Optimization of Machining Parameters for Nimonic PE16 Using Machine Learning Models

Matthew Jansen, Ibrahim Deiab

***Abstract**: Machining high-temperature alloys such as Nimonic PE16 demands precise control of machining parameters to achieve desired outcomes while minimizing tool wear and optimizing surface finish. In this study, we propose using machine learning regression models combined with synthetic data and response surface methodology strategies to optimize machining parameters for PE16. We aim to develop a predictive model that accurately estimates optimal cutting speeds and feed rates based on key output parameters, including cutting forces and surface roughness. Our methodology involves collecting experimental data from controlled machining tests conducted on PE16 samples under varying conditions. We used the datasets to train and validate regression models to establish correlations between input parameters and machining outcomes. The performance of each model is evaluated based on metrics such as mean absolute error and coefficient of determination. These metrics show relationships within the data and can determine a model's success. The proposed machine learning framework offers a data-driven approach to optimize machining processes for PE16, facilitating enhanced efficiency, productivity, and quality in nuclear and other high-performance applications. Our findings contribute to understanding machining dynamics in challenging materials and provide valuable insights for intelligent machining systems.*

***Keywords**: Nimonic PE16, Machine Learning, Machinability, Regression, Response Surface Methodology, Synthetic Data*

I. INTRODUCTION

The demand for high-performance materials is ever-increasing in modern manufacturing, especially in the aerospace, automotive, and energy sectors. Nimonic PE16, a nickel-based superalloy, is widely recognized for its exceptional mechanical properties. These properties include its high strength, corrosion resistance, creep resistance, and ability to maintain them at high temperatures [1]. These optimal material characteristics create significant challenges in the manufacturing process, specifically during machining. This material requires precise control over machining parameters to achieve desired outputs regarding surface finish, tool wear, and overall efficiency. Traditional methods for optimization of machine parameters involve a lengthy trial and error approach; this can be time-consuming and costly to achieve effective results. With the emergence of Industry 4.0, there is a growing interest in utilizing machine learning algorithms to optimize machining parameters. Machine learning algorithms can analyze vast amounts of data, identify complex patterns, and make predictions that can significantly improve the efficiency and accuracy of machining operations. This paper explores the application of machine learning in optimizing machining parameters for Nimonic PE16. By developing and implementing ML models, we seek to predict the optimal cutting conditions that minimize tool wear, cutting forces, and surface roughness. This study will cover machine learning techniques, including single and multiple-variable regression analysis. We also explored the generation of synthetic data and the response surface methodology. Ultimately, the integration of machine learning in machining parameter optimization promises to streamline the manufacturing process and contribute to the broader goals of sustainable and intelligent manufacturing. Through this research, we aim to demonstrate the potential of machine learning to revolutionize the machining of difficult-to-machine materials like Nimonic PE16, leading to significant improvements in efficiency, cost-effectiveness, and product quality in the manufacturing industry.

II. METHODOLOGY

A. Experimental Setup

We conducted a series of turning experiments to study the optimization of machining parameters for Nimonic PE16 [15] [16]. We programmed a CNC lathe for this experimental setup (HAAS ST 10). Cutting inserts purchased from Kennametal of type (CNMG 433RP grade KCS10B) were used. The manufacturer's specifications recommended these inserts for superalloys. A cylindrical bar of Nimonic PE16, 23mm in diameter, was used as the workpiece.

B. Selection of Machining Parameters

The key machining parameters for this study were cutting speed (Vc), feed rate (f), and depth of cut (d). A range of values was chosen for the feed rate and cutting speed while keeping the depth of cut consistent. We determined these ranges from the literature on similar Nimonic materials and estimated cutting parameters from the tool manufacturer [2],[3],[4][5][12][13].

The final chosen range of machining parameters is visible in Table I. The selected range was significant as it covers a broad spectrum of potential operating conditions, allowing for a comprehensive understanding of the material's machinability under various scenarios.

