A Surface Roughness Prediction Model for SKT4 Steel Milling

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ABSTRACT

Predicting surface roughness is critical in manufacturing processes like grinding, particularly for materials such as SKT4 steel, where a precise surface finish is imperative. Precise roughness prediction facilitates the optimization of process parameters to achieve the desired surface quality, consequently diminishing the need for supplementary operations such as grinding or polishing. This, in turn, decreases costs and lead times. This study aimed to develop a surface roughness prediction model tailored for milling SKT4 steel by designing experiments to analyze the influence of cutting parameters on surface roughness, collecting and analyzing data related to machining parameters in process modeling, and developing and validating the model. The analysis of variance (ANOVA) results highlights the significant influence of the interaction between rotational speed and cutting depth on skin roughness. The linear regression model demonstrates clear variability in the data (R^2 of approximately 99.74%) and exhibits effective predictive capabilities (pred. R^2 of approximately 83.56%). The maximum impact on skin roughness was observed at a rotational speed of 1500 RPM, a feed rate of 300 mm per minute, and a cutting depth of 0.2 mm. Increasing rotational speed leads to smoother skin, whereas higher feed rates result in decreased smoothness. However, skin roughness shows minimal fluctuation with changes in feed rate and cutting depth. The model accurately predicts the average skin roughness values.

Keywords-surface roughness; hard milling; SKT4 steel; model development

I. INTRODUCTION

The mold and die production industry widely utilizes JIS SKT4, a well-known type of hot-work die steel. Its popularity stems from its exceptional combination of properties: high toughness, elevated hardness, and excellent resistance to high-temperature fatigue. Predicting surface roughness is crucial in manufacturing and metal processing, especially in the milling of SKT4 steel. The main focus is on developing high-quality production processes, improving milling settings, and selecting appropriate cutting tools to enhance efficiency, extend tool life, reduce costs, and increase overall effectiveness. This steel is a material of choice for hot extrusion die manufacturing, casting molds, and forging dies, proving invaluable in applications demanding resilience under challenging conditions. The typical mold and die manufacturing sequence involves initial rough machining, followed by a meticulous heat treatment process, and finishes with a precision grinding operation. Despite its effectiveness, this multistep process is inherently both costly and time-consuming.

Milling is the most efficient method for mold formation [1]. However, like other machining processes, various factors influence the result. Among these, surface roughness is a popular choice for evaluation. Achieving improved surface accuracy requires first optimizing cutting conditions [2-4]. This is important because surface roughness directly affects the functionality and longevity of the final product. Several studies have been conducted on machining technology for various material types, including research on the flatness of the tool during milling [5]. Determining the optimal parameters to achieve the smoothest surface finish while minimizing surface roughness and tool wear is paramount [6, 7]. These studies encompass the development of surface roughness models and the identification of optimal cutting parameters to minimize surface roughness when milling with TiAlN+TiN-coated cutting tools [8]. The model incorporates spindle speed, feed rate, cutting depth, and tool radius as key input variables that influence the surface roughness in hard milling. Hard turning quality of the surface is greatly influenced by a variety of variables, entailing feed rate, cutting speed, geometry and radius of the cutter nose, cutting time, workpiece hardness, machine tool stability, and workpiece setup [9, 10].

Surface roughness is a key quality indicator that also governs the final stages of machining control, making it crucial for evaluating processing performance [11, 12]. Ball-end milling's mastery of free-form surfaces, including arcs, is undeniable. However, to truly unlock its potential, the hurdles of improper pathing and unpredictable influences must be overcome. By optimizing path intervals and accounting for potential disruptions, excessive residue can be eliminated, keeping those pesky scallops at bay, and achieving exquisite surface quality [13]. However, due to the inappropriate selection of path intervals and the impact of uncertain factors, excessive cutting residues ended up on the arc surface, leading to the generation of scallop heights and resulting in lower surface quality. Meanwhile, the reliability of the optimization results is critically dependent on the predictive accuracy of the model.

