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Surface Roughness Optimization in Hard Turning of AISI D2 Steel Using RSM and Machine Learning

Mauli S. Sudake[1] Aditya A. Pujari[2] Avinash A. Somatkar[3], Vishal V. Chahare[4]

[1-2]Research Scholar, Vishwakarma Institute of Information Technology, Pune, India
[3]Assistant Professor, Vishwakarma Institute of Technology, Pune, India
[4]Assistant professor, Deogiri Institute of Engineering and Management Studies, Chhatrapati Sambhajinagar, India

Correspondence: [1]mauli.22420282@viit.ac.in; [2]aditya.22420277@viit.ac.in; [3]avinash.somatkar@vit.edu; [4]vishalchahare@dietms.org

Abstract

Ultra-precision hard turning of hardened steels offers a promising alternative to grinding for achieving high surface quality; however, predicting surface roughness remains challenging due to complex parameter interactions. This study investigates the prediction and optimization of surface roughness (Ra) in hard turning of AISI D2 steel (62 HRC) using a cubic boron nitride (CBN) tool. Experiments were conducted by varying cutting speed, feed rate, and depth of cut under controlled conditions. Response Surface Methodology (RSM) was used to model and optimize the process, while machine learning models including Support Vector Machine (SVM), Artificial Neural Network (ANN), Gaussian Process Regression (GPR), and Adaptive Neuro-Fuzzy Inference System (ANFIS) were developed for prediction. Model performance was evaluated using R, RMSE, and MAPE. Results indicate that feed rate is the most significant factor affecting surface roughness, followed by cutting speed, while depth of cut has minimal influence. Among the models, ANFIS achieved the highest accuracy (R = 0.81, RMSE = 0.17). Optimal conditions (Vc = 100 m/min, f = 0.025 mm/rev, ap = 0.09 mm) yielded a minimum surface roughness of 0.207 µm. The integration of RSM and machine learning provides an effective and reliable framework for accurate prediction and optimization in ultra-precision hard turning.

Keywords: Ultra-precision machining; Hard turning; Surface roughness prediction; Machine learning; Optimization.

1. Introduction

The increasing demand for high-performance components in aerospace, automotive, and precision engineering industries has intensified the need for superior surface integrity and dimensional accuracy. Surface roughness is a critical quality indicator, as it directly influences functional performance, wear resistance, fatigue life, and tribological behavior of machined components. Consequently, achieving an optimal surface finish during machining has become a key objective in advanced manufacturing.

Hard turning has emerged as a viable alternative to conventional grinding for machining hardened steels, typically above 45 HRC. The process offers advantages such as reduced production time, elimination of multiple finishing operations, and improved process flexibility. In ultra-precision hard turning, these benefits are further enhanced, enabling the production of components with very low surface roughness and high geometric accuracy. However, the quality of the machined surface is strongly governed by machining parameters such as cutting speed, feed rate, and depth of cut, whose complex and nonlinear interactions make prediction and optimization challenging.

Traditional approaches, particularly Response Surface Methodology (RSM), have been widely employed to model machining processes and determine optimal parameter settings. While RSM provides valuable insights into parameter effects and interactions, its capability to accurately represent highly nonlinear relationships remains limited. To overcome these limitations, machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Gaussian Process Regression (GPR), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been increasingly applied for modeling machining performance due to their ability to capture complex data-driven relationships.

Despite these advancements, most existing studies focus on individual predictive techniques or are conducted under varying experimental conditions, making it difficult to establish a consistent comparison of model performance. Furthermore, limited attention has been given to ultra-precision hard turning of AISI D2 steel under controlled conditions using integrated statistical and machine learning approaches. This creates a gap in understanding the relative effectiveness of different predictive models for surface roughness under identical machining environments.

In this context, the present study aims to investigate the prediction and optimization of surface roughness in ultra-precision hard turning of AISI D2 steel using a cubic boron nitride (CBN) tool. A systematic experimental approach is combined with Response Surface Methodology and multiple machine learning models, including SVM, ANN, GPR, and ANFIS, to analyze parameter effects and develop predictive models. The outcomes of this study are expected to provide a reliable framework for selecting optimal machining conditions and improving surface quality in precision manufacturing applications.

