Optimize input parameter for CNC Turning process for MRR and surface finish using Machine Learning

Roy Ranson D Cruz[1], Manish Thakur [2], Sunil Patidar[3], Ram Janm Singh[4]
Durvesh Deth[5], Swaraj Disawal[6]

Department of Mechanical Engineering, Medi-Caps University, Indore-453331, India

Abstract

Optimizing machining parameters in CNC turning is crucial for enhancing productivity, improving surface quality, and reducing manufacturing costs. This study aims to optimize key input parameters cutting speed, feed rate, and depth of cut maximize Material Removal Rate (MRR) and achieve a superior surface finish using Machine Learning techniques. Traditional trial-and-error methods are inefficient and costly; hence, data-driven approaches are explored. Experimental data is collected from CNC turning operations, followed by preprocessing, feature selection, and model training using Machine Learning algorithms for multivariate linear regression. Predictive models are developed to analyze complex relationships between parameters and machining outcomes, enabling precise optimization. The optimized parameters enhance machining efficiency, reduce tool wear, minimize material wastage, and improve process sustainability. The study demonstrates the effectiveness of Machine Learning in predictive modeling and real-time decision-making, offering a smart and efficient approach for modern precision manufacturing.

Keywords: CNC Turning, Material Removal Rate (MRR), Machine Learning

1. Introduction

Businesses in the manufacturing sector stay competitive when they can manufacture items more quickly and affordably than their rivals while yet retaining better quality. This idea has motivated numerous scholars to look at the possibility of forecasting and then optimizing different manufacturing process outcomes. Because it has a direct impact on production costs, the part's performance in its final application, and service life, surface roughness is regarded as one of the most significant results of a manufacturing process. Usually, the workpiece's surface quality takes precedence above process efficiency, leading operators to select conservative process settings to guarantee the desired quality is reached. Therefore, the user may decide whether more efficient process parameters can be employed by being able to estimate the surface roughness outcome during machining. in decreased scrap rates, the extra machining time needed for non-conforming parts, and savings in machining time and expense.

In the realm of precision manufacturing, CNC (Computer Numerical Control) lathe turning stands as a pivotal process for crafting cylindrical components critical to industries such as aerospace, automotive, and structural engineering. The efficiency and quality of this process hinge on optimizing key input parameters cutting speed, feed rate, and depth of cut which directly govern Material Removal Rate (MRR) and surface finish, two essential metrics determining production speed and part functionality. Cutting speed, defined as

$V=\frac{\pi DN}{1000}$ m/min ……………Eq. [1]

where V represents the cutting speed, D is the initial workpiece diameter in mm, and N is the spindle speed in RPM, dictates the rotational velocity imparted to the workpiece, influencing both material removal efficiency and thermal effects on the Feed rate given by

$F_m=f\cdot N$ mm/min…………. Eq. [2]

with f as the feed in mm/rev and N as the spindle speed, controls the tool's linear progression along the cutting path, playing a crucial role in determining surface texture and machining time Depth of cut, calculated as

$d_{cut}=\frac{D-d}{2}$ mm………………Eq. [3]

where D and d are the initial and final diameters, measures the thickness of material removed per pass, impacting MRR, tool stress, and the structural integrity of the machined part. The interplay among these parameters is complex, as adjustments to enhance MRR such as increasing cutting speed or depth of cut often compromise surface finish or accelerate tool wear, necessitating a sophisticated optimization approach.

