Optimal Surface Grinding Regression Model Determination with the SRP Method

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ABSTRACT

The construction of the regression models used to control machining processes is the objective of many experimental studies. Therefore, the effectiveness of the machining process control largely depends on the regression model's accuracy. This study was conducted to determine the optimal regression model of surface grinding. Accordingly, eight different surface grinding regression models were constructed, including one model without data transformation and seven models that utilized various data transformations. The seven data transformations employed entailed square root transformation, logarithmic transformation, inverse transformation, exponential transformation, asinh transformation, Box-Cox transformation, and Johnson transformation. The process of determining the optimal model was carried out considering five parameters: R^2, R^2(adj), R^2(pred) (predicted R^2), MAE (Mean Absolute Error), and MSE (Mean Squared Error). SRP (Simple Ranking Process) was the optimization method followed to identify the best regression model. The Box-Cox transformation was recognized as the most accurate surface grinding regression model.

Keywords-surface roughness model; grinding; data transformation method; multi-objective optimization

I. INTRODUCTION

The grinding method is deployed as a precision machining process for surfaces demanding fine roughness. Numerous studies have utilized surface grinding regression models as a basis for controlling the grinding process [1, 2]. Surface roughness is often chosen as the parameter to be measured in the grinding process because it has a significant impact on the wear resistance, chemical corrosion resistance, and fatigue of the machine components. In other words, surface roughness greatly influences the durability and lifespan of products [3]. Additionally, measuring surface roughness is more convenient than measuring other parameters, such as the cutting force, cutting heat, etc. [4]. The efficiency of controlling the grinding process depends significantly on the accuracy of the regression model. To assess the accuracy of a regression model, five parameters are typically considered: R^2, R^2(adj), R^2(pred), MAE, and MSE [5]. R^2 measures the variability of the model compared to the actual data. R^2(adj) assesses the model's explanatory power for the dependent variable based on the number of independent variables. R^2(pred) evaluates the model's predictive ability for new data. MAE calculates the average absolute deviation between the predicted and the actual values. MSE computes the average of the squared deviations between the predicted and the actual values. A lower value indicates a better predictive performance of the model. The values of R^2, R^2(adj), R^2(pred) range from 0 to 1, and higher values are preferable, whereas lower values of MAE and MSE are preferred [6]. However, if the regression model is directly constructed from experimental data, its accuracy might not be high, meaning R^2, R^2(adj), R^2(pred) could have low values, and MAE and MSE could have high values. This stresses the necessity to enhance the accuracy of the regression models. To address this limitation, some studies have performed data transformations to improve the accuracy of the regression models. Seven data transformations, namely square root transformation, logarithmic transformation, inverse transformation, exponential transformation, asinh transformation, Box-Cox transformation, and Johnson transformation, are commonly employed [7]. The square root transformation has been implemented to transform surface roughness data when grinding JIS-S45C steel flatly and has resulted in a regression model with higher accuracy compared to a model without data transformation [8]. The usage of the Box-Cox transformation has led to the development of regression models with higher accuracy compared to models without data transformation when milling EN 353 steel [9], AISI 1019 steel [10], AISI 1045 steel [11], 080A67 steel [12], and centerless grinding SCM435 steel [13]. Both the Box-Cox and Johnson transformations have been engaged to improve the accuracy of the surface grinding models when milling 3X13 steel. In [14], it was demonstrated that the model using the

Box-Cox transformation had the highest accuracy, whereas the model without data transformation had the lowest accuracy [14]. Both Box-Cox and Johnson transformations were also used to enhance the accuracy of the surface grinding models when grinding 65G steel. In [15], it was concluded that the model employing the Johnson transformation had the highest accuracy, whereas the model without data transformation had the lowest one. In [16], both Box-Cox and Johnson transformations were identified to be equally effective in improving the accuracy of cutting force regression models when milling SCM440 steel.

