http://www.journalmt.com

Normalized Statistical Evaluation of Machining Parameters and Cutting Forces in Turning

Tanuj Namboodri (0000-0002-6256-7075)[1*], Csaba Felhő (0000-0003-0997-666X)[1], Ashwani Kumar (0000-0003-4099-935X)[2]
[1]Institute of Manufacturing Science, University of Miskolc, Miskolc-Egyetemváros H-3515.
E-mail: tanuj.namboodri@student.uni-miskolc.hu, csaba.felho@uni-miskolc.hu
[2]Technical Education Department, Uttar Pradesh, Kanpur 208024, India. E-mail: drashwanikumardte@gmail.com
Correspondence: tanuj.namboodri@student.uni-miskolc.hu

The investigation of cutting forces in metal cutting is of great importance for defining the effectiveness of production and its impact on product quality. Several researchers have studied the effect of cutting parameters on cutting forces through statistical analysis; however, very few studies have used data normalization. Normalization reduces the skewness in the data and increases the accuracy of the results, which can be beneficial in the modern industry where AI is being integrated with manufacturing. This study aimed to perform a statistical analysis of cutting parameters and cutting forces using log-normalization and compare the results with absolute data to check the accuracy. In addition, this study highlights the effects of cutting parameters and conditions on cutting forces. This study used a three-axis piezoelectric dynamometer to measure the cutting forces during the turning of X5CrNi18-10 steel. The results suggest that the feed is the dominant factor influencing the cutting forces during machining. As the cutting speed increased, the cutting forces decreased. The coolant helps reduce the cutting forces during the turning of austenitic stainless steel. Log normalization of the data increased the accuracy of the results. The results presented in this paper can be used to predict the cutting forces by changing the feed during the turning of chromium-nickel alloy steel.

Keywords: Statistical Analysis; Cutting Forces; Tangential Force; Log-normalization; Turning Operation.

1 Introduction

The investigation of cutting forces in metal cutting is of great importance for defining the effectiveness of production and its impact on product quality, especially in turning operations. In turning operations, the cutting forces can affect the shape and accuracy of machined parts [1]. Variations in the cutting forces can lead to deviations in the desired dimensions, thereby affecting the overall quality of the workpiece. The magnitude and stability of the cutting forces are important for achieving a high-quality surface finish [2]. Unstable or excessive cutting forces can result in poor surface quality and increased surface roughness. In addition, the cutting forces directly affect the tool wear and life [3]. Higher cutting forces can lead to increased tool wear, reducing the tool lifespan and necessitating more frequent replacement. The relationship between the cutting forces and tool wear is significant, as increased friction and cutting forces can accelerate wear, particularly flank wear, which affects the cutting-edge geometry and increases the friction component of the cutting force. To minimize the impact of cutting forces, it is necessary to understand the factors that influence the cutting forces.

Cutting forces are influenced by several factors, such as parameter selection, material properties, tool properties, and machining environment [4]. The critical factor that influences the cutting force is the material quality. Soft materials are easy to cut, as they do not exhibit any type of resistance; however, hardened steel shows resistance during machining. Harder materials require more force to cut, which can lead to higher cutting forces. Overall, this leads to a reduction in efficiency and machined product quality [5].

It can be challenging to understand the effects of machining parameters and cutting forces, as determining the individual effects can be problematic owing to several factors, such as material characteristics and machining environment. Correlation analysis is a valuable tool for identifying and quantifying the relationships between complex machining parameters, such as cutting speed, feed, and depth of cut. Also, workpiece hardness and cutting forces in the hard turning of steel [6]. Statistical methods such as Pearson's correlation and regression analyses have been used to reveal strong associations [6].

Madić et al. [7] studied the correlation between cutting parameters and cutting forces components

using an artificial neural network (ANN). They highlighted that an artificial neural network (ANN) architecture trained with Levenberg-Marquardt (LM) and Bayesian regularization (BR) algorithms on a small dataset can effectively model multiple outputs with high prediction accuracy. In this study, the absolute value of the measured cutting forces was used, and it was found that the feed and depth of cut had a greater influence on the cutting forces. Rastorguev et al. [8] studied the prediction of cutting force using ANN and neuro-fuzzy modeling. They highlighted that the normalization of the initial data is necessary to reduce various parameters to a common scale. However, it is unclear whether normalization of the outputs was involved. Hanief et al. [9] studied the modeling and prediction of cutting forces during the turning of C2300 using an ANN and regression analysis. The cutting forces increased as the feed, cutting speed, and depth of cut increased. Aziz et al. [10] investigated the modeling of cutting forces and machining parameters through statistical analysis and emphasized that depth of cut, workpiece hardness, and feed are the primary factors influencing cutting forces. Similarly, Aouici et al. [11] examined the components of cutting forces and conditions in hard turning to predict their effects on the workpiece. The study [12] analyzed the influence of cutting parameters on cutting forces and surface roughness using analysis of variance (ANOVA) and regression methods. The study [13] explored the effects of cutting parameters on surface roughness and cutting forces using ANOVA and response surface methodology (RSM) techniques. The study [14] conducted predictive analysis of surface roughness and cutting forces using machine learning algorithms. Likewise, numerous studies [4,15–21] were carried out to examine the relationship between machining parameters and cutting parameters.

However, very few studies have used data normalization to develop models. Logarithmic normalization is often used in regression analyses to linearize the relationships between variables [22]. Logarithmic normalization reduces the skewness of the machining data, making the correlation coefficient more reliable. In brief, it is crucial to establish the relationship between cutting forces and machining parameters using log-normalized data to develop a linear regression model, thereby bridging the gap in understanding the effect of cutting parameters on cutting forces during the turning of austenitic stainless steel.

