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RESEARCH

# Modeling and Prediction of Surface Roughness in the End Milling Process using Multiple Regression Analysis and Artificial Neural Network

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A B S T R A C T

*In recent years, trends have been towards modeling machine processing using artificial intelligence. Artificial neural network (ANN) and multiple regression analysis are methods used to model and optimize the performance of manufacturing technologies. ANN and multiple regression analysis show high reliability in the prediction and optimization of machining processes. In this paper, machining parameters such as spindle speed, feed rate and depth of cut were used in end milling process to minimize surface roughness. The influence of the parameters on the surface roughness was investigated using an artificial neural network and multiple regression analysis, and results are compared with the measured results.*



## 1. INTRODUCTION

In manufacturing industries, metal cutting is the most important and widely used production process. Parameters such as spindle speed, feed rate and depth of cut are very important in the machining process [1]. An indicator related to the quality of the machined parts is surface quality [2]. Measure that represents the quality of the machined surface is the arithmetic roughness (Ra) [3]. In milling process, low roughness indicates high quality of surface. Low roughness values imply that material properties such as fatigue strength and aesthetic appeal are improved [4]. Modeling techniques help in improving of machining operations, and reducing the manufacturing time and costs that will be beneficial to the manufacturing industry [5].

Artificial intelligence based modeling approaches are advisable for real time applications out of which Artificial Neural Network (ANN) was found to be reliable, viable, and attractive. The ANN based approach has been successfully implemented by many researchers and it produced acceptable results [6]. Many researchers investigated the influence of different parameters on the surface roughness, and then, using artificial neural networks and regression model, developed models for the selection of optimal machining parameters.

Yung et al. [7] developed in their study prediction models using parameters such as depth of cut, spindle speed and feed rate at process of end milling. Multiple regression analysis and artificial neural network (ANN) were used for developing prediction model. As a result, we can see that the effects of depth of cut and spindle speed have a direct influence on surface roughness.

Rajesh and Manu [8] developed a model for prediction of surface roughness by using of artificial neural network. They used parameters like speed, feed rate, cutting depth and step over for the development of freeform surfaces. For minimizing prediction errors, they used back propagation neural network.

Kosarac et al. [9] in their research used ANN for minimizing surface roughness in machining AA7075 aluminum alloy. They concluded that Ra can be predicted by using ANN trained with small data.

Cirak [10] in his research investigated influence of various parameters on surface roughness. The ANN model has 4 input neurons, 7 neurons in the hidden layer and 1 output neuron. The developed ANN model uses a multi-layer feed forward network architecture and was trained with experimental data using back propagation. With correlation coefficients, the ANN model can be predicted with great certainty.

Nalbant et al. [11] use artificial neural networks (ANN) and multiple regression analysis to investigate the effects of cutting tools, various depths of cuts, different insert nose radii and different feed rates on the surface quality of the AISI 1030 steel workpieces. For prediction of surface roughness, ANN model showed better results than multiple regression analysis.

Hossein et al. [12], in their research, predicted and minimized surface roughness in process of milling. They used two model approaches which are Artificial Neural Network and Multiple regression analysis. For predicting the minimum value of Ra, predicted model must be compared with real Ra experimental data after the milling process. In both approaches, results showed almost same values.

Paturi et al. [13] in their study used an artificial neural network and regression analysis for predicting the surface roughness during hard turning of AISI 52100 steel. The surface roughness data is required to generate and evaluate RA and ANN models. The predicted results using RA and ANN model indicate a similarities between the experimental and predicted values.

Karabulut et al. [14] investigated the effects of the chip thickness variation and lead angle on surface roughness during the machining of compacted graphite iron. For predicting the surface roughness values, after the face milling process, they developed analytical models. They used experimental data and imported to the artificial neural network model. To predict surface roughness, they used an artificial neural network and regression analysis. Results of this research indicated an improvement in the surface roughness value with decreasing lead angle value. For predicting surface roughness,

Alauddin et al. [15] used parameters as feed and speed for developing a mathematical model. The surface roughness contours thus obtained could select a combination of parameters for realizing machining time reduction without increasing the surface roughness.

According to Gjelaj et al. [16], there are two approaches to researching surface roughness by using ANN. First, surface roughness can be measured after machining, and the second is to compare the measurement in a theoretical way. In both cases, the main parameters are used.

Shaik and Srinivas [17] used multi-objective optimization technique to improve surface roughness. Vibration amplitude and surface roughness models were generated using multiple regression on experimental results data. However, small amplitude vibrations can't be controlled and they might be harmful to the workpiece surface because they can cause poor surface roughness.

This paper presents a comparison of multiple regression analysis and artificial neural network with measured results of surface roughness.

## 2. MATERIALS AND METHODS

### 2.1 Surface roughness prediction by using artificial neural network

ANN is a data processing and modeling technique that came due to the need for mathematical modeling and imitation of the learning process that is inspired by the functioning of the brain. ANNs can associate input data, defined as a function of one or more parameters, related to a system with outputs of that system, defined as a function of a number of parameters [18].

