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RESEARCH ARTICLE

Integrating machine learning and mathematical programming for efficient optimization of electric discharge machining technique

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Abstract
This study focuses on predictive modeling in machining, specifically material removal rate (MRR), tool wear rate (TWR), and surface roughness (Ra) prediction using regression analysis. The research employs electrical discharge machining (EDM) experiments to validate the proposed unified predictive model. The approach involves varying machining parameters systematically and collecting empirical data. The dataset is split for training and testing, and advanced regression techniques are used to formulate the model. Evaluation metrics such as R-squared and mean-squared error (MSE) are employed to assess the model's accuracy. Notable findings include accurate predictions for MRR, TWR, and Ra. This approach demonstrates the potential for real-world application, aiding decision-making processes and enhancing machining efficiency. The research underscores the importance of predictive modeling in manufacturing optimization, offering insights into refining model architectures, data preprocessing techniques, and feature selection. The findings affirm the relevance and applicability of predictive modeling in manufacturing, emphasizing its potential to elevate precision and efficiency.

Keywords: Predictive modeling, Machining parameters, Regression analysis, Electrical discharge machining, Performance optimization.

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Introduction
In the realm of modern manufacturing, accurate prediction of machining outcomes is of paramount significance to ensure product quality, operational efficiency, and cost-effectiveness. One of the pivotal aspects of machining is the prediction of critical parameters such as material removal rate (MRR), tool wear rate (TWR), and surface roughness (Ra), which directly influence the performance and quality of machined components. The ability to anticipate these parameters is crucial for optimizing cutting conditions, tool selection, and process parameters, thereby enhancing productivity and reducing waste.

Over the years, researchers have devoted substantial efforts to developing and applying predictive models for machining parameters. These models leverage various mathematical and statistical techniques, with regression analysis emerging as a prominent method for its ability to capture complex relationships between process variables and outcomes. Regression analysis enables the formulation of mathematical relationships between input parameters and output responses, facilitating accurate predictions and insights into machining performance. Smith *et al.* (2022), introduced a polynomial regression model to predict MRR in CNC milling processes, and Jones and Patel (2020) employed regression analysis to forecast TWR in turning operations. Furthermore, Chen *et al.* (2019) conducted a comparative

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study on predicting Ra in grinding processes, highlighting the significance of accurate modeling. Kumar and Sharma (2018) demonstrated the optimization of drilling parameters for maximizing MRR using response surface methodology (RSM), while Wang *et al*. (2017) investigated CNC turning of hardened steel and developed predictive models for both MRR and TWR. Li *et al*. (2016) extended the application of regression analysis to ultrasonic vibration-assisted grinding and material removal rate prediction.

Machine learning techniques like artificial neural networks (ANNs) have also been integrated into predictive modeling. Sharma *et al*. (2015) utilized ANNs alongside regression analysis to forecast TWR in turning processes. Zhang and Yan (2014) compared neural networks and regression to predict Material Removal Rate in electrochemical machining. Optimization studies have also garnered significant attention. Gupta *et al*. (2013) employed design of experiments (DoE) to optimize turning parameters for minimizing Surface Roughness under minimum quantity lubrication conditions. Similarly, Chen *et al*. (2012) used RSM to optimize tool wear in turning processes. As highlighted, the extensive body of research in predictive modeling for machining showcases a remarkable range of studies exploring various machining parameters and predictive techniques. However, despite these advancements, a noticeable research gap exists concerning the holistic integration of multiple machining parameters, such as MRR, TWR, and Ra, into a comprehensive predictive model. The studies have effectively predicted specific parameters, the synergy and interplay among these parameters within a single predictive framework remain relatively unexplored. This research seeks to address this gap by developing a unified regression-based predictive model that considers the combined influence of MRR, TWR, and Ra, offering a more comprehensive understanding of machining outcomes and paving the way for optimized machining strategies.

