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Artificial neural network in the prediction of surface roughness: A comparative study

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Abstract

Surface roughness is a key parameter to consider in the machining of aluminum alloy. It is rendered as one of the important determinants of the performance of mechanical instruments or components. Owing to its excellent mechanical properties, and ease of machinability, Aluminum 6061 (Al6061) is rendered a popular choice in many industries. Achieving a desired surface finish is crucial for the performance and longevity of machined components. This study aimed to compare the predictive performance of the artificial neural network (ANN) model versus the response surface methodology (RSM) in the prediction of surface roughness in the turning process of Al6061. ANN performed better than RSM in the prediction of surface roughness (A20 index 0.93 and 0.86 for ANN and RSM models respectively). MAPE and sMAPE were also found to be lower in the ANN model compared with the RSM model (8.06 versus 9.69, and 0.039 versus 0.047 respectively) indicating that the ANN model had a better predictive performance compared with the RSM model. Both ANN and RSM models showed that cutting speed and feed rate were the most important determinants of surface roughness in the turning process of Al6061 in other words to achieve a smoother surface during the turning process of Al6061 high cutting speed and low feed rate should be used. The findings of this study reflect the potential utility of ANN in the prediction and subsequently optimizing cutting parameters to achieve a smoother surface.

Keywords: ANN, Artificial intelligence, Prediction, Aluminum 6061, Turning

1. Introduction

Surface roughness (Ra) often quantified as average roughness (Ra) is a key parameter to consider in the machining process of aluminum alloys. It can be defined as the irregularities in the workpiece surface that occur during the machining process [1]. Achieving a desired level of surface roughness is rendered as one of the key performance indicators of machining process quality [2]. Also, surface finish is considered a critical attribute in the machining process of materials used in many industries; For instance, in aerospace applications, surface roughness is considered a key performance indicator for many machining processes' quality [3]. In medical applications, a smooth surface finish is essential to reduce friction and prevent bacterial growth on the surface of implants and devices [4].

Owing to its excellent mechanical properties such as light weight, durability, resistance to corrosion, and ease of forming and machinability; Therefore, Aluminum 6061 is one of the most commonly used aluminum alloys in a diversity of industries [5]. Several factors can contribute to the quality of the produced surface finish when machining aluminum alloys, this can include factors related to the machined material and factors associated with the machining process such as the use of coolant and machining parameters e.g. speed, feed, and depth of cutting [6-8]. However, it is challenging to control surface roughness in manufacturing processes and can potentially increase manufacturing costs [9]. This shows the importance of the establishment of a concerted understanding of the impact of machining parameters on the generated surface roughness can provide potentially important inputs that can guide the selection of the optimal machining parameters that generate the most optimal surface finish [10].

Response surface methodology (RSM) is considered a combination of experimental and statistical techniques utilized to establish models to analyze and optimize the influence of input variables on the outcome of interest, thus, it is widely used by researchers to obtain the most effective combination of machining parameters to optimize the machining parameters to obtain the most optimal surface finish [11]. By utilizing RSM, with minimal experimentation empirical models that describe complex relationships between input factors (independent variables) and response variables (dependent variable) can be established [12]. Due to these properties, RSM is widely and frequently utilized in the optimization of a variety of machining and manufacturing processes [13, 14]. RSM has been used by studies in the literature to optimize machining parameters and to predict Ra during a variety of machining processes including the turning process [15]. For instance, RSM was used to analyze the effects of machining parameters on the generated Ra in hard hard-turning process of AISI 4340. The study reported that RSM efficiently predicted Ra in the turning processes of AISI 4340 [16]. Even though RSM is rendered as a convenient method for establishing predictive models. However, its accuracy can be limited to a narrow range of input parameters, and in highly non-linear processes it often requires a larger number of experimentations, such limitations led to the utilization of artificial neural network (ANN) based models in the prediction of outcome of interest [17].