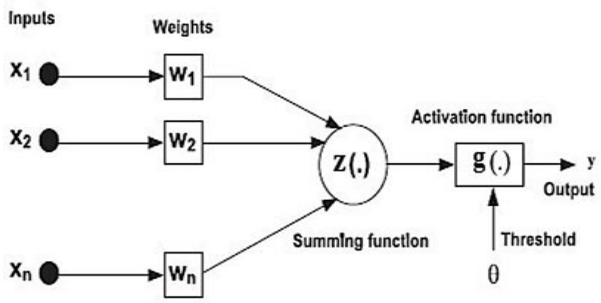


**Fig. 1.** Mathematical model for ANN.

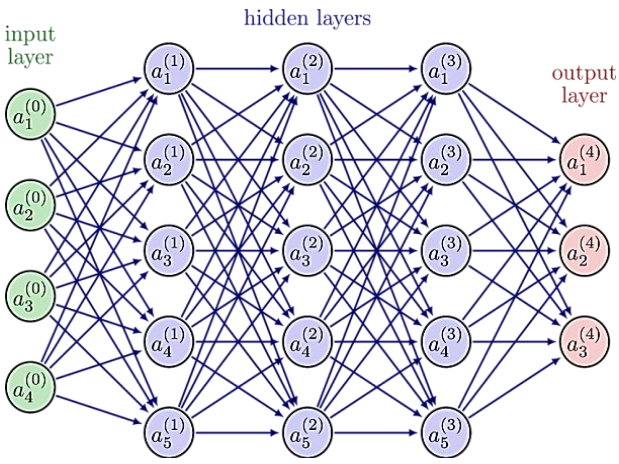


**Fig. 2.** Structure of ANN.

$R_a$ is one of the performance measures employed mostly by researchers using the ANN technique. It obviously indicate that ANN has been successfully applied by for modeling Ra prediction in the machining process. For the Ra prediction in machining process, there are a very limited number of studies of using ANN in the milling process. Cutting speed, feed rate and depth of cut are the most frequently used parameters for predicting Ra by using ANN [19]. One of conclusion, for the milling, is that ANN model leads to a slightly more accurate surface roughness prediction than a conventional model [20]. The ANN network structure have an input layer (this layer consists of input parameters x), contains the same number of neurons as there are input parameters, a hidden layer there can be more of them - it contains the number of neurons that we define, and an output layer, has only 1 – the number of neurons dependent on the number of function outputs.

Parameters like the number of training data and hidden layer, learning rate, and number of iterations can affect the accuracy of a neural network. Each layer has an activation vector:

$$a^{(0)} \rightarrow a^{(n)} \tag{1}$$

Where $a^{(0)}$ is the input layer and $a^{(n)}$ is the output layer. All layers between input and output are hidden layers. Input layer activation is equal to the input. Each connection between neurons has its own weight w. The output layer is calculated using the forward propagation algorithm and algorithm training is done by back propagation algorithm. Back propagation is calculated as follows:

$$dZ^{[L]} = A^{[L]} - Y \tag{2}$$

$$dW^{[L]} = \frac{1}{m} dZ^{[L]} A^{[L]^T} \tag{3}$$

$$db^{[L]} = \frac{1}{m}(1 \quad \dots \quad 1) dZ^{[L]} \tag{4}$$

$$(1 \quad \dots \quad 1) dZ^{[L]} \tag{5}$$

we sum up all the rows in the matrix into one column:

$$\mathrm{dZ}^{[\mathrm{L}-1]} = \mathrm{dW}^{[\mathrm{L}]^{\mathrm{T}}} dZ^{[L]} g'^{[L]}(Z^{[L-1]}) \tag{6}$$

$$dZ^{[1]} = dW^{[L]^T} dZ^{[2]} g'^{[1]}(Z^{[1]}) \tag{7}$$

$$dW^{[1]} = \frac{1}{m} dZ^{[1]} A^{[1]^T} \tag{8}$$

$$db^{[1]} = \frac{1}{m}(1 \quad \dots \quad 1) dZ^{[1]} \tag{9}$$

For each i:

$$W^{[i]} = W^{[i]} - \alpha dW^{[i]} \tag{10}$$

$$b^{[i]} = b^{[i]} - \alpha db^{[i]} \tag{11}$$

Z[L] (where L is the layer number) denotes the sum of all weights multiplied by the activation of the previous corresponding neuron, dW - derivative of W, dZ - derivative of Z, A[L] - represents the calculated function of neurons on layer L - when we execute g(Z).

### 2.2 Multiple regression analysis for prediction of surface roughness

Multiple regression analysis is a technique that allows us to determine the correlation between a continuous dependent variable and two or more continuous or discrete independent variables [21]. This method handles interval, ordinal, or categorical data and provides estimates of the magnitude and statistical significance of relationships between variables. To predict the roughness of the final surface through predictor variables, such as spindle speed, feed and depth of cut, the method of multiple regression analysis can have a great contribution [22]. To predict surface roughness, the second-order regression equation can be expressed as:

$$Ra = \Theta_0 + \Theta_1 * n + \Theta_2 * V_f + \Theta_3 * a_p + \Theta_4 * n^2 + \Theta_5 * n * V_f + \Theta_6 * n * a_p + \Theta_7 * V_{f^2} + \Theta_8 * V_f * a_p + \Theta_9 * a_{p^2} \quad (12)$$

and a third-order as :

$$Ra = \Theta_0 + \Theta_1 * n + \Theta_2 * V_f + \Theta_3 * a_p + \Theta_4 * n^2 + \Theta_5 * n * V_f + \Theta_6 * n * a_p + \Theta_7 * V_{f^2} + \Theta_8 + \Theta_9 * a_{p^2} + \Theta_{10} * n^3 + \Theta_{11} * n^2 * V_f + \Theta_{12} * n^2 * a_p + \Theta_{13} * n * V_{f^2} + \Theta_{14} * n * V_f * a_p + \Theta_{15} * n * a_{p^2} + \Theta_{16} * V_{f^3} + \Theta_{17} * V_{f^2} * a_p + \Theta_{18} * V_f * a_p + \Theta_{19} * a_{p^3} \quad (13)$$

R*a* is estimated surface roughness, n is a spindle speed, $V_f$ is feed rate and $a_p$ depth of the cut. The coefficients $\Theta_0$, $\Theta_1$, $\Theta_2$ … $\Theta_9$, for second order equation and $\Theta_1$, $\Theta_2$, $\Theta_3$ … $\Theta_{19}$ for a third-order equation, are to be estimated using suitable methods.

