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Forecasting the Surface Quality in the Machining Process of C35E Steel

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Abstract: Considered an important measurement parameter in the machining industry, surface roughness has a fundamental role in ensuring the quality of the final product. In turning operations, existing approaches to predicting surface quality rely heavily on factors related to tool-workpiece interaction, heat, and material. The objective of this research is to create a forecasting model that will help analyze the effect of the rake angle on surface quality when machining C35E steel. Taguchi's factorial design methodology is used in the experimental design. The parameters selected for this study are cutting speed, cutting depth, feed rate, and angle of attack. Using a conventional lathe and a P25 carbide tool, a set of 30 experimental data on C35E steel was used in this research. In order to evaluate surface roughness during the turning process and compare the experimental results with the predicted results, a linear regression model is used. To determine the accuracy of the predicted values, the coefficient of determination, the regression graph, and the mean square error were used. This research then presents a learning model that can predict surface roughness by mainly modifying the angle of attack when machining C35E steel. The ideal choice of this angle will improve the efficiency of turning C35E steel and increase the quality of the finished components. The application of the model thus developed demonstrates its reliability, as the discrepancy between the experimental and predicted results is negligible.

Keywords: *Roughness, Machining, Linear Regression, Angle of Attack.*

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I. INTRODUCTION

The contact surface of parts that perform relative movements greatly influences the efficiency of mechanical power transmission. Turning is one of the most widely used machining processes in the manufacturing industry for producing precision cylindrical parts. (1)

Surface quality is frequently quantified by measuring surface roughness (Ra), which is mainly used as an indicator for evaluating the machined surface. Surface roughness is closely related to the fit properties, wear resistance, fatigue resistance, contact stiffness, vibration, and noise of mechanical parts, and has a significant impact on the service life and reliability of mechanical products. (2)

After machining, fine marks will remain on the surface of the workpiece, and the smaller the surface roughness, the smoother the surface. During the turning operation, many parameters directly or indirectly influence surface roughness, namely cutting parameters such as feed per revolution, rotational speed, depth of cut, and cutting forces generated at the tool-workpiece contact points, the workpiece material, and tool vibrations due to cutting phenomena. C35E steel, as a material commonly used in mechanical applications, has ideal properties for machining, but its finish quality can vary considerably depending on the machining parameters applied. In order to reduce machining costs and obtain the required surface quality of machined parts, many studies have been conducted to understand the effects of cutting conditions on surface roughness through the creation of appropriate models. Authors (3), revealed that the surface finish after machining depends mainly on machining parameters such as the principal direction angle, machining speed, feed rate, cutting depth, and tool radius, which impact the radial force and surface roughness. Authors (3), analyzed surface quality using

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neural networks to examine cutting temperature during the turning of XC48 steel with a carbide tool, taking into account cutting speed, feed rate, and depth of cut. Examination of the variance for roughness indicates that feed and radius exert the most significant influence, while for force, depth of cut and feed have the greatest impact.(5)

Author (6)**,** used response surface methodology (RSM) and analysis of variance (ANOVA) to develop mathematical models to predict and identify the best cutting conditions, gray relational analysis (GRA) and desirability function were used to reduce surface roughness and tangential vibrations (Vtng). Others researchers compared various regression analysis and artificial neural networks to evaluate surface roughness.(7)

The tuned neuro-fuzzy inference systems and a neural network employed to improve surface quality during selective laser melting of 316L stainless steel.(8)

As for (9), their results demonstrated that the use of artificial intelligence once again proves its ability to manage complex relationships. The roughness observed after machining with a blunt tool can be evaluated or modeled using parametric CAD software.(10)

The prediction of the surface roughness parameter can be used by a radial basis function (RBF) artificial neural network (ANN) and a Takagi - Sugeno - Kang fuzzy model .(11)

The results of (12) indicated that surface roughness is strongly influenced by the feed rate, the tool nose radius, and, additionally, the workpiece taper angle.

The application of the ANN method reveal the optimal values of the examined parameters, which represent the best combination of input technical variables leading to the best results in output economic parameters.(13)

This literature review shows that surface roughness is a key factor in characterizing surface quality and that the multiple linear regression model is also a good alternative for predicting this characteristic based on different input parameters in different machining processes. The objective of this research is to forecast the surface roughness of C35E steel during turning operations by employing a linear regression model that incorporates four input variables: cutting speed, cutting depth, feed rate, and angle of attack. To conduct this study, a series of 30 observations was collected using a conventional lathe and a P25 carbide tool. In this same process of exploring the relationships between turning parameters and surface roughness, it is imperative to determine the optimal machining conditions to ensure a high-quality surface finish.