In this study, a three-component piezoelectric dynamometer was used to measure the cutting forces during the turning of X5CrNi18-10 steel. The primary aim of this study was to perform a logarithmic normalization-based statistical analysis to develop a linear regression model and compare the difference between using absolute and normalized values to mark the importance of normalization. ANOVA was used to test the significance of the model. In addition, this study highlights the effects of cutting parameters, such as cutting speed, feed, and machining environment (dry and wet), on the cutting forces.

2 Material and Methods

2.1 Machine Tools

CNC turning HAAS ST-20 Y was used to perform the experiments, as shown in Fig. 1. Carbide-coated inserts DNMG150604-MF1 CP500 were used for all tests [23]. The tool nose radius was 0.4 mm, which was used for finishing and semi-finishing operations. The test length was sufficiently small that the tool wear did not affect the cutting force values. Tool holder DDJNL2525M15 with shank height (H) and breadth (B) of 25 mm was used in the experiment [23]. To ensure reliability, the inserts were changed when the machining condition was changed from dry to wet.
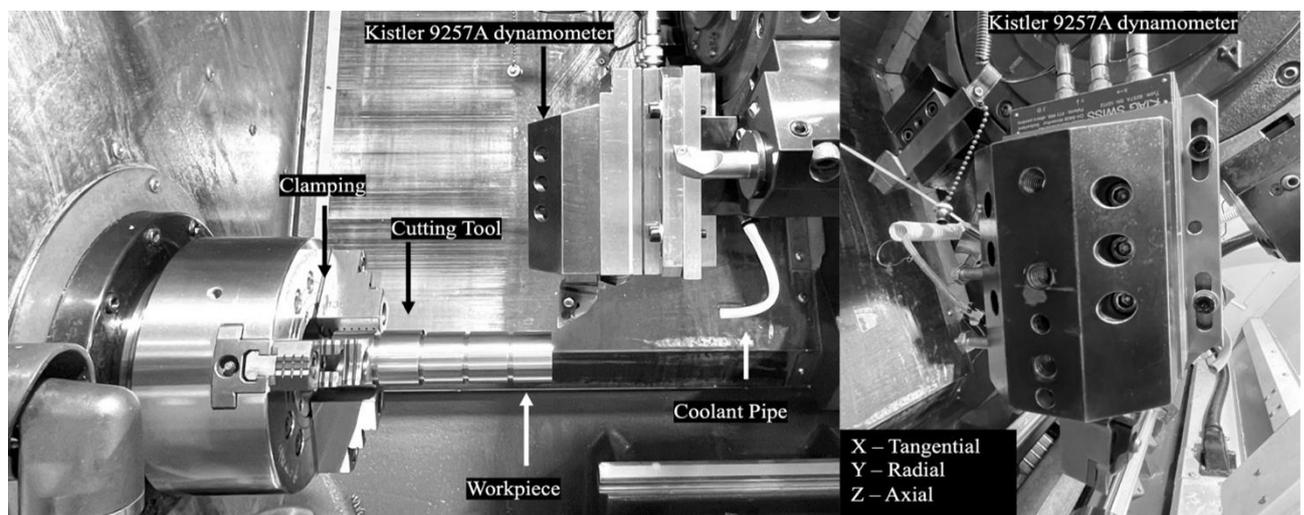
Fig. 1 *Experimental setup for analyses of cutting forces*

2.2 Workpiece Preparation

Outer diameter (OD) turning experiments were performed on austenitic stainless steel X5CrNi18-10. The mechanical properties of the material, such as its tensile strength of 500-750 MPa, hardness of 220 HB, and ductility of 35-45 percent elongation, influence the work hardening in the cutting zone. This steel is widely used in the marine and food industries because of its corrosion resistance and mechanical strength. The workpieces were cylindrical bars divided into three equal sections, each 30 mm long, with a deep groove of 5 mm separated by a 4 mm gap. These sections were used to machine the surfaces under varying machining environments. Before machining, the workpiece diameters were measured; all the specimens were Ø 45 mm. Fig. 2 shows a sketch of the workpiece used in this study.
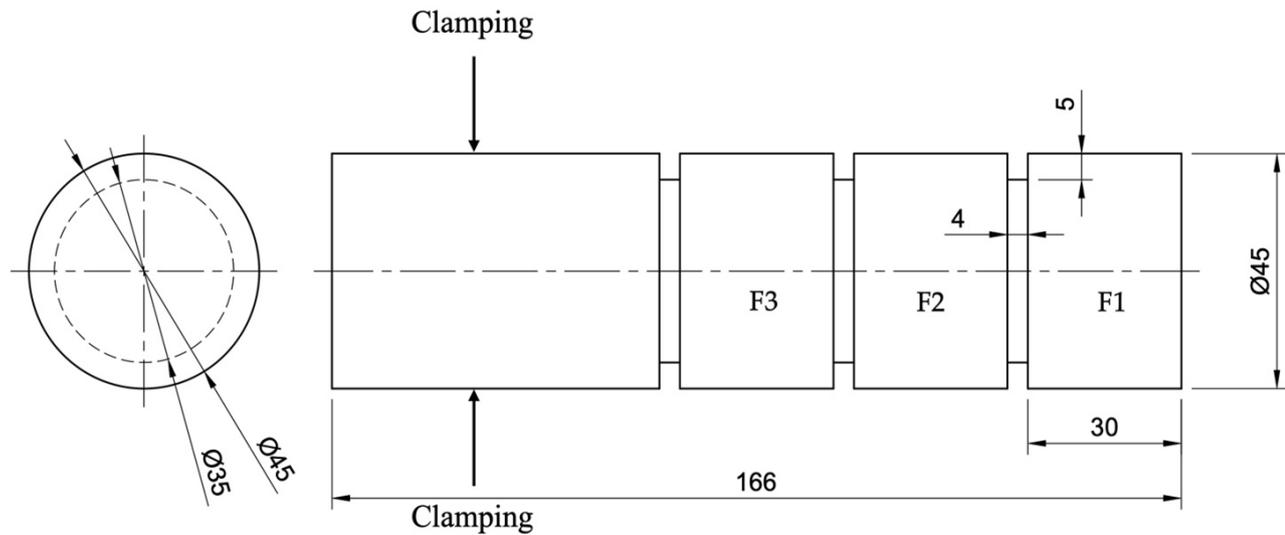

