Improving the Accuracy of Surface Roughness Modeling when Milling 3x13 Steel

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Abstract-In this study, a milling experiment was performed, with 3x13 steel selected as the experimental material along with TiAlN coated inserts. The Box-Behnken method was used to design the experimental matrix with a total of eighteen experiments. Cutting speed, feed amount, and depth of cut were selected as the input parameters. Three regression models of surface roughness have been established, one using the experimentally measured surface texture, one using the Johnson transform to convert the surface texture data, and one using Box-Cox transformation to convert the surface texture data. A comparison of the accuracy of the three models was performed. The results show that the model using the Box-Cox transformation has the highest accuracy, followed by the model using the Johnson transformation. In addition, the influence of cutting parameters on surface roughness is also discussed in detail.

Keywords-milling; 3x13 steel; surface roughness; regression model; Johnson transformation; Box-Cox transformation

I. INTRODUCTION

Experimental research to build a regression model representing the relationship between the input and the output parameters is a commonly used practice in general and in the research on mechanical machining processes in particular. This method has been used for a long time, but it is still not obsolete because its results can be applied directly in the production process. Regression models after being built will be used for many different purposes, such as determining the influence of input parameters on the output parameters, predicting the output from defined values of input parameters, or to determine the value of input parameters that ensure a certain purpose of the output parameters. However, those jobs only achieve high efficiency if the regression model has a high accuracy. The four parameters commonly used to evaluate the accuracy of a regression model include the coefficient of determination *R-Sq*, the coefficient of determination *R-Sq(adj)*, the Percentage of Absolute Error (*PAE*), and the Mean Square Error (*MSE*) of the results calculated by the regression model and the experiments [1, 2]. The significance of these coefficients has been discussed in [1-3]. The regression model has high accuracy when the two parameters *R-Sq* and *R-Sq*(*adj*) are as large as possible, and close to 1, while *PAE* and *MSE* are as small as possible.

Two data transformations, Johnson and Box-Cox are known for being able to improve the accuracy of the regression model [4, 5, 8]. The Johnson transformation has been used to improve the accuracy of the surface roughness model when milling AISI 1045 steel [6]. In this study, the regression model of surface roughness without data transformation has *R-Sq* equal to 0.8571, *PAE* equal to 12.11%, and *MSE* equal to 2.54%. Meanwhile, this model using Johnson transform has *R-Sq*, *PAE*, and *MSE* values of 0.8686, 9.22%, and 2.25% respectively. The Box-Cox transformation has been used to improve the accuracy of the surface roughness model when centerless grinding of SCM435 steel [7]. The value of *R-Sq* in the model without data transformation and in the model using data transformation is 0.7801 and 0.8322 respectively. The *PAE* of the model without data transformation is 17.59%, while it is 13.66% when using the Box-Cox transformation. The value of *MSE* in the model without data transformation is 5.71% and for the model using data transformation, it is 4.15%. In [9], the Box-Cox method was also used to improve the accuracy of the surface roughness model when milling AISI 1019 steel. Parameters *R-Sq*, *R-Sq(adj)*, *PAE*, *MSE* of the model without metric transformation had values of 0.898, 0.8899, 14.2%, and 4.53% respectively, while they were equal to 0.9326, 0.927, 8.7%, and 2.28% in the model using Box-Cox transformation. Both the Johnson and the Box-Cox metric transformations were used to improve the accuracy of the surface roughness regression model when surface grinding 65G steel [10]. In this study, three regression models of surface roughness, namely the model without data transformation, the model using the Johnson transformation, and the model using the Box-Cox transformation were built. The conclusion was that the regression model using the Box-Cox transformation has the highest accuracy, and the regression model that does not use the data transformation has the lowest accuracy.

In [11], both Johnson and Box-Cox metric transformations were used to improve the accuracy of the shear force model when milling SCM440 steel. It was found that the two models had similar accuracy, and are more accurate than the model without data transformation. Authors in [12] also applied both Johnson and Box-Cox transformations to improve the accuracy of surface roughness model when turning 3x13 steel. It was noted that the surface roughness model using the Johnson

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transformation had higher accuracy than the model using the Box-Cox transformation, and the model not using a metric transformation had lower accuracy. Both Johnson and Box-Cox metric transformations were applied to improve the accuracy of surface roughness modeling when turning 9XC steel [13]. This study determined that the model that uses the Box-Cox transformation has the highest accuracy, while the model that does not use the metric transformation has the lowest accuracy.

