surface roughness but poor for overcut. Linear Regression and SVR were moderate to poor, indicating their low applicability to model nonlinear and high-dimensional interactions of ECDM processes. These results are encapsulated in the table 2: According to the analysis, Random Forest Regressor is proposed for precise prediction of surface roughness and overcut in ECDM. It provides maximum accuracy, good generalization and parameter variance robustness. The findings validate the application of ensemble machine learning methods to predictive models in non-conventional machining. Future work can further investigate hyperparameter optimization, deep neural networks and meta-heuristic optimization methods for further improvement.

Table 2. Machine learning Model summary table

Model	Response	R^2	MAE (µm)	RMSE (µm)
Linear Regression	Ra	0.746	0.138	0.161
	Overcut	0.685	11.76	13.19
Decision Tree	Ra	0.906	0.069	0.098
	Overcut	0.424	12.20	17.85
Random Forest	Ra	0.932	0.067	0.083
	Overcut	0.843	7.65	9.32
SVR	Ra	0.780	0.119	0.150
	Overcut	-0.346	19.78	27.29

The bar chart shows a comparative study of four machine learning models Linear Regression, Decision Tree, Random Forest and Support Vector Regression (SVR) based on their R^2 values for the predictions of surface roughness (Ra) and overcut in the ECDM process. The Random Forest model had the largest values of R^2 for both responses (Ra and overcut), showing its better capability to model complex nonlinear relationships. The Decision Tree model performed well on surface roughness but not on overcut. Linear Regression performed moderately for both outputs but was constrained by its linearity assumption.

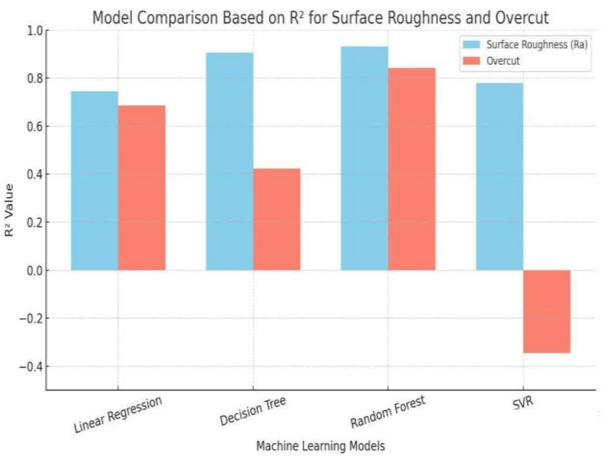

Figure 4: Model comparison plot

On the contrary, SVR performed reasonably for surface roughness but not for overcut, with a negative R^2 score, which demonstrates how sensitive it is to parameter tuning and kernel selection. In general, the story validates Random Forest as the best and most dependable model for multi-response prediction in ECDM.

CONCLUSIONS

In this research, the application of machine learning algorithms to simulate and forecast two significant output responses surface roughness (Ra) and overcut of the ECDM process was studied. Performing 27 well-designed experiments and utilizing four distinct regression models Linear Regression, Decision Tree, Random Forest and Support Vector Regression (SVR) an exhaustive comparison was carried out to assess predictive accuracy, model generalization and parameter sensitivity. On the basis of model performance measures (R^2, MAE, RMSE) and visual examinations, the following inferences were made:

- Random Forest Regressor was found to be the best predictive model for both surface roughness and overcut with maximum R^2 values (0.932 and 0.843 respectively) and minimum error scores, proving its strength in identifying nonlinear and complex relationships in the ECDM process.
- Decision Tree Regressor was exceptionally good at the prediction of surface roughness (R^2 = 0.906) but

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underperformed at overcut prediction ($R^2 = 0.424$), showing its susceptibility to overfitting and inability to generalize without ensemble averaging.

- Support Vector Regression gave decent predictions for surface roughness ($R^2 = 0.780$) but was overwhelmingly poor at overcut prediction ($R^2 = -0.346$), implying it is not good for high-dimensional or complex data without careful kernel and parameter tuning.
- Linear Regression was an adequate baseline model that demonstrated moderate performance on both responses but was hampered by its linearity assumption and thus not optimal for capturing the nonlinear dynamics of ECDM.

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