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Cutting Parameter Optimization of Single Point Cutting Tool of CNC Lathe Machine Using Machine Learning Algorithm

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In this study, two machine learning models, Random Forest Regressor (RFR) and Decision Tree Regressor (DTR), were applied to predict surface roughness (SR) in machining processes (turning) based on key input parameters: spindle speed (SS), feed rate (FR), and depth of cut (DOC). The performance of both models was evaluated using R^2 (R-squared), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The Decision Tree Regressor achieved near-perfect accuracy with an R^2 score of 0.9999 and minimal error metrics. The Random Forest Regressor also performed exceptionally well, with an R^2 of 0.9988 and similarly low error values. Visual analyses, including residual and radar plots, confirmed the high accuracy of both models, with the Decision Tree Regressor slightly outperforming the Random Forest model. However, the Random Forest Regressor's ensemble structure provides better generalization and robustness, making it a more reliable model for larger or more complex datasets. This study concludes that both models are highly effective for predicting surface roughness, but the choice between them should depend on the specific trade-offs between accuracy and generalization needed in a given application.
Keywords: Turning, Machine learning, Spindle, Feed, Depth of cut, Machining.

1. Introduction

To meet human requirements, manufacturing entails transforming raw resources into completed items. The physical characteristics, size, and shape of a material are changed as a result of several manufacturing processes that are used to convert raw materials. Figure 1 shows the results of turning, a type of machining that removes material to make pieces that can rotate. A lathe or turning machine, a workpiece, a fixture, and a cutting tool are all necessary for turning. The turning machine spins at high speeds while the work piece, which is a pre-shaped piece of material, is fastened to a fixture. The cutter is usually a machine-secured, single-pointed cutting tool, while multi-point tools are used in some activities. To achieve the required shape, the cutting tool is fed into the spinning work piece and chips away material.

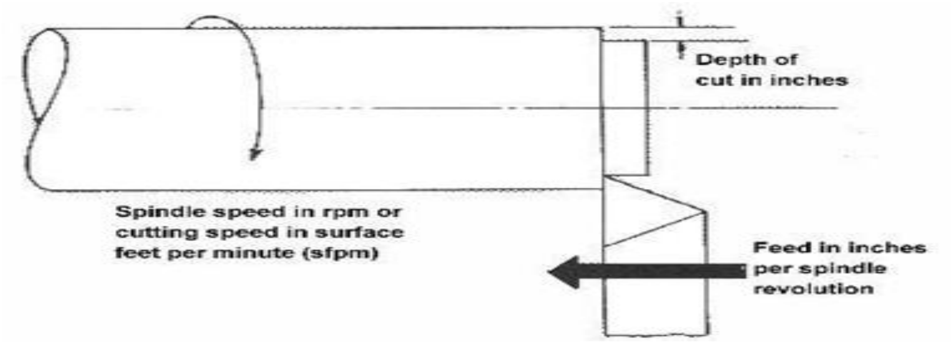

Figure 1. Turning Process

components with several characteristics, including holes, grooves, threads, tapers, different diameter steps, and even curved surfaces, may be produced by turning. These components are usually axi-symmetric. Components used in small numbers, maybe for prototypes, such custom-designed shafts and fasteners, are common in parts that are manufactured entirely by turning. Adding or refining features on items that were made using a different technique is a frequent secondary usage for turning. For parts with a basic shape already produced, turning is the appropriate process for adding precise rotating features because of the high tolerances and surface finishes it can deliver. Any discussion of spindle or work piece speed must include both.

$V = \frac{\pi DN}{1000} \text{m min}^{-1}$

Here, v is the cutting speed in turning,

D is the initial diameter of the work piece in mm and N is the spindle speed in RPM.

Feed is the rate at which the tool advances along its cutting path. The feed of the tool also affects to the processing speed and the roughness of surface.

$F_m = f.\ N \text{ mm. min}^{-1}$

Here, Fm is the feed in mm per minute, f is the feed in mm/rev and N is the spindle speed in RPM.

Depth of cut is practically self explanatory. It can be defined as the thickness of the layer being removed (in a single pass) from the work piece or the distance from the uncut surface of the work to the cut surface, expressed in mm.

$d_{cut} = \frac{D-d}{2}$ mm

Here, D and d represent initial and final diameter (in mm) of the job respectively.