2. Literature Review

The machining of hardened steels has been extensively studied due to its significance in achieving high surface quality and dimensional precision. In hard turning operations, surface roughness is primarily influenced by machining parameters such as cutting speed, feed rate, and depth of cut. Several studies have emphasized the importance of optimizing these parameters to enhance machining performance and product quality [3], [4].

Response Surface Methodology (RSM) has been widely applied as a statistical tool to model the relationship between process parameters and response variables. It enables the evaluation of individual and interaction effects of machining parameters and facilitates process optimization. Previous studies have demonstrated the effectiveness of RSM in predicting surface roughness and identifying optimal cutting conditions in hard turning processes [10]. However, RSM is inherently limited in capturing complex nonlinear relationships that arise in machining operations.

To address these limitations, machine learning techniques have gained significant attention in recent years. Artificial Neural Networks (ANN) have been successfully employed for predicting surface roughness due to their ability to approximate nonlinear input–output relationships [8]. Similarly, Support Vector Machines (SVM) have demonstrated strong predictive performance in machining applications, particularly when dealing with nonlinear datasets and limited experimental samples [1].

Gaussian Process Regression (GPR) has emerged as an effective probabilistic modeling technique, offering both prediction accuracy and uncertainty estimation. This makes it particularly suitable for machining problems involving small or noisy datasets [1]. In addition, hybrid approaches such as the Adaptive Neuro-Fuzzy Inference System (ANFIS) combine the learning capability of neural networks with fuzzy logic reasoning, resulting in improved prediction accuracy in complex and uncertain machining environments [5].

Advancements in cutting tool materials have also contributed to improved machining performance. Cubic boron nitride (CBN) tools are widely used for hard turning of materials such as AISI D2 steel due to their high hardness, thermal stability, and wear resistance. Studies have reported that the use of CBN tools leads to improved surface finish and dimensional stability under high-speed machining conditions [6], [7].

Despite these developments, most existing studies focus on individual predictive models or are conducted under different experimental conditions, limiting the ability to directly compare model performance. Furthermore, there is a lack of comprehensive studies that integrate statistical and machine learning approaches for the prediction and optimization of surface roughness under consistent ultra-precision hard turning conditions. Therefore, a systematic comparative evaluation of multiple predictive techniques under identical machining environments is required to establish their relative effectiveness.

3. Experimental Setup and Methodology

3.1 Design of experiment

The experimental investigation was conducted to evaluate the influence of machining parameters on surface roughness during ultra-precision hard turning. The workpiece material selected for this study was AISI D2 tool steel with a hardness of 62 HRC, which is commonly used in die and mold applications due to its high wear resistance and mechanical stability.

Machining trials were performed on a CNC lathe under controlled operating conditions. A cubic boron nitride (CBN) cutting insert (SECO, DCGW11T308S-01020-L1-B CBN010) was employed owing to its high hardness, thermal resistance, and suitability for machining hardened materials. The tool geometry included a nose radius of 0.8 mm, a chamfer width of 0.10 mm, and a rake angle of 20°.

The workpiece was cylindrical, with an outer diameter of 60 mm, an inner diameter of 12 mm, and a length of 40 mm. All experiments were carried out under dry machining conditions to maintain consistency and eliminate the influence of coolant on surface finish.

Surface roughness measurements were obtained using a Mitutoyo SJ-400 surface roughness tester equipped with a diamond stylus tip of radius 2 µm. To ensure measurement reliability, each experimental run was repeated three times, and the average surface roughness (Ra) value was considered for further analysis.