It can be concluded that Box-Cox and Johnson are the two data transformations most commonly utilized to ameliorate the regression models' accuracy in mechanical machining. However, these two transformations exhibit different effectiveness in specific cases [14, 15, 17]. Additionally, the application of the remaining five data transformations is still very limited. It can even be argued that there has been no study applying all the seven transformations in a specific case. This is the reason why they are all deployed in this study. However, it is not certain that a regression model using a specific data transformation is the best model in terms of all five parameters (R^2, R^2(adj), R^2(pred), MAE, and MSE) compared to the other models [16]. This means that determining the best model among the created ones must be carried out by applying multi-objective optimization methods [18, 19]. The SRP method was adopted in this study because it is a very simple and recently emerging approach [20].

II. MATERIALS AND METHODS

A. Data Transformations

The formulas for each of the seven considered transformations are presented below [5, 6]. Here, R_a represents the surface roughness value in the experiment and y_i (with i=2÷8) denotes the surface roughness value after performing the transformations.

1) Square Root Transformation

$$y_2 = \sqrt{Ra} \tag{1}$$

2) Logarithmic Transformation

$$y_3 = \log(Ra) \tag{2}$$

3) Reciprocal Transformation

$$y_4 = \frac{1}{Ra} \tag{3}$$

4) Exponential Transformation

$$y_5 = e^{Ra} \tag{4}$$

5) Asinh Transformation

$$y_6 = \ln(Ra + \sqrt{Ra^2 + 1}) \tag{5}$$

6) Box-Cox transformation

$$y_7 = \begin{bmatrix} Ra^{\mu} & if & \mu \neq 0 \\ ln(Ra) & if & \mu = 0 \end{bmatrix} \tag{6}$$

where μ is the parameter of the transformation.

7) Johnson Transformation

$$y_8 = \lambda + \beta \cdot ln\left(\frac{Ra-\gamma}{\delta-Ra}\right) \tag{7}$$

where λ, β, γ, δ are parameters of the transformation.

B. Evaluation Parameters

The coefficients R^2, R^2(adj), R^2(pred) can be easily found using Minitab software for result analysis. MAE and MSE are calculated by [11, 15]:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_p-y_e}{y_e}\right| \cdot 100 \tag{8}$$

$$\text{MSE} = \frac{1}{n}\sum_{1}^{n}\left(y_p - y_e\right)^2 \cdot 100 \tag{9}$$

where n is the number of observations (number of experiments), y_p is the predicted value of observation i (the ith experiment), and y_e is the actual value (experimental value) of observation i.

C. Optimization Method

The SRP method was deployed to identify the best model. With m surface grinding models, each model is characterized by five parameters (R^2, R^2(adj), R^2(pred), MAE, and MSE). The identification of the optimal model with the SRP method is conducted as follows [20]:

- Internally rank the models, i.e. rank the surface grinding models for each parameter.
- Calculate scores for each model using (10).

$$S_i = \sum_{j=1}^{5} r_{ij} \cdot w_j \tag{10}$$

where w_j is the weight of the j^{th} parameter.

- Rank the models based on increasing scores.

D. Metal Grinding Experiments

This study performed flat grinding experiments. A summary of some conditions of the grinding process follows. The experimental steel is C45 steel, heat-treated to achieve a hardness of 45-45HRC. This type of steel is designated according to the DIN standard of Germany. This steel type is equivalent to S45C steel (JIS/Japan), AF65C45 (AFNOR/France), 070M46 (BS/England), C45k (UNE/Spain), 1650 (SS/Sweden), 45 (PN/Poland), 12050 (CSN/Czechia), C45SW (ONORM/Austria), 45 (GOST/Russia). The basic physical properties of this type of steel are summarized in Table I. The flat grinding machine employed was APSG-820/2A. The aluminum oxide grinding wheel utilized was WA46J7V1A.