### 2.3 Experimental setup

The experimental measurement of surface roughness in the end milling process was conducted using workpiece material of aluminum alloy 6082-T6, with chemical composition (95,2-98,3 Al, 0,7-1,3 Si, 0,6-1,2 Mg, 0,4-1 Mn, 0,5 Fe, 0,25 Cr, 0,2 Zn, 0,1 Ti, 0,15 others), and mechanical properties (Tensile strength-305,6 MPa, Yield stress-245,1 MPa, Hardness-95 HRB,HB). Process of milling was performed on a universal milling machine with carbide end mill, manufactured by SECO, Fig. 3, and the cutting geometry of used carbide end mill is given in Table 1.

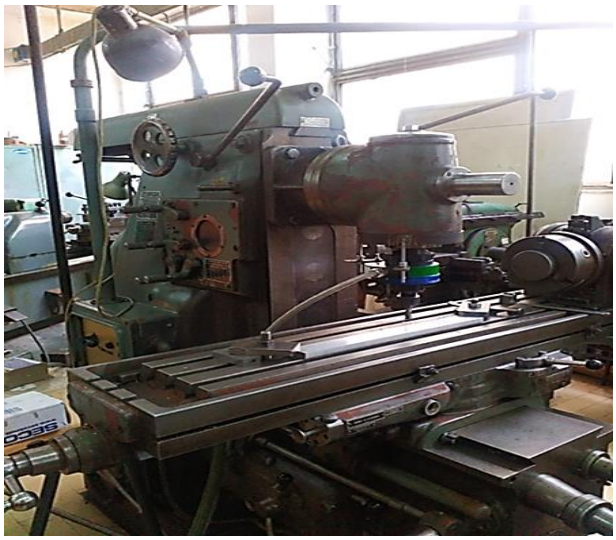

**Fig. 3**. Universal milling machine.

**Table 1.** Cutting geometry of carbide end mill.

| Description | Value |
|---|---|
| Depth of cut maximum in feed direction, Cutting diameter | 32 mm |
| Shank diameter | 16 mm |
| Flute helix angle | 16 mm |
| Shanktype | 40 deg |
| Overall length | 100 mm |
| Number of teeth | 3 |

After milling operations, the Surface roughness was measured on a Mahr profilometer under the laboratory conditions, Fig. 4.