Fig. 2 *Workpiece drawing for sample preparation*

2.3 Measurement Setup

During the turning process, the cutting forces were measured using a three-component piezoelectric dynamometer from Kistler Corporation – model 9257 was mounted on the tool holder [6]. The dynamometer output was amplified using a Kistler Model 5015 A charge amplifier for the three force components F_x, F_y, and F_z, connected to a National Instruments CompactDAQ-9171 four-channel USB data acquisition unit [6]. The amplified signals from the charge amplifier were sent to the data acquisition system, converted into digital form, and transmitted to a computer, as shown in Fig. 3. The recorded cutting force data were saved in [dot]txt format and later converted into a spreadsheet for analysis.
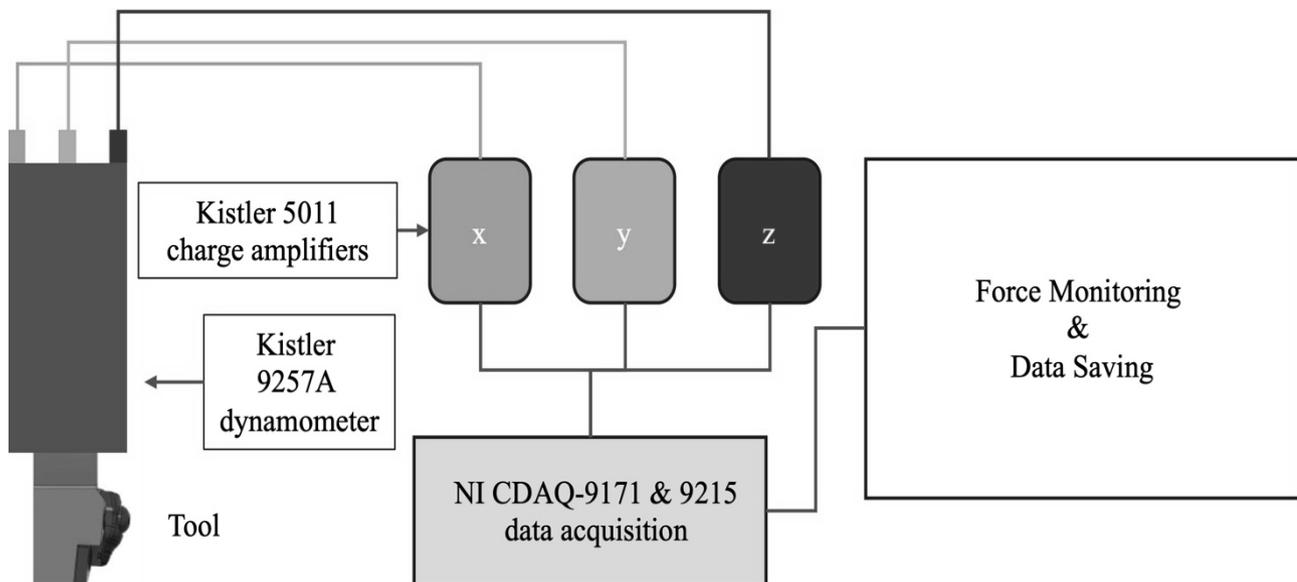

Fig. 3 *Schematic diagram of the measurement setup of the dynamometer*

2.4 Experimental Design

The machining parameters examined were the spindle speed and feed. Based on the tool insert manufacturer's specifications and previous studies [24], [6], the recommended cutting parameters were a spindle speed of up to 2000 rpm and a maximum depth of cut of 2 mm with a feed of maximum 0.4 mm/rev. In the experiments, the cutting speed (v_c) was tested at three levels: 141.4, 212.1, and 282.7 rpm [23]. The feed (f) was set at two levels: 0.1 and 0.3 mm/rev, whereas the depth of cut (a_p) was kept constant at 0.5 mm. To evaluate the influence of the machining environment, tests were conducted under dry and wet conditions. Based on the selected parameters, a full factorial design of the experiment was created. Tab. 1 provides a brief overview of the variations in the cutting parameters for the force measurements.

Tab. 1 *Experimental design showing variations in cutting parameters*

Force measurement no.	Cutting speed	Feed	Environment
	v_c (m/min)	f (mm/rev)	
F1	141.4	0.1	Dry
F2	212.1	0.3	Dry
F3	282.7	0.1	Dry
F4	141.4	0.3	Dry
F5	212.1	0.1	Dry
F6	282.7	0.3	Dry
F7	141.4	0.1	Wet
F8	212.1	0.3	Wet
F9	282.7	0.1	Wet
F10	141.4	0.3	Wet
F11	212.1	0.1	Wet
F12	282.7	0.3	Wet

2.5 Data Processing and Statistical Analysis

The sampling frequency was set to 5 kHz. The data were organized in a spreadsheet and processed using Origin Pro 2025a academic license software. Each file consisted of the data of three measurements, which were further analyzed through graphics first and then divided into separate spreadsheets for further analysis.

After the data were divided into separate measurements, the RMS value of each component was calculated for each measurement using Equation 1.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i)^2} \qquad (1)$$

Fig. 4 shows the components of the cutting forces during the turning operation. $\overrightarrow{F_c}$ is the tangential force, or the most significant force responsible for the machining operation. $\overrightarrow{F_p}$ or $\overrightarrow{F_r}$ is the radial force, and $\overrightarrow{F_f}$ is the feed force (also called the axial force) during the machining operation. The resultant force was the combination of the cutting, feed, and tangential forces.

