Investigation of the effect of cutting speed on the Surface Roughness parameters in CNC End Milling using Artificial Neural Network

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Abstract. This research presents the effect of high cutting speed on the surface roughness in the end milling process by using the Artificial Neural Network (ANN). An experimental investigation was conducted to measure the surface roughness for end milling. A set of sparse experimental data for finish end milling on AISI H13 at hardness of 48 HRC have been conducted. The artificial neural network (ANN) was applied to simulate and study the effect of high cutting speed on the surface roughness.

1. Introduction

In finishing end milling, not only good accuracy but also good roughness levels must be achieved. Thus, determining the optimum cutting levels to achieve the minimum surface roughness is important for it is economical and mechanical issues [1]. Surface roughness is a result of process parameters such as tool geometry and cutting conditions.

Sahin & Motorcu [2] found out through an experimental study that the surface finish of machined parts has a considerable effect on some properties such as wear resistance and fatigue strength. Hence, the quality of the surface is of a significant importance when evaluating the productivity of machine tools and mechanical parts. Then, predicting the quality of the surface roughness is important for its economical and mechanical properties.

Fnides et al. [3] claimed that the importance of surface roughness comes from its relation to many properties of machine elements such as wear resistance, the capacity of fit and sealing.

Cutting speed, feed rate and depth of cut are parameters that mostly influence the Ra value of surface quality in machining, particularly in the milling machining process. The set of parameters that are thought to influence the Ra value could be summarized in a fishbone diagram as shown in Fig. 1. The figure classified the factors that affect the surface roughness into four main categories: cutting tool properties, machining parameters, work piece properties and cutting phenomena. the final roughness of the machining process is actually is a result of all these factors, thus predicting and modeling by using the deterministic methods the surface roughness is a complex and difficult mission, thus the non

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Several methods for modelling the surface roughness have been reported in different research works. These methods can be classified into: statistical, mathematical and artificial intelligence techniques. Some of the researchers used the statistical techniques [3,5,6,7,8,9,10], others used the neural network techniques [4,11,12, 13,14]. Other researchers applied the ANN and the regression techniques and compared the results [15,16,17,18,19]. End milling is a type of face milling, and is used for facing, profiling and slotting processes. The end milling process is complex compared with turning because of its more complicated machine tool linear motions and its repeated intermittent engagement and disengagement of rotating cutting edges [20].

In finishing end milling, not only good accuracy but also good roughness levels must be achieved. The quality of the surface is of a significant importance when evaluating the productivity of mechanical parts. Thus, predicting and simulating the surface roughness quality is utmost important for it is economical and mechanical issues.

The real surface geometry is so complicated that one parameter can describe the surface roughness. There are more than 59 surface roughness parameters [21] and classified into three different categories of surface roughness parameters; amplitude, spacing and hybrid parameters.

Many parameters can be used to describe surface finishes and these are explained in the ISO 4287 and the ISO 4288.

This classification is based on the direction of measurement, vertical, horizontal or both together. The amplitude is used to measure the vertical characteristics of surface deviation while the spacing is used to measure the horizontal characteristics of surface deviation [21]. In machining process the most important parameters are the amplitude parameters.

This research will consider four amplitude parameters; arithmetic mean roughness (Ra), total roughness (Rt), mean depth of roughness (Rz) and the root mean square (Rq) as concluded in table 1.

### Table 1. Surface Roughness Parameters

| Parameter | Definition |
|-----------|------------|
| Ra        | Mean value of the absolute value of the profile departure y within the reference length |
| Rt        | Total height between highest peak and deepest valley |
| Rz        | Mean of distance between the five highest peaks and five deepest valleys |
| Rq        | Root mean square average of the profile ordinates |

2. Artificial Neural Network

The recent developments of predicting models concern the use of artificial intelligence such as neural network and fuzzy logic. Neural network (NN) and fuzzy logic present the next generation in computerizing the human thought processes [22]. The neural network technique is a method that
makes a computer simulates the behaviour of human brain neurons by using a set of data consisting of input and output variables. In the training process, the structure of the model is self adjusted to the data, and the final model can be used for predictions [23].

The training algorithm is defined as a procedure that consists of adjusting the weights and biases of a network that minimize selected function of the error between the actual and desired outputs [24, 25]. Figure 2 describes the training and adjusting procedure. The process of training a neural network can be broadly classified into two typical categories: supervised learning and unsupervised learning.

![Figure 2: training and adjusting the weights](image)

Back-propagation is one of the supervised learning. It is the most popular and well-studied training algorithm. It is a gradient-descendent method that minimizes the mean-square error of the difference between the network outputs and the targets in the training set [26]. It is used usually with the multi-layer structures. The basic procedure for training a network can be concluded as in the following steps:

a. Apply an input data to the neural network and calculate the corresponding output value.
b. Compare the output with the target and determine the measure of error.
c. Determine differences and the direction (positive or negative) in the weights to change each weight to reduce the error.
d. Determine the values for the new weights.
e. Apply the corrections to the weights.
f. Repeat the previous steps with all training vectors in the training set such that the error is reduced to an acceptable value.