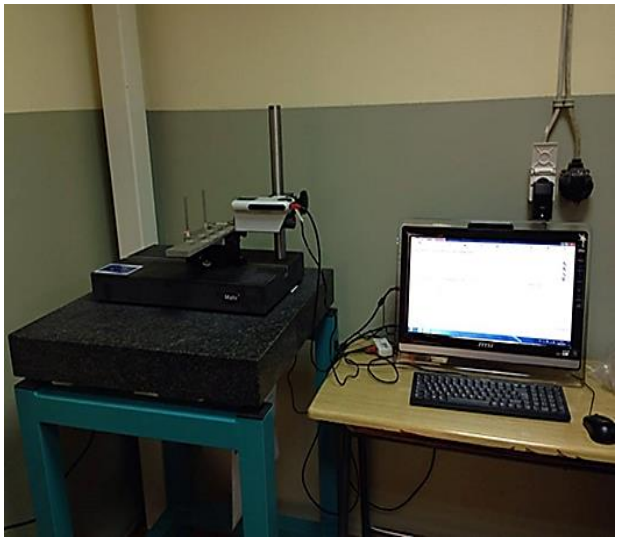

**Fig. 4**. Measuring surface roughness on Mahr profilometer.

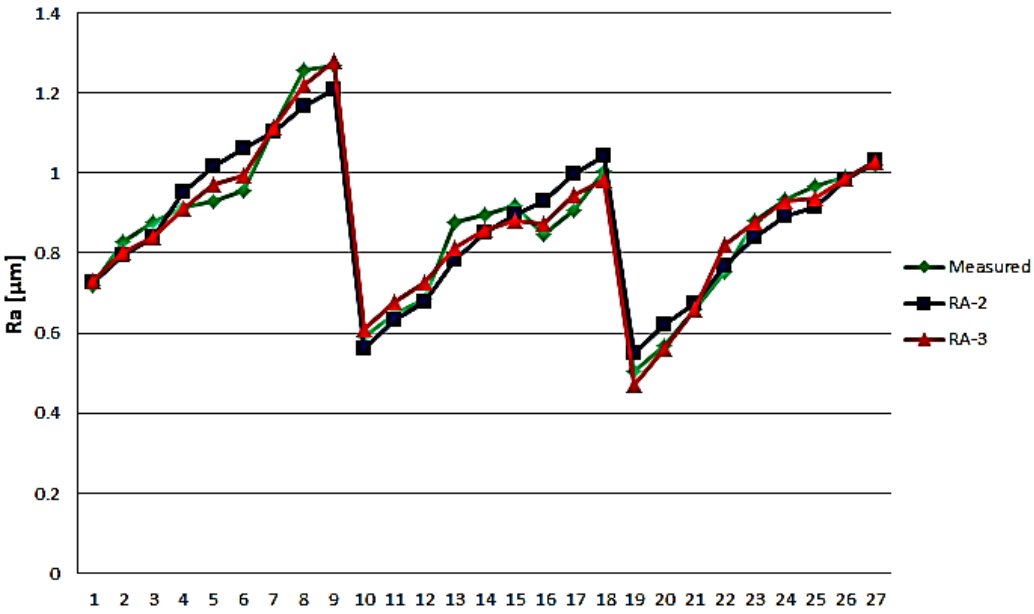


**Fig. 5.** Measured and predicted data of surface roughness for multiple regression analysis.

**Table 2**. Experimental data for model constructions.

| Test no. | $n$ [rev/min] | $V_f$ [mm/min] | $a_p$ [mm] | $Ra$ [µm] |
|---|---|---|---|---|
| 1 | 405 | 93 | 1.5 | 0.717 |
| 2 | 405 | 93 | 2 | 0.828 |
| 3 | 405 | 93 | 2.5 | 0.878 |
| 4 | 405 | 175 | 1.5 | 0.915 |
| 5 | 405 | 175 | 2 | 0.928 |
| 6 | 405 | 175 | 2.5 | 0.954 |
| 7 | 405 | 350 | 1.5 | 1.115 |
| 8 | 405 | 350 | 2 | 1.256 |
| 9 | 405 | 350 | 2.5 | 1.269 |
| 10 | 560 | 93 | 1.5 | 0.589 |
| 11 | 560 | 93 | 2 | 0.646 |
| 12 | 560 | 93 | 2.5 | 0.686 |
| 13 | 560 | 175 | 1.5 | 0.878 |
| 14 | 560 | 175 | 2 | 0.896 |
| 15 | 560 | 175 | 2.5 | 0.918 |
| 16 | 560 | 350 | 1.5 | 0.846 |
| 17 | 560 | 350 | 2 | 0.908 |
| 18 | 560 | 350 | 2.5 | 1.003 |
| 19 | 775 | 93 | 1.5 | 0.503 |
| 20 | 775 | 93 | 2 | 0.569 |
| 21 | 775 | 93 | 2.5 | 0.658 |
| 22 | 775 | 175 | 1.5 | 0.753 |
| 23 | 775 | 175 | 2 | 0.88 |
| 24 | 775 | 175 | 2.5 | 0.934 |
| 25 | 775 | 350 | 1.5 | 0.967 |
| 26 | 775 | 350 | 2 | 0.989 |
| 27 | 775 | 350 | 2.5 | 1.018 |

The roughness parameters generally depend on the manufacturing conditions like feed, depth of cut, cutting speed, machine tool etc. In this experiment, three main parameters are selected: n (spindle speed), $V_f$ (feed rate) and $a_p$ (depth of the cut). Experimental data of aluminum alloy 6082-T6 and total of 27 experiments were performed, which are given in Table 2.

## 3. RESULTS AND DISCUSSION

The results obtained from the multiple regression and neural networks are compared and discussed in this section.

### 3.1 Multiple regression analysis

The data from Table 2 have been used to build the multiple regression model. The coefficients $\Theta_0$, $\Theta_1$ ... $\Theta_9$ for a second-order equation and $\Theta_0$, $\Theta_1$ ... $\Theta_{19}$ for a third-order equation were estimated using PYTHON-3.10. Figure 5 shows a comparison of the measured values with the values obtained through multiple regression analysis, and we can see that with a greater polynomial order, we get better results, but with the third order, where we have 20 parameters on 27 training examples, this type of machine learning does not give satisfactory results. The equation of the second-order model for surface roughness is given as follows:

$$Ra = 1{,}09910122 - 0{,}003774 * n + 0{,}004723 * V_f + 0{,}275694 * a_p + 0.0000027487991 * n^2 - 0{,}0000000976597967 * n * V_f + 0{,}0000368573497 * n * a_p - 0{,}00000720123043 * V_{f^2} - 0{,}0000251552254 * V_f * a_p - 0{,}0442222222 * a_{p^2} \quad (14)$$

and third-order model:

$$Ra = - 1{,}40520969 + 0{,}00251411833 * n - 0{,}00222507059 * V_f + 2{,}88873468 * a_p - 0{,}00000418903955 * n^2 - 0{,}00000660724985 * n * V_f - 0{,}00136539907 * n * a_p + 0{,}0000394391273 * V_{f^2} - 0{,}000188806107 - 1{,}17679194 * a_{p^2} - 0{,}000000000981037549 * n^3 + 0{,}0000000182216428 * n^2 * V_f + 0{,}000000738427850 * n^2 * a_p - 0{,}0000000263182961 * n * V_{f^2} - 0{,}00000158456909 * n * V_f * a_p + 0{,}000212551291 * n * a_{p^2} - 0{,}0000000610481948 * V_{f^3} + 0{,}00000317601920 * V_{f^2} * a_p - 0{,}0000913170467 * V_f * a_p + 0{,}1713502140 * a_{p^3} \quad (15)$$

### 3.2 Artificial neural networks results

To obtain a predictive model through ANN, we used parameters from Table 2. Two activation function was used, Relu and Tahn, and four different structures, 7-S-R, 10-S-R, 5-S-T, 5*2-S-R. The learning parameters of the proposed ANN structure are presented in Table 3.