It is important to note, though, that the diameter of the work piece is reduced by two times the depth of cut because this layer is being removed from both sides of the work. While turning flame-hardened medium carbon steel with inserts coated with TiN, Al2O3, and TiCN, Khrais et al. used a multiple regression model to determine surface roughness as a function of cutting parameters [1]. The impact of turning parameters on the surface finish of the workpiece was investigated using Taguchi approach in conjunction with an experimental design and signal-to-noise ratio (S/N). Analysis of variance (ANOVA) was used to study the impact of turning factors. The feed rate, cutting speed, and cutting depth were the factors that were evaluated. The interplay between depth of cut and feed was determined to be the most significant among the turning characteristics that were investigated. Inserts coated with TiN-Al2O3-TiCN had an average surface roughness (Ra) of around 2.44 μm and a minimum value of 0.74 μm, as reported in references [2-4]. Furthermore, surface roughness levels were also reasonably predicted by the regression model when compared to experimental values. Optimising the machining parameters (feed rate, cutting speed, and depth of cut) in relation to surface roughness was studied by Yadav et al. [5]. This study makes use of an L'27 orthogonal array, the signal-to-noise ratio (S/N), and analysis of variance (ANOVA). Experiments are conducted on a STALLION-100 HS CNC lathe using three levels of machining settings. It turns out that 0.89 is the sweet spot for surface roughness (Ra). Further analysis reveals that feed rate, followed by depth of cut, determines surface roughness to the greatest extent. When it comes to factors influencing surface roughness, cutting speed is the least important [6-9]. In the end, confirmation trials are used to confirm the best outcomes. While turning Ti-6Al-4V alloy under dry, flooded, and Minimum Quantity Lubrication (MQL) conditions, Ramana et al. used Taguchi's robust design methodology and multiple regression analysis to optimise process parameters for surface roughness [10]. In comparing the outcomes of dry, flooded, and MQL lubricant conditions, it is evident that MQL exhibits superior performance and an improvement in reducing surface roughness. Compared to dry and flooded lubricant conditions, Analysis of Mean (ANOM) shows that MQL is appropriate at deeper depths of cut [11–14]. According to ANOM, tools that are not coated perform better than tools that are coated with CVD or PVD under MQL circumstances, whereas tools that are coated with CVD perform better in dry and flooded lubricant conditions than tools that are not coated with either PVD or CVD. The analysis of variance also shows that feed rate is a key factor in achieving the ideal surface roughness. The impact of process parameters on material removal rate (MRR) during C34000 turning was studied by Hassan et al. [15]. Applying the Taguchi approach, we are able to optimise the MRR and other single-response optimisation issues. To optimise MRR in the experimental domain, twenty-seven runs of the Taguchi method's L'27 orthogonal array are run. These runs yield objective functions. By itself, optimising the MRR yields an MRR of 8.91. We have found the best values for the process parameters that optimise MRR simultaneously. Verification trials were conducted to provide the best possible outcomes. [16] Manish kumar Thakur et al. used a deep neural network in conjunction with the tried-and-true linear regression technique in order to predict certain cutting parameters of CNC milling tool wear, to build their predictive models and found that the accuracy of the hybrid model that included machine learning methods was higher than that of traditional linear regression.

2. Materials and Methods

2.1. Data collection and pre-processing

The dataset used in this study was obtained from machining experiments conducted using a lathe machine, where the cutting conditions, such as spindle speed (SS), feed rate (FR), and depth of cut (DOC), were systematically varied. The surface roughness (SR) of the machined parts was measured as the primary response variable to evaluate the quality of the machining process. The data includes a total of 9 samples augmented to 500 rows, with 70% used for model training and 30% for testing. Before applying machine learning techniques, the data was preprocessed. Missing values were checked, and none were found. All features were normalized to ensure uniformity and prevent bias during model training. The dataset was then split into independent variables (SS, FR, and DOC) and the dependent variable (SR). The final dataset was divided into training and testing sets with a 70:30 ratio, ensuring that the model could be adequately trained while preserving data for unbiased performance evaluation. The cutting parameters and design of experiments to calculate surface roughness are shown in Table 2 and 3.

Table 1. Cutting parameters and levels for dry turning

Parameters/Factors		level		
		1	2	3
A	Spindle speed (rpm)	160	320	620
B	Feed rate (mm/rev)	0.3	0.4	0.5
C	Depth of cut (mm)	0.7	0.8	0.9

Table 2. Design of Experiments

Experiment no.	Spindle speed (rpm), N	Feed rate (mm/rev), f	Depth of cut (mm), A	Surface roughness, Ra (µm)
1	160	0.3	0.7	2.24
2	160	0.4	0.8	5.67
3	160	0.5	0.9	5.93
4	320	0.3	0.8	5.34
5	320	0.4	0.9	4.87
6	320	0.5	0.7	6.07
7	620	0.3	0.9	2.91
8	620	0.4	0.7	3.78
9	620	0.5	0.8	5.05

3. Machine Learning Algorithm: Random Forest Regressor

To predict the surface roughness based on the machining parameters, two machine learning regression models were applied: Random Forest Regressor (RFR) and Decision Tree Regressor (DTR).