After calculating the RMS, the resultant cutting force RMS was computed using Equation 2.

$$\overrightarrow{F_R} = \sqrt{F_C^2 + F_r^2 + F_f^2} \qquad (2)$$

The resultant cutting force RMS for each measurement was normalized using logarithmic normalization for further analysis.
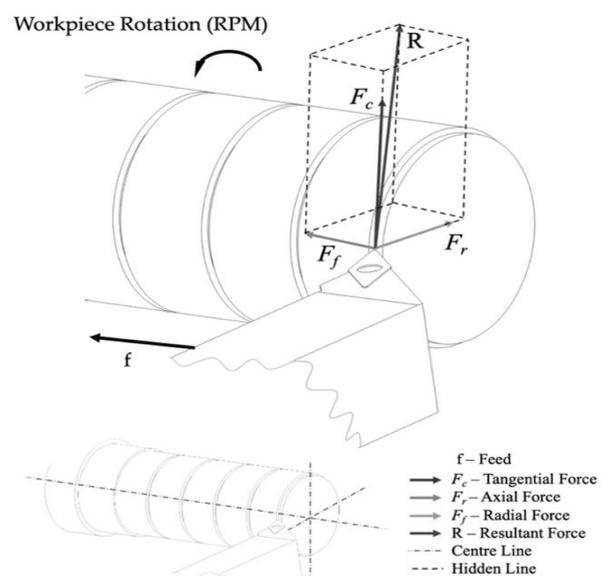
Fig. 4 *Cutting force components in turning operation (adapted from [6])*

3 Results and Discussion

Logarithmic normalization was performed on the cutting parameters, cutting forces, and resultant cutting force RMS. Tab. 2 presents the logarithmic calculations for the variables. No. in Tab. 2 represents the force measurement. ln (v_c) represents the logarithmic normalization of the cutting speed. Where, ln (f) represents the logarithmic normalization of the feed, ln $(\overrightarrow{F_c})$, ln $(\overrightarrow{F_r})$, and ln $(\overrightarrow{F_f})$ represent the logarithmic normalizations of the cutting forces in the x-, y-, and z-directions, respectively, ln $(\overrightarrow{F_R})$ is the logarithmic normalization of the resultant cutting force. In the next step, Pearson's correlation analysis was used to determine the correlation between the machining parameters and cutting forces, and further comparison was performed.

Tab. 2 *Cutting parameters and cutting force values (log-normalized)*

No.	ln (v_c)	ln (f)	ln $(\overrightarrow{F_c})$	ln $(\overrightarrow{F_r})$	ln $(\overrightarrow{F_f})$	ln $(\overrightarrow{F_R})$
F1	4.95	-2.30	5.08	4.58	2.87	5.243
F2	5.36	-1.20	5.93	4.99	4.57	6.032
F3	5.64	-2.30	5.07	4.56	3.02	5.226
F4	4.95	-1.20	5.94	5.10	4.50	6.047
F5	5.36	-2.30	5.08	4.59	2.98	5.244
F6	5.64	-1.20	5.82	4.94	4.46	5.927
F7	4.95	-2.30	4.97	4.56	2.73	5.154
F8	5.36	-1.20	5.76	4.95	4.35	5.873
F9	5.64	-2.30	4.94	4.59	2.64	5.149
F10	4.95	-1.20	5.80	5.11	5.11	5.932
F11	5.36	-2.30	4.98	4.61	2.70	5.174
F12	5.64	-1.20	5.69	4.91	4.29	5.808

3.1 Effect of machining parameters and conditions on $\overrightarrow{F_R}$

Fig. 5 shows a systematic investigation of the machining parameters, cutting speed, feed, and influence of the machining environment on the resultant cutting force. The axes in Fig. 5 represent ln $(\overrightarrow{F_R})$ RMS. The X-axis represents the experiment number or force measurement number [Refer to Tab. 1 and 2]. The header of the chart defines the machining parameters. The first row defines the feed with green and blue at 0.1 mm/rev and 0.3 mm/rev, respectively. The second row specifies the cutting speed with orange, pink, and red at 141.4 m/min, 212.1 m/min, and 282.7 m/min, respectively. The bars in the chart represent the cutting forces in dry and wet machining environments. The brown and grey bars represent the cutting forces measured under dry and wet machining environments, respectively.

The analysis of the cutting forces and parameters suggested that the feed had the most pronounced effect on the cutting forces. Comparing the groups with the same cutting speed but different feeds, it can be observed that as the feed increased, the cutting forces also increased. This is a well-established relationship in machining processes. As the feed increased, the cross-sectional area of the uncut chip increased, requiring a greater force. By adjusting the feed, the operator can manage the cutting forces.

To visualize the effect of the cutting speed is more complex; however, it can be seen that for the same feed under a dry machining environment, the cutting force remained the same at 141.4 m/min and 212.1 m/min; however, it slightly decreased at 282.7 m/min. In the wet machining environment, the results were similar at 141.4 m/min and 282.7 m/min, and a slight increase was observed at 212.1 m/min. During machining, the generation of higher temperatures in the shear zones at higher speeds thermally softens the workpiece material, making it easier to cut.

The effect of the machining environment on the cutting forces can be observed in this chart. Using the same machining parameters, the cutting forces decreased when the coolant was used. The use of coolant reduces friction during the tool-chip interface and consequently reduces the cutting force. Fig. 5 presents the critical interactions between the machining parameters and highlights the importance of selecting the parameters and environmental strategy to minimize the cutting force.