ANN is a type of computing system that acts, analyzes, functions, and predicts by mimicking the structure human brain's neural system. It is made up of interconnected nodes that work together to solve complex problems, including function approximation, classification, and time-series prediction [18]. Recently, there has been an increase in the trends of using ANN to address and model complicated issues, as well as to overcome nonlinearity and complexity between input variables in a variety of fields and applications [18]. ANN models were found to perform better than RSM in the prediction of Ra in different machining processes. With this regard, Yanis et al. (2021) compared the performance of ANN with RSM in the prediction of Ra in the machining process of low-carbon steel, they reported that the ANN model predicted the Ra more accurately when compared with the RSM model [19]. Moreover, in another study, the ANN model outperformed the RSM model when predicting Ra in the burnishing process of Aluminum alloys 6061 [17]. In addition, ANN demonstrated a better predictive performance than the RSM model in the prediction of surface roughness in the 3D-printing process [20]. However, there is are lack of studies that compared the performance of ANN with RSM modeling in the prediction of Ra in the turning process of Aluminum alloy 6061. Therefore, this study aimed to compare the performance of the ANN model with the RSM model in the prediction of surface roughness when tuning Al6061.

2. Research method

2.1. Materials used

An aluminum alloy 6061 workpiece in size of 30mm diameter was used in this study. The tool used a tool holder section 25x25mm, with a titanium carbonite-coated carbide insert. Every run (cutting stroke) equaled 50mm, and the cutting test was taken. After that, the surface roughness measurement was done to obtain the experimental Ra. Subsequently, experiments were repeated to obtain accurate results. Figure 1 shows the conceptual framework of the study.

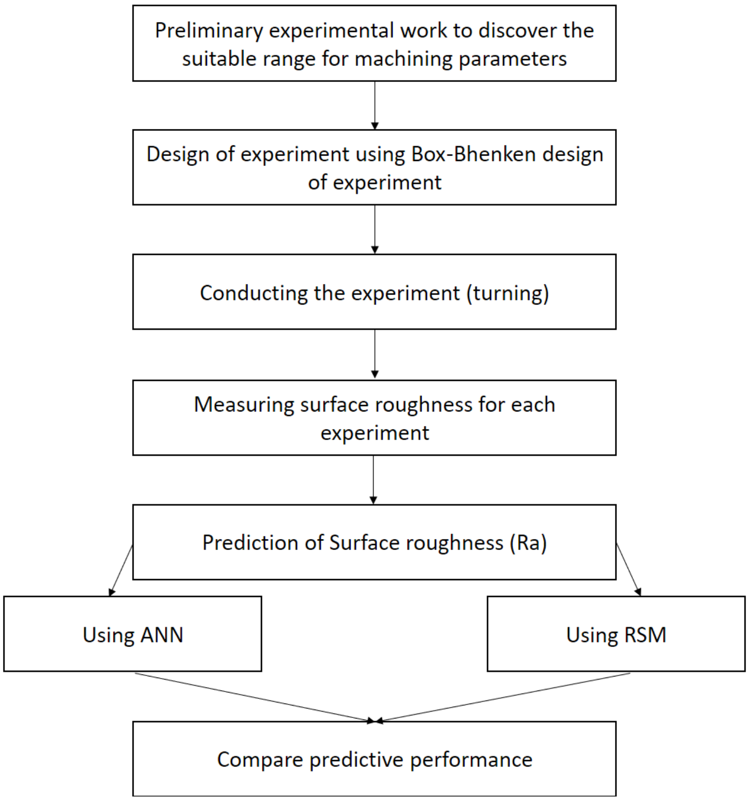

Figure 1. Study conceptual framework

2.2. Response surface methodology model

Utilizing designs of the experiment such as Box Behnken Design, allows efficient assessment of the model's coefficients. BBD also has fewer points of design, which makes it a less expensive method to implement compared with designs such as central composite design (CCD) that have a similar number of input variables. Moreover, because BBD lacks axial points, this ensures that all points of design fall within the safe operating point. BBD also ensures that machining parameters are not set at their highest values together. Therefore, a 3-factor Box Behnken design was used in this study on the levels of 3-factors. Preliminary tests were done to identify a suitable cutting speed, feed rate, and cutting depth, as indicated in Table 1.