The neural networks pass the output of their layers through activation functions. These activation functions scale the output of the neural network into proper ranges. The default choice for the feed forward Layer is the sigmoid activation function as in Equation (1).

$$f(x) = \frac{1}{1 + e^{-x}}$$  \hspace{1cm} (1)

The term sigmoid means curved in two directions, like the letter “S.” You can see the sigmoid function in Figure 3.

![Figure 3: sigmoid function](image)

A typical neuron consists of a linear activator followed by a nonlinear inhibiting function as in figure 3. The linear activation function yields the sums of weighted inputs plus an independent term so-called bias [26]. The hidden layer uses a sigmoid-type transference function:
\[ f(x) = \frac{1}{1 + e^{(-b - \sum w_i x_i)}} \]  
\[ \text{output} = \left( \sum_{i=0}^{n-1} x_i w_i \right) + (b_n) \]

3. Research methodology
The research methodology of this research can be concluded as the following:
1. Theoretical study
2. Experimental work
3. Design the experimental work by using the DoE software
4. Measuring the roughness parameters
5. Develop a model by using the artificial neural network
6. Adjust the model for minimum error
7. Simulate the results
8. Analyzing
These steps are shown in figure 4.

4. Experimental work
Machining was conducted using vertical milling centre type MAZAK machine (Model Nexus 410A-II). It has been done at high cutting speed from 150 up to 250 m/min, low feed rate 0.05-0.15 mm/rev and low depth of cut 0.1-0.2 mm. The experiments for this research were performed on AISI H13 at hardness of 48 HRC as work material. In the experiment, 20 samples of data set concerned with the end milling process have been collected based on five-level of central composite Design (CCD) as
shown in table 2. All the experiments done by using indexable tool holder Sandvick Coromill R490 and the insert was PVD coated TiAlN carbide.

Table 2. Experimental Design

| Cutting Speed (m/min) | Feed Rate (mm/tooth) | Depth of Cut (mm) |
|-----------------------|-----------------------|-------------------|
| Actual | Coded | Actual | Coded | Actual | Coded |
| 250  | 1     | 0.05  | -1    | 0.10  | -1    |
| 250  | 1     | 0.15  | 1     | 0.10  | -1    |
| 250  | 1     | 0.05  | -1    | 0.20  | 1     |
| 250  | 1     | 0.15  | 1     | 0.20  | 1     |
| 150  | -1    | 0.05  | -1    | 0.10  | -1    |
| 150  | -1    | 0.15  | 1     | 0.10  | -1    |
| 150  | -1    | 0.05  | -1    | 0.20  | 1     |
| 150  | -1    | 0.15  | 1     | 0.20  | 1     |
| 200  | 0     | 0.10  | 0     | 0.15  | 0     |
| 200  | 0     | 0.10  | 0     | 0.15  | 0     |
| 200  | 0     | 0.10  | 0     | 0.15  | 0     |
| 200  | 0     | 0.10  | 0     | 0.15  | 0     |
| 200  | 0     | 0.10  | 0     | 0.15  | 0     |
| 134  | α     | 0.10  | 0     | 0.15  | 0     |
| 265  | α     | 0.10  | 0     | 0.15  | 0     |
| 200  | 0     | 0.034 | α     | 0.15  | 0     |
| 200  | 0     | 0.166 | α     | 0.15  | 0     |
| 200  | 0     | 0.10  | 0     | 0.084 | α     |
| 200  | 0     | 0.10  | 0     | 0.216 | α     |

The experiment setup is shown in Figure 5.

![Figure 5. Experiment setup](image-url)
The results of the experiment have been used to design a new model for predicting the arithmetic mean roughness (Ra), root mean square (Rq), depth of roughness (Rz), and total roughness (Rt) by using three inputs: cutting speed, feed rate and depth of cut as shown in Figure 6.

The neural network architecture, learning system, algorithm, and activation function are concluded in table 3.

| Tool          | MATLAB 2009 |
|---------------|-------------|
| Tool box      | Nftool      |
| Architecture  | Feed forward|
| Learning system | Supervised learning: target values for the output are presented to the network |
| Algorithm     | Back propagation Levenberg-Marquardt algorithm (LM), Update weight and Bias values |
| Activation Function | Sigmoid (logistic function) |
| Number of layers | 3 layers (input, hidden and output) |
| Number of hidden layers | 20 |
| Data ratio    | 70:15:15    |

5. Results and discussions
Performance plot is generated. Performance is measured in terms of mean squared error and shown in log scale for each of the training, validation and test sets. The performance plot shows that the best validation is in epoch 4 as shown in Figure 7.
The regression plot for training, testing and validating the model are summarized in Figure 8. The plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line (dash line), where the network outputs are equal to the targets. For this study, the fit is very good for all data sets, with R values in each case of 0.92 or above.