To statistically understand the results, a correlation analysis was performed between the machining parameters and the cutting forces.
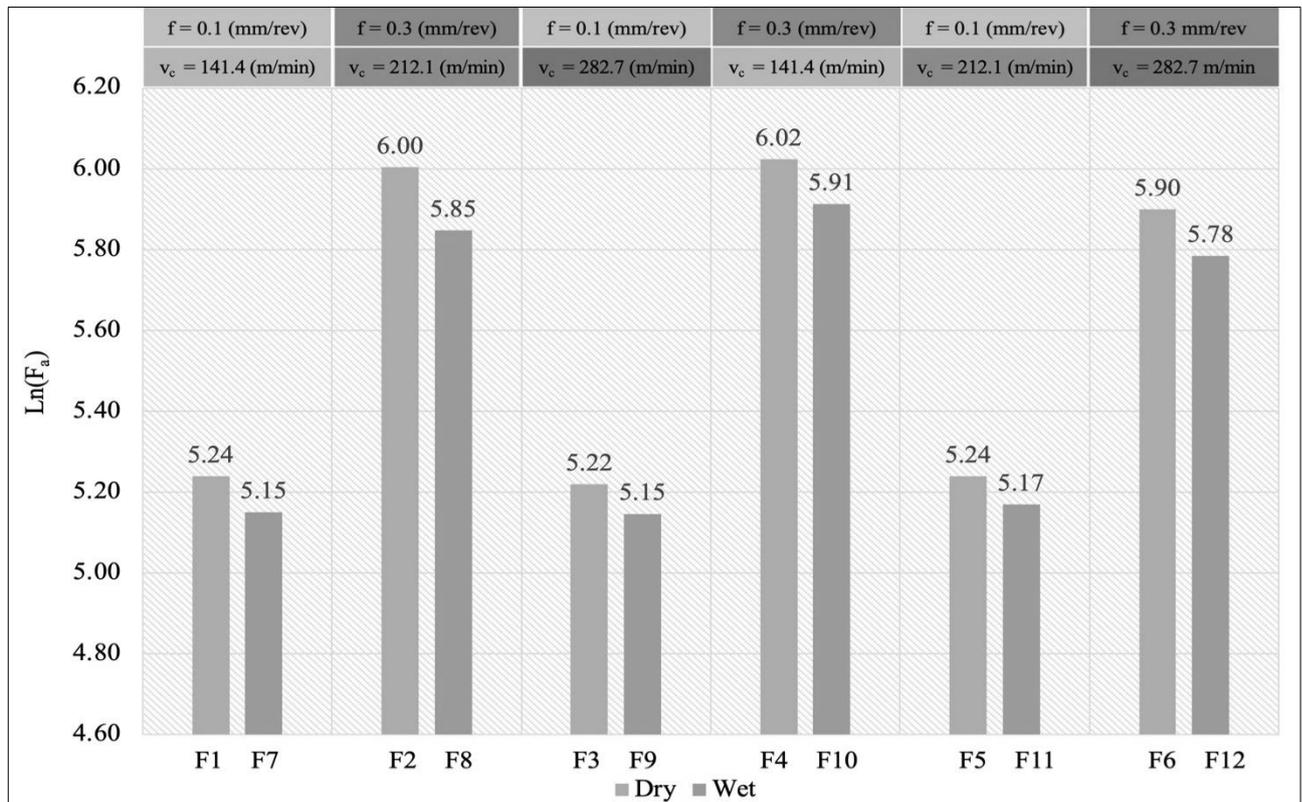
Fig. 5 *The main cutting force under varying cutting speed, feed, and machining environment*

3.2 Correlation analysis of cutting parameters and cutting forces (Absolute)

From Tab. 3, it can be seen that the cutting speed v_c shows weak and negative correlations with all force components, which suggests that the cutting speed does not affect the cutting forces. This indicates that an increase in the cutting speed slightly reduces the cutting forces; however, the relationship is not statistically significant.

Tab. 3 *Correlation analysis v_c, f, $\overrightarrow{F_c}$, $\overrightarrow{F_r}$, $\overrightarrow{F_f}$, and $\overrightarrow{F_R}$*

Variables	Force RMS (X) $\overrightarrow{F_c}$	Force RMS (Y) $\overrightarrow{F_r}$	Force RMS (Z) $\overrightarrow{F_f}$	Resultant Force RMS $\overrightarrow{F_R}$
Cutting speed vc (m/min)	-0.088	-0.201	-0.21	-0.096
Feed f (mm/rev)	0.973**	0.949**	0.879**	0.974**

In contrast, the feed (f) showed a strong positive correlation with all the components of the forces and the resultant cutting force RMS. This indicates that as the feed increases, the forces increase significantly, mainly $\overrightarrow{F_c}$, with a correlation coefficient (r) of 0.973.

3.3 Correlation analysis of cutting parameters and cutting forces (Log-Normalized)

Tab. 4 presents the correlation coefficients between the variables. It can be observed that after the log-transformation, the results are quite similar to the absolute value. $\ln(v_c)$ was negatively correlated with $\ln(\overrightarrow{F_c})$, $\ln(\overrightarrow{F_r})$, $\ln(\overrightarrow{F_f})$, and $\ln(\overrightarrow{F_R})$. However, the correlation coefficient value changed, but it was not significant.

$\ln(f)$ showed a strong positive correlation with the component of forces and the resultant cutting force. The correlation coefficient between $\ln(f)$ and $\ln(\overrightarrow{F_R})$ was 0.985.

Tab. 4 *Correlation analysis of $\ln(v_c)$, $\ln(f)$, $\ln(\overrightarrow{F_c})$, $\ln(\overrightarrow{F_r})$, $\ln(\overrightarrow{F_f})$, and $\ln(\overrightarrow{F_R})$*

Variables	$\ln(\overrightarrow{F_c})$	$\ln(\overrightarrow{F_r})$	$\ln(\overrightarrow{F_f})$,	$\ln(\overrightarrow{F_R})$
$\ln(v_c)$	-0.065	-0.164	-0.094	-0.066
$\ln(f)$	0.983**	0.965**	0.970**	0.985**

In both the absolute and log-transformed data, the feed was the dominant factor affecting the cutting forces. The mechanics of chip formation can explain the strong influence of the feed on the cutting forces. As the Feed increased, the uncut chip thickness and chip cross-sectional area also increased. Because the cutting forces are proportional to the chip thickness, which is related to the feed, higher feed values result in significantly larger cutting forces. The cutting speed showed a weak negative correlation with all cutting force components. This indicates that the influence of the cutting forces is minimal compared to the feed rate. To understand the significance of the cutting speed on the cutting forces, the estimated marginal means were computed.