TABLE I. PHYSICAL PROPERTIES OF C45 STEEL

Young's modulus	Yield strength	Tensile strength	Poisson coefficient	Elongation
200 GPa	480 MPa	720 MPa	0.32	20%

TABLE II. INPUT PARAMETERS

Parameter	Code	Value at leves		
		-1	0	1
v	x_1	15	20	25
f	x_2	3	5	7
a_p	x_3	0.005	0.01	0.015

The coolant sprayed into the grinding area was an emulsion type with a flow rate of 4.6 l/min and a coolant concentration of 15%. The wheel dressing was carried out prior to each experiment using a single-point diamond dressing tool. The corresponding depth and feed rate of the diamond tool dressing are 0.01 mm and 150 mm/min, respectively. Three cutting parameters were varied in each experiment: cutting speed v (m/s), cross-feed rate f (mm/stroke), and depth of cut a_p (mm). Each parameter was varied at three values corresponding to three encoding levels as portrayed in Table II [21, 22]. Eighteen experiments were designed in the Box-Behnken design as observed in Table III. This is a commonly deployed method for designing experimental matrices [15, 16]. The surface roughness was measured using an SJ-301 machine (Mitutoyo - Japan). At each experiment, measurements were conducted at least three times, perpendicular to the direction of the cutting velocity vector during grinding. The surface roughness value for each experiment is the average of these consecutive measurements. The experimental results (R_a) are listed in the last column of Table III.

TABLE III. EXPERIMENTAL RESULTS

Exp. No.	Code value			Real value			R_a (μm)
	x_1	x_2	x_3	v (m/s)	f (mm/stroke)	a_p (mm)	
1	0	0	0	20	5	0.01	2.61
2	-1	-1	0	15	3	0.01	0.83
3	0	-1	1	20	3	0.015	0.72
4	1	0	1	25	5	0.015	0.62
5	0	-1	-1	20	3	0.005	0.69
6	0	0	0	20	5	0.01	2.45
7	0	0	0	20	5	0.01	2.40
8	0	1	1	20	7	0.015	2.02
9	0	0	0	20	5	0.01	0.88
10	-1	0	1	15	5	0.015	1.02
11	1	0	-1	25	5	0.005	0.67
12	0	0	0	20	5	0.01	2.58
13	1	1	0	25	7	0.01	1.22
14	-1	0	-1	15	5	0.005	0.82
15	0	1	-1	20	7	0.005	1.88
16	1	-1	0	25	3	0.01	0.72
17	-1	1	0	15	7	0.01	1.19
18	0	0	0	20	5	0.01	2.55

III. RESULTS AND DISCUSSION

Considering the experimental data values of R_a in Table II and with the assistance of Minitab software, the corresponding values of μ, λ, β, γ, δ were determined to be -0.5, 0.136718, 0.283804, 0.61858, and 2.61372, respectively. The surface roughness values after performing the transformations are summarized in Table IV. From the data in Table IV, regression equations (11) to (18) were established. For each equation, three coefficients R^2, R^2(adj), and R^2(pred) are also listed.

Without transformation: R^2 = 0.7520; R^2(adj) = 0.4730; R^2(pred) = 0.1484:

$$y_1 = Ra = 2.2450 - 0.0787 \cdot x_1 + 0.4187 \cdot x_2 + 0.0400 \cdot x_3 - 0.9000 \cdot x_1^2 - 0.3550 \cdot x_2^3 - 0.5625 \cdot x_3^2 + 0.0350 \cdot x_1 \cdot x_2 - 0.0625 \cdot x_1 \cdot x_3 + 0.0275 \cdot x_2 \cdot x_3 \quad (11)$$

Square root transformation: R^2 = 0.7656; R^2(adj) = 0.5020; R^2(pred) = 0.1269:

$$y_2 = 1.4785 - 0.0448 \cdot x_1 + 0.1936 \cdot x_2 + 0.0176 \cdot x_3 - 0.3636 \cdot x_1^2 - 0.1261 \cdot x_2^3 - 0.2345 \cdot x_3^2 + 0.0190 \cdot x_1 \cdot x_2 - 0.0338 \cdot x_1 \cdot x_3 + 0.0080 \cdot x_2 \cdot x_3 \quad (12)$$

