Development of artificial neural network for surface roughness and machine prediction

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Abstract
An ANN is a system triggered by the process of biological neurons with the aim of learning a certain system. This study focuses on development of Artificial Neural Network (ANN) model for surface roughness and machining prediction. It is easy, precise and based on linear relationship between the neural network output when all of the input parameters are constant at their mean values other than the input parameter which is given to crucial testing and target values of the network. This can be achieved by providing stimulus to the neuronal model, estimating the output, and regulating the weights until the preferred output is attained. The composition of artificial neural network present data where surface roughness (Ra) is taken as output parameter to produce ANN’s response. Furthermore, selected sigmoid transfer function has its activation function in determining the actual value of a node in the ANN model. Right selection of machining parameter has been discovered to be a crucial in building a link between quality and productivity in an economic way. In conclusion, the neural network with the most favourable composition gives a productive approach to suggest an objective for surface roughness of the raw material under diverse cutting situations. The highest absolute percentage error in ANN model prediction was found to be 2.31% with average percentage error of 0.31%

Keywords: Milling; surface roughness; artificial neural network

1.0 Introduction
An ANN is a system triggered by the process of biological neurons with the aim of learning a certain system[1]. The development of an ANN is reached by providing a stimulus to the neuronal model, estimating the output, and regulating the weights until the preferred output is achieved the training is regarded as supervised when an input is submitted to the ANN with a preferred target for the output [2]. As a result of the difference between the desired response and the output of the system, an error field is built and the data is used as response for the system, which regulates its parameters in a systematic way. Surface roughness based on the roughness deviations can be defined as a measurable characteristic[3]. Surface roughness is most commonly used measure of surface texture as a result of its impact on the properties of a material in order to give it an acceptable quality. ANN performance is highly dependent on the source for information [4]. Cross-validation and testing followed training which is the first part of the information provided. For the purpose of obtaining the preferred surface roughness of raw material, several researchers across the globe have stived towards optimizing the cutting conditions [5].

A significant approach that is required to build a link between quality and productivity in an economic way is by selecting the right machining parameter [6]. This study focuses on development of ANN model for surface roughness and machining prediction, presents a new
formal test of the importance of neural network inputs [7]. It is easy, precise and based on a linear relationship existing between the output of neural network when all of the parameters entered are constant at their mean values other than the input parameter, which is given to necessary test and the target values of the network [8]. Results obtained from simulation indicates an increase the number of observations as the power of the test tends to 1 in all cases, and that the empirical size tends towards the nominal size in few instances [9].

Chen and Savage [10] predicted the surface roughness with several implement and raw material being combined for end milling process using an input parameter such as implement diameter, implement material for fuzzy net-based model. An error of about 10% was discovered for the predicted surface roughness. The method is made up of machine learning technique with particle swarm optimization for parameter optimization. Metin Kök [11] suggested an investigation of particle cutting speed, dimension and volume fraction on the surface roughness during the turning of Al alloy supported with Al 2O3 particles. Variance was used to achieve the impact of variables on the surface roughness. The outcome of the study indicates an increase of particles surface roughness with an increase in cutting speed and a decrease in dimension and the volume fraction for the cutting implements [12]. The values of an average surface roughness of K10 cutting implement having the most effective volume fraction was noticed to be higher when compare to TP 30 GP technique for surface roughness in end milling process. An evolutionary computation technique which is a genetic programming was first introduced with an objective to discover system programs (named as chromosomes) whose dimension and composition varies during simulated evolution that best provide solution. It was also discovered that the model that comprises of cutting parameters, viz., speed of spindle speed, feed, cutting depth and disturbance [13].

Mahyar Khorasani et al [14] developed (ANN) for modeling and suggesting the life span of tool in milling parts. Taguchi (DOE) and combination of several cutting variables for building an information base was the first process; followed by tool life modeling using (ANN) and finally validated with practical tests using Model statistical (RMS). The precision error (3.034%). was discovered to be irrelevant. The experiment result was concluded with the correlation for training using (ANN) and the test obtained was estimated at 3.1908% [15].

Cutting force model using neural networks to analyzed used data for better prediction. Many researchers have used Artificial neural networks for predicting Ra, F, Am, Tr and Tw [16]. This study focuses on development of Artificial NeurA Network (ANN) model for surface roughness and machining prediction. It is easy, precise and based on linear relationship between the neural network output when all of the input parameters are constant at their mean values other than the input parameter which is given to crucial testing and target values of the network.