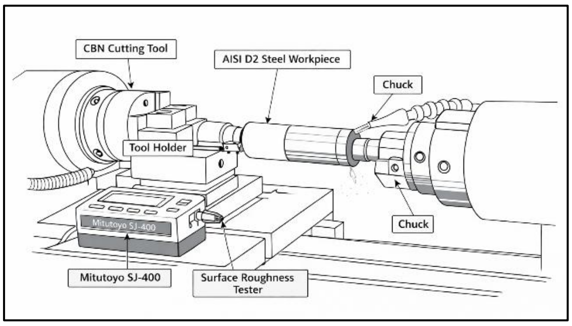

Figure 1: *Experimental Setup for Ultra-precision Hard Turning*

3.2 Machining Parameters

The primary machining parameters considered in this study were cutting speed (Vc), feed rate (f), and depth of cut (ap), as these are known to significantly influence surface roughness.

Table 1: Machining Parameters and Their Levels

Parameter	Levels	Values
Cutting Speed (Vc)	3	75, 125, 175 m/min
Feed Rate (f)	3	0.025, 0.075, 0.125 mm/rev
Depth of Cut (ap)	3	0.06, 0.08, 0.10 mm

The selected parameter ranges were based on preliminary trials and recommendations from existing literature to ensure stable machining conditions. This combination enabled a systematic evaluation of both individual and interaction effects of the parameters on surface roughness.

3.3 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a statistical and mathematical technique used to model and analyze the relationship between input process parameters and the corresponding response. In machining applications, RSM is widely employed to evaluate the effects of multiple variables and to determine optimal process conditions.

In general, the relationship between the response and the independent variables can be expressed as:

$$Y = f(X_1, X_2, X_3, \dots, X_k) + \varepsilon$$

where Y represents the response variable (surface roughness), $X_1, X_2, X_3, \dots, X_k$ denote the input process parameters, and ε is the random experimental error.

In the present study, a second order (quadratic) regression model was adopted to represent the relationship between surface roughness (Ra) and the machining parameters, namely cutting speed (V_c), feed rate (f), and depth of cut (a_p). The mathematical model is given by:

$$Ra = \beta_0 + \beta_1 V_c + \beta_2 f + \beta_3 a_p + \beta_{12} V_c f + \beta_{13} V_c a_p + \beta_{23} f a_p + \beta_{11} V_c^2 + \beta_{22} f^2 + \beta_{33} a_p^2$$

where $\beta_0$is the intercept term, $\beta_i$are the coefficients of the linear terms, β_{ij}represent the interaction effects between parameters, and β_{ii}correspond to the quadratic coefficients.

The experimental data obtained from machining trials were used to estimate the coefficients of the regression model. Statistical analysis was carried out using Minitab 21 software. Analysis of Variance (ANOVA) was employed to evaluate the significance of individual parameters as well as their interaction effects on surface roughness.

The developed model was further utilized to analyze the response surface and to identify the optimal combination of machining parameters for minimizing surface roughness.

3.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised machine learning technique widely applied to regression and classification problems. In the present study, SVM was utilized to predict surface roughness based on machining parameters, namely cutting speed (V_c), feed rate (f), and depth of cut (a_p).

For regression applications, SVM is implemented in the form of Support Vector Regression (SVR), where the objective is to determine a function that approximates the relationship between input variables and the response with minimal error. The model constructs an optimal hyperplane in a high-dimensional feature space by transforming the original input data using a kernel function. This transformation enables the model to effectively capture nonlinear relationships between machining parameters and surface roughness.

The SVR model aims to minimize the structural risk by balancing model complexity and prediction accuracy. It introduces an insensitive loss function, where errors within a specified margin are ignored, thereby improving generalization performance. This characteristic makes SVM particularly suitable for machining datasets, which often involve nonlinear interactions and limited experimental samples.

In this study, the machining parameters (V_c, f, and a_p) were used as input variables, while surface roughness (Ra) was considered as the output. The experimental dataset was divided into training and testing subsets to evaluate the predictive capability of the model. Model performance was assessed using statistical indicators such as correlation coefficient (R), root mean square error (RMSE) and mean absolute percentage error (MAPE).