This study aimed to develop a surface roughness prediction model for milling SKT4 steel based on experimental data. The experiments involved varying the spindle speed, feed rate, and cutting depth and measuring the resulting surface roughness. Accurate prediction of surface roughness is highly beneficial and largely depends on cutting parameters, such as feed rate, speed, and cutting depth. However, other factors may occasionally come into play [14]. This study used a vertical milling machine with three-axis CNC control to conduct the experiments. The SKT4 steel workpiece was machined with uncoated tungsten carbide inserts with a nose radius of 5 mm. The cutting speed ranged from 100 to 500 m/min, the feed rate from 0.05 to 0.25 mm/rev, and the cutting depths from 0.1 to 0.5 mm [15].

II. EXPERIMENTAL PROCESS

The experimental research process aimed to investigate the factors that influence the surface roughness of SKT4 tool steel when machined using a vertical CNC milling machine. It is necessary to control the surface roughness (R_a) value within a specified range to ensure that the parts meet the quality standards. The average value for the absolute values of the surface profile deviations from the mean line denotes the value of the surface roughness (R_a) parameter, representing the average roughness of a surface and serving as a criterion for evaluating the surface texture. Furthermore, surface roughness (R_a) is widely used to evaluate the surface roughness of stainless-steel workpieces after the milling process [16, 17]. The dimensions of the steel samples were 50 mm in height, 100 mm in length, and 10 mm in width. Table I portrays the chemical composition and properties of the workpiece materials used in the experiments. The hardness of all steel workpieces was consistently measured at approximately 52 HRC. The Mitutoyo surftest SJ-301 was utilized in experiments. Figure 1 displays the research steps for producing the surface roughness prediction model for SKT4 steel.

TABLE I. CHEMICAL COMPOSITION OF SKT4 STEEL

C (%)	**Si** (%)	**Mn** (%)	**Cr** (%)	**Ni** (%)	**Mo** (%)	**V** (%)
0.55	0.30	0.80	1.20	1.6	0.50	0.10

Figure 2 depicts the Chevalier QP 2026-L (3-axis) vertical CNC milling machine employed to investigate the factors that affect surface roughness when machining SKT4 steel workpieces. Carbide ball nose endmills of the hard series were used, specifically model 5R×10×60L having a diameter of 10 mm. Three measurements of the surface were taken, as evidenced in Figure 3. Surface roughness was calculated in each experiment by taking the average of the three successive measurements.

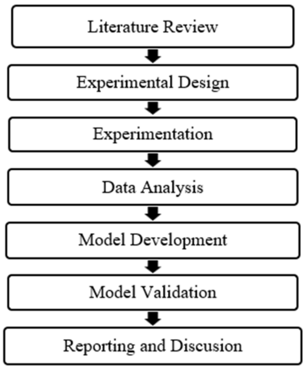

Fig. 1. Research steps.

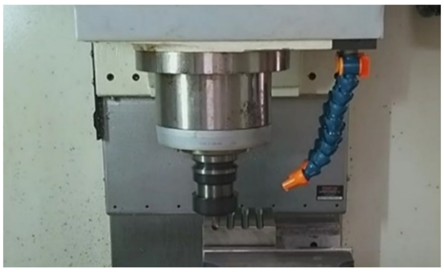

Fig. 2. Milling the experimental workpiece with an automatic milling machine.

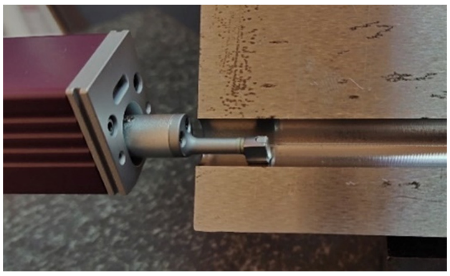

Fig. 3. Using tools to check the surface roughness of work-pieces.

The relative contributions of spindle speed, feed rate, and cutting depth to surface roughness were analyzed employing an analysis of variance (ANOVA). Adhering to the principles of the 2k full factorial design method, an experimental matrix was designed, resulting in a total of eight experiments. This study deployed the Design Of Experiments (DOE) methods and multiple regression analysis to investigate the influence of machining parameters on surface finish quality [18, 19]. To evaluate the effects of cutting parameters, each experiment involved controlled variations in spindle speed, feed rate, and cutting depth. Table II shows the configurations of the cutting parameters and their levels, coded as -1 and +1. Specific parameter values were determined based on a [20]. Table III illustrates the configuration of the milling and surface roughness processing parameters.