Johnson and Box-Cox transformations have been successful in improving the accuracy of the regression model (mostly the surface roughness model). However, when applying both transformations, it was found that each of them showed different conclusions. For every study that suggests that the Johnson transformation is better than the Box-Cox transformation, there is a study with the opposite conclusion. Thus, in order to improve the accuracy of the regression model, it is necessary to use both transformations to determine the regression model with the highest accuracy. 3x13 steel (according to GOST standard) is commonly used to make parts in shipbuilding, petroleum, chemical technology, food processing technology, etc. [15]. Research on surface roughness when processing this steel or equivalent steels has been carried out in [12-16]. However, up to now, no studies have been found that apply the Johnson transformation and (or) the Box-Cox transformation to improve the accuracy of the surface texture model when milling 3x13 steel. So, in this study, 3x13 steel milling experiments were conducted. Two metric transformations, Johnson and Box-Cox were used to improve the accuracy of the surface roughness model. The main purpose of this study is to build a surface roughness model with higher accuracy.

II. MILLING EXPERIMENT

The 3x13 steel samples used in the experiment are box-shaped steel blocks with dimensions of 70×40×45mm. All six surfaces of the samples were rough milled on prior to testing. A 3-axis CNC milling machine was used for this experiment (Figure 1). TiAlN coated cutting inserts and 42mm diameter tips were used. TiAlN coated cutting pieces are better than many other cutting inserts such as TiN coated chips and TiCN coated cutting pieces in improving milling quality and productivity [17]. Each of the 4 cutting pieces was used for one test to reduce the error of tool wear to surface roughness. The basic parameters of the cutting piece are: L-type cutting insert, 0.3mm tip radius, 0.8mm back cutting edge length, 3.59mm cutting thickness, and 90^0 main cutting angle [17]. Three easily adjustable parameters, namely cutting speed, feed amount, and depth of cut were selected as input parameters for the experimental process. The selected values of the cutoff parameters at each level are shown in Table I [17, 18]. The experimental matrix was designed according to the Box-Behnken method. This type of design is commonly used to design experimental matrices in optimization research [1, 2]. Of course, building a regression function representing each relationship between input and output parameters is the basis for optimization, so in this study, the Box-Behnken method was also used to design the experimental matrix. With three input parameters, each parameter has three levels of values, so the number of experiments of the experimental matrix is 18, as shown in Table II. Surface roughness was measured with an SJ-301. The roughness probe has a diameter of 0.005mm, 0.8 is the standard length installed for the gauge. Each test specimen was measured at least 3 times to determine the surface roughness as the average of 3 consecutive measurements. In addition, a water-based emulsion solution was used during the experiment, with a flow rate of 12lt/min [12].

TABLE I. INPUT PARAMETERS

Parameter	Sign	unit	Value at level		
			1	0	1
Cutting velocity	v_c	m/min	168	240	312
Feed rate	f_z	mm/tooth	0.075	0.150	0.225
Cutting depth	a_p	mm	0.14	0.20	0.26

TABLE II. EXPERIMENTAL MATRIX AND RESULTS

Trial	Code value			Real value			Response		
	v_c	f_z	a_p	v_c (m/min)	f_z (mm/tooth)	a_p (mm)	R_a (µm) in experiments	After Johnson transformation	After Box-Cox transformation
1	0	0	0	240	0.150	0.20	0.99	0.24407	1.02030
2	-1	0	1	168	0.150	0.26	1.14	0.68393	0.76947
3	1	0	-1	312	0.150	0.14	0.75	-1.36782	1.77778
4	0	0	0	240	0.150	0.20	0.96	0.12678	1.08507
5	1	1	0	312	0.225	0.20	1.37	1.11439	0.53279
6	-1	0	-1	168	0.150	0.14	0.92	-0.05376	1.18147
7	0	1	-1	240	0.225	0.14	2.11	1.85155	0.22461
8	1	-1	0	312	0.075	0.20	0.81	-0.78032	1.52416
9	-1	1	0	168	0.225	0.20	1.33	1.05213	0.56532
10	0	0	0	240	0.150	0.20	0.97	0.16740	1.06281
11	0	0	0	240	0.150	0.20	0.92	-0.05376	1.18147
12	-1	-1	0	168	0.075	0.20	0.93	-0.00563	1.15620
13	0	-1	1	240	0.075	0.26	0.81	-0.78032	1.52416
14	1	0	1	312	0.150	0.26	0.69	-1.95000	2.10040
15	0	-1	-1	240	0.075	0.14	0.77	-1.16138	1.68663
16	0	0	0	240	0.150	0.20	0.92	-0.05376	1.18147
17	0	0	0	240	0.150	0.20	1.04	0.41348	0.92456
18	0	1	1	240	0.225	0.26	2.26	1.95000	0.19579

Fig. 1. CNC milling machine.