Table 1. Coding of independent variables and their corresponding values

Levels	Unit	Low	Medium	High
Coding		-1	0	1
Feed rate (*F*)	mm/rev	0.5	1.5	2.5
Speed (*V*)	m/min	415	642.5	870
Cutting depth (*CP*)	mm	1	1.5	2

Analysis of Variance (ANOVA) test was used to evaluate the developed model and to identify the level of contribution of each independent variable i.e. (cutting speed, cutting depth, and feed rate) on the dependent variable (i.e. surface roughness). Furthermore, the Paretto effect chart was utilized to visualize the impact of each of the dependent variables on the surface roughness. Statistical analysis was done by utilizing Minitab Statistical Software. Statistical significance was determined if the p-value was less than 0.05.

2.3. Artificial neural network (ANN) model

To develop the ANN model and to evaluate the importance of input variables (i.e. cutting parameters) in the prediction of Ra, a multilayer perceptron function (MLP) using Statistical Package for Social Sciences (SPSS), version 25.0 [21] was used. The activation functions hyperbolic-tangent function and identity function was in the two hidden layers, and the output layer respectively. The neural network consisted of two hidden layers with seven and five units in the first and second layers respectively. Figure 2 shows the basic elements of an ANN model. The performance of the ANN and RSM models was evaluated and compared using mean absolute percentage error (MAPE) and symmetric mean absolute percentage error (sMAPE). In addition, the A20 index is used to assess the effectiveness of artificial intelligence models. This index measures the number of samples that accurately predict values within a deviation of ±20% when compared to experimental values, as outlined in Equation No.1. Where: m^{20} = the samples with (actual/predicted) value falls between 0.80 and 1.20; M= total number of data.

$$A20\ index = \frac{m^{20}}{\mathrm{M}} \tag{1}$$

In addition, the independent variable importance generated from the ANN model was used to identify the most important independent variable (i.e. cutting parameters) in the prediction of the dependent variable (i.e. Ra).

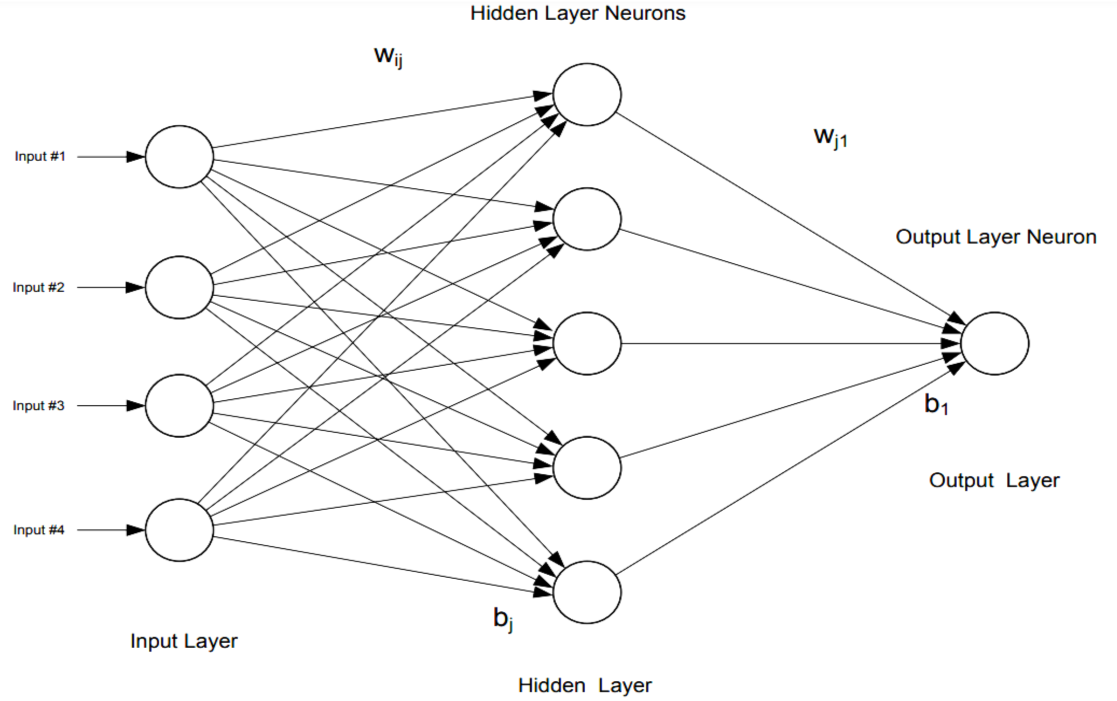

Figure 2. Components of a typical ANN model [22]

