Estimation of Surface Roughness Value Using Back Propagation Neural Network on Green Machining

M. Yanis†, Arie Y.B†, Aneka F†, Nova Y‡

† Department of Mechanical Engineering-Faculty of Engineering-Sriwijaya University, 60662, Indonesia
‡ Department of Chemistry-Faculty of Mathematics and Natural Science-Sriwijaya University, 60662, Indonesia
*Corresponding Author Email: yanis@unsri.ac.id

ABSTRACT

This study discusses the prediction of surface roughness during the side milling of AISI 1045 material. Surface roughness is an indicator of surface quality which is one of the most frequently specified customer requirements in the machining process. Experimental and optimization studies were developed using the Artificial Neural Networks (ANN) method. The Levenberg-Marquardt algorithm on back propagation is used for training and testing to predict the effect of input variables on surface roughness. The machining variable input consists of cutting speed, feeding rate, radial and axial depth of cut. The machining condition uses coconut oil as the cutting fluid with a Minimum Quantity Lubrication system. The network developed is a structure with one and two hidden layers. The number of neurons 1 to 20 is assigned to this hidden layer. The network structure that offers the surface roughness value closest to the experimental value was 4-10-1 with MSE training 0.00467 ($R^2 = 98.23\%$) and testing 0.0052 ($R^2 = 99.47\$). This shows that a network structure with more hidden layers does not increase network functionality. The average error percentage between experimental results and ANN predictions is 1.43% (training) and 6.87% (testing). The effect of machining variables on surface roughness shows that the surface roughness value decreases (smooth) with increasing cutting speed. And increasing the feed rate and depth of cut will increase the surface roughness value.

KEYWORDS

Artificial Neural Networks, Input Variable, LM-Algorithm, Surface Roughness

INTRODUCTION

Previous studies have shown that measuring surface roughness in milling operations using Artificial Neural Networks (ANN) has been studied by many researchers. ANN is an Artificial Intelligent (AI) model that uses a non-conventional approach. The ANN gave better prediction abilities since they usually propose the capability to model highly complex interactions, nonlinearities and unknown functions. The better the results achieved if the more parameters ANN are trained. It is known that the ANN model with an error percentage < 7% is feasible although with small training data. Experimental results applying ANN can be acquired in economical machining and less time [1-5]. Quite a lot of research has been done on the use of ANN in predicting surface roughness. Ikhas et al [6] found that ANN provides a higher R2 coefficient compared to RSM when measuring the surface roughness of AISI 4140 steel in the turning process. Saglam et al [7] applied ANN in predicting surface roughness in milling C 1040 steel. Chen et al [3] claimed that ANN undertook better surface roughness prediction with the superior non-linear mapping ability than RSM in turning Ti6Al4V.

Sangwan et al [8] obtained a higher mean absolute percentage error (MAPE) according to RSM compared to ANN when analyzing surface roughness in turning Ti alloys. Sahoo et al [9] revealed the surface roughness maximum error RSM is more significantly than ANN when turning AISI 1040 in dry environment, and Kant & Sangwan [10] when milling AISI 1060 in a dry cutting. Sehgal & Meenu [11] also found that RSM predicts with lower accuracy than ANN during milling ductile iron in dry machining. According to international standards, the surface quality is investigated in terms of surface roughness [7]. Surface roughness is a very studied thing related to the machining process [11]. Surface roughness affects the work properties such as aesthetics, tribology, lubrication properties, sealing, hydrodynamic, corrosion resistance, electrical conduction, fatigue life

241
improvement and thermal conduction [3,7]. Surface roughness indicates other resources and the amount of energy involved when machining [8].