**Table 3.** The training parameters.

| The number of layers | 3 and 4 |
|---|---|
| The number of neurons on the layers | Input 3, Hiden 5,7,10, Output 1 |
| The initial weights and biases | Randomly between 0 and +1 |
| Activation function | Relu and Tanh |
| Learning rate | 0,03 |
| The normalization of data | -0.5 - +0.5 |
| The number of iteration | 10000-30000 |

After the network has completed the training stage, the results were obtained and compared. The determination coefficient ($R^2$) was used as a criterion for comparison.

$$R^2 = 1 - \left(\frac{\sum i\,(y_i - \hat{y}_i)^2}{\sum i\,(\hat{y}_i)^2}\right) \quad (16)$$

Where $y$ presenting the exact value (measured), $\hat{y}$ presenting the obtained value. The activation function ReLU (equation 17) and tanh (equation 18) in this study are as follows:

$$g(z) = \max(0, z) \quad (17)$$

$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad (18)$$

### 3.3 Obtained evaluation

Experimental design is implemented to seek the influence of the various cutting parameters such as feed rate, spindle speed and depth of cut on the surface roughness. After the milling operation, the measurements of surface roughness were recorded. Multiple regression models and artificial neural networks were developed to predict the surface roughness using the experimental data. The results obtained through the proposed models are showed in Table 4. The ANN model show that the model is suitable for predicting surface roughness, and the statistical value of the ANN model, the determination coefficient ($R^2$), is in acceptable range. Table 5 presents comparison results according to accuracy values of the multiple regression models and neural network models.

**Table 5**. Comparison results according to accuracy values of multiple regression model and neural network model.

| | | $R^2$ |
|---|---|---|
| Multiple regression model | R2 | 0,996421 |
| Multiple regression model | R3 | 0,998763 |
| ANN model | 7-S-R | 0,999473 |
| ANN model | 10-S-R | 0,999519 |
| ANN model | 5-S-T | 0,999086 |
| ANN model | 5x2-S-R | 0,999526 |

In Fig. 6 we see that with a neural network out of 35 parameters we get negligible ones errors in the model. Percent number of parameters is greater than the number of training examples, we can consider this model to be overfit, since it is not single species regularization used. So, in the real world we can assume to give worse results than some a smaller scale model.

**Table 4.** Obtained results.

| *R a* [μm] | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Measured | RA-2 | RA-3 | 7-S-R | 10-S-R | 5-S-T | 5x2-S-R |
| 1 | 0.717 | 0.727613 | 0.728801 | 0.717012 | 0.717624 | 0.732038 | 0.716683 |
| 2 | 0.828 | 0.794365 | 0.801242 | 0.826899 | 0.828964 | 0.824378 | 0.829514 |
| 3 | 0.878 | 0.839006 | 0.838133 | 0.877627 | 0.87893 | 0.877577 | 0.875589 |
| 4 | 0.915 | 0.950268 | 0.912087 | 0.854424 | 0.915017 | 0.914855 | 0.914688 |
| 5 | 0.928 | 1.015989 | 0.972269 | 0.927445 | 1.009926 | 0.969409 | 0.929126 |
| 6 | 0.954 | 1.059598 | 0.993157 | 1.000465 | 0.955034 | 0.977964 | 0.952637 |
| 7 | 1.115 | 1.101571 | 1.115091 | 1.121859 | 1.116457 | 1.114598 | 1.179874 |
| 8 | 1.256 | 1.165091 | 1.220532 | 1.19488 | 1.211366 | 1.213296 | 1.224968 |
| 9 | 1.269 | 1.206499 | 1.278689 | 1.267901 | 1.270473 | 1.269186 | 1.270063 |
| 10 | 0.589 | 0.560912 | 0.61006 | 0.588734 | 0.574667 | 0.575767 | 0.58879 |
| 11 | 0.646 | 0.63052 | 0.678142 | 0.639789 | 0.66232 | 0.670958 | 0.643386 |
| 12 | 0.686 | 0.678017 | 0.727146 | 0.690844 | 0.687189 | 0.738727 | 0.689461 |
| 13 | 0.878 | 0.782326 | 0.813002 | 0.877178 | 0.877878 | 0.797646 | 0.872801 |
| 14 | 0.896 | 0.850902 | 0.858755 | 0.897127 | 0.896695 | 0.869142 | 0.896313 |
| 15 | 0.918 | 0.897368 | 0.881686 | 0.917076 | 0.918699 | 0.88838 | 0.919824 |
| 16 | 0.846 | 0.93098 | 0.874486 | 0.845776 | 0.846714 | 0.849905 | 0.846803 |
| 17 | 0.908 | 0.997355 | 0.944007 | 0.918797 | 0.909301 | 0.939312 | 0.911344 |
| 18 | 1.003 | 1.04162 | 0.982716 | 0.991818 | 1.00421 | 1.002564 | 1.003506 |
| 19 | 0.503 | 0.548322 | 0.470829 | 0.502389 | 0.503608 | 0.50303 | 0.503451 |
| 20 | 0.569 | 0.621893 | 0.562235 | 0.567642 | 0.57041 | 0.568961 | 0.572324 |
| 21 | 0.658 | 0.673352 | 0.657412 | 0.657479 | 0.658064 | 0.639964 | 0.642903 |
| 22 | 0.753 | 0.768014 | 0.819897 | 0.753754 | 0.760488 | 0.773575 | 0.75416 |
| 23 | 0.88 | 0.840553 | 0.875005 | 0.843591 | 0.848141 | 0.879847 | 0.846321 |
| 24 | 0.934 | 0.890981 | 0.930142 | 0.933427 | 0.935795 | 0.934781 | 0.938483 |
| 25 | 0.967 | 0.912994 | 0.938747 | 0.966392 | 0.968073 | 0.924657 | 0.968395 |
| 26 | 0.989 | 0.983332 | 0.987814 | 0.986341 | 0.98965 | 0.989071 | 0.984692 |
| 27 | 1.018 | 1.031559 | 1.028919 | 1.016918 | 1.019659 | 1.017058 | 1.076854 |