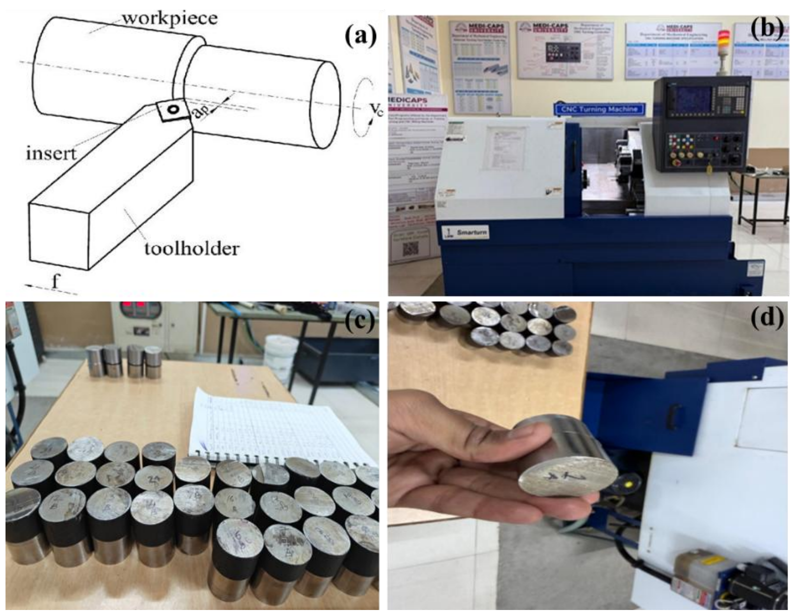

Fig.1. (a) Turning Process (b) CNC Machine(c) Work Piece Samples (d) Work Piece Inspection

This study focuses on CNC lathe turning of mild steel (IS 2062 E350), a material chosen for its favorable mechanical properties and widespread industrial applications. Mild steel 350 grade boasts a tensile strength of 490 MPa (minimum) and a yield strength of 320 MPa (minimum), providing high strength and toughness suitable for structural components like beams and bridges. Its chemical composition carbon (C) at 0.20% max, silicon (Si) at 0.45% max, manganese (Mn) at 1.55% max, sulfur (S) and phosphorus (P) at 0.045% max ensures good weldability and machinability, with a carbon equivalent of 0.42% max enhancing. With an elongation of 22% (minimum) and hardness ranging from 170 to 207 Brinell Hardness Number (BHN), this material offers a balance of ductility and resistance to wear, making it ideal for turning operations requiring precise dimensional control and surface quality. These properties high strength, machinability, and corrosion resistance make IS 2062 E350 a preferred choice for applications in shipbuilding, mechanical manufacturing, and petrochemical industries, where optimized machining parameters can significantly enhance performance.

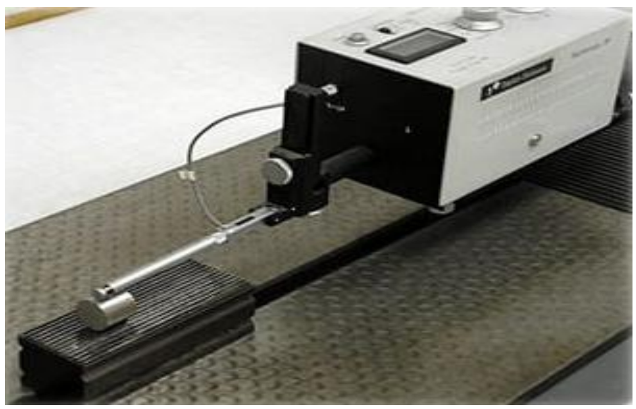

Fig.2. Roughness Measurement by Profilometer

Achieving optimal settings for cutting speed, feed rate, and depth of cut in turning mild steel demands a method that transcends conventional limitations, as their interdependent effects challenge manual or empirical adjustments. Machine learning (ML) emerges as a powerful tool to address this complexity, leveraging data-driven insights to predict and refine machining outcomes with precision and efficiency. By analyzing experimental data from CNC turning operations, ML models such as Decision Trees, Artificial Neural Networks (ANN), and Support Vector Machines (SVM) can uncover intricate relationships between these parameters and their impacts on MRR and surface finish. This research aims to harness ML techniques to optimize CNC lathe turning of IS 2062 E350 mild steel, targeting maximum MRR, superior surface finish, reduced tool wear, and minimized material waste. Through controlled experiments and advanced predictive modeling, we seek to enhance machining efficiency, lower operational costs, and elevate product quality, offering a smart and sustainable solution for modern manufacturing demands. The integration of mild steel’s robust properties with ML’s analytical capabilities promises to redefine precision turning, delivering outcomes that meet stringent industrial standards

