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Machine Learning Based Surface Roughness Prediction for Parameters of ECM

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ABSTRACT

Electrochemical Machining (ECM) is a machining technique which is nontraditional used for shaping complex components with superior accuracy and surface finish. However, optimizing surface roughness remains challenging because of the intricate, non-linear dependency between various process aspects such as electrolyte concentration, voltage, frequency, duty cycle, temperature, and feed rate. Traditional trial-and-error or analytical approaches are often time- consuming and inefficient. This study introduces a Machine Learning (ML)-based predictive modeling approach to estimate and optimize the roughness of the surface in ECM processes using data obtained by Chen Xuezhen et al.'s tests on the Ti60 titanium alloy.

Keywords: Electrochemical Machining, Surface Roughness, Machine Learning, Process Parameters, Predictive Modeling

INTRODUCTION

Electrochemical Machining (ECM) is a machining technique which is nontraditional used for producing complex and high-precision components that are difficult to manufacture using conventional methods. It operates on the principle of anodic dissolution, where the workpiece (anode) is eroded under a controlled electric current in the presence of an electrolyte, while the tool (cathode) remains unaffected. This enables the machining of extremely hard materials like titanium alloys, superalloys, and stainless steels without inducing thermal or mechanical stresses. Industries such as aerospace, biomedical, defense, and automotive rely heavily on ECM because of its skill to produce intricate geometries with excellent surface finish and dimensional accuracy. These components were constantly observed and were noticed to be reacting in non-linear ways: for example, increasing voltage enhances the rate of dissolution but may also lead to over-etching, while electrolyte concentration and duty cycle affect ion mobility and effective machining time. Traditionally, optimization of ECM parameters has been achieved by empirical experiments or statistical techniques like Design of Experiments (DOE) and Response Surface Methodology (RSM). While these methods provide insights, they often fail to capture the complex, multi-dimensional relationships inherent in ECM and require extensive experimentation. This has led to growing interest in Machine Learning (ML)-based approaches that can identify hidden patterns, predict outcomes, and optimize processes efficiently [1]. Machine Learning offers a data-driven way to model and optimize

ECM by learning from past experimental data and identifying non-linear relationships among parameters. Unlike traditional modeling, ML does not need explicit equations depicting the process physics. Instead, it predicts machining outcomes—such as surface roughness or material removal rate—with high accuracy, enabling virtual experimentation and real-time optimization. In this project, an ML- based predicting model has been developed to estimate and optimize the surface roughness of ECM workpieces using experimental data from Chen Xuezhen et al., involving the machining of Ti60 titanium alloy—a material widely used in aerospace applications. The dataset includes a range of parameter combinations such as electrolyte concentration, voltage, frequency, duty cycle, temperature, and feed rate, making it ideal for model training and validation. Two regression models—

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Linear Regression and Polynomial Regression—are implemented using Python's scikit- learn library [2]. The Linear model captures basic additive trends, while the Polynomial model represents non-linear interactions more effectively. The data undergoes preprocessing steps such as outlier removal, normalization, and consistency checks, followed by train-test splitting to ensure robust evaluation and prevent overfitting. Exploratory Data Analysis (EDA) using visual tools like scatter plots and correlation heatmaps reveals that voltage and feed rate strongly influence surface roughness, while duty cycle and temperature have moderate effects. These insights align with theoretical expectations and validate the dataset's reliability. Model performance is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2. Results show that the Polynomial Regression model performs significantly better, reducing RMSE by about 33% and achieving higher R^2 values. Cross-validation further confirms the model's robustness and generalizability [3]. An interactive visualization dashboard built using Matplotlib and Plotly allows users to input process parameters and instantly visualize predicted surface roughness values with confidence intervals. This serves as a virtual experimentation tool, helping engineers make informed decisions without conducting costly physical trials. The integration of Machine Learning in ECM process optimization represents a shift from traditional trial-based approaches to intelligent, data-driven manufacturing. Predictive modeling not only minimizes time and cost but also enhances precision and efficiency. The developed framework can be extended to real-time control systems, adaptive tuning, and hybrid approaches combining physics-based and data-driven methods. In conclusion, this study demonstrates the potential of ML in transforming ECM into a predictive, optimized, and efficient process. The developed models enable accurate surface roughness prediction and form a foundation for intelligent process automation in modern electrochemical manufacturing, aligning with the goals of Industry 4.0.