TABLE II. INPUT PARAMETER

Parameter	Code	Unit	Value at level	
			-1	1
Spindle Speed	N	rpm	1200	1500
Feed rate	F	m/min	300	500
Depth of cut	ap	mm	0.1	0.2

TABLE III. EXPERIMENTAL DESIGN MATRIX WITH SURFACE ROUGHNESS RESULTS

Trial no.	Code			Real value			R_a (avg) (µm)
	N	F	ap	N (rpm)	F (m/min)	ap (mm)	
1	-1	-1	-1	1200	300	0.1	1.118
2	1	-1	-1	1500	300	0.1	0.403
3	-1	1	-1	1200	300	0.2	1.679
4	1	1	-1	1500	300	0.2	0.506
5	-1	-1	1	1200	500	0.1	0.260
6	1	-1	1	1500	500	0.1	0.901
7	-1	1	1	1200	500	0.2	0.366
8	1	1	1	1500	500	0.2	0.361

III. RESULTS AND DISCUSSION

Minitab version 17 was used to analyze the experimental results. The surface roughness regression model was created utilizing Minitab, incorporating both deterministic and stochastic factors [21, 22]. The ANOVA results, noticed in Table IV, revealed a significant interaction effect between spindle speed and depth of cut on surface roughness (R_a), with a p-value of 0.047 (less than 0.05). This indicates that the combined influence of spindle speed and cutting depth has a significant impact on surface roughness. In statistical inference, a low p-value indicates that the observed effect in the mentioned source is unlikely to be due to random factors, suggesting that the relationship is statistically significant [23, 24]. This result is consistent with those of other studies [25-30].

TABLE IV. ANOVA RESULTS FOR SURFACE ROUGHNESS

Source	DF	Adj. SS	Adj. MS	F-value	p-value	Significance
Model	6	1.71507	0.285844	64.70	0.095	Not significant
Linear	3	0.61569	0.205230	46.45	0.107	Not significant
N	1	0.19594	0.195938	44.35	0.095	Not significant
F	1	0.00661	0.006613	1.50	0.436	Not significant
ap	1	0.41314	0.413140	93.51	0.066	Not significant
2-Way Interactions	3	1.09937	0.366458	82.95	0.080	Not significant
N×F	1	0.15235	0.152352	34.48	0.107	Not significant
N×ap	1	0.79632	0.796322	180.24	0.047	Significant
F×ap	1	0.15070	0.150701	34.11	0.108	Not significant
Error	1	0.00442	0.004418			
Total	7	1.71948				

The linear regression model demonstrates a high ability to explain the variability of the data with an R^2 of approximately 99.74%, with the adjusted R^2 accounting for the number of independent variables in the model at 98.20%. Furthermore, this model exhibits effective predictive capabilities with a pred. R^2 of approximately 83.56%, as manifested in Table V. The surface roughness model was constructed using (1). The ANOVA results were put into service to construct an empirical model to predict surface roughness (R_a) [33]. The development of both a quadratic and a linear model suggests an interaction between the machining parameters spindle speed, feed rate, and cutting depth [31].

TABLE V. LINEAR REGRESSION MODEL SUMMARY

S	R^2	R^2(adj)	R^2(pred)
0.0664680	99.74%	98.20%	83.56%

$$\begin{aligned} R_a = {} & 0.6992 - 0.1565 \bullet N + 0.0287 \bullet F \\ & -0.2273 \bullet ap - 0.1380 \bullet N \bullet F + 0.3155 \bullet N \bullet ap \\ & -0.1373 \bullet F \bullet ap \qquad (1) \end{aligned}$$

Figures 4-9 present the main effects and interaction plot for surface roughness fitted means. In Figure 4, the Pareto chart of the standardized effect shows that the bar graph of the joint influence factor AC (spindle speed and cutting depth) exceeds the critical line, indicating that it has a significant effect on the result. The interaction between cutting speed and axial cutting depth exerts a significant influence on surface roughness values [32].