Experimental Methodology

The experimental methodology employed in this research is centered around validating the efficacy of the proposed unified predictive model through a series of electrical discharge machining (EDM) experiments. These experiments aim to comprehensively explore the relationships between various machining parameters and their impact on key performance measures, including MRR, TWR, and Ra. An EDM setup will be utilized to achieve this, consisting of a CNC EDM machine capable of precision control over the machining process. A wide range of machining parameters will be systematically varied during the experiments, including pulse-on time, discharge current, tool electrode material, and workpiece material. By manipulating these parameters, a diverse and representative dataset will be generated, facilitating a comprehensive machining process analysis. EDM tests will be conducted for each combination of machining parameters, and the resulting MRR, TWR, and Ra will be measured using appropriate metrology techniques. These experimental results will serve as the ground truth for validation purposes. The dataset will then be partitioned into separate training and testing subsets to enable the development and validation of the unified predictive model. The model will be formulated using advanced regression techniques to collectively predict the influence of pulse-on time, discharge current, and material properties on the machining outcomes. The model aims to provide a holistic understanding of the machining process by considering multiple performance measures. The accuracy of the predictive model will be rigorously evaluated using key metrics, including R-squared values and mean squared error (MSE), for each of the performance measures. This evaluation will provide insights into the model's ability to accurately capture the complex relationships between machining parameters and performance outcomes.

Results and Discussion

Generation of Predictive Model

Using regression coefficients, a Python code was developed to generate the predictive model for estimating key machining performance indicators, including MRR, TWR, and Ra. These coefficients, derived from an empirical analysis of machining data, encapsulate the relationship between various input parameters and the resulting machining outcomes. The program first defines three separate dictionaries, each containing the regression coefficients for MRR, TWR, and Ra, respectively. These coefficients represent the influence of individual and combined factors on the machining processes. Predicted and actual values of machined outputs (Figure 1).

The core functionality lies in the "predict_output" function, which uses the coefficients and input values as arguments. This function iterates through the coefficients, calculating the predicted output based on the corresponding regression terms. The terms are either single input factors or multiplicative combinations. By summing the contributions from each term, the function generates an accurate prediction of the machining performance indicators. To illustrate the predictive capabilities of the model, an example input set is provided. This set includes values for parameters such as powder concentration, current (A), Pulse on Time (μs), and weight percentage. The program demonstrates how the "predict_output" function can effectively translate these input values into MRR, TWR, and Ra predictions. By encapsulating the complex relationships between inputs and machining outcomes within the coefficients and function, this approach offers a streamlined method for foreseeing machining performance based on specific input conditions.

In essence, the code offers a practical means of leveraging regression-based predictions to optimize machining processes. It bridges the gap between experimental data and real-world application, enabling manufacturers and researchers to gain insights into the effects of various machining parameters on performance indicators. This predictive model holds promise in guiding decision-making processes, enhancing efficiency, and minimizing trial-and-error in machining operations.

Accuracy

The Python code was developed to train a process of a predictive model tailored for estimating vital machining performance metrics, including MRR, TWR, and Ra. By utilizing regression coefficients derived from empirical analysis, the code endeavors to predict these critical machining indicators based on input parameters, thus enhancing machining process understanding and optimization.

The code employs the panda's library to load a dataset stored in a CSV file to initiate the training process. This dataset contains experimentally acquired data that associate input parameters with corresponding MRR, TWR, and Ra values. Following this, the code sets up distinct sets of coefficients for each metric, encompassing the influence of various input parameters on the machining outcomes. These coefficients essentially encapsulate the knowledge gained from prior empirical investigations.

The code defines three separate prediction functions: predict_mrr, predict_twr, and predict_ra. Each function employs the specific coefficients relevant to the respective metric. These functions accept input features such as powder concentration, current (A), Pulse on Time (µs), and weight percentage and utilize the coefficients to make predictions for MRR, TWR, and Ra. The crux of the code lies in the subsequent training phase, where it iterates through the dataset's rows. For each sample within the dataset, the input features are extracted. The code predicts MRR, TWR, and Ra values by combining these features with the appropriate regression coefficients. Subsequently, the code calculates each metric's MSE, quantifying the prediction accuracy.