3.4 Estimated Marginal Means of Cutting Speed

In the previous section on correlation analyses, it can be seen that the cutting speed shows a negative correlation with the cutting forces; however, this is not fully representative of a real machining environment. To understand the actual behavior of the cutting speed of the cutting forces $\vec{F_c}$, $\vec{F_r}$, and $\vec{F_f}$, the estimated marginal means plot was plotted. This method is suitable for visualizing the influence of the cutting speed on the cutting forces. This provides a more reliable representation of the factor effects.

The estimated marginal mean plots illustrate the influence of the cutting speed on the cutting forces. An inverse relationship between the cutting speed and cutting force components $\vec{F_c}$, $\vec{F_r}$, and $\vec{F_f}$ was observed. The reduction in the cutting force components can be observed with increasing speed. This behavior can be justified by the increase in speed, which leads to thermal softening of the material. The correlation analysis showed a weak linear relationship, suggesting that the cutting speed has a secondary influence compared to the feed.
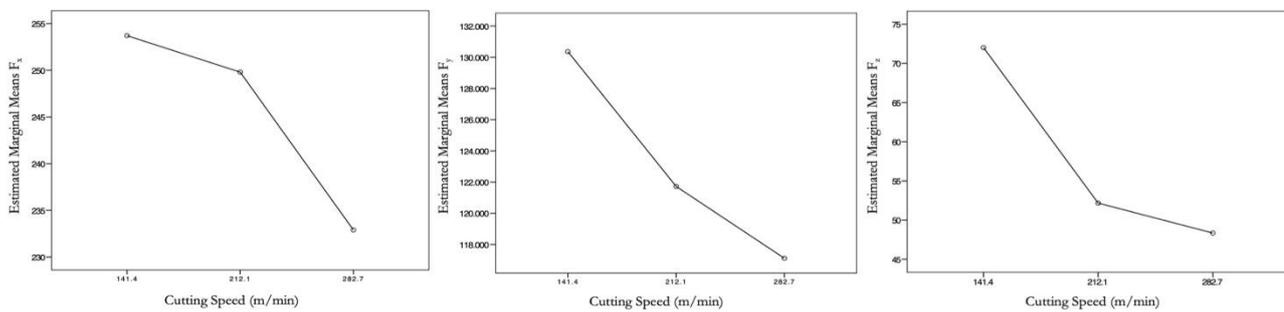

Fig. 6 *The influence of cutting speed on cutting force components*

3.5 Curve estimation and ANOVA of Feed

The curve estimation for the linear regression analysis was performed between the machining parameters, specifically the feed and resultant cutting force RMS, with and without normalization. The curve estimation helps to understand the relation between the independent variable (x) and the dependent variable (y). The coefficient of determination (R^2) was evaluated for both models, indicating the proportion of variation in y that was accounted for by x. Analysis of variance was used to test whether the regression model significantly explained the variation in the dependent variable compared to using the mean.
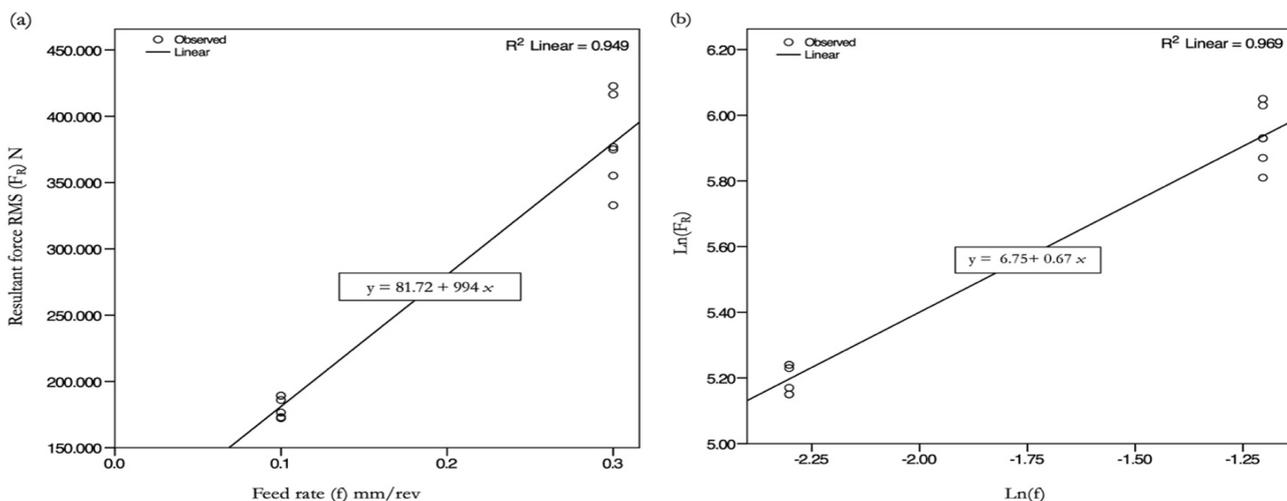

Fig. 7 *Linear regression line for (a) $\vec{F_R}$ and f, and (b) ln ($\vec{F_R}$) and ln (f)*

Fig. 7(a) shows the linear regression between $\overrightarrow{F_R}$ and f, where the $\overrightarrow{F_R}$ resultant cutting force RMS is in Newtons (N), and the feed is in millimeters per revolution (mm/rev). The graph provides a linear regression line, where the observed data are represented by circles. It can be noticed that the data points are scattered away from the line for Feed 0.3 mm/rev. For a feed of 0.1 mm/rev, the data points were very close to the line.