II. MATERIALS AND METHODS

In our research, we chose to implement a Taguchi $L_{30}(3^4)$ experimental design in order to reduce the number of tests, thereby lowering costs and saving time. (14)

In this methodological plan, the variables considered are cutting speed (V_c), feed rate (V_a), cutting depth (P) and angle of attack (α). This approach is justified by the fact that a full factorial design would require 81 tests, whereas we only performed 30. Most of the experiments were conducted in the Mechanics laboratories of the University of Burundi and the Center for Studies and Research in Applied Sciences at the Higher Institute of Education (ENS) of Burundi. The tools and operating conditions used to carry out this work are explained in the following paragraphs.

- *Machine Tool*

The manufacturing work was carried out on a horizontal parallel lathe, model SNB320 (Fig 1). The lathe has a motor power of 2.5 kW, operates on a three-phase 380V power supply, and runs at a current of 20A at a frequency of 50Hz. Its spindle speed ranges from 45 to 2000 revolutions per minute. The experiments were carried out on C35E steel parts using a P25 carbide-cutting tool. The treated parts have a diameter of 50 millimeters. The machining consists of a finishing turning operation.

Fig 1 Parallel Tower SNB320

- *Tool and Tool Holder*

The geometric features of the cutting tool employed in the experiment are detailed as follows: cutting angle:12°, rake angle:7°, inclination angle:5°, cutting edge radius: 0.4 millimeters, insert thickness: 3 millimeters. The cutting tool used is the TIZIT brand carbide tool type: ISOP25S22T (Fig 2).

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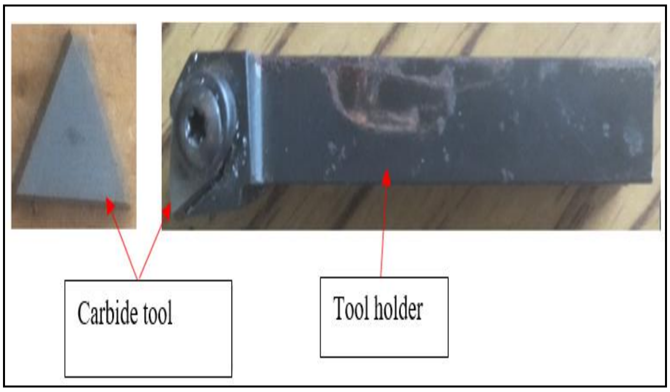

Fig 2 P25 Carbide Tool and CTGNR1212F11 Toolholder Set

➢ *Roughness Measuring Instrument*

In mechanics, surface condition is a criterion used to describe a part, indicating the function, roughness, shape, and appearance of machined surfaces. A profile comparator is used to observe or touch the outline of a surface and compare it with different reference surfaces on the comparator. There are plates called Rugotests, specific to each machining process.

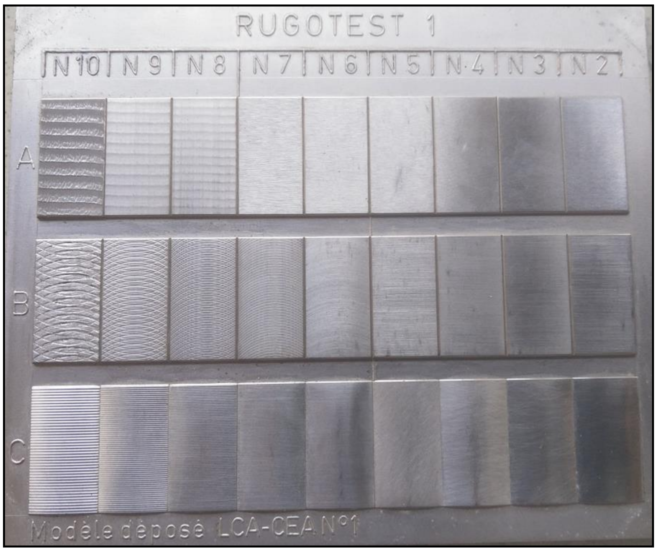

Fig 3 Rugotests (Registered Design L.C.A. – C.E.A Compliant with Standards NF/E05-ISO/DIS/2632)

These rugotests come with a sheet that specifies the values related to the standard plates for surface condition.