III. RESULTS AND DISCUSSION

The results of surface roughness measurement (*Ra*) are presented in Table II. Table III presents some parameters obtained when analyzing the experimental results with Minitab 16 software, with a chosen significance level of 0.05 [1, 2]. From the results in this Table, it can be seen that the feed rate is a parameter that has a great influence on surface texture because the *P-value* of this quantity is much smaller than the significance level [1]. Similarly, the quantity f_z^2 also has a significant effect on the surface texture. Since the coefficient of the feed rate parameter is positive, it shows that increasing the feed rate increases the surface roughness. As the feed rate increases, the contact time between the work surface and the cutting-edge decreases, reducing the number of times the cutting edge hits the part surface, leading to an increase in surface roughness. On the other hand, when the feed increases, the surface roughness will increase, which is also consistent with the theoretical formula for calculating surface roughness as follows: $Ra = 1000 \times 0.0321 \times f_z^2/r$, where f_z is the feed rate and r is the tip radius [19].

Cutting speed and depth of cut have little influence on surface texture, because the *P-values* of these two parameters are 0.335 and 0.662 respectively, which are larger than the significance level. However, the effect of cutting speed on surface roughness is greater than that of the depth of cut. Increasing cutting speed reduces surface roughness, while increasing cutting depth increases it. The magnitude of the surface undulation is inversely proportional to the cutting velocity and proportional to the depth of cut [18, 20].

From the data in Table III, the surface roughness model shown in (1) has been built.

$$R_{a(exp.)} = 0.9667 - 0.0875 \cdot v_c + 0.4687 \cdot f_z + 0.0436 \cdot a_p - 0.2346 \cdot v_c^2 + 0.3779 \cdot f_z^2 + 0.1429 \cdot ap2 + 0.04 \cdot v_c \cdot f_z - 0.07 \cdot v_c \cdot a_p + 0.0275 \cdot f_z \cdot a_p \quad (1)$$

This model has coefficients *R-Sq* and *R-Sq*(*adj*) equal to 0.8563 and 0.6945 respectively. The values of these parameters are as close to 1 as possible. The value of the coefficient *R-Sq* can be increased if (1) is supplemented with higher order quantities (larger exponents, for example v_c^3, f_z^3, etc). However, doing so will increase the complexity of the model [1, 2]. Only 69.45% of the change in surface roughness is due to the change of input parameters. Thus, if model (1) is used to predict surface roughness, the accuracy will be limited. Therefore, we need to increase the values of *R-Sq* and *R-Sq*(*adj*) in the regression model without making the model complicated (without using ternary, quaternary, etc.). Two metric transformations, Johnson and Box-Cox, will be used to solve this task. The condition to perform the data transformation according to these two transformations is that the data set must not be distributed according to the normal rules [1, 2]. The distribution rule of surface roughness values while testing is presented in Figure 2. This Figure is acquired in Minitab when determining the distribution rule of surface roughness. Each red dot represents the surface roughness value at an experiment. These red dots are located far from the middle line, there are even red dots lying on either side of the two curves on either side. At the same time, the *P-value* < 0.005, which is much smaller than the significance level. This confirms that the surface roughness datasets are not normally distributed, that is, they are eligible to perform the Johnson and Box-Cox data transformations.

TABLE III. EXPERIMENTAL DATA ANALYSIS RESULTS

	Coefficients	Standard error	*t* stat	*P-value*
Intercept	0.9667	0.0985	9.816	0.000
v_c	- 0.0875	0.0853	- 1.026	0.335
f_z	0.4687	0.0853	5.496	0.001
a_p	0.0436	0.0853	0.513	0.622
v_c^2	- 0.2346	0.1155	- 2.031	0.077
f_z^2	0.3779	0.1155	3.273	0.011
a_p^2	0.1429	0.1155	1.238	0.251
$v_c \cdot f_z$	0.0400	0.1206	0.332	0.749
$v_c \cdot a_p$	- 0.0700	0.1206	- 0.580	0.578
$f_z \cdot a_p$	0.0275	0.1206	0.288	0.825
R-Sq = 85.63%		*R-Sq(adj)* = 69.45%		