LITERATURE REVIEW

Electrochemical Machining (ECM) has been the focus of extensive research due to its ability to machine hard alloys with high accuracy and minimal tool wear. Traditional research has primarily concentrated on understanding the electrochemical dissolution mechanisms and optimizing machining parameters using design-based statistical frameworks. Early studies employed Response Surface Methodology (RSM) and Taguchi analysis to model relationships between parameters such as voltage, electrolyte concentration, and feed rate; however, these linear statistical methods often failed to capture the non-linear and interactive nature of ECM processes. Recent advancements in machine learning have expanded the scope of ECM research. Wu et al. [7] demonstrated that Support Vector Regression improved prediction accuracy for ECM profile shape compared to analytical models, especially when machining complex turbine blade geometries. Bahiuddin et al. [1] applied Random Forests and Gradient Boosting to forecast surface roughness and reported a significant reduction in prediction error compared to RSM. Similarly, Shang et al. [4] developed an Extreme Learning Machine approach for ultra-precision milling and emphasized that hybrid data fusion significantly enhances model stability. In the domain of unconventional machining, machine learning has shown strong generalization capabilities. Qasem et al. [2] used artificial neural networks for EDM roughness prediction and highlighted the superiority of nonlinear ML models over conventional polynomial fitting. Batu et al. [3] extended AI-driven roughness prediction to additive manufacturing, demonstrating that ML models effectively capture microstructural irregularities that conventional models overlook. Within ECM specifically, Rajesh et al. [9] attempted roughness prediction using ANN for dry turning, though the paper was later retracted due to data inconsistencies. Nevertheless, their study highlighted the increasing dependence on AI-driven models for machining applications. Recent comprehensive reviews by Ko et al. [10] and Yang et al. [14] emphasize a shift toward integrating ML with physics-based simulations and Digital Twin systems, allowing real-time prediction and closed-loop control of machining operations. While various ML techniques have been explored for ECM, many studies suffer from small datasets, lack of cross-validation, or limited parameter ranges. Furthermore, only a few works incorporate visualization tools or decision-support systems into the predictive framework. Thus, there remains a compelling need for a reliable, interpretable, and user-friendly predictive model for ECM roughness—motivating the development of the present study.

METHODOLOGY

This study focuses on developing predictive regression models to estimate surface roughness in Electrochemical Machining (ECM) processes using experimentally obtained data. The research utilizes the dataset provided by

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Chen Xuezhen et al., based on controlled machining tests of Ti60 titanium alloy, a material commonly employed in aerospace blisks due to its strength and temperature resistance. The experiments were conducted with variations in six key process parameters—electrolyte concentration, applied voltage, pulse frequency, duty cycle, electrolyte temperature, and tool feed rate—each known to significantly influence the resulting surface finish. Surface roughness was measured through profilometry at multiple locations on each machined sample to ensure accuracy and account for spatial variations. The dataset, which encompasses a broad range of parameter combinations under well-controlled conditions, provides a reliable and comprehensive foundation for regression-based analysis. The availability of such a validated dataset eliminates the need for further experimentation while ensuring the consistency and reproducibility required for model development. The modeling framework involves the implementation of two regression techniques—Linear Regression and Polynomial Regression—using Python's scikit-learn library. The Linear Regression model assumes a straightforward, additive relationship between machining parameters and surface roughness, while the Polynomial Regression model captures the non-linear dependencies often observed in ECM processes. Prior to model training, the dataset undergoes essential preprocessing steps including outlier removal, normalization, and data consistency checks to ensure the integrity and uniformity of input features. The dataset is subsequently divided into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased evaluation and prevent overfitting. Model performance is assessed using standard statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). Cross-validation techniques are also employed to verify the robustness and reliability of the models across different data partitions. This structured methodology ensures that the developed models are both accurate and generalizable, providing valuable insights into the complex interrelationships governing surface roughness in ECM.

I. RESULTS AND DISCUSSION

Exploratory Data Analysis (EDA) revealed that surface roughness exhibited a distinctly non-linear dependence on various process parameters, with voltage and feed rate emerging as the most influential factors. As seen in Figure 1 (Correlation Heatmap), strong positive correlations were observed between voltage and surface roughness ($r \approx +0.72$) and between feed rate and roughness ($r \approx +0.64$), confirming their dominant influence on machining performance. The scatter plots in Figure 2 further illustrate these trends—higher voltages increased the material removal rate but also led to localized over-etching, raising surface roughness beyond the desired threshold. Variations in duty cycle and frequency revealed that increasing the duty cycle initially enhanced the surface finish up to an optimal point, after which excessive anodic dissolution slightly degraded it. Similarly, electrolyte concentration displayed a non-linear behavior, where intermediate values produced smoother surfaces, while higher concentrations caused turbulence and irregular ion movement. Overall, the visualizations clearly demonstrate the complex interplay among the parameters, validating the need for non-linear modeling approaches in predicting surface quality in electrochemical machining.