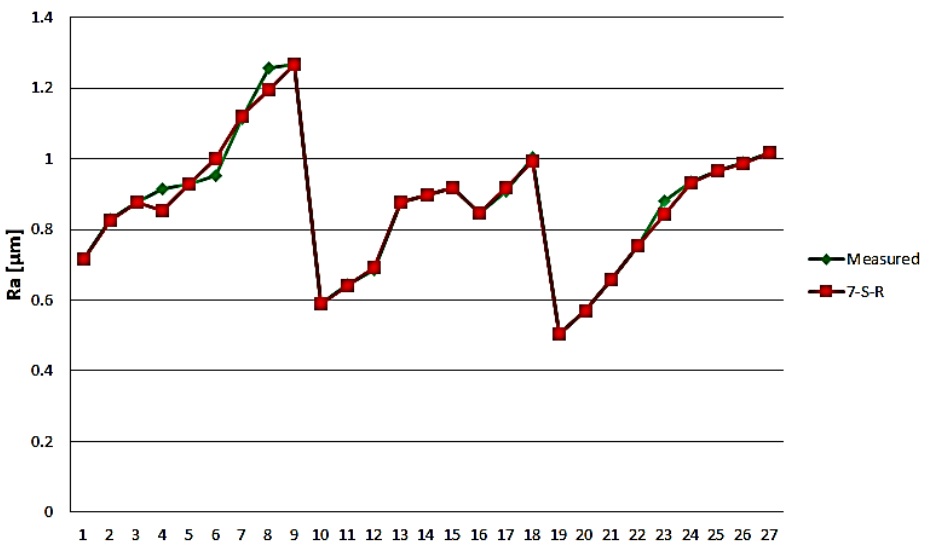


**Fig. 6**. Measured and predicted data of the surface roughness for ANN 7-S-R model.

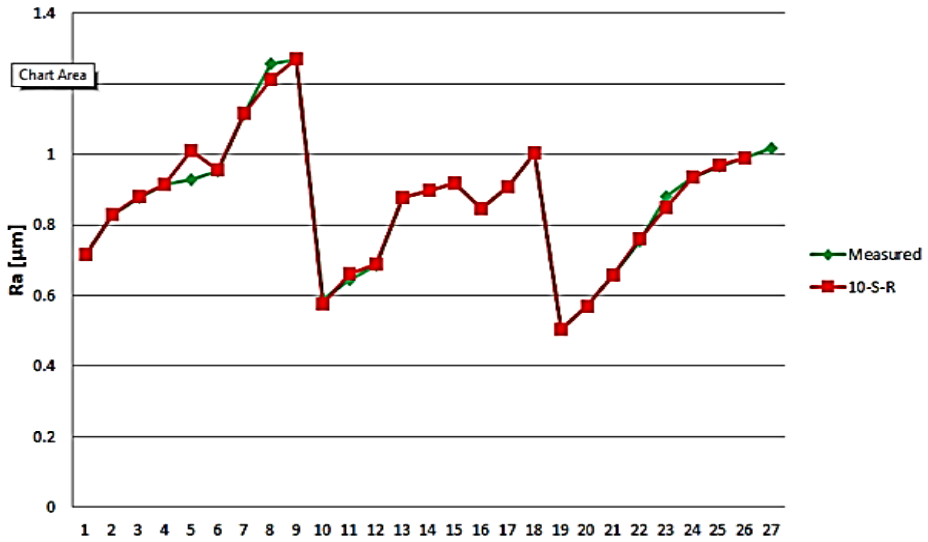


**Fig. 7**. Measured and predicted data of the surface roughness for ANN 10-S-R model.

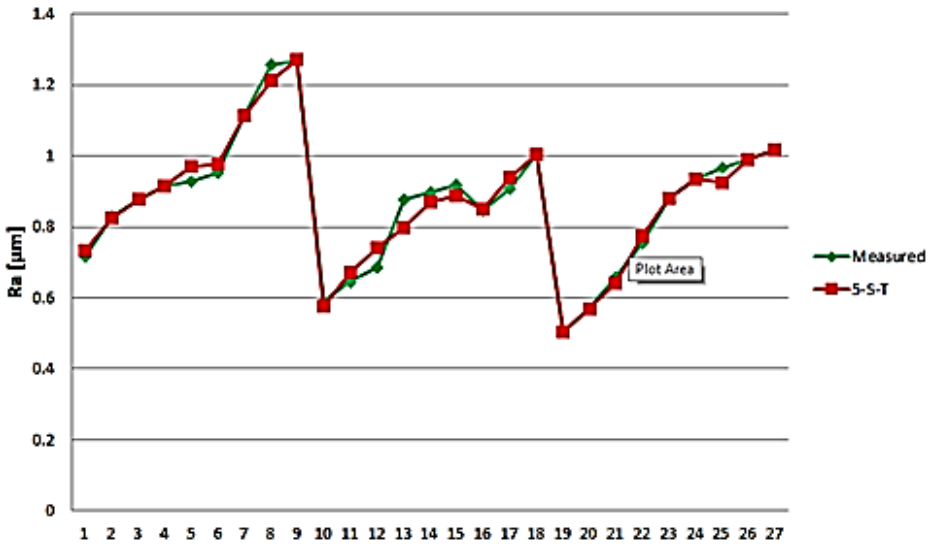


**Fig. 8.** Measured and predicted data of the surface roughness for ANN 5-S-T model.

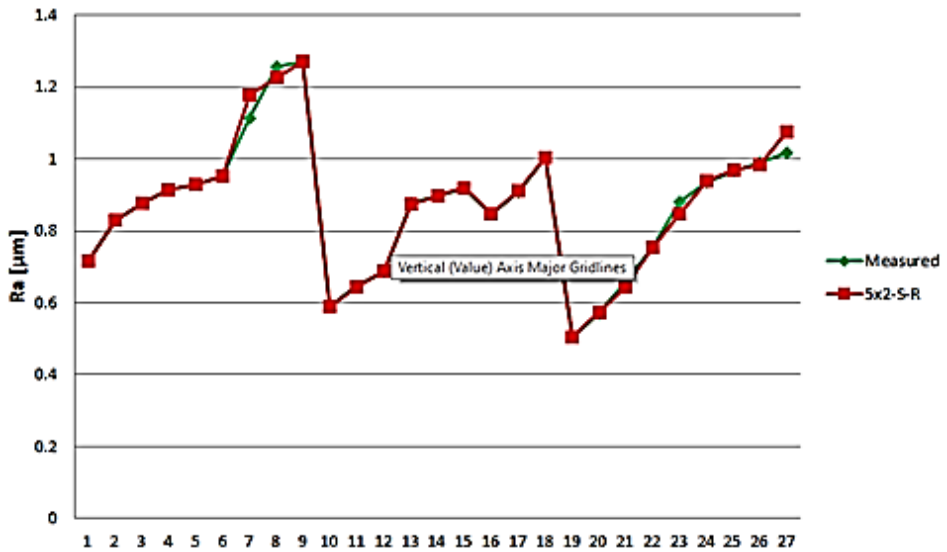


**Fig. 9.** Measured and predicted data of the surface roughness for ANN 5x2-S-R model.

In Fig. 7 we can see that with neural networks, accuracy increases with the number of parameters training together. Same as in Fig. 6, this model with 40 parameters without regularization we can assume that it gives bad results in the real world, although almost perfect follow exact values. Also, we see that accuracy compared to 7-S-R increased by just 0.000046, so we get to everything diminishing returns. In Fig. 8 we see that we can use the most basic neural networks with 25 parameters and we can get better results rather than polynomial regression. This is the desired result because too much accuracy in the training session or the number of parameters is greater than the number of training example, almost always means that it is a function chaotic, because in the real world it would give bad results. As for the previous figures, in Fig. 9, with number parameters greater than the number of training examples, we see that the results increase with the number of neurons. This model has 55 parameters, which is almost double the number of training examples. If we were to release this model, or the previous ones models that have a larger number of parameters than training examples for multiple iterations, we would arrive at an ideal correlation function with training data. This behavior, though numerically ideal, meaning that the function itself it has a chaotic shape and would not give good results in the real world. We can potentially fix this with L1 or L2 regularization, or by increasing the number example training.

