A Comparative Analysis of Data Transformation Methods for Constructing a Surface Roughness Model in Turning Processes

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***Abstract*—Data conversion methods are used to transform datasets into new datasets, which may exhibit a distribution pattern different from the original dataset. Enhancing model accuracy is one of the applications of data transformation. This study compared the effectiveness of three data transformation methods: square root, logarithmic, and inverse transformation. This comparison was conducted in the context of constructing a surface roughness model for a turning process. Surface roughness plays a crucial role in determining corrosion resistance, chemical corrosion resistance, fatigue strength, and joint accuracy. These parameters significantly impact the product's operational ability and durability. An experimental turning process was performed, comprising a total of eighteen experiments designed using the Box-Behnken method. Surface roughness was selected as the response for each experiment. The three aforementioned data transformation methods were applied to the surface roughness dataset. Four surface roughness regression models were constructed, including a model without data transformation, a model with square root transformation, a model with logarithmic transformation, and a model with inverse transformation. The effectiveness of the three data transformation methods was compared using four metrics: Coefficient of Determination (R^2), Adjusted Coefficient of Determination ($R^2(adj)$), Mean Absolute Error (*%MAE*), and Mean Squared Error (*%MSE*). The study revealed that the logarithmic transformation was the most effective, followed by the square root transformation. The accuracy of the surface roughness regression model improved when utilizing these two transformations. The inverse transformation exhibited the least effectiveness among the three data transformation methods.**

***Keywords*—square root transformation, logarithmic transformation, reciprocal transformation, surface roughness, turning**

I. INTRODUCTION

Data conversion methods are employed to transform one dataset into another. This process alters the distribution model of the dataset, which in turn changes its variance through the execution of data transformation operations [1]. Another objective of data transformation methods is to improve the accuracy of the relationship between input parameters and output parameters of a given operation.

Constructing regression models to depict the relationship between output parameters and input parameters is a widely used method in experimental research, particularly in the field of mechanical machining. Four commonly used metrics are employed to assess the accuracy of regression models: R^2, $R^2(adj)$, *%MAE*, and *%MSE* [2, 3]. R^2 measures the model's explanatory power for the dependent variable, indicating the percentage of variation in the dependent variable explained by the model. A higher R^2 value suggests a better model, although it does not evaluate the predictive quality. $R^2(adj)$ is similar to R^2 but adjusts for the reduction in R^2 value when adding independent variables, helping to prevent improvement through unnecessary variables. *%MAE* measures the average difference between predicted and actual values, expressed as a percentage, providing an overall view of the model's deviation. *%MSE* measures the average squared difference between predicted and actual values, also as a percentage, often more sensitive to larger values [4]. The first two metrics range from 0 to 1, with higher values indicating better performance, while the latter two range from 0 to 1, with lower values considered better. A regression model is deemed accurate when R^2 and $R^2(adj)$ approach one and *%MAE* and *%MSE* approach 0 [5]. Various data transformation methods have been employed to enhance the accuracy of regression models. The use of data transformations can affect the values of R^2, $R^2(adj)$, *%MAE*, and *%MSE* metrics. Transformations that enhance linearity can increase R^2, while those introducing complexity or non-linearity may decrease it. Improving

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the model without unnecessary complexity may increase $R^2(adj)$, but adding insignificant transformations may decrease it. If a transformation enhances model fit, *%MAE* may decrease, indicating reduced prediction error, whereas introducing variability or noise may lead to an increase. Reducing error spread may decrease %MSE, indicating improved model accuracy, while increasing variability may lead to an increase [6, 7].

The Box-Cox transformation was employed to enhance the accuracy of the surface roughness model when milling EN 353 steel [8]. This study demonstrated that the surface roughness model established using the Box-Cox transformation had higher accuracy than the model without data transformation. Specifically, the model without data transformation had values of the four metrics R^2, R^2(adj), *%MAE*, and *%MSE* as 92.07%, 90.62%, 7.934%, and 1.69%, respectively. In contrast, for the model using the Box-Cox transformation, these four metrics had values of 96.66%, 95.93%, 4.7%, and 0.68%, respectively.