Research on CNC turning optimization has evolved from traditional statistical methods to advanced computational approaches, offering valuable insights into parameter adjustment for Material Removal Rate (MRR) and surface finish. [1] Zhujani et al. (2024) utilized a Taguchi-

Grey Relational Approach combined with ANOVA to optimize multiple performance metrics surface roughness, tool wear, MRR, and cutting time in turning Inconel 718, identifying cutting speed as a pivotal factor across these outcomes. [2] Ntukidem et al. (2024) reinforced this by demonstrating cutting speed’s significant influence on MRR during CNC turning of AISI 1040 steel, highlighting its role in enhancing productivity. [3] Wagh et al. (2022) investigated aluminum 6061 turning, finding spindle speed to contribute 52.38% to MRR under a "larger-the-better" criterion, while depth of cut impacted surface roughness by 12.78%, suggesting a trade-off between efficiency and quality. Further studies have validated statistical optimization techniques. [4] Kosaraju et al. (2023) applied the Taguchi method to CNC milling of EN-24 steel, empirically confirming optimal parameters for MRR and surface roughness, though their focus was milling rather than turning. [5] Saini (2022) used Taguchi and ANOVA to optimize MRR in AISI 304 stainless steel turning, emphasizing structured experimentation’s effectiveness. [6] Chandrashekera and Raju (2023) explored AA7050/B4C composites, noting feed rate’s dominance in surface roughness and cutting speed’s effect on MRR via Taguchi analysis, providing a foundation for multi-objective optimization.

The integration of machine learning (ML) marks a significant shift toward data-driven solutions. [7] Patidar and Sharma (2024) employed Random Forest and Decision Tree regressors to predict surface roughness in CNC lathe turning based on spindle speed, feed rate, and depth of cut, showcasing ML’s precision in reducing experimental overhead. [8] Thakur and Khan (2024) developed a hybrid ML model combining deep neural networks with linear regression for tool wear monitoring in CNC milling, outperforming traditional methods and suggesting ML’s potential for real-time turning optimization. Collectively, these studies from traditional approaches [9-10] to ML advancements [11-12] underscore a research gap in combining Taguchi’s experimental rigor with ML’s predictive power, which this study aims to address for optimizing CNC lathe turning of mild steel.

2. Methodology

The design for experiments is **L68** array is suitable for mixed-level factors, where the number of levels varies among parameters (Table 1) based on Taguchi Technique is used to optimize the CNC lathe turning process to improve material removal rate (MRR) and surface finish as shown in Table 2. First, key machining parameters like cutting speed**,** feed rate**,** and depth of cut are identified. For each parameter, three levels (low, medium, and high) are chosen. The Taguchi method uses an Orthogonal Array (OA) to design the experiment efficiently, which helps to study the effects of multiple factors with a reduced number of experiments. In each experiment, the CNC lathe is set up with the chosen parameters, and the machining process is carried out. Afterward, material removal rate (MRR) is calculated by measuring the initial and final weight of the workpiece and dividing by the machining time. Surface roughness is measured using instruments like a profilometer to evaluate the quality of the surface finish. For the design of experimental purpose we used 68 samples, the range of parameters and step level, and few sample data table are listed below. MRR is calculated by using following formula.