## 4. CONCLUSIONS

In this study, for prediction surface roughness of aluminum alloy 6082-T6, multiple regression analysis and artificial neural network models were used. The parameters such as spindle speed, feed rate, and cutting of depth were measured. The obtained data were used to develop the surface roughness models. The following conclusions can be presented from this study.

1. The developed models were evaluated for their prediction capability with measured values. The proposed models can be used effectively to predict surface roughness.
2. Both models indicate a good agreement between the predictive and measured values.
3. The determination coefficient ($R^2$) is 99.9 % in the neural network model (the best is for 5x2-S-R), while it is achieved as 99.6 % for second-order equation and 99.8 % for a third-order equation in multiple regression analysis.

## REFERENCES


[1] M. Kumar, A.K. Sarathe, *Prediction of Surface Roughness on CNC Machine: A Review*, International Journal of Engineering Research & Technology, vol. 5, iss. 7, pp. 300-307, 2016.

[2] A.M. Khorasani, M.R.S. Yazdi, M.S. Safizadeh, *Analysis of machining parameters effects on surface roughness: A review*, International Journal Computational Materials Science and Surface Engineering, vol. 5, no. 1, pp. 68–84, 2012, doi: 10.1504/IJCMSSE.2012.049055

[3] C. Lu, *Study on prediction of surface quality in machining process,* Journal of Materials Processing Technology, vol. 205, iss. 1-3, pp. 439–450, 2008, doi: 10.1016/j.jmatprotec.2007.11.270

[4] N. Fountasa, K.E. Aslanib, J. Kechagiasc, P. Kyratsisd, N. Vaxevanidisa, *Experimental and Statistical Study of Surface Roughness in CNC Slot Milling of AL 7075 Alloy Using Full and Fractional Factorial Design*, Tribology in Industry, vol. 44, no. 2, pp. 283-293, 2022, doi: 10.24874/ti.1151.07.21.11

[5] C.A. van Luttervelt, T.H.C. Childs, I.S. Jawahir, F. Klocke, P.K. Venuvinod, Y. Altintas, E. Armarego, D. Dornfeld, I. Grabec, J. Leopold, B. Lindstrom, D. Lucca, T. Obikawa, Shirakashi, H. Sato, *Present Situation and Future Trends in Modelling of Machining Operations Progress Report of the CIRP Working Group Modelling of Machining Operations*, CIRP Annals, vol. 47, iss. 2, pp. 587-626, 1998, doi: 10.1016/S0007-8506(07)63244-2