Similar improvements in accuracy using the Box-Cox transformation have been reported for surface roughness modeling in grinding and milling various steels. Examples include grinding SCM435 steel [9], milling AISI 1019 steel [10], and milling AISI 1045 steel [11].

However, comparisons between the Box-Cox transformation and the Johnson transformation reveal that the effectiveness of each transformation depends on the input data. For instance, in a study on grinding 65G steel, the Johnson transformation resulted in a model with higher accuracy than the Box-Cox transformation model [12]. Conversely, a study on milling 3×13 steel found that the Box-Cox transformation led to a model with the highest accuracy compared to the Johnson transformation model [13].

Moreover, the effectiveness of both the Box-Cox and Johnson transformations for improving regression models has also been demonstrated in cutting force prediction. A study investigating milling SCM440 steel found that the Box-Cox transformation yielded the most accurate cutting force regression model, followed by the Johnson transformation model. Unsurprisingly, the model without data transformation exhibited the lowest accuracy [14].

So, it was evident that both the Box-Cox and Johnson data transformations have successfully improved the accuracy of regression models in various scenarios, particularly in the field of mechanical machining. In addition to Box-Cox and Johnson, three other transformations (square root transformation, logarithmic transformation, and inverse transformation) are also simple and can be manually performed or implemented in widely used statistical software such as Excel. The square root transformation has been utilized to enhance the accuracy of forecasting models for the number of COVID-19-related deaths in Florida counties (USA) [15]. Logarithmic transformations have improved forecasting models for microbial counts [16]. Two transformation methods, logarithmic and square root, have been employed to enhance the accuracy of revenue forecasting models [17]. Comparison between two transformations, logarithmic and inverse, has been experimented with to improve the accuracy of economic forecasting models. The results indicate that the model using logarithmic transformation effectively enhances the accuracy of prediction outcomes. Conversely, the use of inverse transformation tends to decrease the accuracy of the predicted results [18]. However, the limited application of these transformations in improving the accuracy of regression models in the general field of mechanical machining, specifically in turning technology, is the motivation for this study. This research aims to compare the effectiveness of three transformations, namely square root transformation, logarithmic transformation, and inverse transformation, in building surface roughness regression models during turning.

II. Materials and Methods

A turning process was conducted using a Box-Behnken design matrix with a total of eighteen experiments. The specimens are steel blanks with a diameter of 28 mm and a length of 300 mm, made from SCM440 steel. The cutting tool used is a TiN-coated cutting insert, with corresponding rake angle, clearance angle, plane point angle, and chip breaker angle parameters set at 7°, 5°, 75°, and 7°, respectively. This type of tool is widely used for its high corrosion resistance [19]. The experimental process was carried out on a lathe machine labeled Lynx 220L (manufactured by DOOSAN Corporation—South Korea), as shown in Fig. 1.

Fig. 1. Lynx 220L lathe machine.

The SJ-301 machine from Mitutoyo was utilized to measure surface roughness. Surface roughness measurements on each steel blank were conducted at least three times consecutively, and the surface roughness value for each experiment represents the average value of these consecutive measurements. Three cutting parameters were varied in each experiment, including cutting speed, feed rate, and cutting depth. The experiment investigated three cutting parameters: cutting speed (X_1), feed rate (X_2), and depth of cut (X_3). Many studies have indicated that they significantly impact surface roughness [20–22]. Furthermore, machine operators can quickly adjust all three of these parameters [23]. Each parameter was assigned three values corresponding to three levels of encoding: –1, 0, and 1, as shown in Table I.

TABLE I. CUTTING PARAMETERS

Parameters	Unit	Symbol	Value at Levels		
			–1	0	1
Cutting speed	m/min	X_1	40	70	100
Feed rate	mm/rev	X_2	0.03	0.05	0.07
Depth of cut	mm	X_3	0.2	0.4	0.6

Table II shows the experimental matrix with eighteen experiments.

After conducting experiments, the data transformation will be performed.