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Table I: Experimental Turning Parameters

Depth of Cut	1 mm		
Feed Rate	0.2 mm/rev	0.3 mm/rev	
Cutting Speed	75 m/min	100 m/min	150 m/min

C. Data Collection

The critical outputs considered for determining the efficiency of machining parameters were cutting forces, surface roughness, and tool wear. We meticulously designed the data collection process to ensure the reliability of our research. Firstly, cutting forces were measured using a Dynamometer attached to the cutting tool and mounted on the CNC lathe turret. The type of Dynamometer used was Kistler Multicomponent Dynamometer 9257B. This measuring device, combined with a Kistler Type 5070 amplifier, converts the voltage signals into force outputs.

The Dynamometer measures forces in the x, y, and z directions. In the case of this experimental setup, the Fz component makes up the main cutting force during the turning process. Using Kistler's software Dynoware, the average Fz value from each cut can be determined and used for further analysis. Secondly, the surface roughness output was measured using a Mitutoyo SJ-210 surface roughness tester. Three surface roughness measurements were taken on the workpiece in different areas and averaged to obtain the surface roughness value. This device used the ISO 4287:1997 standard to measure the surface after each experiment [6]. This standard was revised and combined to create a new standard, ISO 21920-2:02021 [7][14].

The measuring parameters for the surface roughness tester following ISO 4287:1997 were a Measuring Speed of 0.02 in/s and Cutoff Length (λc) = 0.03 inch. The surface roughness tester measured the arithmetic mean surface roughness value (Ra) in microinches. Lastly, the tool wear for each insert was measured. The tool wear responsible for the failure of turning inserts is most commonly flank wear and crater wear. In this experiment, we considered flank wear as the significant parameter for tool wear. Flank wear was measured using a VHX digital microscope and virtual measurement tools. The standard used for measuring the flank wear of a cutting insert is ISO 3685 and was adhered to during the data collection stage [8]. This systematic and meticulous methodology collected comprehensive data on cutting forces, surface roughness, and tool wear. This data enables the development of machine-learning models to optimize the machining parameters for Nimonic PE16.

D. Data Analysis

These measured output parameters can be analyzed through machine learning and statistical techniques to optimize the combination of parameters. We conducted the data analysis for this paper using Anaconda's Jupyter Notebooks. The standard machine learning libraries within the software, such as Scikit-learn, were also utilized. A challenge with machine learning techniques and difficult-to-machine materials can be the cost associated with data collection. High-strength materials and the extensive data needed for machine-learning techniques can cause financial challenges. One technique employed to solve this problem is the generation of synthetic data. Synthetic data helps to supplement costly trials. We generated synthetic data for this experiment to double the original experimental data set from sixteen data points to thirty-two. There are several regression models to choose from, including Linear regression, multiple regression, polynomial regression, support vector regression, and decision tree regression [9],[10]. The models chosen to determine patterns between machining parameters are linear regression, multiple regression, and response surface models. Multiple regression models are ideal for modeling the relationship between input variables and one or more output variables [11]. Linear regression helps show the relationship between each variable individually. Another form of optimization is using Response Surface Methodology (RSM). The primary goal of RSM is to optimize the output response influenced by various input variables. This methodology aims to find the optimal combination for the different machining outputs. We see the combination by fitting a second-order polynomial.

$$Y = \beta_0 + \sum \beta_i X_i + \sum \beta_{ii} X_i^2 + \sum \beta_{ij} X_i X_j + \epsilon$$

Y is the response variable, Xi and Xj are input variables, Bo, Bi, Bii, and Bij are coefficients, and ϵ is the error term. With this fitted model, we can then perform the optimization process. We performed the optimization using the Sequential Least Squares Programming method (SLSQP).

III. RESULTS

A. Linear Regression

Firstly, each input and output parameter had a linear regression model of their relationship generated. Without synthetic data, the mean absolute errors and r-squared values were either impossible or inaccurate. After adding synthetic data to the dataset, we created linear regression models. We calculated metrics for each set of variables and displayed them in Table II. The R-squared values show impossibility and extremely low correlation. Ultimately, these metrics show a low reliability for relationship determination.