The R^2 value for the linear regression analysis performed between $\overrightarrow{F_R}$ and f was 0.948, and the regression line is expressed by Equation 3.

$$y = 81.72 + 994\,x \tag{3}$$

The R^2 value of 0.948 indicates a strong linear correlation, meaning that the feed explains 94.8% of the force variation. The ANOVA p-value of 0.00 confirms that the model is statistically significant, as shown in Tab. 5.

Tab. 5 *ANOVA results of $\overrightarrow{F_R}$ and f*

ANOVA – $\overrightarrow{F_R}$ and f					
	Sum of Squares	df	Mean Square	F	p
Regression	118516.812	1	118516.812	186.5	0.00
Residual	6352.094	10	635.209		
Total	124868.905	11			
The independent variable is Log Feed f (mm/rev).					

In machining, a linear increase indicates that as the feed increases, the tool engages a greater volume of material per revolution, resulting in higher cutting forces. It was also observed in the previous study [6]. Fig. 7(b) shows the linear regression between ln $(\overrightarrow{F_R})$ and ln (f).

The R^2 for the linear regression analysis performed between ln $(\overrightarrow{F_R})$ and ln (f) is represented by Equation 4.

$$y = 6.75 + 0.67\,x \tag{4}$$

The R^2 value of 0.968 indicates a strong linear correlation, suggesting that the feed explains 96.8% of the variation in force data. The ANOVA results are presented in Tab. 6. This indicates that the model is significant. This correlation was not coincidental.

Tab. 6 *ANOVA results of ln $(\overrightarrow{F_R})$ and ln (f)*

ANOVA – ln $(\overrightarrow{F_R})$ and ln (f)					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.643	1	1.643	315.5	0.00
Residual	0.052	10	0.005		
Total	1.695	11			
The independent variable is ln (f).					

3.6 Comparison with and without log-normalization

The correlation analysis showed a notable improvement in accuracy after logarithmic transformation. The correlation coefficient increased for the feed influence on the cutting parameters. The $\overrightarrow{F_c}$ showed the increment of 1 percent, $\overrightarrow{F_r}$ showed the increment of around 1.7 percent, and $\overrightarrow{F_f}$ showed the increment of 10.4 percent. The increase in the correlation coefficient indicates that the relationship between the feed and feed force became much stronger and clearer after applying the log transformation. Log normalization reduced the data scatter and captured the actual dependence of the feed force on the feed.

In curve estimation, both models were significant, but the model with normalization fit the data better than the model without normalization. It also provides a minor residual error, indicating that the predictions are more reliable. The linear regression model of data with a logarithmic transformation showed better results than that without data normalization.

The effect of log normalization was to determine the model behavior. Log normalization linearizes the nonlinear relationship, which is common in machining processes. After normalization, the R^2 increased by two percent, showing an improvement. Both models establish that the feed is a strong dominating factor in the cutting forces during the turning operation. The linear regression line describes the trend in process monitoring. The proposed normalized model could lead to more precise control strategies in automated systems.

4 Conclusion

This study focused on examining the effect of machining parameters on cutting forces during the turning of chromium-nickel alloy steel using log-normalization and evaluating its impact on prediction accuracy. The conclusions derived from this study are as follows:

- Feed is the most significant factor affecting the cutting force during machining. This statement can be supported by a correlation analysis.

- The cutting speed has an inverse relationship with the cutting forces; as the cutting speed increases, the cutting forces decrease. This can be seen in the estimated marginal means plot.

- The combination of a lower feed and higher cutting speed can result in lower cutting forces during turning.

- The coolant helps reduce the cutting forces during the turning of chromium-nickel alloy steel.

- Correlation analysis suggests that the cutting speed has a secondary influence on the cutting forces in the turning of chromium-nickel alloy steel; however, the feed shows a strong positive correlation with $r = 0.974$ without normalization and $r = 0.985$ with normalization.

- The R^2 of 0.968 suggests that with logarithmic normalization, 96.8 percent of the force variation is explained by the feed, and without logarithmic normalization, the feed explains 94.8 percent of the force variation.

- Log-normalization increased the accuracy of the resultant cutting force model by two percent, which can be used to predict the cutting forces in an automated system. The results demonstrate the increased accuracy of the results with log-normalization.

This research can be applied to the prediction of cutting forces during the turning of X5CrNi18-10 steel and to develop an AI model to predict the cutting forces.

Funding

References

[1] SZTANKOVICS, I., EL, M. W. Preliminary study on the cutting force and shape error in turning of X5CrNi18-10 shafts with small feed. *Journal of Production Engineering*. 2024, vol. 27. DOI: 10.24867/JPE-2024-02-021.

[2] ÖZDEMIR, M., KAYA, M. T., AKYILDIZ, H. K. Analysis of surface roughness and cutting forces in hard turning of 42CrMo4 steel using Taguchi and RSM method. *Mechanika*. 2020, vol. 26, pp. 231–241. DOI: 10.5755/j01.mech.26.3.23600.

[3] KHAMEL, S., OUELAA, N., BOUACHA, K. Analysis and prediction of tool wear, surface roughness, and cutting forces in hard turning with CBN tool. *Journal of Mechanical Science and Technology*. 2012, vol. 26, pp. 3605–3616. DOI: 10.1007/s12206-012-0853-1.

[4] SUJUAN, W., TAO, Z., WENPING, D., ZHANWEN, S., TO, S. Analytical modeling and prediction of cutting forces in orthogonal turning: a review. *International Journal of Advanced Manufacturing Technology*. 2022, vol. 119, pp. 1407–1434. DOI: 10.1007/s00170-021-08114-y.

[5] TANG, L., CHENG, Z., HUANG, J., GAO, C., CHANG, W. Empirical models for cutting forces in finish dry hard turning of hardened tool steel at different hardness levels. *International Journal of Advanced Manufacturing Technology*. 2015, vol. 76, pp. 691–703. DOI: 10.1007/s00170-014-6291-8.