3. Results and discussion

The experimental results are shown in Figure 3. Experiment numbers 6, 4, 2, and 8 produced the finest surface roughness 140.21, 234.24, 239.10, and 260.45 nm respectively. In contrast, experiments 3, 7, and 5 yielded the highest surface roughness values 668.82, 451.34, and 597.96 nm respectively.

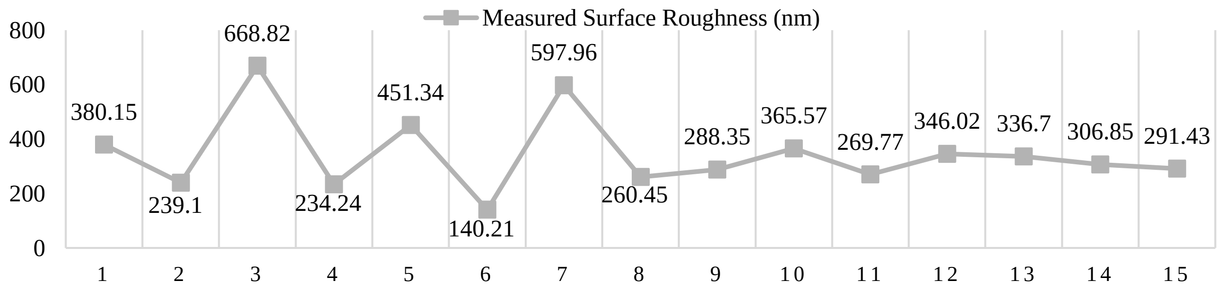

Figure 3. Experimental surface roughness

With regards to the impact of machining parameters on Ra, increasing cutting speed was found to be significantly associated with lower surface roughness. In addition, by using a lower feed rate surface roughness significantly decreases. Moreover, by inspecting the Pareto chart for standardized effect Figure 4, it can be seen that cutting speed was the most influential machining parameter that can significantly influence the surface roughness followed by feed rate. Moreover, the two-way interaction model showed that the combination of cutting speed and feed rate were identified as the most influential factors that can contribute to the variation in surface roughness Figure 4.

Table 2 demonstrates that cutting speed and feed rate have the most significant impact on Ra, contributing the highest percentages. Moreover, the two-way interaction model shows that cutting speed and feed rate significantly explains the variance in surface roughness. Cutting speed was the most contributing parameter in all models, as evidenced by P-values less than 0.05 implying that the model performed well in fitting the data. [23]. In this study, the P-value for lack of fit was more than 0.05 which indicates that the model was adequate. This finding suggests that the parameters, i.e. speed and feed rate, play a crucial role in determining Ra, and their effects should be considered when optimizing machining processes. Equation no. 2 shows the prediction equation for the surface roughness according to the developed model.

Table 2. ANOVA table

Source	DF	Contribution	F-Value	P-Value
Model	9	94.22%	9.05	0.013
Linear	3	81.37%	23.45	0.002
Cutting speed	1	70.00%	60.53	0.001
Feed rate	1	8.93%	7.72	0.039
Cutting depth	1	2.44%	2.11	0.206
Square	3	4.73%	1.36	0.355
Cutting speed*Cutting speed	1	4.47%	3.87	0.106
Feed rate*Feed rate	1	0.21%	0.17	0.697
Cutting depth*Cutting depth	1	0.05%	0.05	0.840
2-Way Interaction	3	8.11%	2.34	0.190
Cutting speed*Feed rate	1	8.05%	6.96	0.046
Cutting speed*Cutting depth	1	0.07%	0.06	0.822
Feed rate*Cutting depth	1	0.00%	0.00	0.993
Error	5	5.78%		
Lack-of-Fit	3	5.39%	9.07	0.101
Pure Error	2	0.40%		
Total	14	100.00%		