Logarithmic transformation: R^2 = 0.7825; R^2(adj) = 0.5379; R^2(pred) = 0.1085:

$$y_3 = 0.3247 - 0.0443 \cdot x_1 + 0.1586 \cdot x_2 + 0.0138 \cdot x_3 - 0.2619 \cdot x_1^2 - 0.0782 \cdot x_2^3 - 0.1776 \cdot x_3^2 + 0.0181 \cdot x_1 \cdot x_2 - 0.0321 \cdot x_1 \cdot x_3 + 0.0031 \cdot x_2 \cdot x_3 \quad (13)$$

Reciprocal transformation: R^2 = 0.8207; R^2(adj) = 0.6189; R^2(pred) = 0.0473:

$$y_4 = 0.5206 + 0.1336 \cdot x_1 - 0.3431 \cdot x_2 - 0.0270 \cdot x_3 + 0.4514 \cdot x_1^2 + 0.0913 \cdot x_2^3 + 0.3542 \cdot x_3^2 - 0.0511 \cdot x_1 \cdot x_2 + 0.0898 \cdot x_1 \cdot x_3 + 0.0058 \cdot x_2 \cdot x_3 \quad (14)$$

Exponential transformation: R^2 = 0.7320; R^2(adj) = 0.4304; R^2(pred) = 0.3042:

$$y_5 = 10.7710 - 0.1712 \cdot x_1 + 1.5463 \cdot x_2 + 0.1816 \cdot x_3 - 5.1681 \cdot x_1^2 - 2.8473 \cdot x_2^3 - 3.3886 \cdot x_3^2 + 0.0847 \cdot x_1 \cdot x_2 - 0.1495 \cdot x_1 \cdot x_3 + 0.2310 \cdot x_2 \cdot x_3 \quad (15)$$

Asinh transformation: R^2 = 0.7682; R^2(adj) = 0.5075; R^2(pred) = 0.1155:

$$y_6 = 1.5102 - 0.0622 \cdot x_1 + 0.2676 \cdot x_2 + 0.0242 \cdot x_3 - 0.4843 \cdot x_1^2 - 0.1600 \cdot x_2^3 - 0.3115 \cdot x_3^2 + 0.0265 \cdot x_1 \cdot x_2 - 0.0473 \cdot x_1 \cdot x_3 + 0.0095 \cdot x_2 \cdot x_3 \quad (16)$$

Box-Cox transformation: R^2 = 0.8015; R^2(adj) = 0.5782; R^2(pred) = 0.0851:

$$y_7 = 0.7030 + 0.0583 \cdot x_1 - 0.1754 \cdot x_2 - 0.0146 \cdot x_3 + 0.2571 \cdot x_1^2 + 0.0644 \cdot x_2^3 + 0.1863 \cdot x_3^2 - 0.0230 \cdot x_1 \cdot x_2 + 0.0406 \cdot x_1 \cdot x_3 - 0.0001 \cdot x_2 \cdot x_3 \quad (17)$$

Johnson transformation: R^2 = 0.7499; R^2(adj) = 0.4685; R^2(pred) = 0.00:

$$y_8 = 0.9125 - 0.2850 \cdot x_1 + 0.3876 \cdot x_2 - 0.0753 \cdot x_3 - 0.9710 \cdot x_1^2 - 0.2881 \cdot x_2^3 - 0.8296 \cdot x_3^2 + 0.0615 \cdot x_1 \cdot x_2 - 0.3137 \cdot x_1 \cdot x_3 - 0.0035 \cdot x_2 \cdot x_3 \quad (18)$$