Table II: Linear Regression Metrics

Parameters	R-Squared	Mean Absolute Error
Cutting Speed & Surface Roughness	-1.32	1199.35
Cutting Speed & Cutting Force	-0.16	1607.94
Cutting Speed & Flank Wear	-0.14	0.01
Feed Rate & Surface Roughness	-0.21	812.79
Feed Rate & Cutting Force	-0.00	1262.75
Feed Rate & Flank Wear	0.08	0.01

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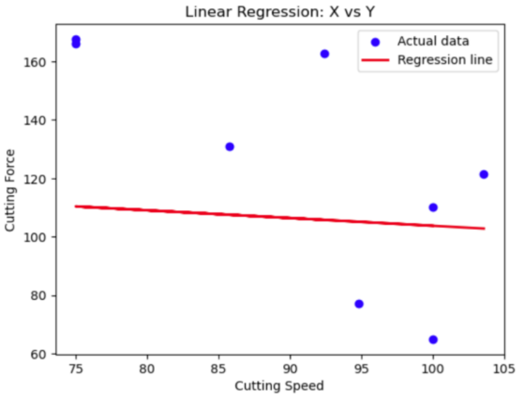

Figure 1: Linear Regression of Cutting Force and Cutting Speed

The trendline in Figure 1 has a slight negative slope, suggesting a weak inverse relationship between cutting speed and cutting force. As cutting speed increases, the cutting force appears to decrease slightly. However, the scatter of the data points around the trendline indicates high variability in the cutting force that cutting speed alone does not explain. The trendline needs to capture the variability in the data well, suggesting that cutting speed alone is not a strong predictor of cutting force. These results show that simple linear regression is not an accurate predictor for machining parameters, and a multi-variable analysis tool might be more suitable.

B. Multiple Regression

Each graph compares the actual and predicted values for the respective output variables. The red line represents the ideal line where the predicted values match the exact values.

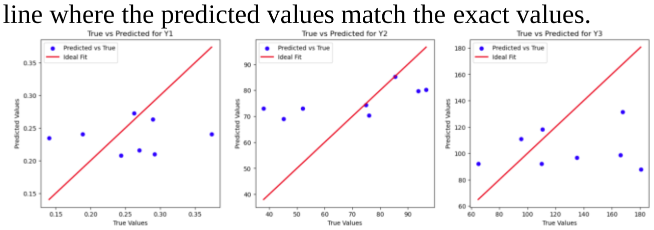

Figure 2: Multiple Regression Results

For Flank Wear depicted on the leftmost graph, the points are close to the ideal line but show a fair amount of scatter. This pattern indicates that while the model has some predictive power, there was considerable error in the predictions. For Surface Roughness depicted in the center graph, the points are scattered widely around the ideal line, indicating a poor fit. The model could be more accurate in predicting cutting force. Like Surface Roughness, the points for Cutting Force depicted in the rightmost graph show a wide scatter around the ideal line, indicating an inaccurate prediction.

Table III: Multiple Regression Metrics

Output Variable	R-Squared	Mean Absolute Error
Flank Wear	-0.18	0.01
Surface Roughness	0.23	340.57
Cutting Force	-0.50	2162.82

The metrics for the multiple regression plots coincide with the visual analysis of the plots. The low correlation of the R-squared values shows an inaccurate prediction model. Also measured are high and impossible mean absolute error values, which show a need for more data or new analysis methods.

C. Response Surface Methodology

Using the response surface methodology (RSM) with the combination of synthetic data production, a good prediction of optimal machining parameters can be determined for each output variable (surface roughness, cutting force, and flank wear. Figure 3 is the response surface of surface roughness. This graph shows the three-dimensional layout of surface roughness values based on the combinations of input variables, feed rate, and cutting speed.

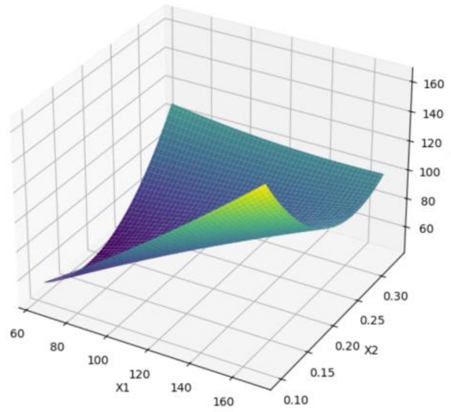

Figure 3: Response Surface of Surface Roughness

Minimizing the output variables through RSM could help find the optimal input parameters. Table IV shows the overall outputs for each SLSQP optimization run. These results show an output parameter's optimal feed rate and cutting speed combination.