In milling steel and Ti alloy, the smoother surface roughness were revealed at low depth of cut, low feed rate and high cutting speed [4,7]. Besides the statistical ANOVA analysis indicate that surface roughness is regularly influenced by the feed rate, followed by the depth of cut and cutting speed [3]. Although only a small change in these variables can cause a significant influence on surface roughness. In consequence, it is necessary to model the connection between surface roughness and the variables that influence this value [8,10]. To minimize the use of cutting fluid, Beatrice et al [5] also applied the ANN model on surface roughness experiments during the turning of AISI H13 steel. The cutting fluid is used to improve the quality of the machining results. However, the application of cutting fluid can have an impact on waste, pollution and operator health. The current trend is to minimize the use of cutting fluids, one of which is for green machining purposes. The three techniques categorized as green machining are cryogenic machining, dry cutting, and minimum quantity lubrication (MQL). It is understood that MQL is superior to wet and dry machining in improving surface quality. Advanced green machining including the utilization of vegetable oil in MQL [12-14]. This study applies ANN in predicting and optimizing surface roughness to investigate its closeness to experimental data. The machining was carried out in the AISI 1045 side milling process with an uncoated carbide tool and coconut oil cutting fluid was applied using the MQL system. The selected machining input variables were cutting speed, feed rate, radial and axial depth of cut.

METHODOLOGY

Experimental Setup

The experiment was performed using a conventional vertical milling machine (1.5 kW). The cutting tool used was a 10 mm diameter end mill (K2 EMC 54100) uncoated carbide, 60° helical angles and 4 flutes. AISI 1045 steel with a dimension of 25 x 100 x 200 mm was used as a workpiece on the side milling process. Material and tool specifications were shown in Table 1 and Table 2. The machining process with the MQL method uses coconut oil as a cutting fluid. It has been considered as one of the environmentally friendly cutting fluids for machining. It has the following specifications: density at 15°C (kg/m³) of 925.8, an absolute viscosity at 40°C (cP) of 1.84 and flash point of 286°C C [14]. The machining input variables used were cutting speed (Vc), feed rate/tooth (fz), radial (ar) and axial (az) depth of cut. Arithmetic surface roughness (Ra) was considered as the output of machining performance.

Table 1. Chemical composition, mechanical and physical properties of AISI 1045

<table>
<thead>
<tr>
<th>Chemical composition (%)</th>
<th>C</th>
<th>Si</th>
<th>Mn</th>
<th>P</th>
<th>S</th>
<th>Ni</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.42 – 0.48</td>
<td>0.15 – 0.35</td>
<td>0.60 – 0.90</td>
<td>≤ 0.03</td>
<td>≤ 0.035</td>
<td>≤ 0.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Mechanical and physical properties</th>
<th>Tensile strength (N/mm²)</th>
<th>: 565</th>
<th>Elongation (%)</th>
<th>: 16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hardness (Brinell)</td>
<td>: 163</td>
<td>Density (g/cm³)</td>
<td>: 7.87</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Chemical composition of uncoated carbide tool (%)

<table>
<thead>
<tr>
<th>Ti</th>
<th>Co</th>
<th>W</th>
</tr>
</thead>
<tbody>
<tr>
<td>19.91 ± 1.79</td>
<td>8.78 ± 0.51</td>
<td>71.31 ±1.97</td>
</tr>
</tbody>
</table>

Design of Experimental

Central Composite Design (CCD) was performed to show the relationship between input variables and machining performance. Figure 1 shows the main points of the variable input values as variations in machining data, namely factorial points, axial points, and center points. The factorial, center and axial points are marked as level ±1, level 0 and level ± 2. The distance between the axial point and the center point is called radius rotatable (α), where $\alpha =$
and \( k \) is the number of input variables [15]. The input variable value range was selected according to the capacity of the machine tool used. The values for each level at the main CCD points were listed in Table 3.

![Figure 1](image-url)  
*Figure 1.* The main components of the CCD - factorial, axial and center points

**Table 3. Input variables and values on the main components of the CCD (Level)**

<table>
<thead>
<tr>
<th>Input Variables</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-2</td>
</tr>
<tr>
<td>Cutting Speed ( V_c ) (m/min)</td>
<td>8.9</td>
</tr>
<tr>
<td>Feed Rate ( f_z ) (mm/tooth)</td>
<td>0.0365</td>
</tr>
<tr>
<td>Radial Depth of Cut ( a_r ) (mm)</td>
<td>0.2</td>
</tr>
<tr>
<td>Axial Depth of Cut ( a_x ) (mm)</td>
<td>4</td>
</tr>
</tbody>
</table>