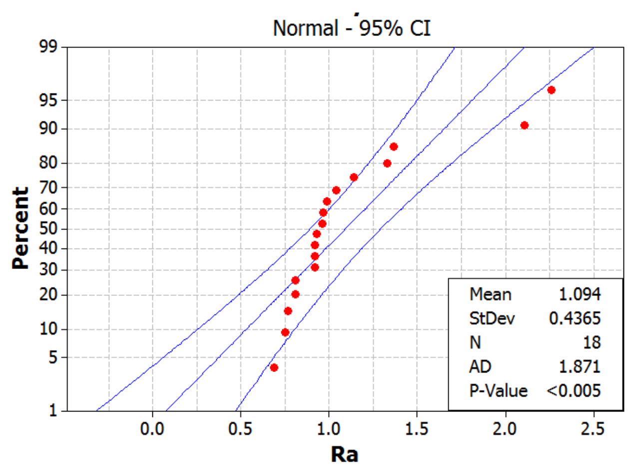

Fig. 2. Probability plot of surface roughness (*Ra*).

Minitab is again used to convert data. Figure 3 shows the graph of the Johnson transformation. The upper left image section is the pre-conversion metric information discussed above. The data set after Johnson transformation has also been included in Table II. The lower left part of the figure shows the rule of the data set after the transformation. All the red dots have fit in between the two limiting curves, many of which are already very close to the line, and *P-value* = 0.587, which is much larger than the significance level. This confirms that the data set after the Johnson transformation has a normal distribution. Observing the upper right Figure also shows that the data set after transformation is distributed according to normal rules. The relationship between the data before and after the Johnson transformation is found in the lower right Figure (in Figure 3). So, a new model of surface roughness has been established as shown in (2). Transforming (2) we get the surface roughness model as in (3). This model has coefficients *R-Sq* and *R-Sq*(*adj*) of 0.8669, 0.7172 respectively.

Figure 4 shows a graph of the Box-Cox transformation. The value of the dataset after Box-Cox transformation has also been included in Table II. The distribution rule of the dataset after Box-Cox transformation is shown in Figure 5. All red dots are located between the two limit curves. The *P-value* is 0.655, which is much larger than the significance level. That shows that the data set after Box-Cox transformation is also distributed according to normal rules.

Since the lambda exponent of the transformation is equal to -2.00 (Figure 4), a new model of the surface roughness is established as shown in (4). This model coefficients *R-Sq* and *R-Sq*(*adj*) of 0.8787 and 0.7422 respectively.

$$\begin{aligned} -1.35178 + 0.941864 \cdot \mathrm{Asinh}\left(\left(R_{a(John.)} - 0.751544\right)/0.0906774\right) \\ = 0.1407 - 0.5826 \cdot v_c + 1.0869 \cdot f_z + 0.0794 \cdot a_p - 0.4662 \cdot v_c^2 + 0.6707 \cdot f_z^2 \\ - 0.3464 \cdot a_p^2 + 0.2092 \cdot v_c \cdot f_z - 0.3299 \cdot v_c \cdot a_p - 0.0707 \cdot f_z \cdot a_p \end{aligned} \tag{2}$$

$$Ra = 0.751544 + 0.0906774 \cdot \mathrm{Sinh}\begin{pmatrix} 1.5846 - 0.6186 \cdot v_c + 1.1540 \cdot f_z + 0.0843 \cdot a_p \\ -0.4950 \cdot v_c^2 + 0.7121 \cdot f_z^2 - 0.3678 \cdot a_p^2 \\ +0.2221 \cdot v_c \cdot f_z - 0.3503 \cdot v_c \cdot a_p - 0.0751 \cdot f_z \cdot a_p \end{pmatrix} \tag{3}$$