Table IV: RSM Optimal Parameters

Output Parameter	Cutting Speed	Feed Rate
Surface Roughness	128.4 m/min	0.2250 mm/rev
Cutting Force	63.94 m/min	0.1695 mm/rev
Flank Wear	95.29 m/min	0.2400 mm/rev

D. Model Validation

The results achieved from the RSM are within a close range of the data set created and should optimize one of the output parameters. These parameters were tested in the original experimental setup to validate the model's results. The validation turning results are shown in Table V below.

Table V: RSM Validation Results

Parameters	Surface Roughness (Micro-Inch)	Cutting Force (Newtons)	Flank Wear (Micrometers)
Optimal Cutting Force	91.950	150	137
Optimal Surface Roughness	33.400	80	87
Optimal Flank Wear	66.275	225	47

These results can be compared with the average values from the first experimental trials to determine the optimization methods' measure of success. The flank wear, cutting force, and surface roughness were 260 micrometers, 77.6 micro-inches, and 112N, respectively.

The RSM was able to find optimal parameters for the surface roughness and flank wear while struggling to optimize the cutting force effectively. The RSM method achieved an 81.9% reduction in flank wear, a 57% decrease in surface roughness, and a 33.9% increase in cutting force.

IV. CONCLUSION AND FUTURE SCOPE

Ultimately, linear and multiple regression analysis to optimize machining parameters needs further research. With the implementation of synthetic data, the regression model metrics and means for prediction improved, meaning that with enough data, they could be viable. For this experiment, RSM combined with synthetic data generation was the most successful in optimizing machining parameters. However, RSM was still limited in its ability to optimize cutting force. With the implementation of more trials and reiteration of the RSM process, the model could predict cutting force. For the future scope of this research, the results from the validation of the models should be re-trained into the data set. This continuous validation can further optimize the RSM output parameters and improve accuracy.