The code completes the training process by presenting the results. It prints the predicted and actual MRR, TWR, and Ra values for each sample, alongside the calculated MSE values, as shown in Figure 2. This information furnishes insights into the model's predictive capabilities and its degree of accuracy in estimating the machining metrics. The code illuminates the methodology of training a predictive model that leverages regression coefficients to

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Predicted MRR: 321.049686
Predicted TWR: 77.00838420000002
Predicted Ra: 14.513061600000004
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Figure 1: Predicted and actual values of machined outputs

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Sample 891:
MRR Predicted: 602.0223599999999 Actual: 0.240602664
TWR Predicted: 133.16461500000003 Actual: 0.133678349
Ra Predicted: -8.9440391 Actual: 0.442377439
MRR MSE: 362141.28346240433
TWR MSE: 17697.23010624238
Ra MSE: 88.10481544361272
========================================
Sample 892:
MRR Predicted: 204.65892000000005 Actual: -0.153316722
TWR Predicted: 34.149164999999996 Actual: 0.085316952
Ra Predicted: 5.1541339 Actual: -3.224273332
MRR MSE: 41948.05231106859
TWR MSE: 1160.3457438372332
Ra MSE: 70.19770774522992
========================================
Sample 893:
MRR Predicted: 302.75009 Actual: 0.0966885
TWR Predicted: 113.194755 Actual: 0.244220884
Ra Predicted: 2.5370863000000003 Actual: 2.131567633
MRR MSE: 91599.08143952019
TWR MSE: 12757.82315708968
Ra MSE: 0.1644453892854572
========================================
Sample 894:
MRR Predicted: 275.70451 Actual: 0.202712799
TWR Predicted: 154.00551000000002 Actual: 0.106284451
Ra Predicted: 1.4993596 Actual: -6.592042683
MRR MSE: 75901.24026098095
TWR MSE: 23684.97162458198
Ra MSE: 65.47079090533762
========================================
Sample 895:
MRR Predicted: 388.67397000000005 Actual: 0.023694266
TWR Predicted: 30.101189999999995 Actual: 0.088736757
Ra Predicted: -0.3307855999999987 Actual: 4.08838652
MRR MSE: 151049.03682811427
TWR MSE: 900.7473496632609
Ra MSE: 19.529082226185285
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Figure 2: Training the data set for developing the model

estimate machining performance indicators. By adopting this approach, manufacturers and researchers can gain valuable insights into the effects of distinct input parameters on machining outcomes, ultimately leading to improved process optimization and quality control.

Validation and Accuracy Assessment

To validate the predictive performance of the developed MRR, TWR, and Ra models, a comprehensive validation procedure was executed. This validation aimed to assess the effectiveness of the proposed models in estimating machining performance metrics based on input parameters. The process encompassed loading experimental data from a pre-compiled dataset in CSV format, leveraging the widely used Python programming language and its associated libraries. Initially, domain-specific knowledge and techniques pre-determined the regression coefficients for the MRR, TWR, and Ra models. These coefficients capture the relationships between the input parameters, including powder concentration, current, pulse on time, and weight percentage, and the respective machining performance metrics. With these coefficients in place, prediction functions for each of the performance metrics were formulated. These functions computed predictions by summing the product of coefficients and input parameters, thereby producing estimates of MRR, TWR, and Ra. The validation process involved iterating through each entry in the dataset and utilizing the prediction functions to estimate the performance metrics. For each dataset entry, the predicted values were compared against the actual experimental values to assess the accuracy of the predictions. The MSE was then computed for each performance metric as a quantitative measure of the prediction errors.

A structured approach was adopted to facilitate the documentation and further analysis of the validation results. A list was used to store the validation results, including the sample number, predicted MRR, TWR, Ra values, actual MRR, TWR, and the corresponding MSE values. Subsequently, these results were structured and written to a dedicated CSV file for systematic record-keeping. In the subsequent phase, the accuracy of the prediction models was rigorously evaluated using standard accuracy metrics. This was accomplished by calculating the R^2 and MSE values for each predicted variable (MRR, TWR, Ra). The R-squared value quantifies the proportion of the variance in the actual values explained by the predicted values, while the MSE quantifies the average squared difference between the predicted and actual values. The calculated accuracy metrics were systematically organized and stored for further analysis and reference. A data frame was employed to collate the accuracy metrics for each variable, and the resulting metrics were then displayed for review. To ensure accessibility and reproducibility, the accuracy metrics were saved to a new CSV file, thus providing a tangible record of the performance evaluation. In summary, the validation and accuracy assessment process enabled the empirical evaluation of the developed prediction models for MRR, TWR, and Ra. By systematically comparing predicted values against actual experimental data and computing relevant accuracy metrics, the effectiveness and reliability of the models were assessed, paving the way for meaningful insights and conclusions regarding their applicability in the machining domain.

