Improving the Accuracy of the Surface Roughness Model in Grinding Through Square Root Transformation

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***Abstract*—Surface roughness is a crucial parameter for mechanical products. To achieve small surface roughness, the grinding method is often chosen as the final machining process. The regression model of surface roughness forms the basis for controlling the grinding process and predicting surface roughness under specific conditions. The effectiveness of process control and the accuracy of predicted surface roughness depend on the precision of the surface roughness regression model. This study aims to enhance the accuracy of the surface roughness regression model by employing square root transformation. An experimental process was conducted with a total of eighteen experiments. In each experiment, three cutting parameters, including workpiece speed, tool feed rate, and cutting depth, were varied. Surface roughness was measured in each experiment. After conducting experiments, a surface roughness regression model was established, denoted as Model (1), without using any data transformation. The square root transformation was applied to convert the surface roughness dataset into another set of data. From this dataset, another surface roughness model, referred to as Model (2), was developed. Both models were used to predict surface roughness, and the predicted results were compared with the actual surface roughness in the experiments. Four parameters were used to compare Models (1) and (2), including the coefficient of determination (*R-Sq*), adjusted coefficient of determination (*R-Sq(adj)*), mean absolute error percentage (*%MAE*), and mean squared error (*%MSE*). All four parameters for Model (2) were superior to those for Model (1). The results confirmed that the square root transformation successfully improved the accuracy of the surface roughness regression model in grinding applications.**

***Keywords*—surface roughness, grinding, square root transformation**

I. Introduction

Grinding is a widely used machining method in mechanical production. This method is often employed for finishing surfaces with small roughness requirements [1–3]. In the study of grinding technology, a commonly used approach is to construct a regression model of the surface roughness, which represents the mathematical relationship between the surface roughness and cutting parameters [4–6]. The established regression models of surface roughness will be utilized for selecting values of cutting parameters and predicting the achievable surface roughness corresponding to specific values of cutting parameters. Therefore, controlling the grinding process and predicting the surface roughness during grinding heavily rely on the accuracy of these regression models. This highlights the importance of researching and improving the accuracy of surface roughness models in grinding.

II. Literature Review

To assess the accuracy of the regression model, four commonly used parameters are *R-Sq*, *R-Sq(adj)*, *%MAE*, and %MSE [7, 8]. The first two parameters have values ranging from 0 to 1, with higher values indicating better performance. The values of the remaining two parameters also range from 0 to 1, with lower values indicating better performance. A regression model is considered accurate when *R-Sq* and *R-Sq(adj)* approach 1, while *%MAE* and *%MSE* approach zero [9]. To improve the accuracy of regression models, some studies have been conducted using data transformation methods. The Box-Cox transformation was employed to enhance the accuracy of the surface roughness model when milling EN 353 steel [10]. This study demonstrated that the surface roughness model established using the Box-Cox transformation exhibited higher accuracy compared to the model without data transformation. Specifically, the model without data transformation had values for four performance metrics *R-Sq*, *R-Sq(adj)*, *%MAE*, and *%MSE* as 92.07%, 90.62%, 7.934%, and 1.69%, respectively. In contrast, for the model utilizing the Box-Cox transformation, these four metrics had corresponding values of 96.66%, 95.93%, 4.7%, and 0.68%. The Box-Cox transformation was also utilized to improve the accuracy of the regression model for surface grinding of eccentrically turned SCM435 steel [11]. The three coefficients *R-Sq*, *%MAE*, and *%MSE* in the model

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without data transformation had corresponding values of 78.01%, 17.59%, and 5.71%. For the surface grinding model using the Johnson transformation, *R-Sq* was 83.22%, *%MAE* was 13.66%, and *%MSE* was 4.15%. Therefore, it is evident that the use of the Johnson transformation significantly enhanced the accuracy of the surface grinding model in this study. The Box-Cox transformation has also been employed to enhance the accuracy of the surface roughness model when milling AISI 1019 steel [12]. This study demonstrated that without using data transformation, *R-Sq* is 98.80%, *R-Sq(adj)* is 88.99%, *%MAE* is 14.2%, and *%MSE* is 4.53%. In contrast, when applying the Box-Cox transformation, *R-Sq* becomes 97.15%, *R-Sq(adj)* is 96.41%, *%MAE* is 5.98%, and *%MSE* is 1.27%. This clearly affirms that the use of the Box-Cox transformation significantly improved the accuracy of the surface roughness model. The Johnson transformation was employed to enhance the accuracy of the surface roughness model when milling AISI 1045 steel [13]. This study utilized three parameters to assess the accuracy of the regression models, namely *R-Sq*, *%MAE*, and *%MSE*. The surface roughness regression model without the Johnson transformation yielded values of 85.71%, 12.11%, and 2.54% for *R-Sq*, *%MAE*, and *%MSE*, respectively. In contrast, for the model using the Johnson transformation, these three parameters had corresponding values of 86.86%, 9.22%, and 2.25%. Both the Box-Cox transformation and the Johnson transformation were simultaneously employed to enhance the accuracy of the regression model for surface grinding of 65G steel [14]. This study demonstrated that the surface grinding model utilizing the Johnson transformation exhibited the highest accuracy, followed by the model using the Box-Cox transformation. The surface grinding model without data transformation had the lowest accuracy. Both the Box-Cox and Johnson transformations were also employed to enhance the accuracy of the surface grinding model for milling 3×13 steel [15]. This study, once again, demonstrated that the use of the Box-Cox transformation resulted in the construction of a surface grinding model with the highest accuracy, surpassing the model utilizing the Johnson transformation. The model without data transformation had the lowest accuracy. Both the Box-Cox and Johnson transformations were simultaneously applied to enhance the accuracy of the cutting force model when milling SCM440 steel [16]. This study also indicated that utilizing the Box-Cox transformation allowed for the construction of the cutting force regression model with the highest accuracy, followed by the model using the Johnson transformation. The cutting force model without data transformation had the lowest accuracy.