![Figure 8. Plot of data regression (training, validation, testing)](image)

The weights of the final model are concluded in table 4 and table 5.

| hidden layer | Cutting speed | Feed rate | Depth of cut | Bias |
|--------------|---------------|-----------|--------------|------|
| 1            | -1.786        | -2.888    | -1.149       | 3.992|
| 2            | -1.119        | 2.888     | -2.499       | 3.009|
| 3            | -1.874        | 3.259     | 0.711        | 2.751|
| 4            | -0.551        | -1.788    | -3.156       | 2.637|
| 5            | -0.191        | -2.879    | 2.702        | 1.925|
| 6            | 2.391         | 0.793     | -2.563       | -1.973|
| 7            | 2.675         | -0.627    | 2.400        | -1.658|
| 8            | -1.177        | 2.893     | -1.639       | 1.504|
| 9            | 2.708         | 2.187     | 1.591        | -0.256|
| 10           | 2.113         | 1.017     | -2.875       | -0.487|
| 11           | 2.222         | 2.785     | 1.272        | 0.010|
| 12           | 0.207         | -2.636    | -2.736       | 0.486|
| 13           | -2.461        | -1.002    | 2.532        | -1.116|
| 14           | 2.556         | -2.763    | 0.038        | 1.431|
| 15           | 1.365         | -3.502    | 0.191        | 1.885|
| 16           | -3.319        | 0.718     | -1.736       | -2.063|
| 17           | 3.063         | -1.235    | -1.220       | 2.977|
| 18           | -2.437        | 2.740     | -0.029       | -3.183|
| 19           | 3.448         | 0.977     | 0.103        | 3.674|
| 20           | -2.526        | -2.419    | -0.409       | -4.041|

| Layer | Ra   | Rq   | Rz   | Rt   |
|-------|------|------|------|------|
| 1     | -0.407 | -0.391 | 0.083 | 0.074 |
| 2     | -0.140 | 0.385 | 0.226 | 0.228 |
| 3     | 0.104  | 0.054 | -0.012 | -0.052 |
| 4     | -0.298 | 0.427 | 0.252 | -0.479 |
| 5     | 0.144  | -0.080 | 0.023 | -0.183 |
| 6     | -0.164 | 0.197 | 0.292 | -0.526 |
| 7     | -0.325 | 0.133 | 0.482 | 0.089 |
| 8     | 0.167  | -0.057 | 0.285 | 0.314 |
| 9     | 0.340  | 0.075 | -0.551 | 0.803 |
| 10    | 0.221  | -0.332 | -0.331 | 0.319 |
| 11    | 0.133  | 0.073 | 0.401 | -0.634 |
| 12    | 0.588  | -0.040 | 0.232 | 0.915 |
| 13    | 0.420  | 0.304 | 0.467 | 0.489 |
| 14    | -0.170 | 0.060 | 0.078 | -0.244 |
| 15    | 0.168  | 0.074 | -0.521 | 0.351 |
| 16    | -0.014 | 0.093 | -0.092 | -0.629 |
| 17    | 0.546  | 0.294 | 0.721 | 0.537 |
| 18    | 0.544  | 0.480 | 0.263 | 0.979 |
| 19    | 0.075  | 0.598 | -0.139 | -0.896 |
| 20    | -0.329 | 0.073 | -0.375 | -0.272 |
| Bias  | -0.660 | -0.544 | -0.893 | -0.342 |

6. Validation

A comparison of the measured and the predicted values to determine the deviation between the theoretical and actual value that comes out from ANN models have been conducted. The average deviation of the models is concluded in Figure 9.
7. Simulation

The effect of cutting speed and feed rate with constant depth of cut equal to 0.1mm on the different roughness parameters has been simulated. The results have been concluded in Figures 10-13.

**Figure 9.** Surface roughness models accuracy

**Figure 10.** The effect of feed rate and cutting speed on Ra
It was found that the best cutting speed for minimum $Ra$ are in the range of 200mm/min for all the feed rates. The figure shows that the roughness decreases until a specific point then start to increase with increasing the cutting speed for all feed rates.

![Graph showing the effect of feed rate and cutting speed on Rq and Rz.](image)

**Figure 11.** The effect of feed rate and cutting speed on Rq

It was found that the minimum values of $Rq$ was with feed rate equal to 0.05 mm/tooth and cutting speed 185 mm/min

![Graph showing the effect of feed rate and cutting speed on Rz.](image)

**Figure 12.** The effect of feed rate and cutting speed on Rz
Figure 12 shows that the minimum Rz can be achieved with feed rate of 0.05 mm/tooth and cutting speed equal to 240m/min.

![Figure 12](image_url)

**Figure 13.** The effect of feed rate and cutting speed on Rt

The simulation results gave to minimum values for different feed rate 0.05 and 0.1 mm/tooth. These values are almost the same; however the cutting speed with 0.05 mm/tooth as feed rate is higher.

**8. Conclusions**

This study has been involved with the ANN technique for development of models to predict the values of surface roughness parameters in the end milling machining operation. These models used to simulate the different cutting speeds and feed rates to estimate and predict the best cutting parameters for minimum values of surface roughness parameters. In the next stage, consideration should be on studying the optimization of the cutting factors in order to minimize the surface roughness parameter, which is an important issue.

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