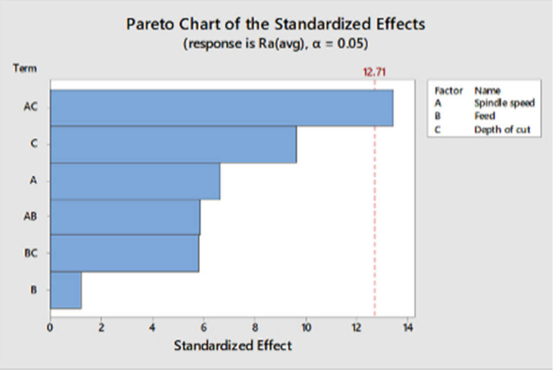

Fig. 4. Pareto chart showing the standardized effect of cutting parameters on surface roughness.

The upper left graph in Figure 5 exhibits a normal probability plot. Scattering data points around a straight line suggest that the residuals are normally distributed. The bottom left figure displays a histogram resembling a bell-shaped curve, indicating that the residuals follow a normal distribution. The upper right figure displays a scatter plot where data points are scattered above the center line without a discernible pattern. This suggests that the residuals are randomly distributed and have constant variance. The lower right figure shows a versus order plot with data points evenly scattered above and below the center line, indicating that the residuals are independent and the model is unbiased.

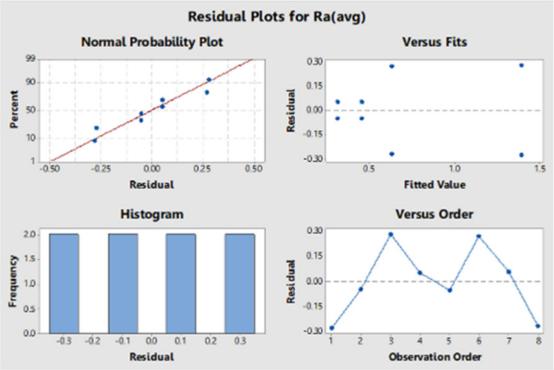

Fig. 5. Residual plot analysis for surface roughness.

In Figure 6, the interaction plot for the average surface roughness (R_a(avg)) can describe the effects of the cutting parameters as follows:

- Effect of spindle speed: As the spindle speed increases from 1200 to 1500 rpm, the average surface roughness tends to decrease, which means that the surface finish becomes smoother.
- Effect of feed rate: As the feed rate increases from 300 to 500 m/min, the average surface roughness tends to increase, which means that the surface becomes rougher.
- Effect of cutting depth: When comparing cutting depths of 0.1 mm and 0.2 mm, it is found that at a spindle speed of 1200 rpm, a cutting depth of 0.1 mm gives a better average surface roughness, but at a spindle speed of 1500 rpm, there is not much difference in average surface roughness between the two cutting depths.

In summary, using a high spindle speed and a low feed rate combined with a cutting depth of 0.1 mm produces the smoothest surface finish.

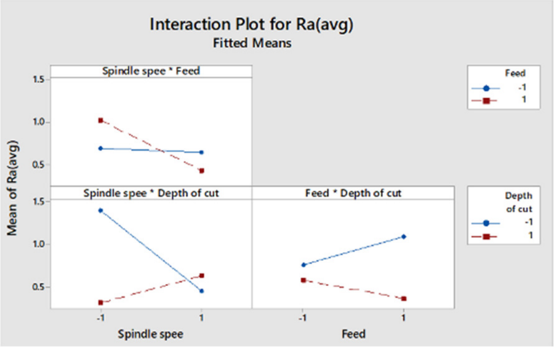

Fig. 6. Interaction plot for average surface roughness.

In Figure 7, the main effects of plot for average surface roughness (R_a(avg)) can describe the effects of the factors as follows:

- Effect of spindle speed: As the spindle speed increases from 1200 to 1500 rpm, the average surface roughness decreases, which means that the surface becomes smoother.
- Effect of feed rate: As the feed rate increases from 300 to 500 m/min, the average surface roughness increases, which means that the surface becomes rougher.
- Effect of cutting depth: As the cutting depth increases from 0.1 to 0.2 mm, the average surface roughness also increases, which means the surface becomes rougher.

In summary, using a high spindle speed, a low feed rate, and a shallow cutting depth will produce the smoothest surface finish.