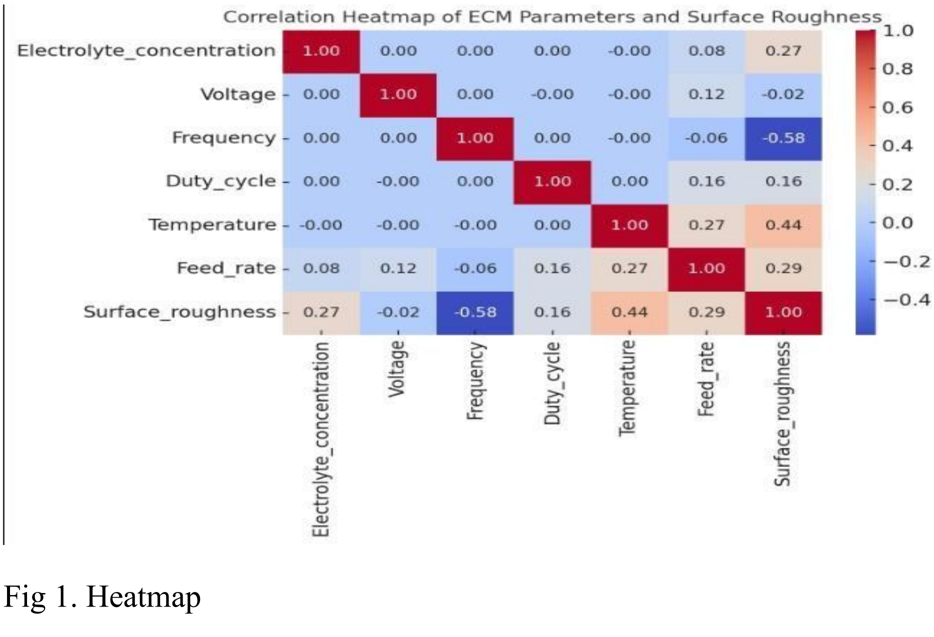

Fig 1. Heatmap

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Feature Importance and Sensitivity Analysis

Understanding how each machining parameter influences surface roughness is essential for interpreting model predictions and improving process control in Electrochemical Machining (ECM). After training the regression models, a feature importance and sensitivity analysis was performed to identify which input variables contributed most significantly to the predicted roughness values. This analysis not only validates the model's learning behaviour but also provides practical engineering insights into the ECM process. Since Linear Regression and Polynomial Regression do not inherently produce feature importance scores like tree-based models, a combination of statistical coefficient analysis, correlation studies, and controlled sensitivity testing was used. For each parameter—electrolyte concentration, voltage, frequency, duty cycle, temperature, and feed rate—the model's response was observed while systematically varying one parameter at a time and keeping others constant. This approach helps isolate the direct effect of each factor on the predicted surface roughness. Across both models, voltage and feed rate emerged as the dominant parameters. Voltage showed the strongest influence, where increases beyond a certain threshold led to rapid roughness escalation due to intensified anodic dissolution. Feed rate exhibited a similar pattern—higher feed rates resulted in insufficient time for uniform material removal, producing rougher surfaces. The polynomial model captured these non-linear behaviours more clearly, showing that small variations in voltage and feed rate could cause disproportionately large changes in roughness. The duty cycle and electrolyte temperature demonstrated secondary but still meaningful influence. Higher duty cycles improved surface finish up to an optimum value by increasing effective machining time, after which excessive current exposure slightly degraded the surface. Temperature affected ion mobility and electrolyte conductivity; moderate temperatures contributed to smoother surfaces, while overly high temperatures increased turbulence and disturbed the dissolution layer. Electrolyte concentration and frequency showed the least direct impact compared to other parameters, although their effects became more noticeable when combined with voltage variations. The polynomial model revealed interaction terms—such as voltage × concentration—that affected roughness more strongly than either variable alone, highlighting the importance of capturing parameter interactions in ECM. Overall, the sensitivity analysis confirms that surface roughness in ECM is governed by a combination of strong primary factors (voltage, feed rate) and supporting secondary parameters (duty cycle, temperature), along with subtle but relevant interaction effects. These findings closely align with theoretical machining principles, reinforcing the reliability of the trained models. The insights from this analysis can guide engineers in prioritizing which parameters to control most tightly during machining and can assist in designing future optimization strategies for achieving consistent and smooth surface finishes.