Estimation of The Machining Process Output using Artificial Neural Networks (ANN)

ANN is artificial intelligence (AI) optimization technique whose working principle is similar to a biological neural systems. This method is one of the best ways to determine the relationship of input and output of data in particular for non-linear. The general structure of ANN consists of neurons as information processing units located in several layers of neurons (input, hidden and output layer). Neurons in one layer will be connected with the before and after layers (except for the input layer and the output layer). Information will be sent to other neurons via a connection line called weights. The unit adds to the signal input from the neuron and is multiplied by the weight. It would be compared with a certain threshold value through the activation function.
ANN structure with two hidden layers and information processing in one neuron

\[ \text{net} = \sum_{i=0}^{n} x_i w_i + b \]  

(1)

In this study, the activation function used was the bipolar sigmoid (tansig), as shown in Equation (2).

\[ f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \]  

(2)

The input and target data for the tansig activation function are in the range ±1, so the data must be converted in that range with the normalization equation as in Equation (3) as follows:

\[ x_i = \frac{2}{(d_{\text{max}} - d_{\text{min}})} (d_i - d_{\text{min}}) - 1 \]  

(3)

where, \( d_i \) is the input or output variable of each set, \( d_{\text{min}} \) and \( d_{\text{max}} \) are the lowest and highest values of the input variable. Network configuration optimization is carried out through the learning process (training and testing) of input and output data. Network performance is calculated by statistical error using Mean Square Error (MSE). The statistical error functions were determined by Equations (4).

\[ \text{MSE} = \left( \frac{1}{n} \sum_{i=1}^{n} (|x_i - y_i|)^2 \right)^2 \]  

(4)

where, \( x_i \) is the target value, \( y_i \) is the output value and \( n \) is the number of total experimental.

RESULTS AND DISCUSSION

The experimental results consisted of 30 arithmetic surface roughness (Ra) values as the output variable for the four machining variables. And four additional data will be used as validation data. All of these data were analyzed using the ANN method. The Feed Forward Back Propagation (BP) network model was used for the learning process (training and testing). BP has been selected by many researchers for ANN analysis because of the combination of a flexible network structure with multiple layers. In this study, modeling optimizations were carried out based on (a) the best learning of all BP algorithms, (b) the number of neurons in the hidden layer and (c) the network structure. The best criteria are based on MSE performance results.

The criteria for the best algorithm in BP are based on the learning that will be carried out for all BP algorithms in the Matlab toolbox. The algorithms are scaled conjugate gradient (trainscg), resilient (trainr), random weight/bias rule (trainrp), levenberg-marquardt-LM (trainlm), one step secant (trainoss), gradient descent with momentum & adaptation learning rate (traindx), gradient descent (traingd), gradient descent with momentum (traingdm), gradient descent with adaptation learning rate (traingda), conjugate gradient with polak-riiere updates (traincgp), conjugate gradient with fletc-reeves updates (traincgf), conjugate gradient with powell-beale restarts (traincgb), bayesian regularization (trainbr), bgf quasi-newton (trainbfg). This training uses the default parameters available in Matlab and some specified inputs, namely: the structure consists of one hidden layer with 10 neurons, learninggd as the type of training, the tansig activation function, MSE as performance criteria. The experimental data used for learning were 30 data for training (88%) and 4 data for validation (12%). The input layer consists of...
neurons for four-machining variables, while the output layer was surface roughness. To develop the networks, the `newff` - network function is used as in Equation (5).

\[
net = \text{newff} \left( PR, \left[ S_1 \ S_2 \ldots \ S_{N_i} \right], \left\{ T_{F1} \ T_{F2} \ldots T_{F_{N_i}} \right\}, B_{TF}, B_{LF}, P_{F} \right)
\]