Due to its robustness in handling nonlinear data and its ability to avoid overfitting, SVM serves as an effective tool for predicting machining performance and was compared with other machine learning models in this study.

3.5 Chemical Composition of Experimental Material

The chemical composition of the workpiece material plays a significant role in determining its machinability, hardness, and surface finish characteristics. In this study, AISI D2 tool steel was selected due to its high wear resistance, dimensional stability, and suitability for hard turning applications.

AISI D2 is a high-carbon, high-chromium cold work tool steel widely used in die and mold manufacturing. Its high chromium content contributes to excellent hardness and abrasion resistance, while the presence of carbon enhances strength and edge retention during machining. These properties make it an appropriate material for evaluating surface roughness under ultra-precision hard turning conditions.

The chemical composition of the AISI D2 steel used in the present investigation is summarized in Table 2.

Table 2: Chemical Composition of AISI D2 Steel

Element	Percentage (%)
C	1.55
Si	0.30
Mn	0.40
Cr	11.80
Mo	0.80

3.6 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are data-driven computational models designed to capture complex and nonlinear relationships between input and output variables. Due to their adaptive learning capability, ANNs are widely used in machining applications for predicting performance characteristics such as surface roughness.

In this study, an ANN model was developed to establish the relationship between machining parameters, namely cutting speed (V_c), feed rate (f), and depth of cut (a_p) and the resulting surface roughness (Ra). The network architecture consisted of three primary layers: an input layer, one or more hidden layers, and an output layer. The input layer receives machining parameters, while the output layer produces the predicted surface roughness value.

Each neuron processes incoming signals by applying weighted connections and a bias term, followed by an activation function to introduce nonlinearity. Through an iterative training process, the network adjusts these weights to minimize the difference between predicted and experimental values. The learning process enables the ANN to generalize underlying patterns within the dataset.

The experimental dataset was divided into training and testing subsets to evaluate model performance. The training phase was used to optimize the network parameters, while the testing phase assessed prediction accuracy on unseen data. Performance of the ANN model was evaluated using statistical measures such as correlation coefficient (R), root mean square error (RMSE) and mean absolute percentage error (MAPE).

Due to its capability to model nonlinear interactions among machining parameters, the ANN model provides an effective approach for predicting surface roughness and was compared with other machine learning techniques in this study.

3.7 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid modeling approach that combines the learning capability of artificial neural networks with the reasoning mechanism of fuzzy logic. This integration enables ANFIS to effectively model complex and nonlinear relationships, particularly in systems where uncertainty and imprecision are present.

In the present study, ANFIS was employed to predict surface roughness based on machining parameters, namely cutting speed (V_c), feed rate (f), and depth of cut (a_p). The model operates by constructing a set of fuzzy if–then rules derived from input–output data. These rules are associated with membership functions that define the degree to which each input belongs to a fuzzy set.

The ANFIS structure typically consists of multiple layers, including fuzzification, rule evaluation, normalization, and defuzzification. During the training process, the system adjusts the parameters of the membership functions using a hybrid learning algorithm that combines least-squares estimation and backpropagation. This allows the model to adapt efficiently to the underlying data patterns.

The dataset obtained from experimental trials was used to train and validate the ANFIS model. Input variables included machining parameters, while surface roughness (Ra) was considered as the output. The predictive performance of the model was evaluated using statistical indicators such as correlation coefficient (R), root mean square error (RMSE) and mean absolute percentage error (MAPE).

Due to its ability to handle nonlinear behaviour and uncertainty in machining processes, ANFIS is considered a robust predictive tool. Its performance was compared with other machine learning models to determine its effectiveness in predicting surface roughness under varying machining conditions.

3.8 Correlation Coefficient (R)

The correlation coefficient (R) is a statistical measure used to evaluate the strength and direction of the relationship between experimental values and predicted results. In the context of this study, it was used to assess the accuracy of the developed predictive models.

The value of the correlation coefficient ranges from −1 to +1. A value close to +1 indicates a strong positive correlation, implying that the predicted values closely match the experimental data. A value near zero suggests weak correlation, while a negative value indicates an inverse relationship.