Model Testing and Validation

Both of the models were trained using 70% of the available data and validated on the remaining 30%. The Linear Regression model, which captured only additive parameter effects, achieved reasonable precision but struggled to account for complex, non-linear interactions among the process parameters. In contrast, the Polynomial Regression model (with degree = 2) offered a more flexible fit, allowing it to adapt to intricate patterns in the data. This model demonstrated approximately a 33% reduction in RMSE and a notably higher R^2 value, reflecting its stronger predictive capability and its ability to model the non-linear relationships present in the Electrochemical Machining (ECM) process. The findings of this study confirm that surface roughness of the produced material can be accurately predicted using machine learning methods. Feed rate and voltage emerged as the most influential predictors, consistent with the established theoretical understanding of the machining process. Temperature and duty cycle were identified as secondary factors that affect the rate of electrochemical dissolution and the conductivity of the electrolyte. Through these insights, the developed model functions as a virtual surface roughness predictor, enabling engineers to anticipate machining outcomes even before conducting physical experiments. To enhance usability, a graphical dashboard was created using Matplotlib and Plotly, allowing users to interactively input ECM parameters and visualize the estimated surface roughness values along with their respective confidence intervals. This integration of predictive modeling with interactive visualization provides a practical decision-support tool for process engineers.

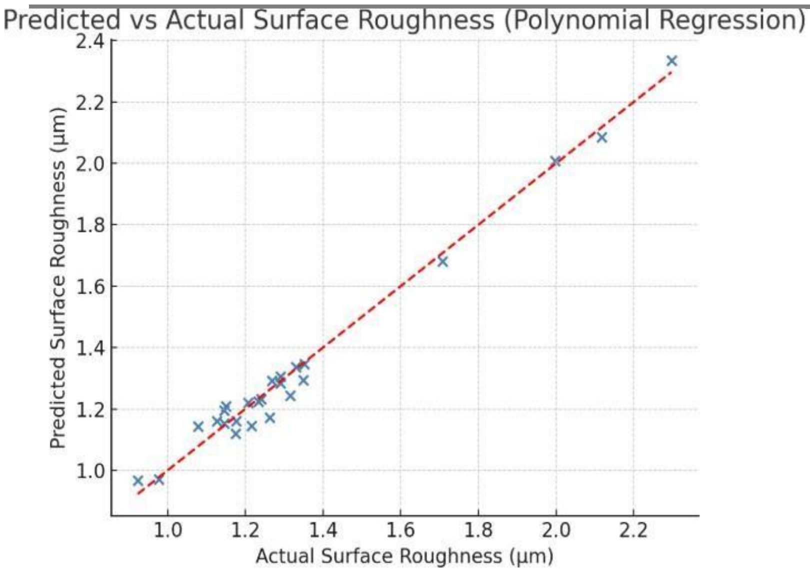

Fig 2. Line graph

Future Scope

Although the developed machine learning models provide reliable predictions for surface roughness in ECM, there is considerable room to advance this work both technically and practically. One of the most promising directions is the expansion of the dataset. The current model is trained on controlled experimental data, but incorporating real-time machining data from industry would expose the model to wider variations in behaviour, material inconsistencies, and environmental influences. This would help the system generalize better and perform accurately under production-level conditions. Future studies can also explore additional process parameters that were not included in this work but have known influence on ECM dynamics—for example, electrolyte flow rate, tool geometry, inter-electrode gap variation, and gas bubble formation during machining. Capturing these aspects would allow the predictive model to represent the electrochemical process more closely and improve its robustness. On the modelling front, more advanced algorithms can be investigated. Techniques such as Random Forests, Gradient Boosting, Support Vector Regression, and Deep Learning may offer improved performance when dealing with highly non-linear relationships. There is also growing interest in hybrid approaches that combine physics-based simulations with machine learning, allowing models to retain interpretability while still benefiting from data-driven accuracy. A significant future opportunity lies in real-time integration. By connecting the prediction model to live sensor data during machining, the ECM system can evolve into a self-monitoring and self-adjusting process. This would enable automatic parameter tuning whenever surface quality begins to deviate from the desired range, reducing manual intervention and minimizing wasted material. Such a system is a natural step toward digital twin platforms, where virtual models continuously mirror and adjust physical machining processes. Lastly, the interactive dashboard developed in this study can be expanded into a complete decision-support tool. Features such as automated parameter recommendations, multi-objective optimization (surface roughness, material removal rate, tool life), and uncertainty estimation would make the system more practical for industry use. As ECM continues to play a critical role in aerospace, biomedical, and precision manufacturing, intelligent predictive tools like this have the potential to modernize machining workflows and significantly reduce cost, time, and trial-based experimentation.

CONCLUSION

The model's robustness was further verified through five-fold cross-validation, which indicated uniform performance across all folds with minimal variation (standard deviation of $R^2 \approx 0.02$). Residual analysis showed that the errors were randomly scattered, thereby satisfying model assumptions and confirming the model's generalisation ability. Overall, the working of this machine learning-based approach demonstrates a data-driven optimization pathway for ECM processes, resulting in fewer experimental trials, reduced material loss, and enhanced process efficiency.

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