(5)

where, \( PR \) is the minimum and maximum value of the matrix \( R \times 2 \) and \( R \) is the number of input variables. \( S_i \) is the number of neurons in the \( i \)-layer, where \( i = 1, 2, \ldots, N_i \). \( T_{Fi} \) is an activation function on \( i \)-layer, \( i = 1, 2, \ldots, N_i \). \( B_{TF} \) is a network training function. \( B_{LF} \) is a training function for weights and \( P_{F} \) is a performance function. The learning output for all algorithms at the BP network model is shown in Figure 3. Based on these results, the three best algorithms were obtained, namely resilient BP (trainrp), Levenberg-Marquardt BP (trainlm) and conjugate gradient BP with Powell-Beale restart (traincgb). In this study, the LM-BP algorithm will be selected for more ANN analysis. It was selected because the training is faster and less memory than the other two best algorithms [16][17][18].

![Figure 3. BP algorithm types vs network performance](image)

The network structure developed was a structure with one hidden layer (4-n-1) and two hidden layers (4-n-n-1). The number of neurons in the hidden layer (n) was selected from 1 to 20. The best network structure was selected from a combination of the smallest \( \text{MSE} \) and the largest determinant coefficient (\( R^2 \)). The training results for both network structures were shown in Figure 4 and Figure 5.

![Figure 4. The Network Structure](image)
Figure 4. Network performance for one hidden layer

Based on these figures, for the number of hidden layer 1 the best network structure is 4-10-1 with MSE training 0.00467 (R² = 98.23%) and testing 0.0052 (R² = 99.47%). And for the number of hidden layer 2 the best network structure is 4-15-15-1 with MSE training 0.0046 (R² = 98.23%) and testing 0.0063 (R² = 98.55%). The minimum MSE in the 4-n-n-1 structure is achieved faster but the training process is longer than in the 4-n-1 structure. From the two structures, 4-10-1 was chosen as the best structure for further analysis. These results indicate that one hidden layer is sufficient to produce the best network structure. The increase in the number of neurons in the hidden layer does not increase the prediction results. Based on the selected network structure (4-10-1), the comparison of experimental values and the predicted results of training and validation are presented in Figure 6 and Figure 7. The percentage of average error was 1.43% (training) with range 0.00% ≤ error ≤ 10.40% and 4.62% with range 1.87% ≤ error ≤ 10.46% (testing). These results indicate that the BP network analysis with the LM algorithm provides good predictions.

Figure 5. Network performance for two hidden layers

Figure 6. Comparison of predicted and experimental values on training data
The effect of machining variables on the surface roughness value that occurs is presented in Figure 8. Increasing the cutting speed will decrease the surface roughness value. Increasing the cutting speed means making more cuts in the same zone so that the surface roughness will be better than the lower cutting speed. If the cutting speed increases, the cutting temperature will increase. This will soften the material and reduce the working cutting energy thus reducing the cutting load and improving the quality of the workpiece. This differs from the feed rate and depth of cut, where the surface roughness increases with the increase in the value of the two machining variables. As the variables feed rate and depth of cut increase, the maximum chip cross-sectional thickness increases, so the formation of a larger uncut area will result in poor surface quality [19][20].

Figure 7. Comparison of predicted and experimental values testing data

Figure 8. The influence of machining variables on surface roughness
CONCLUSIONS

In this study, the ANN method is used to estimate the side milling surface roughness of the AISI 1045 material. The machining process uses coconut oil as cutting fluid using the Minimum Quantity Lubrication (MQL) method. The results of the analysis show that the best BP algorithm in predicting experimental data is Levenberg-Marquardt. The surface roughness values that are closest to the experimental values in the 4-10-1 network structure with MSE training and testing are 0.00467 and 0.0052, respectively. ANN can predict surface roughness with an accuracy of up to 98.23% for training and testing 99.47%. A network structure with a higher number of hidden layers does not necessarily increase network functionality. The average percentage error between experiment and prediction was 1.43% (training) and 6.87% (testing). The effect of machining variables on surface roughness shows that the surface roughness value decreases (smooth) with increasing cutting speed. And increasing the feed rate and depth of cut will increase the surface roughness value.

ACKNOWLEDGEMENTS


REFERENCES