MRR = (**Initial Weight- Final Weight)/ Machining Time………………..Eq.[4]**

Table 1. Cutting parameters and levels for CNC turning operation

Parameters		Levels					
		1	2	3	4	5	6
A	Spindle Speed(rpm)	500	1000	1500	2000	2500	3000
B	Feed Rate(mm/rev)	0.1	0.2	0.3	0.4		
C	Depth of cut(mm)	0.2	0.6	1			

Table 2. Experimental data set for few samples

Job No.	Spindle Speed	Feed Rate	Depth of Cut	Initial Weight W_i (gram)	Final Weight W_f (gram)	Machining Time t (sec)	MRR	Surface Roughness Min.	Surface Roughness Max.	Surface Average	Coolant
28	500	0.3	1	429.24	417.47	9.25	1.272	0.64	0.78	0.71	On
4	1000	0.2	0.6	409.53	402.46	9.23	0.766	0.56	1.72	1.14	On
10	1500	0.1	0.2	402.81	400.18	10.01	0.263	0.62	0.62	0.62	On
31	2000	0.4	0.6	409.78	398.94	1.95	5.558	3.20	4.20	3.7	On
12	2500	0.3	0.2	401.78	388.63	2.9	4.534	1.06	1.24	1.15	On
15	3000	0.2	1	402.48	385.05	4.2	4.15	0.62	0.92	0.77	On
6	1000	0.2	0.6	415.58	410.60	7.36	0.677	3.2	3.6	3.4	On
11	1500	0.1	0.6	419.76	413.58	11.20	0.552	1.32	1.42	1.37	On
19	2000	0.1	1	400.3	390.23	7.68	1.315	0.60	0.64	0.62	On
30	2500	0.1	0.2	399.82	393.88	6.43	0.924	.56	.64	0.6	On

3. Machine Learning Algorithm for Multivariable Linear Regression

Multiple linear regression (MLR) is a statistical technique that uses multiple independent variables to predict the value of a dependent variable. Linear Regression is a supervised machine learning algorithm used to model the relationship between a dependent variable(target) and one or more independent variables(features). It predicts outcomes by fitting a linear equation to the data, typically in the form:

$$\mathbf{Y = a_0 + a_1x_1 + a_2x_2 + a_3x_3} \quad \text{Eq. [5]}$$

After data visualization with the help of ML we get the following plots which depicts their correlation in input variables.