➢ *Characteristics of C35E Steel*

The machinability of metals is improved by modifying the structural state of the machined material, the forging, favorable inclusions, etc. For parts that perform relative movements, the roughness of their surfaces plays a key role in power transmission efficiency. The material machined in this study is a 50 mm diameter forged bar made of C35E steel according to the AFNOR standard. This carbon steel is a material that is extensively used in the production of mechanical components. Its mechanical and chemical characteristics are presented in the table below. (15)

Table 1 Mechanical and Chemical Properties of C35E Steel before Heat Treatment

Chemical composition		**Mechanical characteristics**
Elements	**%**	**For dimensions >16 to100mm**
C	0.35	Hardness (HBW):154 to 207
Mn	0.65	
Si	0.4	
P	0.03	Breaking strength (MPa) : 520 to 700
S	0.035	
Ni	0.4	
Cr	0.4	
Mo	0.1	Elongation (%): 8 to 9
Cr + Mo + Ni	Maxi: 0.63	
Fe	The rest	

➢ *Collection of Experimental Data*

In this study, the experimental design incorporates variations of four factors across three levels, as illustrated in Table 2.

Table 2 Selected Levels of Influencing Factors

Influential factors	**Levels**		
	1	**2**	**3**
Cutting speed V_c in m/min	100	150	200
feed rate V_a in mm/rev	0.05	0.1	0.15
cutting depth P in mm	0.2	0.4	0.6
Angle of attack α in degrees	10	15	20

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The data displayed in Table 3 represents the result of surface roughness measurements taken during the machining of parts.

Turning and dressing operations were taken into account to examine the quality of the machined surface in this analysis. (16) (17)

Factors influencing the Ra roughness of the machined part surface include cutting speed (V_c), feed rate (V_a), cutting depth (P) and angle of attack (α). Furthermore, 30 experiments were carried out according to a complete factorial design of $L_{30}(3^4)$ in order to assess the surface roughness, and a test matrix was developed as shown in the table below.

Table 3 Experimentally Measured Surface Roughness Values

N^0 Exp	V_c	V_a	P	α	Ra measured (in µm)
1	100	0.05	0.2	10	1.4
2	100	0.05	0.4	15	1.6
3	100	0.05	0.6	20	1.7
4	100	0.1	0.2	20	1.5
5	100	0.1	0.4	10	1.6
6	100	0.1	0.6	15	1.8
7	100	0.15	0.2	15	1.5
8	100	0.15	0.4	20	1.7
9	100	0.15	0.6	10	1.8
10	150	0.05	0.2	20	1.3
11	150	0.05	0.4	10	1.5
12	150	0.05	0.6	15	1.5
13	150	0.1	0.2	15	1.4
14	150	0.1	0.4	20	1.5
15	150	0.1	0.6	10	1.6
16	150	0.15	0.2	10	1.5
17	150	0.15	0.4	20	1.5
18	150	0.15	0.6	15	1.8
19	200	0.05	0.2	10	1.2
20	200	0.05	0.4	20	1.3
21	200	0.05	0.6	15	1.4
22	200	0.1	0.2	15	1.5
23	200	0.1	0.4	10	1.3
24	200	0.1	0.6	20	1.6
25	200	0.15	0.2	20	1.5
26	200	0.15	0.4	10	1.5
27	200	0.15	0.6	15	1.4
28	100	0.05	0.2	10	1.3
29	150	0.05	0.2	20	1.4
30	200	0.05	0.2	15	1.3

III. RESULTS OF THE STUDY

➢ *Multiple Regression Results*

In this study, a regression technique is used to model surface roughness based on input variables such as cutting speed, feed rate, cutting depth, and angle of attack. The objective of this multiple linear regression analysis is to highlight the factors and their interactions that significantly influence roughness, and to find the constant of the mathematical model. The effectiveness of the model designed is verified mainly by coefficient values and graphs generated by R (statistical data analysis software). (18)

The table presents the descriptive statistics produced.