$$Surface\ roughness\ Ra(nm) = 602 - 1.385\ Cutting\ speed + 215\ Feed\ rate + 48\ Cutting\ depth + 0.001101\ Cutting\ speed * Cutting\ speed + 11.9\ Feed\ rate * Feed\ rate - 2.7\ Cutting\ depth * Cutting\ depth - 0.323\ Cutting\ speed * Feed\ rate - 0.0193\ Cutting\ speed * Cutting\ depth - 0.2\ Feed\ rate * Cutting\ depth \quad (2)$$

By utilizing the independent variable importance feature in the ANN analysis, cutting speed was identified as the most important determinant of surface roughness followed by feed rate (Figure 5). According to the results of the RSM and ANN models, to achieve the most optimal and lower surface roughness when turning Al6061 a combination of high cutting speed, low feed rate, and low cutting depth should be used in Table 3. Several factors can explain why the use of high cutting speeds was found to be associated with lower surface roughness. For instance, at higher cutting speeds, there is significantly less contact time between the cutting tool and the chip being removed. This results in decreased heat generation at the cutting zone, leading to lower thermal deformation of the workpiece and a smoother surface finish [24]. Moreover, the use of high cutting speed can contribute to a significant reduction in built-up edge formation (BUE) which is rendered as a common cause of poor surface finish in machining processes i.e. higher cutting speeds reduce the likelihood of BUE formation, which in turn leads to a smoother surface on the machined part [24]. Besides, high cutting speeds can promote better chip evacuation from the cutting zone which subsequently results in reducing the odds of chip re-cutting, which can adversely affect the surface finish [25]. When it comes to the impact of feed rates on surface roughness it can significantly contribute to rougher surface in machining processes. Such association can be explained as a result of the larger undeformed chip thickness that results when a high feed rate is used, which subsequently can result in more significant surface irregularities that contribute to a rough surface [26]. In addition, with higher feed rates, the cutting forces applied on the tool and workpiece proportionally increases which results in greater tool deflections and workpiece vibrations, which adversely impact the surface finish [27]. Moreover, higher feed rates accelerate the wear rate of the cutting tool contributing to a change in the tool geometry, leading to a decline in surface finish quality [28].