Combining (1) and (12), the surface grinding model using the square root transformation is formed as (19):

$$R_a = y_2^2 \quad (19)$$

Combining (2) and (13), the surface grinding model utilizing the logarithm transformation is formed as (20):

$$R_a = 10^{y_3} \quad (20)$$

Combining (3) and (14), the surface grinding model employing the reciprocal transformation is formed as (21):

$$R_a = \frac{1}{y_4} \quad (21)$$

Combining (4) and (15), the surface grinding model using the exponential transformation is formed as (22):

$$R_a = ln y_5 \quad (22)$$

Combining (5) and (16), the surface grinding model deploying the asinh transformation is formed as (23):

$$R_a = e^{y_6} - \sqrt{e^{2y_6} - 1} \tag{23}$$

Combining (6) and (17), the surface grinding model utilizing the Box-Cox transformation is formed as (24):

$$R_a = \frac{1}{y_7^2} \tag{24}$$

Combining (7) and (18), the surface grinding model employing the Johnson transformation is formed as (25):

$$R_a = \frac{0.61858 + 2.61372 \cdot e^{0.283804 y_8 - 0.136718}}{1 + e^{0.283804 y_8 - 0.136718}} \tag{25}$$

The models (11), (19), (20), (21), (22), (23), (24), (25) were used to predict the surface roughness with the selected input parameters depicted in Table III. The results are summarized in Table V.

TABLE IV. TRANSFORMED SURFACE ROUGHNESS VALUES

Exp.	R_a	y_2	y_3	y_4	y_5	y_6	y_7	y_8
1	2.61	1.62	0.42	0.38	13.60	1.69	0.62	1.92
2	0.83	0.91	-0.08	1.20	2.29	0.76	1.10	-0.47
3	0.72	0.85	-0.14	1.39	2.05	0.67	1.18	-0.69
4	0.62	0.79	-0.21	1.61	1.86	0.59	1.27	-1.92
5	0.69	0.83	-0.16	1.45	1.99	0.64	1.20	-0.80
6	2.45	1.57	0.39	0.41	11.59	1.63	0.64	0.82
7	2.40	1.55	0.38	0.42	11.02	1.61	0.65	0.74
8	2.02	1.42	0.31	0.50	7.54	1.45	0.70	0.38
9	0.88	0.94	-0.06	1.14	2.41	0.79	1.07	-0.40
10	1.02	1.01	0.01	0.98	2.77	0.90	0.99	-0.25
11	0.67	0.82	-0.17	1.49	1.95	0.63	1.22	-0.89
12	2.58	1.61	0.41	0.39	13.20	1.68	0.62	1.29
13	1.22	1.10	0.09	0.82	3.39	1.03	0.91	-0.10
14	0.82	0.91	-0.09	1.22	2.27	0.75	1.10	-0.48
15	1.88	1.37	0.27	0.53	6.55	1.39	0.73	0.29
16	0.72	0.85	-0.14	1.39	2.05	0.67	1.18	-0.69
17	1.19	1.09	0.08	0.84	3.29	1.01	0.92	-0.12
18	2.55	1.60	0.41	0.39	12.81	1.67	0.63	1.10

TABLE V. SURFACE ROUGHNESS PREDICTED BY THE MODELS

Exp.	Experiment	Using (11)	Using (19)	Using (20)	Using (21)	Using (22)	Using (23)	Using (24)	Using (25)
1	2.61	2.25	2.19	2.11	1.92	2.38	0.11	2.02	1.68
2	0.83	0.69	0.74	0.77	0.82	0.38	0.27	0.80	1.49
3	0.72	0.92	0.87	0.83	0.78	1.08	0.24	0.80	1.46
4	0.62	0.68	0.67	0.66	0.66	0.73	0.29	0.66	1.33
5	0.69	0.90	0.84	0.79	0.75	1.11	0.25	0.76	1.48
6	2.45	2.25	2.19	2.11	1.92	2.38	0.11	2.02	1.68
7	2.40	2.25	2.19	2.11	1.92	2.38	0.11	2.02	1.68
8	2.02	1.81	1.79	1.76	1.66	1.87	0.13	1.72	1.56
9	0.88	2.25	2.19	2.11	1.92	2.38	0.11	2.02	1.68
10	1.02	0.96	0.95	0.94	0.93	1.00	0.22	0.94	1.50
11	0.67	0.73	0.73	0.72	0.72	0.70	0.27	0.72	1.44
12	2.58	2.25	2.19	2.11	1.92	2.38	0.11	2.02	1.68
13	1.22	1.36	1.34	1.31	1.25	1.44	0.17	1.28	1.52
14	0.82	0.76	0.76	0.76	0.76	0.72	0.26	0.77	1.43
15	1.88	1.68	1.65	1.62	1.55	1.73	0.14	1.59	1.58
16	0.72	0.46	0.53	0.58	0.63	-0.05	0.33	0.61	1.40
17	1.19	1.45	1.46	1.48	1.57	1.48	0.16	1.51	1.59
18	2.55	2.25	2.19	2.11	1.92	2.38	0.11	2.02	1.68