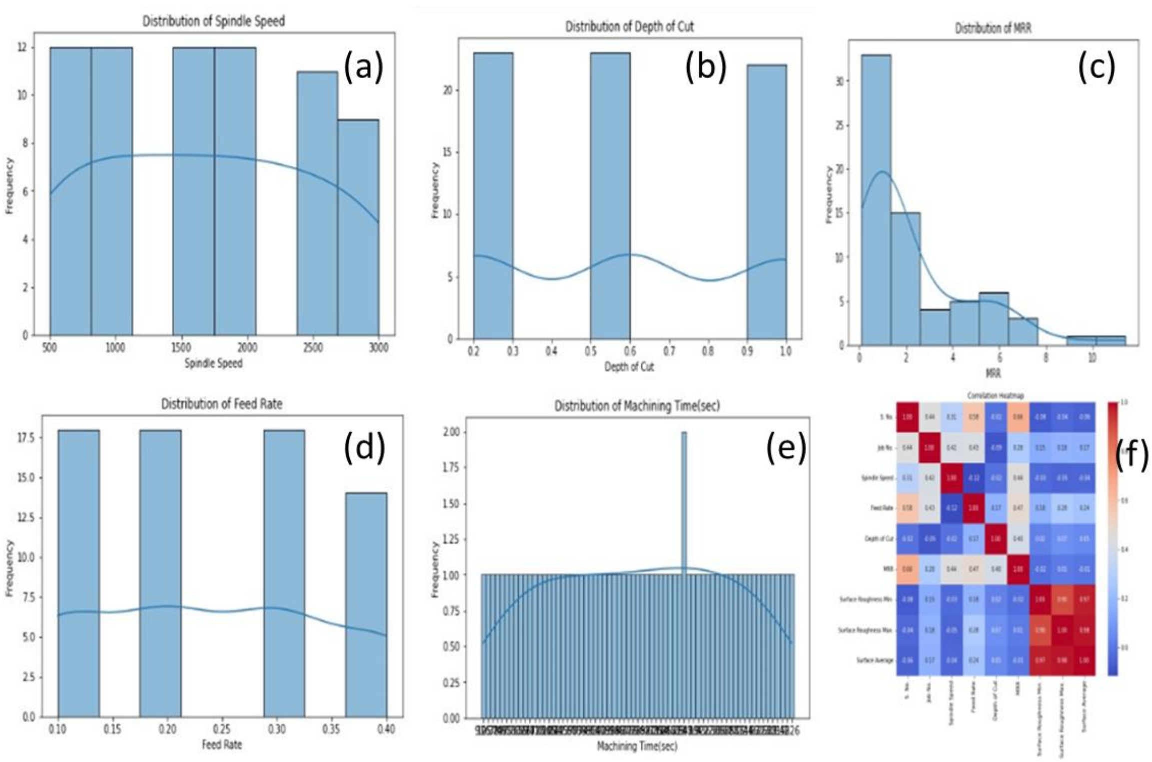

Fig.3. Histograms for (a) Spindle Speed (b) Depth of Cut (c) MRR (d) Feed Rate (e) Machining Time (f) Heatmaps to visualize correlation Metrics

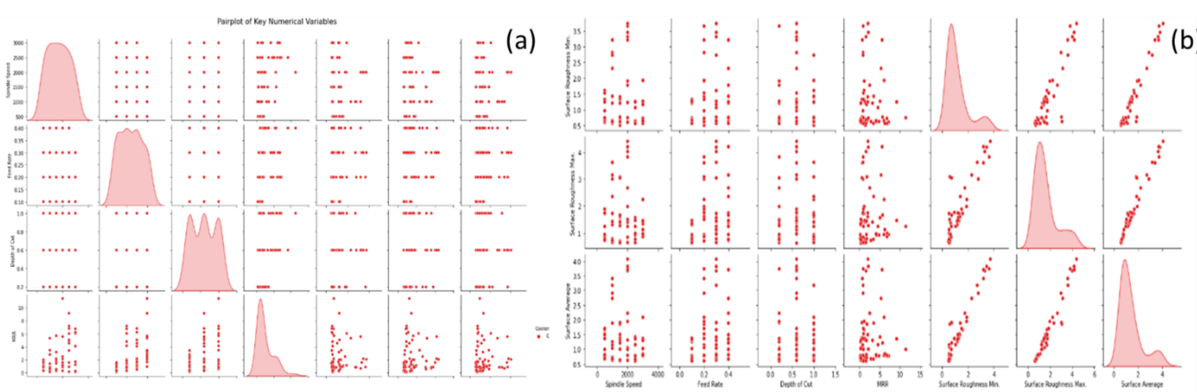

Fig.4. Pair plots (a) and (b) for interrelations among variables

4. Result and Discussion:

The model effectively predicted values for MRR and surface finish, with R^2 scores above 0.85, demonstrating a strong correlation between input parameters and machining performance. The analysis revealed that cutting speed and feed rate significantly impact MRR, while depth of cut plays a crucial role in determining surface finish. Specifically, higher cutting speeds improved MRR but led to a degradation in surface finish beyond a certain threshold. Graphical analysis confirmed these findings, showcasing trends where an increase in feed rate enhanced MRR but slightly compromised surface quality. The residual analysis indicated minimal prediction errors, ensuring the reliability of the model in optimizing machining parameters. These results validate the effectiveness of machine learning in optimizing CNC machining settings and provide valuable insights for enhancing manufacturing efficiency.