The square root transformation is conducted to convert the data according to Eq. (1).

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

TABLE II. EXPERIMENT MATRIX

Experiment	Code Value			Actual Value		
	X_1	X_2	X_3	X_1 (m/min)	X_2 (mm/rev)	X_3 (mm)
1	0	0	0	70	0.05	0.4
2	–1	0	1	40	0.05	0.6
3	1	0	–1	100	0.05	0.2
4	0	0	0	70	0.05	0.4
5	1	1	0	100	0.07	0.4
6	–1	0	–1	40	0.05	0.2
7	0	1	–1	70	0.07	0.2
8	1	–1	0	100	0.03	0.4
9	–1	1	0	40	0.07	0.4
10	0	0	0	70	0.05	0.4
11	0	0	0	70	0.05	0.4
12	–1	–1	0	40	0.03	0.4
13	0	-1	1	70	0.03	0.6
14	1	0	1	100	0.05	0.6
15	0	–1	–1	70	0.03	0.2
16	0	0	0	70	0.05	0.4
17	0	0	0	70	0.05	0.4
18	0	1	1	70	0.07	0.6

Eq. (2) converts the data using the logarithmic transformation.

$$X' = \log(X) \tag{2}$$

Eq. (3) is utilized to convert the data through the inverse transformation.

$$X' = \frac{1}{X} \tag{3}$$

Here, X' and X correspond to the values after and before transformation, respectively.

The values obtained after transformation are used to construct regression functions representing the relationship with input parameters in Eq. (4), where xi represents the input parameters.

$$X' = f(x_i) \tag{4}$$

During the data analysis for regression function construction, two parameters, R^2 and $R^2(adj)$, are always determined.

Four parameters, namely R^2, $R^2(adj)$, *%MAE*, and *%MSE* are also used to compare the effectiveness of data transformations, which is the accuracy comparison of regression models.

%MAE is calculated using Eq. (5) [13, 14].

$$\%MAE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i - p_i}{e_i}\right|\right)\cdot 100 \tag{5}$$

Here, e_i and p_i correspond to the values before and after transformation. In the case of the problem investigated in this study, e_i represents the roughness when measured, while p_i represents the predicted roughness using the models, and n is the number of experiments conducted.

III. RESULTS AND DISCUSSION

Conduct experiments in their sequential order as presented in Table II. The experimental results have been synthesized in Table III.

TABLE III. RESULT EXPERIMENT

Experiment	Code Value			*Ra* (µm)
	X_1	X_2	X_3	
1	0	0	0	0.986
2	–1	0	1	1.142
3	1	0	–1	0.75
4	0	0	0	0.963
5	1	1	0	1.366
6	–1	0	–1	0.918
7	0	1	–1	2.106
8	1	–1	0	0.806
9	–1	1	0	1.333
10	0	0	0	0.974
11	0	0	0	0.918
12	–1	–1	0	0.93
13	0	–1	1	0.806
14	1	0	1	0.694
15	0	–1	–1	0.773
16	0	0	0	0.918
17	0	0	0	1.042
18	0	1	1	2.262

In Fig. 2, the graph represents the influence of cutting parameters on surface roughness.

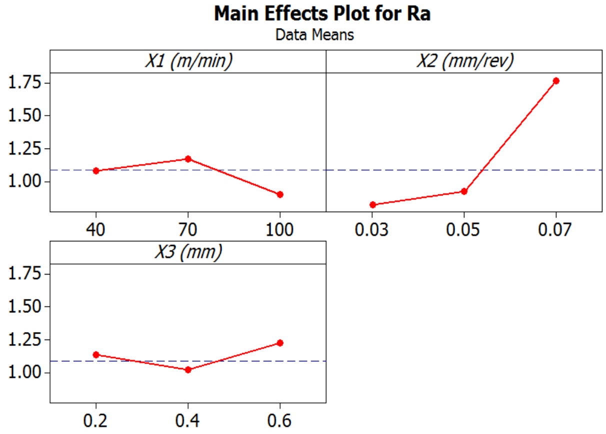

Fig. 2. Influence of cutting parameters on surface roughness.