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
import numpy as np
import matplotlib.pyplot as plt
import numpy as np

# Load the augmented dataset
file_path = r'C:\Users\HP\Downloads\augmented_CPO-Paper.csv'
df = pd.read_csv(file_path)

# Define the feature columns and the target variable
X = df[['SS', 'FR', 'DOC']]
y = df['SR']

# Split the dataset into training and testing sets (70% train, 30% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Apply Random Forest Regressor
rf_regressor = RandomForestRegressor(random_state=42)
rf_regressor.fit(X_train, y_train)

# Make predictions
y_pred = rf_regressor.predict(X_test)

# Calculate R2, RMSE, MSE, and MAE
r2 = r2_score(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_pred)

# Output the results
print(f'R²: {r2}')
print(f'MSE: {mse}')
print(f'RMSE: {rmse}')
print(f'MAE: {mae}')
```

Figure 2. Python code for random forest regressor

3.1 Random Forest Regressor (RFR)

Random Forest Regressor is an ensemble learning method that builds multiple decision trees and combines their results to improve prediction accuracy and reduce overfitting. The key advantage of Random Forest is its ability to capture complex, non-linear relationships within the data while maintaining robust generalization capabilities. The Random Forest Regressor was trained on 70% of the dataset using 100 trees (estimators). Default hyperparameters were used for computational efficiency, while the random state parameter ensured reproducibility. The model combined the results of multiple decision trees to provide more accurate predictions. Once trained, the model was used to predict the surface roughness values for the test set (30% of the dataset).

3.2 Decision Tree Regressor (DTR)

The Decision Tree Regressor is a single-tree model that splits the data recursively based on feature values to predict a continuous target variable. While Decision Trees are easy to interpret and can model complex patterns, they are prone to overfitting, especially with small datasets, leading to reduced generalization performance. The Decision Tree Regressor was also trained on the same 70% of the dataset. The tree was grown to full depth to allow it to capture as much variance in the training data as possible. As with the Random Forest model, the random state parameter was used for reproducibility. Similar to the Random Forest model, the Decision Tree was used to predict surface roughness on the test data.

4. Model Evaluation

Both the Random Forest Regressor and Decision Tree Regressor were evaluated on the test set using the metrics. R-squared (R^2): This metric measures the proportion of variance in the target variable (SR) explained by the input features (SS, FR, DOC). A higher R^2 indicates a better fit of the model to the data. Mean Squared Error (MSE): The average squared difference between actual and predicted values, providing an overall indication of model performance. Root Mean Squared Error (RMSE): The square root of MSE, making it easier to interpret the error in the same units as the target variable (SR). Mean Absolute Error (MAE): The average of the absolute differences between actual and predicted values, indicating the magnitude of errors in predictions.