TABLE VI. PARAMETERS OF THE SURFACE GRINDING MODELS

Model	R^2 (%)		R^2(adj) (%)		R^2(pred) (%)		MAE (%)		MSE (%)	
	value	rank	value	rank	value	rank	value	rank	value	rank
(11)	75.20	6	47.30	6	14.84	2	22.60	5	14.60	2
(19)	76.56	5	50.20	5	12.69	3	21.05	4	14.34	1
(20)	78.25	3	53.79	3	10.85	5	20.25	2	14.78	3
(21)	82.07	1	61.89	1	4.73	7	20.27	3	18.38	5
(22)	73.20	8	30.42	8	43.04	1	31.26	6	20.37	6
(23)	76.82	4	50.75	4	11.55	4	79.62	8	224.46	8
(24)	80.15	2	57.82	2	8.51	6	20.02	1	16.03	4
(25)	74.99	7	46.85	7	0.00	8	60.83	7	47.27	7

Equations (8) and (9) were implemented to calculate MAE and MSE for each surface grinding model. Table VI summarizes all five considered parameters for each model, along with its ranking for each parameter. It is noticeable from Table VI that no model ranks first in all five parameters. Therefore, selecting the optimal model requires the application of the SRP method. So far, no study has addressed which of the five considered parameters is more important. Therefore, this study chose these five parameters with equal weights, all equal to 0.2. Applying (10), the scores of each model were calculated as illustrated in Table VII, and the rank of each model was determined.

TABLE VII. . SCORES (S_i) AND RANKINGS OF SURFACE GRINDING MODELS

Model	Si	Rank
(11)	4.20	5
(19)	3.60	4
(20)	3.20	2
(21)	3.40	3
(22)	5.80	7
(23)	5.60	6
(24)	3.00	1
(25)	7.20	8

The accuracy of the models ranked in a decreasing order is: (24) > (20) > (21) > (19) > (11) > (23) > (22) > (25). This means that the surface grinding model using the Box-Cox transformation has the highest accuracy, the model without data transformation ranks 5th, and the model employing the Johnson transformation has the lowest accuracy. Asserting the model deploying the Box-Cox transformation yields the highest accuracy, similarly to the case of utilizing data transformations to enhance the accuracy of the surface roughness model when milling 3X13 steel [14].

IV. CONCLUSION

This is the first study that applies seven data transformation methods with the aim of improving the accuracy of regression models. The surface roughness model in grinding was selected as the target for performing data transformations. The SRP method was followed to determine the optimal surface roughness model. Eight surface roughness models in grinding were established, including one model without data transformation and seven models that employed data transformation methods. The model utilizing the Box-Cox transformation had the highest accuracy, whereas the model deploying the Johnson transformation had the lowest. Therefore, the Box-Cox transformation surface roughness model with the highest accuracy had metric values of: R^2, R^2(adj), R^2(pred), MAE, and MSE equal to 80.15%, 57.82%, 8.51%, 20.02%, and 16.03%, respectively.

The methods employed in this study not only identified the optimal surface roughness model, but are also expected to be successful in selecting optimal models in other applications.

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