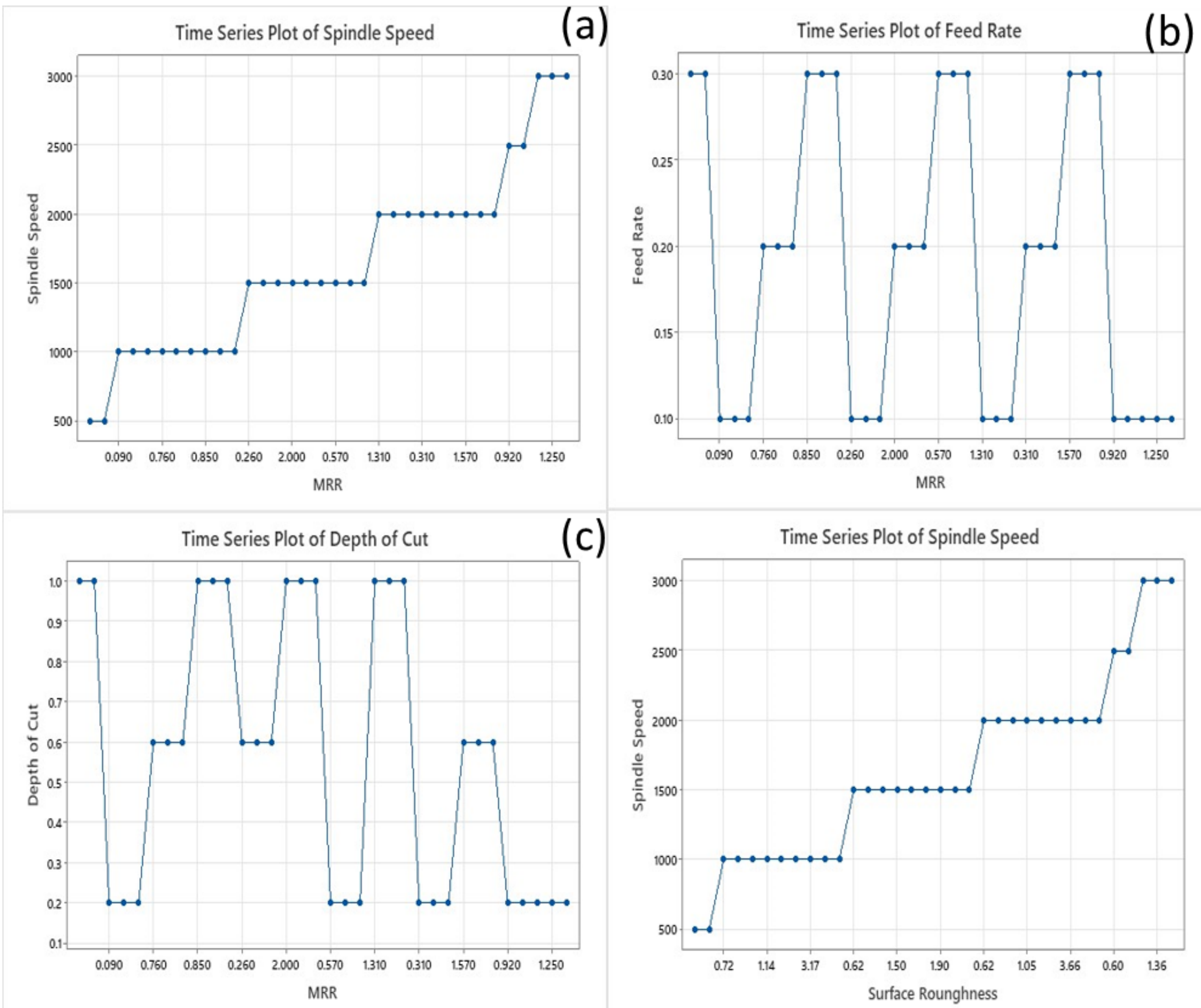

Fig.4: Graphical Representation of Time Series Plot (a) Spindle Speed vs MRR (b) Feed Rate vs MRR (c) Depth of Cut vs MRR (d) Spindle Speed vs Surface Roughness