Thus, it can be observed that the successful application of both the Box-Cox and Johnson data transformations has contributed to enhancing the accuracy of regression models in various cases, particularly within the field of mechanical processing. In addition to Box-Cox and Johnson, the square root transformation is also a well-known data transformation method that has been recognized for a long time. This transformation is straightforward and can be manually performed or executed using commonly available statistical software, such as Excel. However, the absence of applications of this transformation in improving the accuracy of regression models in the field of mechanical processing in general and grinding technology in particular is the motivation behind conducting this research.

III. EXPERIMENT

The aim of this study is to enhance the accuracy of the surface grinding model in flat grinding through the square root transformation. By solely employing the square root transformation, we emphasize the simplicity of this method. This approach can be easily integrated into various regression models without necessitating intricate adjustments. To achieve this objective, the following two purposes need to be accomplished: (1) To construct a surface grinding model without using data transformation, (2) To construct a surface grinding model using the square root transformation, and (3) To compare two surface roughness models.

An experimental process on a surface grinding machine was conducted. The grinding machine manufactured in Taiwan, marked as APSG-820/2A, was utilized (Fig. 1).

Fig. 1. Surface Grinding Machine APSG-820/2A

The grinding stone used was an aluminum oxide abrasive stone with the code WA46J7V1A. The stone had a grit size of 46, and the corresponding outer diameter, inner diameter, and thickness of the grinding stone were 180 mm, 31.75 mm, and 13 mm.

A cube-shaped steel workpiece with all sides measuring 55 mm, made of JIS-S45C steel, was employed in the experimental process. The Box-Behnken experimental design matrix was used to create the experimental plan. This matrix form is widely used in the machining industry [17, 18].

Three cutting parameters were selected to vary their values in each experiment, including workpiece speed, feed rate, and cutting depth. These three parameters were denoted as *A*, *B*, and *C*, respectively. These three parameters were chosen as the inputs for each experiment because they are easily adjustable by machine operators.

Numerous studies have also indicated that they significantly influence surface grinding. Each cutting parameter was selected at three levels. The values of these parameters at the selected levels were based on references from literature [14, 19, 20] and are presented in Table I.

TABLE I. CUTTING PARAMETERS

Parameters	Unit	Symbol	Value at levels		
			–1	0	1
Workpiece velocity	m/min	*A*	10	15	20
Feed rate	mm/stroke	*B*	6	8	10
Depth of cut	mm	*C*	0.005	0.01	0.015

The experimental matrix was designed in the Box-Behnken form, comprising eighteen experiments as listed in Table II. In this table, the parameters *A*, *B*, and *C* were set according to their encoded values.

TABLE II. EXPERIMENTAL MATRIX

Experiment	*A*	*B*	*C*
1	0	0	0
2	–1	0	1
3	1	0	–1
4	0	0	0
5	1	1	0
6	–1	0	–1
7	0	1	–1
8	1	-1	0
9	–1	1	0
10	0	0	0
11	0	0	0
12	–1	–1	0
13	0	–1	1
14	1	0	1
15	0	–1	–1
16	0	0	0
17	0	0	0
18	0	1	1

In each experiment, surface roughness was also measured using a roughness measuring instrument labeled as Sj-201. The roughness values for each experiment were synthesized in Table II.

After measuring the roughness for all experiments, an (Analysis of Variance) ANOVA would be conducted to build a surface roughness model without using data transformation.

To construct a regression model for surface roughness using square root transformation, Eq. (1) would be applied.

$$X' = \sqrt{X} \tag{1}$$

where X' represents the values after transformation, and X represents the values before transformation. After transforming the data, ANOVA analysis would be carried out again to construct the surface roughness regression model.

To assess the accuracy of regression models, in addition to the two parameters *R-Sq* and *R-Sq(adj)*, we also need to consider two additional metrics, namely *%MAE* and *%MSE*. These two metrics are calculated using the respective Eqs. (2) and (3).

$$\%MAE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i - p_i}{e_i}\right|\right)\cdot 100 \tag{2}$$

$$\%MSE = \left(\frac{1}{n}\sum_{i=1}^{n}(e_i - p_i)^2\right)\cdot 100 \tag{3}$$

where e_i is the experimental surface roughness value, p_i is the predicted surface roughness value by the regression model, and n is the number of experiments conducted.