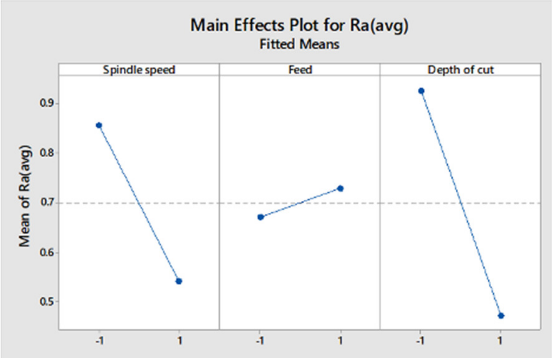

Fig. 7. Effect of cutting parameters on surface roughness.

The cube plot in Figure 8 demonstrates how the feed rate and the spindle speed influence the average surface roughness. As the spindle speed increases, the surface roughness (R_a) values decrease, resulting in smoother surfaces, while higher feed rates result in higher R_a values (rougher surfaces on average). The model can accurately predict the average surface roughness (R_a) values. Figure 9 shows that the desired response value is 1.7025. The 95% confidence interval for the average response, if the experiment is conducted similarly, ranges approximately from 0.9125 to 2.4925, and the 95% prediction interval ranges approximately from 0.5460 to 2.8590.

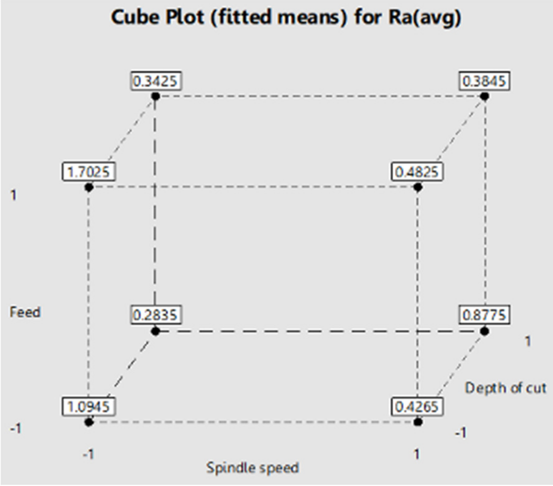

Fig. 8. A cube plot depicting the average value of surface roughness (R_a).

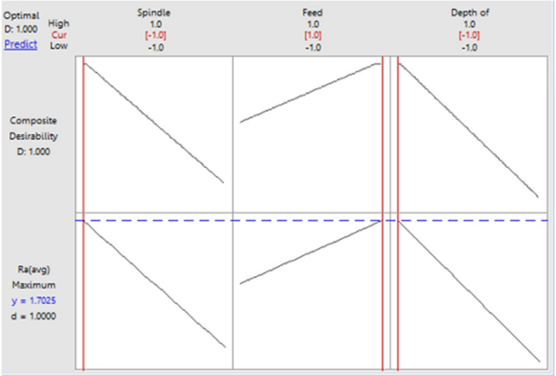

Fig. 9. The response optimizer function finding for optimal factor levels.

IV. CONCLUSIONS

This study developed a surface roughness model for the hard milling of SKT4 steel. An ANOVA on the average surface roughness (R_a) exhibited a significant interaction ($p\text{-value} < 0.05$) between spindle speed and cutting depth. This indicates that the combined effects of these factors influence the results. The combination of a spindle speed of 1500 rpm, a feed rate of 300 m/min, and a cutting depth of 0.2 mm had the most pronounced impact on surface roughness. These results suggest that the proposed surface roughness model displays a high degree of accuracy in explaining the data, achieving an R^2 value of approximately 99.74%.

A. Limitations

- Tool wear significantly affects surface roughness. The model might require incorporating tool wear monitoring or compensation factors.
- The dynamics of the milling process, vibrations, and chatter can influence the surface roughness and are difficult to be modeled accurately.
- Coolant type, lubrication, and environmental conditions can affect surface roughness and may not be fully captured in the model.

B. Future Research

- Develop models that can predict surface roughness across a wider range of milling conditions and material properties for SKT4 steel.
- Integrate sensors to monitor tool wear, cutting forces, and vibrations for real-time adjustments to the model predictions.

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