Table 4 Descriptive Statistics

	β_i	σ	Statistics T	P-value
Intercept	1.3939560	0.0925800	15.057	4.82×10^{-14}
V_c	-0.0019198	0.0003786	-5.071	3.10×10^{-5}
Va	1.4658120	0.3748645	3.910	0.000624
P	0.5053419	0.0937161	5.392	1.36×10^{-5}
α	0.0039599	0.0037858	1.046	0.305580

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The results of the multiple linear regression reveal significant effects of several cutting parameters on the response variable studied (Ra). The intercept, estimated at 1.39, indicates a substantial and highly significant baseline value when independent variables are not present. The variable V_c has a notably negative and statistically significant impact, indicating that an increase in V_c reduces the response variable by 0.00192. Conversely, the variables V_a and P have positive and significant effects, with respective gains of 1.466 and 0.505. The angle of attack is not significant at the 5% threshold, indicating a negligible effect. These results highlight the importance of optimizing V_c, V_a, P, and α to maximize the performance of the turning process while minimizing production costs. Thus, the prediction model obtained in terms of actual factors that influence surface roughness is given in the form of the subsequent linear equation.

$$R_a = 1.394 - 0.002V_c + 1.466V_a + 0.505P + 0.004\alpha \quad (1)$$

The coefficient of determination R-squared, which assesses the quality of the established model, has a value of 0.755, meaning that 75.5% of the variance in roughness is explained by this model.

The adjusted R-squared value indicates that 71.6% of all variability is accounted for by the model after taking into account the significant factors.

➢ *Residue Analysis*

In this analysis, the P-P (probability-probability) plot helps us evaluate the effectiveness of our regression model and identify areas for improvement. By observing different predictor factors (Vc, Va, P, α), we can see in Figure 4 how the points are scattered relative to the reference diagonal. The regression graph in Fig 4 allows us to compare the quantiles of our experimental data distribution with those of a normal distribution of the model's output values.

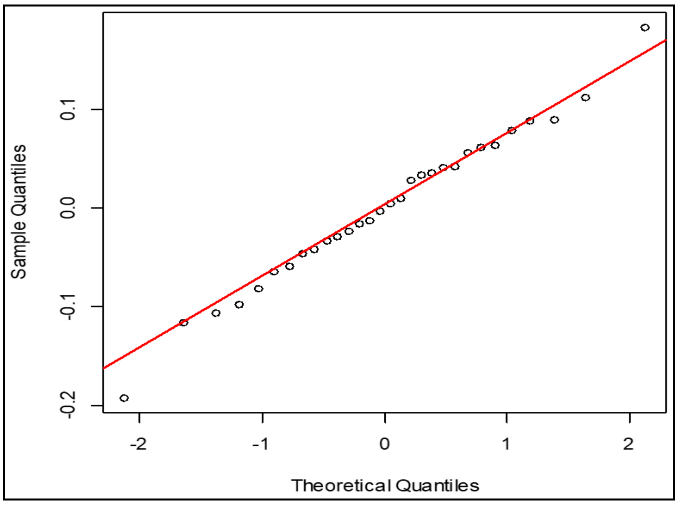

Fig 4 Regression Graph

In this figure, the points represent the surface roughness measurements for each observation across the 30 trials. Thus, Fig 8 illustrates the standard probability distribution of the residuals concerning surface roughness (Ra). It shows that the residual values generally align with the reference line, meaning that the errors are close to the regression line. This evidence is a good sign for the validity of our constructed model. Therefore, the prediction is very accurate, since the points representing the anticipated values of (Ra) closely align with the experimental data.

➢ *A Comparison of Experimental Roughness Values with Predicted Roughness Values*

On the graph in Fig 5, which compares the roughness values measured during the experiments with those estimated by a linear regression model, shows good agreement between these two sets of data. The regression model obtained proves to be a reliable tool for forecasting surface roughness. Figure 5 shows the predicted and observed surface roughness curves. These two curves are very close to each other. Hence, the observed and predicted values are almost identical. Finally, the differences obtained are very small.