We observe that the surface roughness increases very slowly as the cutting speed increases from 40 m/min to 70 m/min. However, the surface roughness decreases when the cutting speed increases from 70 m/min to 100 m/min. Increasing the feed rate from 0.03 mm/rev to 0.05 mm/rev results in a slow increase in surface roughness, but if the feed rate exceeds 0.05 mm/rev, the surface roughness increases rapidly. The surface roughness decreases slowly when the cutting depth increases from 0.2 mm to 0.4 mm.

Conversely, if the cutting depth increases, the surface roughness increases rapidly. The complexity of the influence patterns of cutting parameters on surface roughness indicates the difficulty in determining the values of cutting parameters to ensure a small surface roughness. Therefore, a surface roughness regression model can be developed to identify the cutting parameter values needed to achieve the desired surface roughness. The full quadratic regression model is commonly used in experimental research [2, 3, 5]. Four surface roughness regression models will be constructed to explore the impact of data transformation on model accuracy. The first model will use the raw data, while the remaining three will employ different data transformation techniques. Eqs. (1)–(3) were employed to transform the dataset of surface roughness using the corresponding transformations, namely square root transformation, logarithmic transformation, and inverse transformation. The values obtained after applying these transformations are denoted as $X_{(S)}$, $X_{(L)}$, and $X_{(R)}$, respectively, as shown in Table IV.

TABLE IV. SURFACE ROUGHNESS VALUES AFTER CONVERSION

Experiment	X_1	X_2	X_3	Ra (μm)	$X_{(S)}$ (dimensionless)	$X_{(L)}$ (dimensionless)	$X_{(R)}$ (dimensionless)
1	0	0	0	0.986	0.9930	−0.0061	1.0142
2	−1	0	1	1.142	1.0686	0.0577	0.8757
3	1	0	−1	0.75	0.8660	−0.1249	1.3333
4	0	0	0	0.963	0.9813	−0.0164	1.0384
5	1	1	0	1.366	1.1688	0.1355	0.7321
6	−1	0	−1	0.918	0.9581	−0.0372	1.0893
7	0	1	−1	2.106	1.4512	0.3235	0.4748
8	1	−1	0	0.806	0.8978	−0.0937	1.2407
9	−1	1	0	1.333	1.1546	0.1248	0.7502
10	0	0	0	0.974	0.9869	−0.0114	1.0267
11	0	0	0	0.918	0.9581	−0.0372	1.0893
12	−1	−1	0	0.930	0.9644	−0.0315	1.0753
13	0	−1	1	0.806	0.8978	−0.0937	1.2407
14	1	0	1	0.694	0.8331	−0.1586	1.4409
15	0	−1	−1	0.773	0.8792	−0.1118	1.2937
16	0	0	0	0.918	0.9581	−0.0372	1.0893
17	0	0	0	1.042	1.0208	0.0179	0.9597
18	0	1	1	2.262	1.5040	0.3545	0.4421

TABLE V. COEFFICIENTS OF THE MODELS

Parameter	Without transformation	Square root transformation	Logarithmic transformation	Reciprocal Transformation
Intercept	0.9668	0.9830	−0.0151	1.0363
X_1	−0.0884	−0.0475	−0.0445	0.1196
X_2	0.4690	0.2049	0.1586	−0.3064
X_3	0.0446	0.0186	0.0138	−0.0240
X_1^2	−0.2344	−0.0941	−0.0675	0.1176
X_2^2	0.3763	0.1575	0.1164	−0.2044
X_3^2	0.1436	0.0426	0.0168	0.0309
X_1X_2	0.0393	0.0202	0.0182	−0.0459
X_1X_3	−0.0700	−0.0359	−0.0321	0.0803
X_2X_3	0.0308	0.0086	0.0032	0.0051
R-Sq	0.8571	0.8697	0.8792	0.8874
R-Sq(adj)	0.6964	0.7231	0.7434	0.7606

The complete quadratic model was utilized to depict the relationship between input parameters *(X_1, X_2, X_3)* and output parameters. The output parameters include surface roughness *(Ra)* and the quantities obtained after performing the transformations *($X_{(S)}$, $X_{(L)}$, $X_{(R)}$)*. Table V compiles the coefficients of each model corresponding to four different cases. For each case, two coefficients, R^2 and $R^2(adj)$, are also included in the last two rows of Table V.