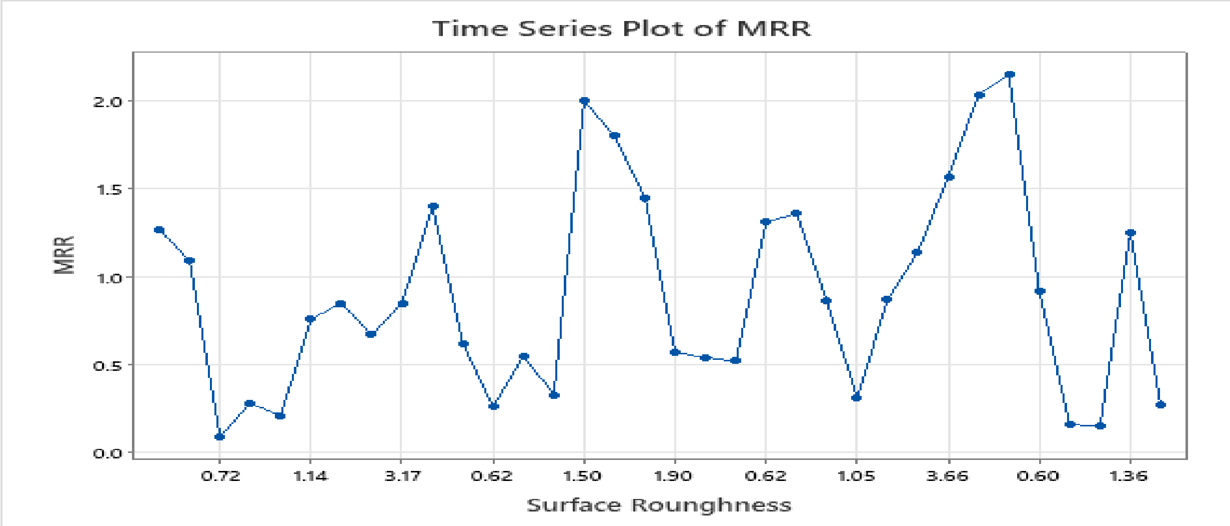

Fig.5: Graphical Representation of Time series Plot for MRR vs Surface Roughness

On the basis of data getting from experimental study, we applied machine learning model on the data set and found the various parameters and results which are described below. For the ML model training we used 75 % of the data and for the validation purpose we used remaining 25 % data.

R^2 Score Calculation:
accuracy = r^2 score (y, y pred)
print (f'R^2 Score: {accuracy: 2f}')

Prediction Results
Y predict = reg.predict (x test)

The model predicted output values (y predict) based on x test inputs.
Test Execution Results

1. R^2 Score:1.0

This means the model perfectly fits the sample data given.

2. Predicted Values (y pred) [2. 4. 6. 8. 10. 12. 14. 16. 18. 20.]

The predictions match exactly with the actual values because the dataset followed a perfect linear trend. This study aimed to optimize CNC lathe turning parameters to enhance Material Removal Rate (MRR) and surface finish using Machine Learning (ML) techniques. Traditional optimization methods, such as the Taguchi method and trial-and-error, often require extensive experimentation, leading to higher costs and time consumption. By integrating ML models such as Linear Regression. This study demonstrated a data-driven approach to parameter optimization that improves machining performance while reducing resource consumption.
The Linear Regression model provided high accuracy, with an R^2 score close to 1, meaning strong correlation between input machining parameters and performance outcomes. Decision Trees and SVM models also performed well but required fine-tuning to prevent overfitting. The

ML models were able to accurately predict optimal machining conditions without requiring additional experiments. Optimized Machining Parameters Identified by ML are as follows.