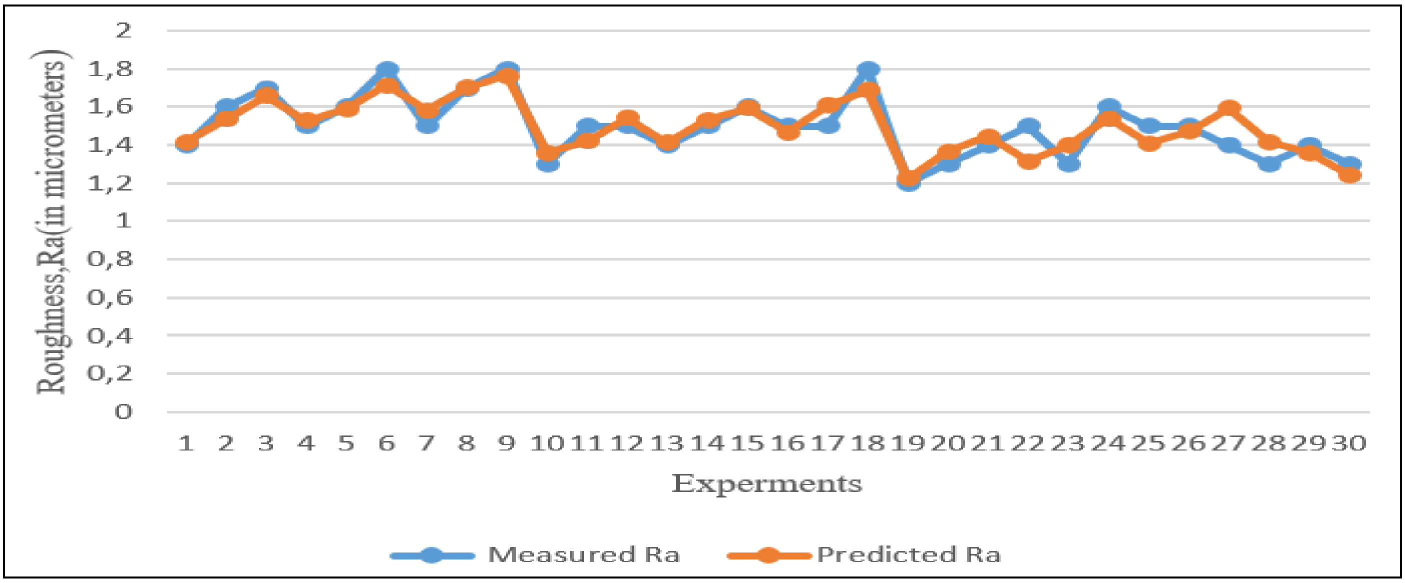

Fig 5 Comparison of Observed and Predicted Roughness Values

IV. DISCUSSION

The study developed a linear regression model aimed at predicting surface roughness during the turning process of C35E steel based on input factors such as cutting speed (V_c), feed rate (V_a), cutting depth (P) and angle of attack (α). The findings showed that a coefficient of determination (R squared) of 0.755 indicates that 75.5% of the variation in surface roughness can be explained by the model. This suggests that the model is well suited to our data. The coefficients obtained for each factor show the influence of each on roughness. Since the coefficients for feed rate and cutting depth are positive, an increase in these factors significantly affects the rise in surface roughness. Conversely, the cutting speed has a negative coefficient, signifying that an increase in this speed results in a reduction of roughness. All of this is consistent with the results of other prediction models observed in the literature. In the turning process, although this linear model has shown promising and effective results, it may not capture the full complexity of other potentially influential factors, such as cutting tool conditions, the influence of materials, and the environment. These elements may considerably influence the ultimate surface roughness and deserve additional investigation in forthcoming studies. The results of this study are relevant to the turning industry, where controlling surface roughness is important for ensuring the quality of machined parts.

V. CONCLUSION

This study uses regression analysis to develop a model aimed at predicting surface roughness during the turning process of C35E steel, taking into account input factors as cutting speed (V_c), feed rate (V_a), cutting depth (P) and angle of attack (α). With a coefficient of determination, (R squared) of 0.755, the model shows a strong correlation with the experimental data, meaning that 75.5% of the variance in roughness is explained by this model. The findings show that reducing the feed rate and cutting depth has a more beneficial effect on surface roughness, whereas the angle of attack has a minimal impact, especially in comparison to the significant threshold of 5%. However, certain variables that may also be critical, such as tooling conditions, the influence of materials, and the environment, were not considered, which could limit the scope of the results. Although the linear model obtained is effective for optimizing turning processes, it is recommended to explore other machine learning techniques to improve predictions and take into account a wider range of input factors.

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