From the data in Table V, the Minitab software has been used to construct four full quadratic regression models as follows:

The surface roughness model without data transformation is presented in Eq. (6).

$$R_{a(without)} = 0.9668 - 0.0884X_1 + 0.4690X_2 + 0.0446X_3 - 0.2344X_1^2 + 0.3767X_2^2 + 0.1436X_3^2 + 0.0393X_1X_2 - 0.07X_1X_3 + 0.0308X_2X_3 \quad (6)$$

The model using the square root transformation is presented in Eq. (7).

$$X_{(S)} = 0.9830 - 0.0475X_1 + 0.2049X_2 + 0.0186X_3 - 0.0941X_1^2 + 0.1575X_2^2 + 0.0426X_3^2 + 0.0202X_1X_2 - 0.0359X_1X_3 + 0.0086X_2X_3 \quad (7)$$

The model using the logarithmic transformation is presented in Eq. (8).

$$X_{(L)} = -0.0151 - 0.0445X_1 + 0.1586X_2 + 0.0138X_3 - 0.0675X_1^2 + 0.1164X_2^2 + 0.0168X_3^2 + 0.0182X_1X_2 - 0.0321X_1X_3 + 0.0032X_2X_3 \quad (8)$$

The model using the inverse transformation is presented in Eq. (9).

$$X_{(R)} = 1.0363 + 0.1196X_1 - 0.3064X_2 - 0.0240X_3 + 0.1176X_1^2 - 0.2044X_2^2 + 0.0309X_3^2 - 0.0459X_1X_2 + 0.0803X_1X_3 + 0.0051X_2X_3 \quad (9)$$

Combining Eqs. (1)–(7) forms the surface roughness regression model in the case of using the square root transformation, as shown in Eq. (10).

$$R_{a(S)} = \begin{bmatrix} 0.9830 - 0.0475X_1 + 0.2049X_2 \\ +0.0186X_3 \\ -0.0941X_1^2 + 0.1575X_2^2 \\ +0.0426X_3^2 \\ +0.0202X_1X_2 - 0.0359X_1X_3 \\ +0.0086X_2X_3 \end{bmatrix}^2 \quad (10)$$

Combining Eqs. (2)–(8) forms the surface roughness regression model in the case of using the logarithmic transformation, as shown in Eq. (11).

$$R_{a(L)} = 10^A \quad (11)$$

where:

$$A = -0.0151 - 0.0445X_1 + 0.1586X_2 + 0.0138X_3 - 0.0675X_1^2 + 0.1164X_2^2 + 0.0168X_3^2 + 0.0182X_1X_2 - 0.0321X_1X_3 + 0.0032X_2X_3$$

Combining Eqs. (3)–(9) forms the surface roughness regression model in the case of using the inverse transformation, as shown in Eq. (12).

$$R_{a(R)} = \frac{1}{B} \quad (12)$$

where:

$$B = 1.0363 + 0.1196X_1 - 0.3064X_2 - 0.0240X_3 + 0.1176X_1^2 - 0.2044X_2^2 + 0.0309X_3^2 - 0.0459X_1X_2 + 0.0803X_1X_3 + 0.0051X_2X_3$$

The surface roughness models in Eq. (6), Eqs. (10)–(12) have been used to predict surface roughness, as presented in Table VI.

Eqs. (5)–(6) were used to calculate the *%MAE* and *%MSE* values for each model. The calculated values have been compiled in Table VII. The R^2 and $R^2(adj)$ coefficients for each model have also been summarized in this table.