[6] B.A. Beatricea, E. Kirubakaranb, P.R.J. Thangaiahc, K.L.D. Winsd, *Surface Roughness Prediction using Artificial Neural Network in Hard Turning of AISI H13 Steel with Minimal Cutting Fluid Application*, Procedia Engineering, vol. 97, pp. 205–211, 2014, doi: 10.1016/j.proeng.2014.12.243

[7] L. Yung-Chih, W. Kung-Da, S. Wei-Cheng, H. Pao-Kai, H. Jui-Pin Hung, *Prediction of Surface Roughness Based on Cutting Parameters and Machining Vibration in End Milling Using Regression Method and Artificial Neural Network*, Applied Sciences, vol. 10, iss. 11, pp. 1-22, 2020, doi: 10.3390/app10113941

[8] M. Rajesh, R. Manu, *Prediction of surface roughness of freeform surfaces using Artificial Neural Network*, in: 5th International & 26th All India Manufacturing Technology, Design and Research Conference (AIMTDR 2014), 12th–14th December, 2014, pp. 1-6.

[9] A. Kosarac, C. Mladjenovic, M. Zeljkovic, S. Tabakovic, M. Knezev, *Neural-Network-Based Approaches for Optimization of Machining Parameters Using Small Dataset,*, Materials, vol. 15, iss. 3, pp. 1-18, 2022, doi: 10.3390/ma15030700

[10] B. Cirak, *Mathematically Modeling and Optimization by Artificial Neural Network of Surface Roughness in CNC Milling – A Case Study*, World Wide Journal of Multidisciplinary Research and Development, vol. 3, no. 8, pp. 299-307, 2017.

[11] M. Nalbant, H. Gokkaya, I. Toktas, *Comparison of Regression and Artificial Neural Network Models for Surface Roughness Prediction with the Cutting Parameters in CNC Turning*, Hindawi Publishing Corporation Modelling and Simulation in Engineering, vol. 2007, pp. 1-15, 2007, doi: 10.1155/2007/92717

[12] H.K. Hussein, I.R. Shareef, I.A. Zayer, *Comparative Prediction and Modelling of Surface Roughness in Milling of AL-7075 Using Regression Analysis and Neural Network*, Mathematical Modelling of Engineering Problems, vol. 9, no. 1, pp. 186-193, 2022, doi: 10.18280/mmep.090123

[13] U.M.R. Paturia, H. Devarasettia, S.K.R. Narala, *Application Of Regression And Artificial Neural Network Analysis In Modelling Of Surface Roughness In Hard Turning Of AISI 52100* Steel, Materials Today: Proceedings, vol. 5, iss. 2, part 1, pp. 4766–4777, 2018, doi: 10.1016/j.matpr.2017.12.050

[14] S. Karabulut, A. Gullu, A. Guldas, R. Gurbuz, *Analytical Modelling of Surface Roughness during Compacted Graphite Iron Milling Using Ceramic Inserts*, World Academy of Science, Engineering and Technology International Journal of Mechanical and Mechatronics Engineering, vol. 9, no. 8, pp. 1478-1483, 2015.

[15] M. Alauddin, M.A. El Baradie, M.S.J. Hashmi, *Optimization of surface finish in end milling inconel 718*, Journal of Materials Processing Technology, vol. 56, iss. 1-4, pp. 54–65, 1996, doi: 10.1016/0924-0136(95)01820-4

[16] A. Gjelaj, B. Berisha, W. Sitek, *An Experimental Based Approach Using Artificial Intelligence Algorithm for Determining the Surface Roughness by Milling Process*, International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies, vol. 13, no. 5, pp. 1-9, 2022, doi: 10.14456/ITJEMAST.2022.86

[17] J.H. Shaik, J. Srinivas, *Optimal selection of operating parameters in end milling of Al-6061 work materials using multi-objective approach*, Mechanics of Advanced Materials and Modern Processes, vol. 3, iss. 1, pp. 1-11, 2017, doi: 10.1186/s40759-017-0020-6

[18] F. Kara, K. Aslantas, A. Çiçek, *ANN and multiple regression method-based modelling of cutting forces in orthogonal machining of AISI 316L stainless steel*, Neural Computing and Applications, vol. 26, pp. 237-250, 2015, doi: 10.1007/s00521-014-1721-y

[19] A.M. Zain, H. Haron, S. Sharif, *Prediction of surface roughness in the end milling machining using Artificial Neural Network,* Expert Systems with Applications, vol. 37, iss. 2, pp. 1755–1768, 2010, doi: 10.1016/j.eswa.2009.07.033

[20] T. Erzurumlu, H. Oktem, *Comparison of response surface model with neural network in determining the surface quality of moulded parts*, Materials & Design, vol. 28, iss. 2, pp. 459–465, 2007, doi: 10.1016/j.matdes.2005.09.004

[21] I. Asiltürk, M. Çunkas, *Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method*, Expert Systems with Applications, vol. 38, iss. 5, pp. 5826–5832, 2011, doi: 10.1016/j.eswa.2010.11.041

[22] B.S. Reddy, G. Padmanabhan, K.V.K. Reddy, *Surface roughness prediction tehniques for CNC turning,* Asian Journal of Scientific Research, vol. 1, iss. 3, pp. 256-264, 2008, doi: 10.3923/ajsr.2008.256.264