In addition to the correlation coefficient, other performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used to provide a comprehensive evaluation of model accuracy. These statistical measures enabled a comparative assessment of different machine learning models, including SVM, ANN, GPR, and ANFIS, in predicting surface roughness.

4. Results and Discussion

The experimental data obtained from ultra-precision hard turning trials were analyzed using Response Surface Methodology (RSM) and machine learning techniques to evaluate the influence of machining parameters on surface roughness (Ra) and to identify optimal machining conditions. The input parameters considered were cutting speed (V_c), feed rate (f), and depth of cut (a_p).

4.1 Analysis of Machining Parameters

The effect of individual machining parameters on surface roughness is illustrated through the main effects plot.

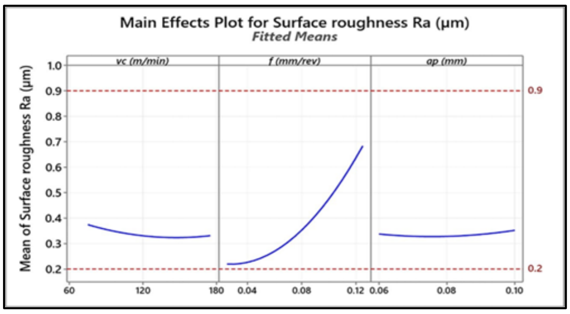

Figure 2: *Main Effect Plot for Surface Roughness*

The results indicate that cutting speed has a noticeable but moderate influence on surface finish. As the cutting speed increases from 75 m/min to approximately 120 m/min, surface roughness decreases significantly. Beyond this range, further improvement becomes marginal, suggesting a saturation effect. This behavior can be attributed to reduced built-up edge formation and smoother chip flow at higher cutting speeds.

Depth of cut shows a comparatively smaller effect on surface roughness within the selected range. A slight improvement is observed as the depth of cut increases from 0.06 mm to 0.08 mm, followed by a minor deterioration at 0.10 mm. This indicates that depth of cut does not play a dominant role under the given machining conditions.

In contrast, feed rate exhibits a strong and direct influence on surface roughness. An increase in feed rate from 0.025 mm/rev to 0.125 mm/rev leads to a substantial increase in surface roughness. This trend is consistent with theoretical expectations, as higher feed rates produce more pronounced feed marks and surface irregularities.

Overall, the analysis confirms that feed rate is the most significant parameter affecting surface roughness, followed by cutting speed, while depth of cut has a relatively minor effect.

4.2 Optimization of Process Parameters

To determine the optimal machining conditions for minimizing surface roughness, RSM-based optimization was performed. The interaction between cutting speed and feed rate is represented using contour plots.

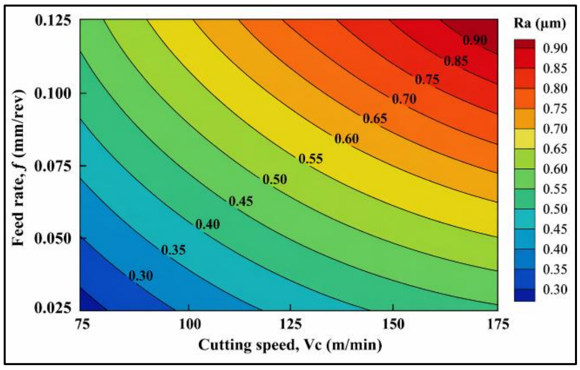

Figure 3: *Response surface (contour) plot illustrating the combined effect of cutting speed (Vc) and feed rate (f) on surface roughness (Ra) at a constant depth of cut of 0.08 mm.*

The contour plot indicates that surface roughness is highly sensitive to variations in feed rate, whereas the influence of cutting speed is comparatively less pronounced. Lower feed rates combined with moderate to high cutting speeds result in improved surface finish.