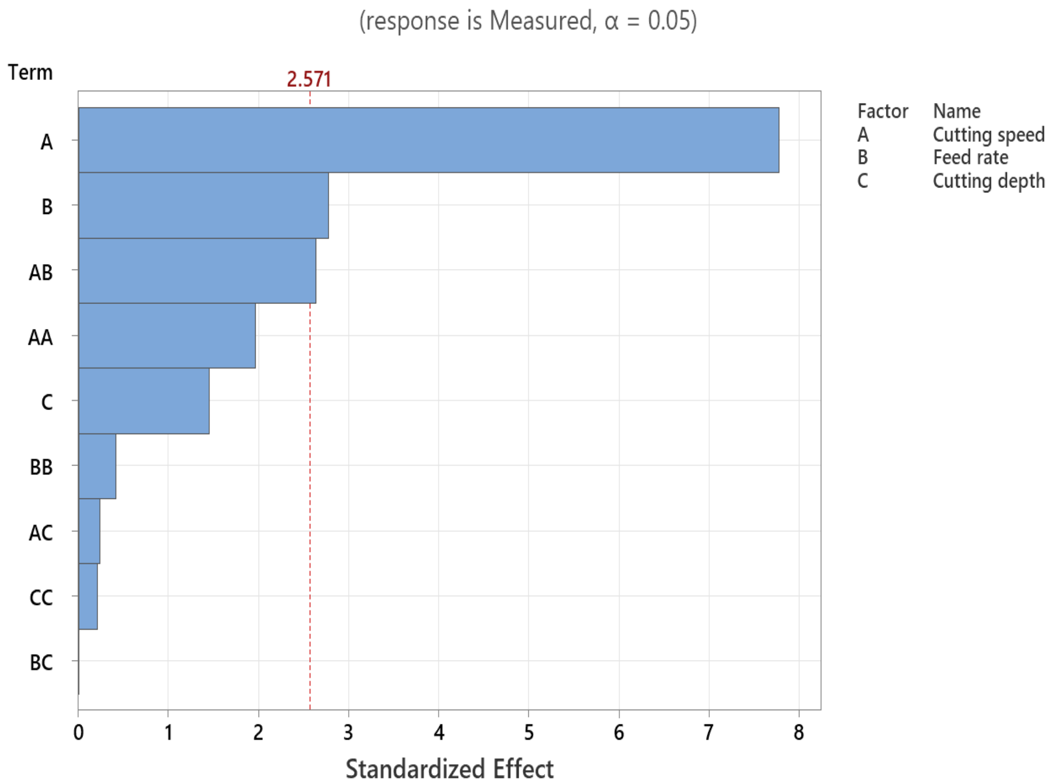

Figure 4. Pareto Chart of the Standardized Effects

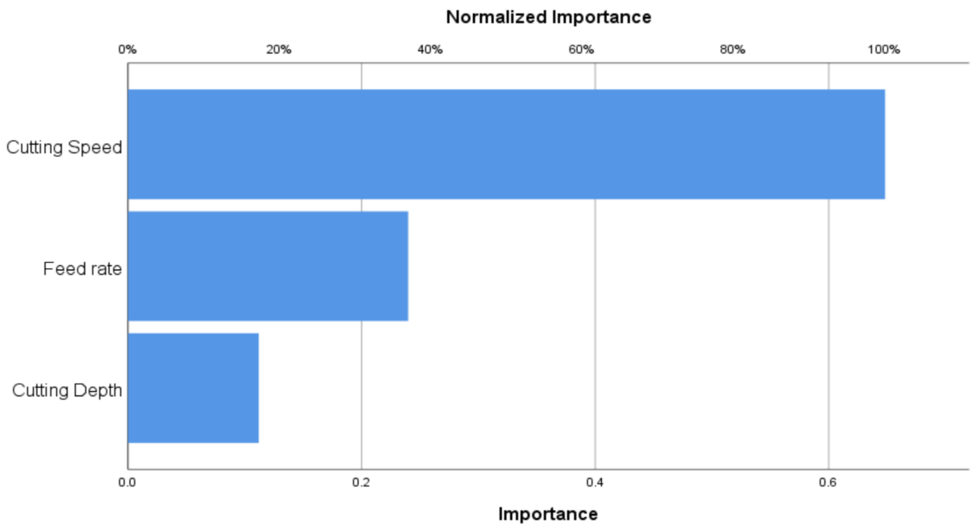

Figure 5. Independent variable’s importance as indicated by the artificial neural network model

Concerning the performance of the developed models in predicting surface roughness, Figure 6 represents the predicted values against the experimental values. This shows that the predicted values from the ANN model were in agreement and more consistent with the experimental values of Ra compared with the RSM model. In addition, Table 3 shows the predicted Ra according to the ANN model versus the RSM model. It can be seen that the ANN model performed better than the RSM model in terms of prediction performance as the A20 index in the ANN model was found to be higher (0.93) when compared with the RSM model (0.86) indicating that the ANN model outperformed the RSM model in terms of prediction accuracy. In addition, the mean absolute percentage error was lower in the ANN model compared with the RSM model (8.06 versus 9.69). The symmetric mean absolute percentage error was also found to be lower in the ANN model (0.039) compared with the RSM model (0.047) indicating the ANN model had a better predictive performance than the RSM model. ANN models are frequently reported to be more accurate than RSM models [17, 19, 29, 30]. This can be due to the fact the ANN models possess the ability to learn, understand, and predict complex patterns and relationships while RSM models typically rely on mathematical functions that can be applied and fitted to experimental data, potentially restricting their capacity to identify complex patterns [29]. In addition, ANN is a type of nonlinear model that can model complex relationships between inputs and outputs. Furthermore. ANN utilizes nonlinear activation functions and can have multiple hidden layers, which allows it to learn complex patterns in the data [31]. In contrast, the RSM model’s accuracy is limited for nonlinear complex processes [29].