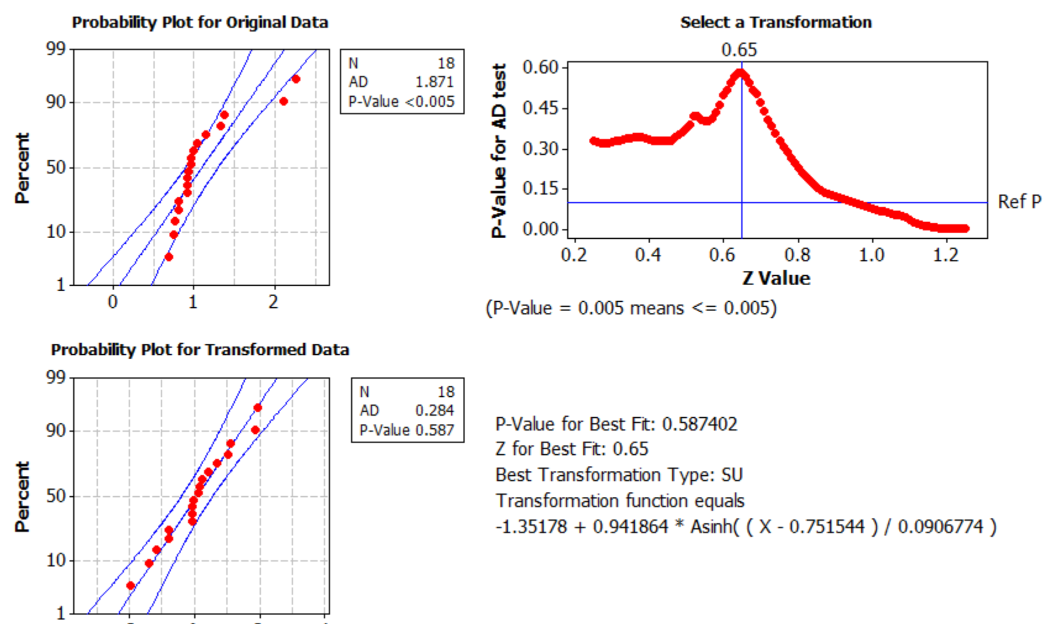

Fig. 3. Johnson transformation for surface roughness (*Ra*).

$$R_{a(Box.)} = \begin{bmatrix} 1.0759 + 0.2828 \cdot v_c - 0.5466 \cdot f_z - 0.0351 \cdot a_p + 0.2091 \cdot v_c^2 \\ - 0.3404 \cdot f_z^2 + 0.1722 \cdot a_p^2 - 0.1001 \cdot v_c \cdot f_z \\ +0.1837 \cdot v_c \cdot a_p + 0.0334 \cdot f_z \cdot a_p \end{bmatrix}^{-1/2} \tag{4}$$

To compare the three established surface roughness models (1), (3), and (4), it is necessary to first use them to calculate the surface roughness and then compare them with the experimental results. Each model was used to calculate the surface roughness with the values of the input parameters as shown in Table II. The results of the surface roughness determination for each experiment using the three models are included in Table IV. The surface roughness value when calculated by the three models will be compared with the surface roughness obtained from the experiment. *PAE* is calculated according to (5). *MSE* is calculated according to (6). In these two equations, $R_{a(exp.)}$ is the roughness value in the experiment; $R_{a(cal.)}$ is the roughness value when calculating. N is the number of experiments.

$$PAE = \frac{1}{N}\left(\sum_{i=1}^{N}\left|\frac{Ra_{(exp.)}-R_{a(cal.)}}{R_{a(exp.)}}\right|\right)\cdot 100\% \quad (5)$$

$$MSE = \frac{1}{N}\left(\sum_{i=1}^{N}\left|R_{a(exp.)} - R_{a(cal.)}\right|^2\right)\cdot 100\% \quad (6)$$

Table V presents some parameters of the 3 surface roughness models. From the data in this Table, the models using Johnson and Box-Cox transformations both have values of *R-Sq* and *R-Sq*(*adj*) larger than the model without a data transformation. The *PAE* and *MSE* of the 2 models using a data transformation are also smaller than those of the model not using any data transformation. Thus, the use of a data transformation has improved the accuracy of the model.

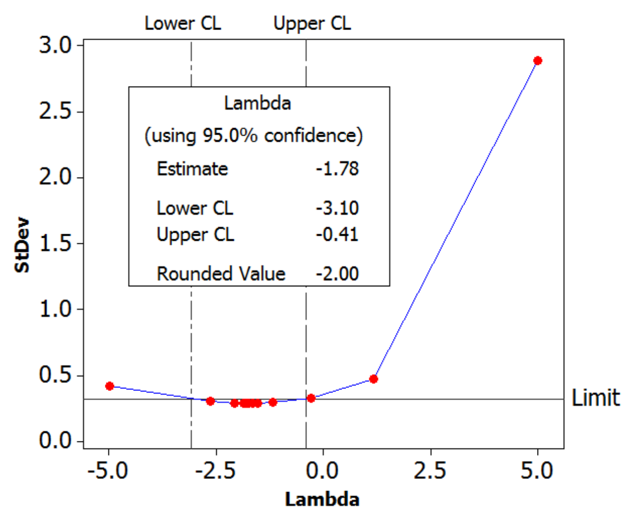

Fig. 4. Box-Cox transformation for surface roughness (*Ra*).