5. Results and discussion

5.1. Random Forest Regressor Results

The Random Forest Regressor demonstrated exceptional performance in predicting surface roughness (SR) based on the given machining parameters. The model achieved an R^2 value of 0.9988, indicating that it explained 99.88% of the variance in surface roughness. The error metrics further supported the model's accuracy, with a Mean Squared Error (MSE) of 0.0020, a Root Mean Squared Error (RMSE) of 0.0449, and a Mean Absolute Error (MAE) of 0.0165. These low error values suggest that the predictions made by the Random Forest model were very close to the actual values, confirming the model's high precision.

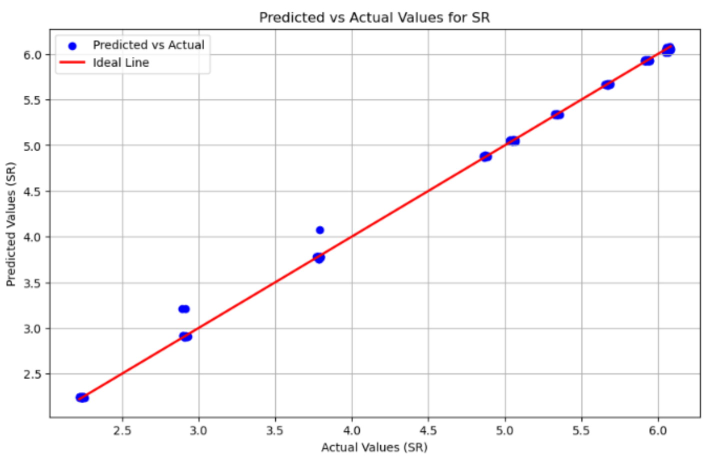

Figure 3. Actual v/s predicted values on mean line for random forest regressor

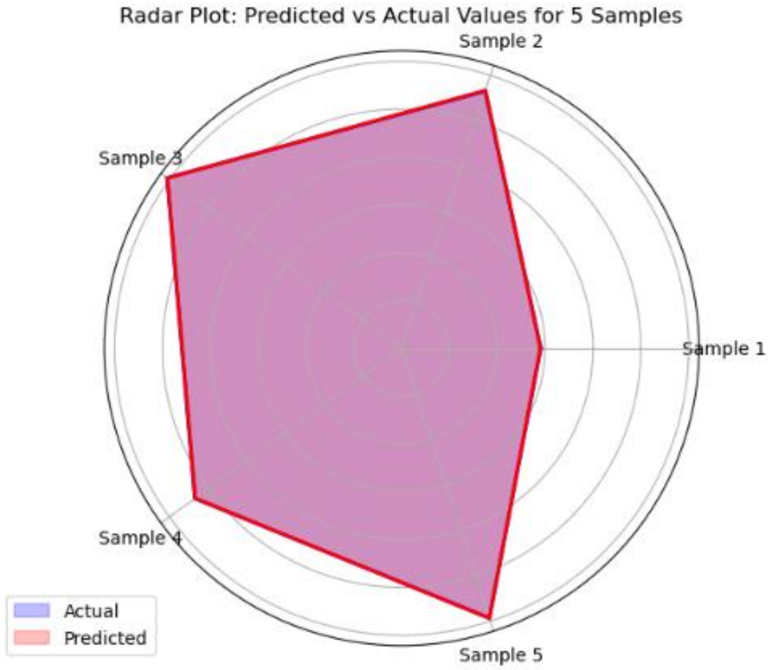

Figure 4. Actual v/s predicted values on spiral chart for random forest regressor

The Residual Plot for the Random Forest Regressor (fig. 3 and 4) further validated the model's accuracy. Most of the residuals (the difference between actual and predicted values) were clustered around zero, indicating minimal errors in predictions. While there were a few outliers with larger residuals (below -0.25), the majority of the residuals remained close to zero, suggesting that the model was able to generalize well to the test data. The Radar Plot, which compared actual and predicted values for five samples, showed near-perfect alignment between the two sets of values. The overlap of the actual and predicted areas on the radar plot highlights the strong predictive power of the Random Forest Regressor.

5.2. Decision Tree Regressor Results

The Decision Tree Regressor also exhibited remarkable performance, achieving an R^2 value of 0.9999, which was slightly higher than that of the Random Forest Regressor. The MSE was 0.0001966, and the RMSE was 0.0140, both of which were very low, indicating extremely accurate predictions. The MAE was also very low at 0.0113, suggesting that the model made only minimal errors in predicting surface roughness.

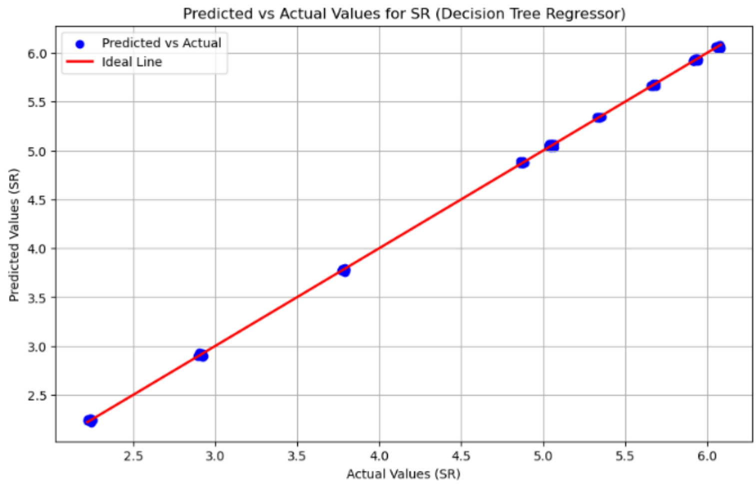

Figure 5. Actual v/s predicted values on mean line for decision tree regressor

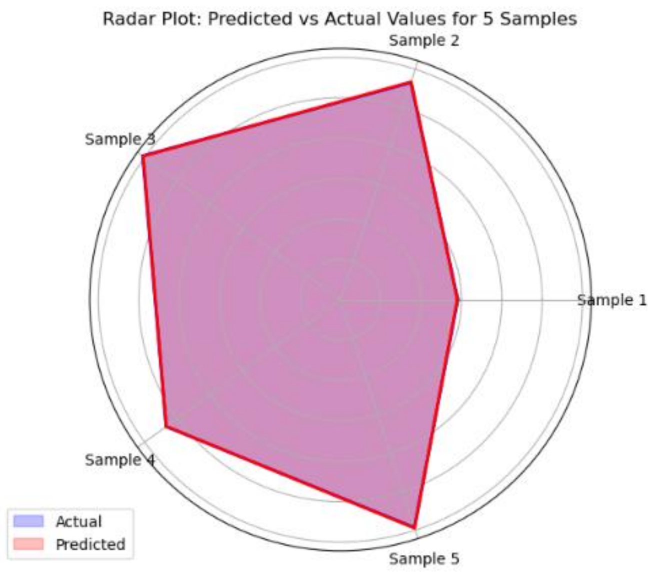

Figure 6. Actual v/s predicted values on spiral chart for decision tree regressor

The visual analysis supported these numerical results. The Predicted vs Actual Plot showed that the predicted values were almost perfectly aligned with the actual values, with very few deviations (fig. 5 and 6). Similarly, the Radar Plot comparing actual and predicted values for five samples demonstrated close alignment, reinforcing the model's predictive accuracy. In this case, the Decision Tree Regressor's predictions were nearly identical to the actual values, further highlighting its strong performance for this dataset.

5.3. Comparative Discussion