[6] FELHŐ, C., NAMBOODRI, T. Statistical Analysis of Cutting Force and Vibration in Turning X5CrNi18-10 Steel. *Applied Sciences*. 2024, vol. 15, p. 54. DOI: 10.3390/APP15010054.

[7] MADIĆ, M., RADOVANOVIĆ, M. Modeling and analysis of correlations between cutting parameters and cutting force components in turning AISI 1043 steel using ANN. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*. 2013, vol. 35, pp. 111–121. DOI: 10.1007/s43430-013-0012-3.

[8] RASTORGUEV, D. A., SEVASTYANOV, A. A. Prediction of cutting force during hard turning of 105WCr6 steel using artificial neural network and neuro-fuzzy modeling. *IOP*

Conference Series: Materials Science and Engineering. 2020, vol. 734. DOI: 10.1088/1757-899X/734/1/012067.

[9] HANIEF, M., WANI, M. F., CHAROO, M. S. Modeling and prediction of cutting forces during the turning of red brass (C23000) using ANN and regression analysis. *Engineering Science and Technology, an International Journal*. 2017, vol. 20, pp. 1220–1226. DOI: 10.1016/j.jestch.2016.10.019.

[10] AZIZI, M. W., BELHADI, S., YALLESE, M. A., MABROUKI, T., RIGAL, J. F. Surface roughness and cutting forces modeling for optimization of machining condition in finish hard turning of AISI 52100 steel. *Journal of Mechanical Science and Technology*. 2012, vol. 26, pp. 4105–4114. DOI: 10.1007/s12206-012-0885-6.

[11] AOUICI, H., YALLESE, M. A., CHAOUI, K., MABROUKI, T., RIGAL, J. F. Analysis of surface roughness and cutting force components in hard turning with CBN tool: Prediction model and cutting conditions optimization. *Measurement*. 2012, vol. 45, pp. 344–353. DOI: 10.1016/j.measurement.2011.11.011.

[12] BARTARYA, G., CHOUDHURY, S. K. Effect of cutting parameters on cutting force and surface roughness during finish hard turning AISI52100 grade steel. *Procedia CIRP*. 2012, vol. 1, pp. 651–656. DOI: 10.1016/j.procir.2012.04.116.

[13] AOUICI, H., YALLESE, M. A., BELBAH, A., AMEUR, M. F., ELBAH, M. Experimental investigation of cutting parameters influence on surface roughness and cutting forces in hard turning of X38CrMoV5-1 with CBN tool. Sadhana 38, 429–445 (2013). https://doi.org/10.1007/s12046-013-0147-z

[14] KUMAR, R., RAFIGHI, M., ÖZDEMIR, M., ŞAHINOĞLU, A., KULSHRESHTA, A., SINGH, J., et al. Modeling and optimization of hard turning: predictive analysis of surface roughness and cutting forces in AISI 52100 steel using machine learning. *International Journal on Interactive Design and Manufacturing*. 2025, vol. 19, pp. 5749–5778. DOI: 10.1007/s12008-024-02166-6.

[15] BALWAN, V. R., DABADE, B., WANKHADE, L. Influence of hard turning parameters on cutting forces of EN 353 steel. *Materials Today: Proceedings*. 2022, vol. 63, pp. 149–156. DOI: 10.1016/j.matpr.2022.02.425.

[16] KORKMAZ, M. E., YAŞAR, N., GÜNAY, M. Numerical and experimental investigation of cutting forces in turning of Nimonic 80A superalloy. *Engineering Science and Technology, an International Journal*. 2020, vol. 23, pp. 664–673. DOI: 10.1016/j.jestch.2020.02.001.

[17] LALWANI, D. I., MEHTA, N. K., JAIN, P. K. Experimental investigations of cutting parameters influence on cutting forces and surface roughness in finish hard turning of MDN250 steel. *Journal of Materials Processing Technology*. 2008, vol. 206, pp. 167–179. DOI: 10.1016/j.jmatprotec.2007.12.018.

[18] BİNALİ, R., KUNTOĞLU, M. Evaluation of Machining Parameters Affecting Cutting Forces in Dry Turning of GGG50 Ductile Cast Iron. *Türk Doğa ve Fen Dergisi*. 2023, vol. 12, pp. 55–60. DOI: 10.46810/tdfd.1210013.

[19] DUBOVSKA, R., MAJERIK, J. Experimental Investigation and Analysis of Cutting Forces When Machining X5CrNi18-10 Stainless Steel. 2015;15(3):322-329. doi: 10.21062/ujep/x.2015/a/1213-2489/MT/15/3/322.

[20] KAROLCZAK, P. Analysis of Cutting Forces with Application of the Discrete Wavelet Transform in Titanium Ti6Al4V Turning. *Manufacturing Technology*. 2023, vol. 23. DOI: 10.21062/mft.2023.062.

[21] SLABEJOVÁ, S., ŠAJGALÍK, M., TIMKO, P., KOZOVÝ, P., NOVÁK, M., CEDZO, M. Analysis of Cutting Forces during Machining with Additive-Produced Milling Head. *Manufacturing Technology*. 2023, vol. 23, pp. 254–259. DOI: 10.21062/MFT.2023.020.

[22] DAMBOLENA, I. G., ERIKSEN, S. E., KOPCSO, D. P. Logarithmic Transformations in Regression: Do You Transform Back Correctly? *PRIMUS*. 2009, vol. 19, pp. 280–295. DOI: 10.1080/10511970802234976.

[23] NAMBOODRI, T., FELHŐ, C., SZTANKOVICS, I. Early Signs of Tool Damage in Dry and Wet Turning of Chromium–Nickel Alloy Steel. *J (Basel)*. 2025, vol. 8, p. 28. DOI: 10.3390/j8030028.

[24] SECO TOOLS. *Official Website*. [online]. [Accessed 01 November 2025]. Available from: https://www.secotools.com/article.