According to the data in Table VII, it is observed that:

- The R^2 coefficient increases in the order of the models, namely the model without data transformation, the model using the square root transformation, the model using the logarithmic transformation, and the model using the inverse transformation.
- For the $R^2(adj)$ coefficient, the model without data transformation has the smallest value, followed by the model using the square root transformation and the model using the logarithmic transformation. The inverse transformation model has the largest $R^2(adj)$ coefficient.
- The *%MAE* coefficient of the model without data transformation is the largest. The *%MAE* values of the model using the square root transformation and the model using the logarithmic transformation are equal, while the *%MAE* of the model using the inverse transformation is the smallest.

- The model using the logarithmic transformation has the smallest *%MSE* coefficient, followed by the two models using the square root transformation and the model without data transformation. In this case, the inverse transformation model has the largest *%MSE* coefficient.

TABLE VI. SURFACE ROUGHNESS VALUES WHEN PREDICTED BY DIFFERENT MODELS

Experiment	Measured	Predicted			
	R_a (μm)	$R^*_{a(without)}$ (μm)	$R^*_{a(S)}$ (μm)	$R^*_{a(L)}$ (μm)	$R^*_{a(R)}$ (μm)
1	0.986	0.967	0.966	0.966	0.965
2	1.142	1.079	1.068	1.058	1.041
3	0.750	0.813	0.812	0.809	0.801
4	0.963	0.967	0.966	0.966	0.965
5	1.366	1.529	1.498	1.466	1.395
6	0.918	0.850	0.855	0.857	0.855
7	2.106	1.881	1.852	1.818	1.738
8	0.806	0.512	0.599	0.649	0.704
9	1.333	1.627	1.635	1.655	1.756
10	0.974	0.967	0.966	0.966	0.965
11	0.918	0.967	0.966	0.966	0.965
12	0.930	0.768	0.827	0.867	0.917
13	0.806	1.032	0.977	0.933	0.877
14	0.694	0.762	0.751	0.744	0.735
15	0.773	1.004	0.937	0.889	0.835
16	0.918	0.967	0.966	0.966	0.965
17	1.042	0.967	0.966	0.966	0.965
18	2.262	2.032	2.003	1.967	1.860

TABLE VII. COMPARISON OF FOUR SURFACE ROUGHNESS MODELS

Models	R^2	$R^2(adj)$	*%MAE*	*%MSE*
Without transformation	0.8571	0.6964	12.16	2.57
Square roox transformation	0.8697	0.7231	10.33	2.10
Logarithmic transformation	0.8792	0.7434	10.33	2.05
Reciprocal Transformation	0.8874	0.7606	8.30	2.92

All the analyses above indicate that the model utilizing the logarithmic transformation has the highest accuracy, followed by the square root transformation model. Meanwhile, the inverse transformation models without data transformation have lower accuracy than the other two models. The use of logarithmic transformations aids in constructing a surface roughness model with the highest accuracy, as it can minimize errors in statistical theory. This has also been referenced in [24]. Furthermore, larger values will be compressed when applying logarithmic transformation while retaining the differentiation among smaller values. This can make the data more uniform and reduce the sensitivity of the model to outliers [25]. The surface roughness model using inverse transformation exhibits low accuracy because the inverse transformation may lead to significant biases with large values [18].

IV. CONCLUSION

A comparison of three data transformations, including square root transformation, logarithmic transformation, and inverse transformation, was conducted to construct the surface roughness model for machining parts. Four metrics were used for comparison, namely R^2, $R^2(adj)$, *%MAE*, and *%MSE*. The logarithmic transformation exhibited the highest efficiency, followed by the square root transformation. Using these transformations significantly improved the accuracy of the surface roughness model.

Based on the established surface roughness models, solving the optimization problem to determine the values of input parameters (X_1, X_2, X_3) ensuring the minimal surface roughness is a task that needs to be carried out shortly to compare the effectiveness of the models with each other.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Hoang Xuan Thinh proposed the idea. Vu Van Khiem conducted the experiments. Nguyen Truong Giang constructed the structure of the paper. All three authors contributed to the completion of the paper. All authors had approved the final version.

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