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APPENDIX

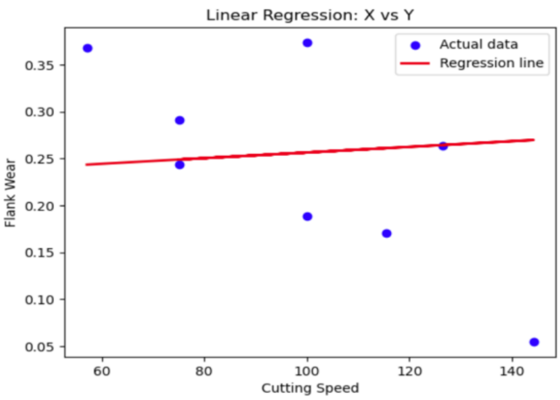

Figure 4: Linear Regression of Flank Wear and Cutting Speed

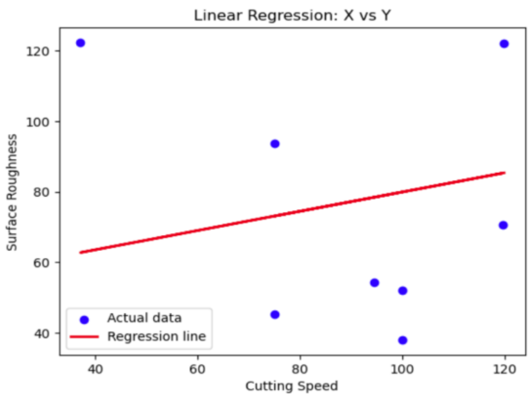

Figure 5: Linear Regression of Surface Roughness and Cutting Speed

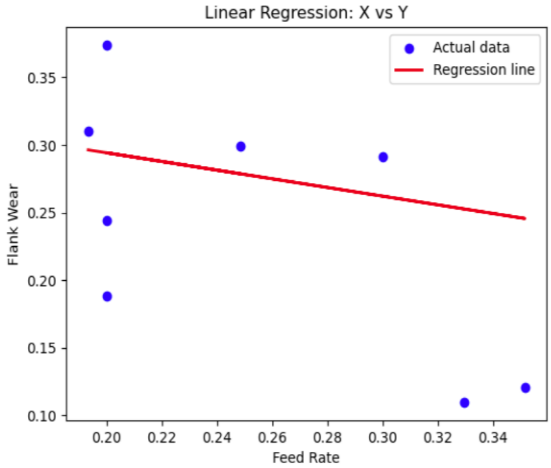

Figure 6: Linear Regression of Flank Wear and Feed Rate

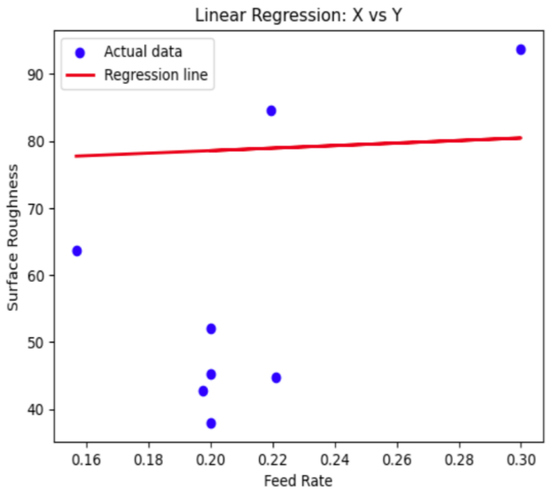

Figure 7: Linear Regression of Flank Wear and Feed Rate

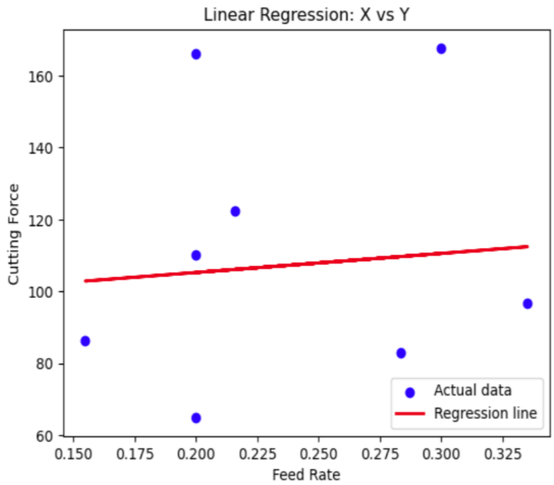

Figure 8: Linear Regression of Cutting Force and Feed Rate

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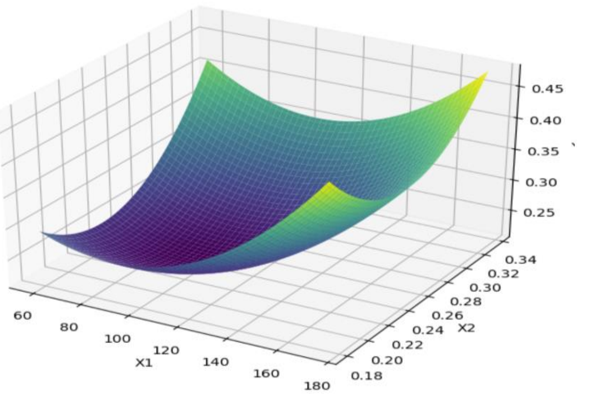

Figure 9: Response Surface of Flank Wear

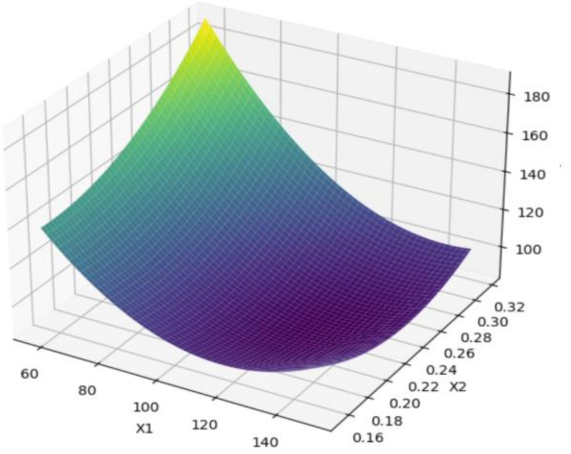

Figure 10: Response Surface of Cutting Force

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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