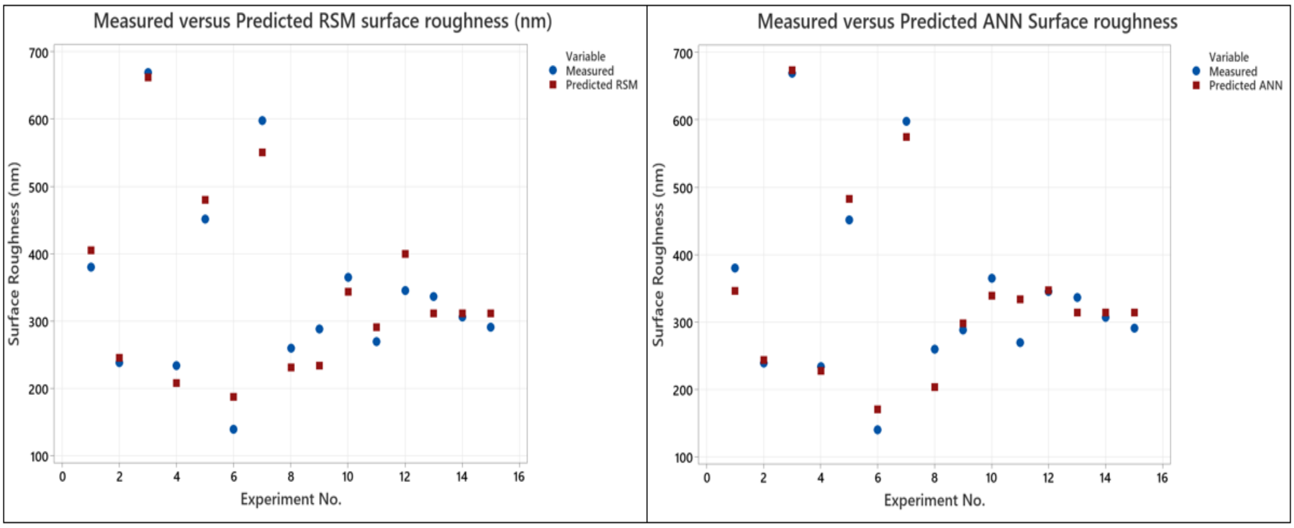

Figure 6. Experimental versus predicted surface roughness from ANN model compared with the RSM model

Table 3. Surface roughness prediction according to the ANN model versus the RSM model

Cutting speed	Feed rate	Cutting depth	Measured Ra (nm)	Predicted Ra – ANN (nm)	Predicted Ra – RSM (nm)
415	1	3	380.15	346.73	405.57
870	1	3	239.1	243.89	246.27
415	3	3	668.82	673.24	661.65
870	3	3	234.24	227.71	208.82
415	2	1.5	451.34	483.02	480.34
870	2	1.5	140.21	171.27	187.46
415	2	4.5	597.96	574.52	550.71
870	2	4.5	260.45	203.88	231.45
642.5	1	1.5	288.35	298.21	233.93
642.5	3	1.5	365.57	339.13	343.74
642.5	1	4.5	269.77	334.03	291.60
642.5	3	4.5	346.02	347.62	400.44
642.5	2	3	336.7	314.51	311.66
642.5	2	3	306.85	314.51	311.66
642.5	2	3	291.43	314.51	311.66
		A20 index		0.93	0.86
		MAPE		8.06	9.69
		sMAPE		0.039	0.047

4. Conclusion

In conclusion, the ANN model and RSM model were successfully developed to predict the machining performance of Aluminum 6061. Both ANN and RSM models revealed that cutting speed was the most important determinant of Ra in the turning process of Aluminum alloy Al6061. ANN performed better than RSM in terms of predictive performance which reflects the importance of the development of personalized ANN models according to the type of machining process, machined material, and type of cutting tool and the potential utility of integrating such models into machines to guide the selection of cutting parameters decision making process.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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