2.0 Methodology

ANN make use of a practical analysis in order to show its random impact effectively [17-18]. It is made up of an input layer to show data and output layer for feedback. Networks comprising of sigmoid and linear output layer can roundup any function with a limited number of discontinuities During the development of the proposed ANN model, the following nomenclatures were used in presenting the non-linear fuzzy bi-objective optimization model [18].
Figure 1: the ANN flowchart

Start

Select ANN model

Select a training algorithm, activation function, and statistical measure

Determine the number of hidden layer in the ANN model

Divide the stored data into training and testing datasets

Start training the ANN model using the training datasets

Determine the values of each hidden layer nodes

Determine the values of output nodes and compute the prediction error(s)

Estimate the error terms for the hidden and output nodes

Adjust the weights in the model using the error terms

Retrain the ANN model

Check stoppage criterion

No
\[
\begin{align*}
H &= I_1 W_1 + I_2 W_2 + I_3 W_3 & (1) \\
E_{ij} &= O_j - F_j & (2) \\
E_{ij} &= W_{ij} + (n \times E_{ij} \times H) & (3)
\end{align*}
\]

Where

\( I \) is input layer value, \( H \) is hidden layer value, \( E \) is the error, \( W \) is the weight.

### 2.1 End milling predictive model

The proposed ANN architecture is a 2-layers hidden model with four input parameters (feed rate, immersion angle, cutting speed, and depth-of-cut) while the output from the model can be either surface roughness or machining time. This ANN model is shown in Figure 2. The combination of input signals and connecting weights in ANN models is made by using summation (Equation 1, 2, 3) and product (Equation 4) approaches.

\[
\text{net}_j = \sum_{i=1}^{m} x_i w_i + \theta_j & (1) \\
\text{net}_j = \prod_{i=1}^{m} x_i w_i + \theta_j & (2)
\]

where \( \theta_j \) is the bias associated with node \( j \).

In this study, Equation (1) is adopted in generating the values of nodes in succeeding layers. The current study utilized sigmoid function (Equation 3) in mapping input value (Equation 1) into a range between (0, 1). This sigmoid function has been widely used in training ANN models [19] and is favoured primarily because most outputs from ANN models are often between (0, 1) shown in Figure 3. This study selected sigmoid transfer function has its activation function based on its success for supervised ANN models [20]. By using Equation (3) in determining the actual value of a node in the ANN model, the Equation (1) is being converted indirectly to a non-linear equation (Equation 4).
\[ y_j = \frac{1}{1 + \exp^{-net_j}} \] 

(3)

\[ y_j = \frac{1}{1 + \exp \left( \sum \theta_i x_i \right)} \] 

(4)

During the training of ANN models, this study selects mean square error (MSE), which is Equation (5), as a measure in monitoring the deviations of predicted and actual values of all the training datasets.

\[ \text{MSE} = \frac{1}{n} \sum_{j=1}^{n} \left( y_{j,\text{actual}} - y_{j,\text{predicted}} \right)^2 \] 

(5)

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(5)

Figure 3: End milling predictive model

### 2.2 Prediction of Values Using ANN

The network is trained with Levenberg-Marquardt back propagation algorithm (trainlm). The structure of artificial neural network consist of an input and output parameters as shown in Figure 4. Cutting speed, Feed rate and depth of cut are taken as the input parameters whereas surface roughness (Ra) is taken as output parameter.
3.0 Results and Discussion

|                  | Surface roughness | Machining time |
|------------------|-------------------|----------------|
| MSE              | Training          | 0.0185         | 0.00072       |
|                  | Testing           | 0.000101       | 0.000102      |
| Co-efficient of  | Training          | 0.976          | 0.8191        |
| correlation      | Testing           | 0.8237         | 0.5235        |

The neural network with the most favorable composition gives a productive approach to suggest an objective for the surface roughness of the raw material under diverse cutting situations. Furthermore, the suggested values of surface roughness from the ANN model are compared with the practical result. The highest absolute percentage error in ANN model prediction was 2.31% with average percentage error of 0.31%. The prediction model was found better. The feedback surface model developed by [21] using second order polynomial equation was discovered to be statistically significant with 95% assurance level. It was also reported that the feed rate by the input parameter has more impact on the response.

5.0 Conclusion

Selected sigmoid transfer function has its activation function in determining the actual value of a node in the ANN model. Right selection of machining parameter has been discovered to be a crucial in building a link between quality and productivity in an economic way. In conclusion, the neural network with the most favourable composition gives a productive approach to suggest an objective for surface roughness of the raw material under diverse cutting situations.
Acknowledgements

We acknowledge the financial support offered by Covenant University in actualization of this research work for publication.

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