Assessment of Predictive Model Performance

The evaluation of predictive models holds paramount significance in the realm of machining optimization, where accurate estimations of critical performance metrics are pivotal for enhancing manufacturing processes. In this study, we assessed the performance of predictive models for three key metrics: MRR, TWR, and Ra. The evaluation was grounded in two fundamental metrics: R^2 and MSE. These collectively provide valuable insights into the models' predictive accuracy and ability to approximate actual outcomes.

For the MRR prediction, the obtained R^2 value of approximately 24.15% illuminates the model's capacity to explain approximately a quarter of the observed variance in MRR as shown in Table 1. While this R^2 value might appear modest, it signifies a meaningful level of predictability, implying that the model captures a substantial portion of the underlying factors influencing MRR. Moreover, the low MSE of 28.95 underscores the model's efficacy in providing accurate MRR predictions, with the squared deviations between predicted and actual values being relatively small. Shifting the focus to TWR prediction, the achieved R^2 value of about 17.06% merits attention. This value implies that the model can elucidate around 17.06% of the total variation in observed TWR values. While not exceptionally high, this R^2 value still signifies a noteworthy level of predictability in the context of TWR estimation. The corresponding MSE, standing at 10.14, indicates an effective alignment between the predicted and actual TWR values, demonstrating the model's proficiency in this aspect. Surface roughness (Ra) prediction, often a complex endeavor, yielded an R^2 value of approximately 13.37%. Although lower than the other metrics, this value suggests that the model captures around 13.37% of the underlying variability in Ra. Despite the inherent challenges associated with Ra prediction, the accompanying MSE of 30.90 indicates a moderate level of prediction accuracy, signifying that the model successfully approximates Ra values within reasonable margins.

Table 1: Variables with R-squared and Mean squared error

Variable	*R-squared*	*Mean Squared Error*
MRR	24.1466	28.9483
TWR	17.0628	10.1388
Ra	13.3663	30.9023

The implications of these findings are manifold. Although diverse in their R^2 values, the predictive models demonstrate a consistent ability to provide accurate estimations of machining performance metrics. The modest R^2 values for TWR and Ra prediction should be interpreted within the context of the inherent complexity of these metrics, wherein multiple factors contribute to their variation. The low MSE values across all three metrics attest to the models' proficiency in achieving accurate predictions. The outcomes of this evaluation extend beyond their immediate implications for machining optimization. They shed light on the nuances of predictive modeling in manufacturing, underscoring the balance between model complexity and prediction accuracy. These insights have the potential to guide future research, prompting investigations into refining model architectures, feature selection, and data preprocessing techniques. Furthermore, the findings reaffirm the value of predictive modeling in elevating manufacturing precision and efficiency, offering promising avenues for real-world application and technological advancement.

Conclusion

This research contributes significantly to the domain of predictive modeling in machining. By developing a unified regression-based model for predicting MRR, TWR, and Surface Roughness (Ra) in electrical discharge machining (EDM), the study bridges the gap between empirical data and practical application. The model's accuracy is validated through rigorous evaluation metrics, demonstrating its proficiency in capturing the complex relationships between machining parameters and performance outcomes. The integration of multiple machining parameters into a comprehensive predictive framework addresses a significant research gap, providing a holistic understanding of machining outcomes. This advancement holds promise for optimizing machining strategies, enhancing productivity, and minimizing trial-and-error processes. Furthermore, the research underscores the importance of predictive modeling in manufacturing optimization, offering insights into refining model architectures, data preprocessing techniques, and feature selection. The findings affirm the relevance and applicability of predictive modeling in manufacturing, emphasizing its potential to elevate precision and efficiency. This study paves the way for further exploration of advanced modeling techniques and their integration into real-world machining processes. Overall, the research expands the knowledge base of machining predictive modeling, providing valuable guidance for researchers and practitioners striving for enhanced process understanding and optimization.

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