The optimal region for minimum surface roughness is observed at low feed rates (around 0.025 mm/rev) and cutting speeds in the range of 100–120 m/min. Depth of cut shows minimal interaction effect within the selected range.

The optimal region for minimum surface roughness lies within:

- Feed rate: 0.025–0.029 mm/rev
- Cutting speed: 77–121 m/min
- Depth of cut: 0.08–0.09 mm

The minimum surface roughness achieved under optimal conditions was **0.207 μm**, corresponding to:

- Cutting speed: 100 m/min
- Feed rate: 0.025 mm/rev
- Depth of cut: 0.09 mm

These results indicate that maintaining a low feed rate is essential for achieving superior surface quality, while moderate cutting speeds help stabilize the cutting process.

4.3 Analysis of Variance (ANOVA)

The statistical significance of machining parameters and their interactions was evaluated using ANOVA.

Table 3: ANOVA for Surface Roughness

Source	DF	Adj SS	Adj MS	F-value	p-value	Remarks
Model	9	1.1198	0.12442	35.38	0	Significant
Linear	3	0.9763	0.32543	92.54	0	Significant
Vc	1	0.0084	0.00841	2.39	0.14	Not significant
f	1	0.9669	0.96693	275	0	Significant
ap	1	0.001	0.00096	0.27	0.608	Not significant
Square	3	0.0964	0.03213	9.14	0.001	Significant

The ANOVA results confirm that the developed model is statistically significant ($p < 0.05$). Among the input parameters, feed rate is identified as the only statistically significant factor influencing surface roughness within the selected range. Cutting speed and depth of cut do not exhibit significant individual effects.

The relatively high F-value associated with feed rate indicates its dominant contribution to surface roughness variation. Additionally, the presence of significant quadratic terms suggests that the response surface exhibits curvature, validating the use of a second-order model.

4.4 Performance Evaluation of Machine Learning Models

The predictive capabilities of different machine learning models—GPR, SVM, ANFIS, and ANN—were evaluated using statistical performance indicators, including correlation coefficient (R), RMSE, and MAPE.

Table 4: Performance Comparison of Predictive Models

Models	*R*	RMSE	MAPE (%)
GPR	0.79	0.19	39.47
SVM	0.79	0.17	34.91
ANFIS	0.81	0.17	32.34
ANN	0.78	0.19	37.95

Among the models considered, ANFIS achieved the highest prediction accuracy, as indicated by the highest correlation coefficient and lowest error values. This can be attributed to its hybrid structure, which effectively combines data-driven learning with fuzzy logic reasoning, enabling better representation of nonlinear relationships.

The SVM model also demonstrated reliable performance, showing good agreement between predicted and experimental values. ANN and GPR exhibited comparatively lower accuracy, which may be due to limitations in capturing complex interactions with the available dataset.

The comparative analysis highlights that hybrid and nonlinear modeling approaches provide improved prediction capability in machining processes. The results also suggest that model selection plays a crucial role in achieving accurate and reliable predictions.

5. Conclusion

This study presented an integrated approach for the prediction and optimization of surface roughness in ultra-precision hard turning of AISI D2 steel using Response Surface Methodology (RSM) and machine learning techniques. The analysis established that feed rate is the most influential parameter governing surface roughness, while cutting speed has a moderate effect and depth of cut contributes minimally within the investigated range.

The RSM model effectively captured parameter interactions and enabled the determination of optimal machining conditions. A minimum surface roughness of 0.207 µm was achieved at a cutting speed of 100 m/min, feed rate of 0.025 mm/rev, and depth of cut of 0.09 mm. Among the predictive models, ANFIS demonstrated the highest accuracy, outperforming SVM, ANN, and GPR, which confirms its suitability for modeling nonlinear machining behavior.

The combined use of statistical and machine learning approaches provides a robust framework for accurate prediction and efficient optimization of machining performance. The findings offer practical guidance for selecting cutting parameters in precision manufacturing and support the development of data-driven, intelligent machining systems. Future work may focus on extending the dataset, incorporating additional process variables, and implementing real-time adaptive control strategies.

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