IV. RESULT AND DISCUSSION

Based on the experimental results presented in Table II, Minitab 16 software was utilized for *ANOVA* analysis, and the regression model was formulated as Eq. (4).

$$\begin{aligned} R_a = {} & 0.8633 - 0.0787A + 0.4187B + 0.0400C \\ & -0.2091A^2 + 0.3358B^2 + 0.1283C^2 \\ & +0.0350AB - 0.0625AC + 0.0275BC \end{aligned} \tag{4}$$

This model exhibited values for the two coefficients *R-Sq* and *R-Sq(adj)* at 85.71% and 69.64%, respectively.

Eq. (1) was employed to transform the R_a dataset into R'_a, yielding results as shown in Table III.

TABLE III. RESULTS OF SURFACE ROUGHNESS DATASET TRANSFORMATION USING SQUARE ROOT TRANSFORMATION

Experiment	R_a	R'_a
1	0.88	0.93808
2	1.02	1.00995
3	0.67	0.81854
4	0.86	0.92736
5	1.22	1.10454
6	0.82	0.90554
7	1.88	1.37113
8	0.72	0.84853
9	1.19	1.09087
10	0.87	0.93274
11	0.82	0.90554
12	0.83	0.91104
13	0.72	0.84853
14	0.62	0.78740
15	0.69	0.83066
16	0.82	0.90554
17	0.93	0.96437
18	2.02	1.42127

ANOVA analysis was performed again, leading to the construction of the surface roughness regression model as depicted in Eq. (3).

$$\begin{aligned} R'_a = {} & 0.9289 - 0.0448A + 0.1936B + 0.0176C \\ & -0.0888A^2 + 0.1486B^2 + 0.0402C^2 \\ & +0.0190AB - 0.0338AC + 0.0080BC \end{aligned} \tag{5}$$

Using Eq. (5), the regression model for surface roughness was developed with square root transformation, resulting in Eq. (6).

$$R_a^{(trans.)} = \begin{bmatrix} 0.9289 - 0.0448A + 0.1936B \\ +0.0176C - 0.0888A^2 \\ +0.1486B^2 + 0.0402C^2 \\ +0.0190AB - 0.0338AC \\ +0.0080BC \end{bmatrix}^2 \quad (6)$$

This model exhibited *R-Sq* and *R-Sq(adj)* values of 86.97% and 72.30%, respectively.

By utilizing Eqs. (2)–(3), the corresponding *%MAE* and *%MSE* values for both models were calculated and compiled in Table IV. The table also includes the *R-Sq* and *R-Sq(adj)* values for both models.

TABLE IV. COMPARISON OF TWO SURFACE ROUGHNESS MODELS

Models	*R-Sq*	*R-Sq(adj)*	*%MAE*	*%MSE*
Without transformation (4)	85.71%	69.64%	12.85%	2.31%
Square Root Transformation (6)	86.97%	72.30%	10.32%	1.67%

As indicated in Table IV, *R-Sq* for (6) at 86.97% is higher than that of (4) at 85.71%. *R-Sq(adj)* for (6) at 72.30% is higher than that of (4) at 69.64%. Both *%MAE* and *%MSE* values for (6) at 10.32% and 1.67%, respectively, are smaller than those of (4). All these findings affirm that the surface roughness regression model using square root transformation achieves higher accuracy compared to the model without data transformation. In other words, the successful implementation of the square root transformation has led to an enhancement in the accuracy of the surface roughness model.

Based on the demonstrated higher accuracy of the model utilizing the square root transformation compared to the model without data transformation, in the near future, the application of these two models in solving optimization problems for the grinding process with a focus on surface quality should be explored. This will further confirm the advantages of the model using the square root transformation over the model without data transformation in achieving the target surface finish.

V. CONCLUSIONS

The construction of a surface grinding regression model for JIS-S45C steel using the APSG-820/2A grinding wheel was carried out in this study. The accuracy of the surface grinding regression model was assessed through four parameters, including *R-Sq*, *R-Sq(adj)*, *%MAE*, and *%MSE*. The use of square root transformation significantly enhanced the accuracy of the surface grinding model. All four parameters, namely *R-Sq*, *R-Sq(adj)*, *%MAE*, and *%MSE*, showed improvement when employing the square root transformation compared to the model without data transformation. Specifically, the surface grinding regression model without data transformation had *R-Sq* of 85.71%, *R-Sq(adj)* of 69.64%, *%MAE* of 12.85%, and *%MSE* of 2.31%. Meanwhile, for the surface grinding model with square root transformation, the corresponding values for the four parameters were 86.97%, 72.30%, 10.32%, and 1.67%, respectively.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Do Duc Trung is the first author who wrote methodology, wring original draft, configured. Nguyen Trong Mai is correspondent who reviewed and edited project administration, methodology. All authors had approved the final version.

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