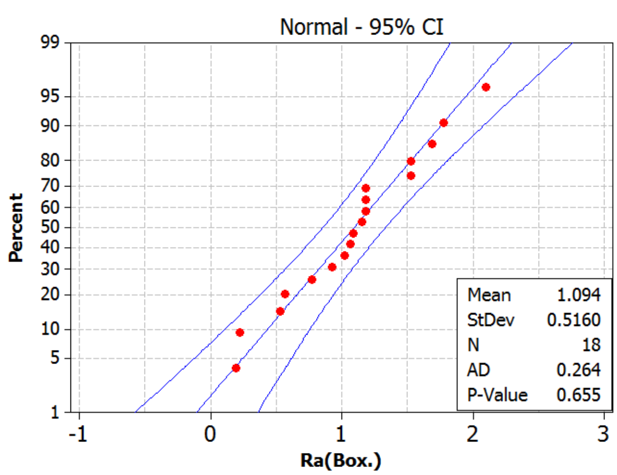

Fig. 5. Probability plot of surface roughness after Box-Cox transformation.

In Table V, both parameters *R-Sq* and *R-Sq*(*adj*) of the model using Box-Cox transformation are larger than those in the other two models. The *PAE* and *MSE* parameters of the model using the Box-Cox transformation are smaller than the other two models. Therefore, we can confirm that the surface texture model using the Box-Cox transformation has the highest accuracy. In contrast, the model that does not use the data transformation has the lowest accuracy. This result is in accordance with the conclusions in [10, 13]. Therefore, it can be said that the Box-Cox transformation is recommended to improve the accuracy of the surface model when milling.

TABLE IV. CALCULATED SURFACE ROUGHNESS

Trial	Measured	Without transformation	Johnson transformation	Box-Cox transformation
1	0.99	0.9667	0.9634	1.0373
2	1.14	1.0761	1.0114	1.1142
3	0.75	0.8139	0.7858	0.7631
4	0.96	0.9667	0.9634	1.0373
5	1.37	1.5312	1.3341	1.4010
6	0.92	0.8489	0.8454	0.9334
7	2.11	1.8851	1.7297	2.2010
8	0.81	0.5138	0.7339	1.3690
9	1.33	1.6262	2.0451	1.3220
10	0.97	0.9667	0.9634	1.0373
11	0.92	0.9667	0.9634	1.0373
12	0.93	0.7688	0.9422	1.0528
13	0.81	1.0349	0.8491	0.8282
14	0.69	0.7611	0.7367	0.7018
15	0.77	1.0027	0.8109	0.7615
16	0.92	0.9667	0.9634	1.0373
17	1.04	0.9667	0.9634	1.0373
18	2.26	2.0273	1.7480	2.2624

TABLE V. PARAMETERS OF THE CALCULATED SURFACE ROUGHNESS MODELS

Surface roghness model	*R-Sq*	*R-Sq(adj)*	*PAE*	*MSE*
Without transformation (1)	0.8563	0.6945	12.20	2.59
Using Johnson transformation (3)	0.8669	0.7172	9.41	2.36
Using Box-Cox transformation (4)	0.8787	0.7422	8.88	2.10

IV. CONCLUSION

From the results of this study, some conclusions when milling 3x13 steel with TiAlN coated cutting pieces were drawn:

- Feed rate is a parameter that has a significant influence on surface roughness. As the feed rate increases, the surface roughness increases. The cutting speed and the depth of cut have no significant influence on the surface roughness.
- A data set that is not distributed according to the normal rules will be distributed according to the normal rules after performing a transformation using the Johnson or Box-Cox method.
- Using Johnson and Box-Cox transformations will increase the accuracy of the regression model. In the specific conditions of this study, using the Box-Cox transformation will build the regression model of the surface texture with the highest accuracy.

- The use of both transformations, Johnson and Box-Cox, to improve the accuracy of the surface roughness model is not only successfully applied in this study as well as in several other published studies, but also it is a tool that improves the accuracy of the regression model in other cases.

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