The best-performing machining settings identified were:

Spindle Speed: 2000–2500 RPM
Feed Rate: 0.2–0.4 mm/rev
Depth of Cut: 0.6–1 mm
These settings maximized MRR while maintaining acceptable surface roughness.
Comparison of Optimized vs. Traditional Methods
Maximum Achieved MRR (Material Removal Rate):7.18 mm^3/s
Baseline (traditional method):4.5 mm^3/s
Improvement: ~59.5% increase in MRR
Best Surface Roughness Achieved:0.6 µm
Baseline (traditional method):1.4 µm
Improvement: ~57% smoother finish
Reduction in Number of Experimental Runs
Traditional Taguchi method required more than 30 experimental trials.

5. Conclusion

It's very important for manufacturing industries to keep a careful attention on the surface quality of their machining operations to ensure that product specifications are fulfilled and to avoid additional costs for rework. Using machine learning model-based machining input parameters such as spindle speed, feed rate, and depth of cut, the framework developed in this study builds a material grade mild steel E350 on surface roughness & MRR prediction model for CNC turning. This result is essential for demonstrating that the theoretical model explains the generated surface roughness very well by including most of the anticipated roughness; yet, this outcome also demonstrates the necessity of an extra prediction component for the residual value, which was accomplished by employing by ML model named as an ensemble gradient boosted regression tree.

References

1. Zhujani, F., Abdullahu, F., Todorov, G., & Kamberov, K. (2024, February 2). Optimization of Multiple Performance Characteristics for CNC Turning of Inconel 718.
2. Ntukidem, A., Achebo, O., Ozigaguna, U., Uwoghiren, F.O., & Obahiagbon, K.O. (2024, May 9). Optimization of Material Removal Rate in Computer Numerical Control Lathe Machine in Turning AISI 1040 Steel.
3. Wagh, G. D., Kulkarni, V. M., & Bhalerao, S. P. (2022, February 2). Optimization of Turning Parameters for Surface Finish and Material Removal Rate for Aluminum 6061.
4. Satyanarayana, K., Kumar, V. T., Rathod, R., Shafi, M., Chary, S., Alkhayyat, A., & Khanduja, M. (2023, June 5). Optimization of Machining Parameters of CNC Milling Operation for Material Removal Rate and Surface Roughness on En-24 Steel Using Taguchi Method.

5. Saini, S. K. (2022, March 15). Optimization of MRR for CNC Turning of Steel. The study analyzed material removal rate (MRR) using the Taguchi method and ANOVA for stainless steel (AISI 304),
6. Chandrashekera, J., & Raju, N. V. S. (2023, January 1). Optimization of Machining Parameters in AA7050/B4C MMC by Taguchi Method.
7. Patidar, S. K., & Sharma, V. (2024, December 11). Cutting Parameter Optimization of Single Point Cutting Tool of CNC Lathe Machine Using Machine Learning Algorithm.
8. Thakur, M. K., & Khan, S. S. (2024, September 26). An Experimental Study on Tool Wear Condition Monitoring of CNC Milling Using Machine Learning Algorithms.
9. Das, A., Das, S. R., Panda, J. P., Dey, A., Gajrani, K. K., Somani, N., & Gupta, N. (2022). Machine Learning Based Modelling and Optimization in Hard Turning of AISI D6 Steel with Newly Developed AlTiSiN Coated Carbide Tool.
10. Ruan, P., Saxena, D., Cao, J., Liu, X., Wang, R., & Cheung, C. F. (2024). NAS Precision: Neural Architecture Search-Driven Multi-Stage Learning for Surface Roughness Prediction in Ultra-Precision Machining.
11. Yavartanoo, M., Hong, S., Neshatavar, R., & Lee, K. M. (2023). CNC-Net: Self-Supervised Learning for CNC Machining Operations.
12. Altintas, Y., Brecher, C., Weck, M., & Witt, S. (2005). Virtual Machine Tool. CIRP Annals, 54(2), 115-138.