Both the Random Forest Regressor and Decision Tree Regressor exhibited outstanding performance in predicting surface roughness based on machining parameters. However, there were some differences worth noting. While the Decision Tree Regressor achieved slightly better accuracy, as indicated by its higher R^2 score and lower error metrics (MSE, RMSE, MAE), the Random Forest Regressor offers superior generalization capabilities. The Residual Plot for the Random Forest model showed a more balanced error distribution, while the Decision Tree model, although highly accurate, is more prone to overfitting, especially when applied to larger or more complex datasets. The error values and R-squared value is shown in Table 3.

Table 3

Model	R^2	MSE	RMSE	MAE
Random Forest Regressor	0.9988	0.0020	0.04487	0.0165
Decision Tree Regressor	0.9998	0.0001	0.0140	0.0112

The Random Forest Regressor, being an ensemble model, is inherently more robust and less likely to overfit compared to a single Decision Tree. This makes Random Forest a better option for applications where generalization to unseen data is critical. Despite the slightly lower accuracy of the Random Forest model in this specific dataset, its ensemble nature ensures that it handles data variability better, making it a more reliable choice for larger and more complex datasets. Summarizing both the techniques, the Random Forest Regressor and Decision Tree Regressor are highly effective at predicting surface roughness from machining parameters, achieving near-perfect accuracy. The Decision Tree Regressor slightly outperformed the Random Forest model in this particular dataset, but the Random Forest Regressor is more robust and generalizable, making it a preferable model in cases where overfitting is a concern or when dealing with more complex datasets. Both models are suitable for use in predictive modelling of machining processes, but the choice of model should depend on the specific requirements of the application, particularly in terms of the balance between accuracy and generalization.

6. Conclusion

This study explored the predictive capabilities of two machine learning models, Random Forest Regressor (RFR) and Decision Tree Regressor (DTR), in estimating surface roughness (SR) based on machining parameters: spindle speed (SS), feed rate (FR), and depth of cut (DOC). Both models demonstrated outstanding predictive accuracy, with near-perfect results in terms of R^2, MSE, RMSE, and MAE. The Decision Tree Regressor exhibited slightly better performance in this dataset, achieving an R^2 score of 0.9999 and lower error values. However, the Random Forest Regressor, while marginally less accurate, offers superior generalization capabilities due to its ensemble nature, which makes it more robust and less prone to overfitting. In practical applications, the Decision Tree Regressor can be highly effective when the focus is on obtaining the most accurate predictions for smaller, simpler datasets. On the other hand, the Random Forest Regressor is the preferred choice for more complex or larger datasets, where overfitting may pose a risk. Overall, both models are well-suited for predictive modelling in machining processes, but the choice between them should depend on the specific requirements of the task, particularly the trade-off between accuracy and generalization.

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