Flank wears Simulation by using back propagation neural network when cutting hardened H-13 steel in CNC End Milling

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Abstract. High speed milling has many advantages such as higher removal rate and high productivity. However, higher cutting speed increase the flank wear rate and thus reducing the cutting tool life. Therefore estimating and predicting the flank wear length in early stages reduces the risk of unaccepted tooling cost. This research presents a neural network model for predicting and simulating the flank wear in the CNC end milling process. A set of sparse experimental data for finish end milling on AISI H13 at hardness of 48 HRC have been conducted to measure the flank wear length. Then the measured data have been used to train the developed neural network model. Artificial neural network (ANN) was applied to predict the flank wear length. The neural network contains twenty hidden layer with feed forward back propagation hierarchical. The neural network has been designed with MATLAB Neural Network Toolbox. The results show a high correlation between the predicted and the observed flank wear which indicates the validity of the models.

1.Introduction
The upper limit of cutting speeds in machining have been increased during the last eighty years from 15m/min in the year 1930 to over 1000m/min after 1990 [1]. The term high speed may not be the same for different materials, as high speed for one material may still be a low speed for another (for example, the high speed for titanium is a low speed for aluminium). Allowed level of speeds has been always restrained by the limitation in flank wear progress, cutting temperature and surface quality. Figure 1 shows the regions of cutting speed for milling a different work pieces and its relation to the conventional and high speed cutting [1, 2].

High speed end milling of hard alloy steels have many advantages such as reduction of machining time, higher metal removal rates, lower machining costs and better surface roughness [3]. However, high speed machining increases the temperature in both work material and cutting tool substantially due to high pressure on the cutting zone [4]. Increasing the cutting temperature has a bad effect on both the cutting tool sand the work piece. In contrast increasing the cutting temperature will reduce the cutting forces [5,6,7]. Thus, predicting and modeling the responses of the machining process such as the temperature, cutting forces, surface roughness and wear progress before the machining process in certain cutting levels become an important issue.

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Dolinsek and Kopac [1] claimed that the characteristic wear of cutting tools is caused by the fact that the cutting speed is no longer the main influential factor on wear, but more likely wear is the consequence of the high-speed of the feed rate.

Many researchers worked in developing different models by using the Neural Network (NN) in terms of cutting parameters. Some of the researchers used the NN in predicting the cutting forces [8], flank wear [9], energy [10], temperature [3], others used the ANN to predict the surface roughness [11].

Many researchers [12,13,14,15] used the neural network to predict the wear rate. Other researchers [9, 16] used two methods such as the neural network and the regression analysis method and then compare the results to find the best model.

Flanks wear length usually used as a reference for estimating the cutting tool life. Therefore, estimating and predicting the flank wear progress early is an important and crucial matter. Adesta et al. [4] classified the methods for estimating the flank wear progress into two main types; direct and indirect methods.

Direct methods based on monitoring and measuring the flank wear length during the cutting time [17] or by estimating the flank wear length mathematically [18, 19, 20].

However, flank wear can be estimated by monitoring the change of other machining parameters such as surface roughness [21], cutting force [22], temperature [23] and vibrations [24], which reflect the flank wear change. Other methods used for measuring the flank wear length such as the acoustic emission method [25].

Milling are considered to be too complex to be modeled accurately by using analytical or even numeric means due to involvement of various control parameters [16].

In this research, new model has been developed to predict the flank wear length in terms of cutting speed, feed rate and depth of cut in high speed end milling process.

2. Experimental work
The machining has been conducted using a vertical milling center type MAZAK machine (Model Nexus 410A-II). The machining was under high cutting speed from 150 up to 250 m/ min, low feed rate 0.05-0.15 mm/ rev, low depth of cut 0.1-0.2 mm and tool diameter was 20 mm. The experiments in this research were performed on AISI H13 at hardness of 48 HRC as work material. Hisomet II tool maker microscope has been used for monitoring and measuring the flank wear length during
machining. 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 1.

| No of run | Cutting Speed m/min | Feed Rate mm/rev | Depth of Cut mm | No of run | Cutting Speed m/min | Feed Rate mm/rev | Depth of Cut mm |
|-----------|---------------------|------------------|----------------|-----------|---------------------|------------------|----------------|
| 1         | 134.2               | 0.1              | 0.10           | 11        | 200                 | 0.10             | 0.15           |
| 2         | 150                 | 0.05             | 0.10           | 12        | 200                 | 0.10             | 0.15           |
| 3         | 150                 | 0.05             | 0.20           | 13        | 200                 | 0.10             | 0.15           |
| 4         | 150                 | 0.15             | 0.10           | 14        | 200                 | 0.10             | 0.22           |
| 5         | 150                 | 0.15             | 0.20           | 15        | 200                 | 0.17             | 0.15           |
| 6         | 200                 | 0.03             | 0.15           | 16        | 250                 | 0.05             | 0.10           |
| 7         | 200                 | 0.10             | 0.08           | 17        | 250                 | 0.05             | 0.20           |
| 8         | 200                 | 0.10             | 0.15           | 18        | 250                 | 0.15             | 0.10           |
| 9         | 200                 | 0.10             | 0.15           | 19        | 250                 | 0.15             | 0.20           |
| 10        | 200                 | 0.10             | 0.15           | 20        | 265.8               | 0.10             | 0.15           |

The research methodology is based on two main parts: experimental work and neural network application. The detailed research methodology illustrated in Figure 2.
3. ANN application

These samples used to train the neural network and to adjust the weights and the biases of each unit in order to reduce the error between the desired output and the actual output. The NFTOOL box in the MATLAB 2009 has been used. The back propagation algorithm applied to determine the layer's weights. Table 2 concluded the architecture, learning system, specifications of the neural network model used in the development of the new model.

Table 2. Modelling by using neural network

| Tool                          | MATLAB 2009                      |
|-------------------------------|----------------------------------|
| Tool box                      | Nftool                            |
| Architecture                  | Feed forward                      |
| Learning system               | Supervised learning               |
| Algorithm                     | Back propagation Levenberg-Marquardt algorithm (LM) |
| Activation Function           | Sigmoid (logistic function)       |
| Number of layers, Data ratio  | 3 layers (input, hidden and output) 70:15:15 |
| Number of hidden layers       | 20                                |

Then the MATLAB-M file is generated from the software as in Figure 3 and the algorithm flow chart is as in Figure 4.

```matlab
function net = create_fit_net (inputs,targets)  
%CREATE_FIT_NET Creates and trains a fitting neural network.
% NET = CREATE_FIT_NET(INPUTS,TARGETS) takes these arguments:
%  INPUTS - RxQ matrix of Q R-element input samples
%  TARGETS - SxQ matrix of Q S-element associated target samples
% arranged as columns, and returns these results:
%  NET - The trained neural network
% For example, to solve the Simple Fit dataset problem with this function:
% load simplefit_dataset
% net = create_fit_net(simplefitInputs,simplefitTargets);
% simplefitOutputs = sim(net,simplefitInputs);
% To reproduce the results you obtained in NFTOOL:
% net = create_fit_net(x',y');
% Create Network
numHiddenNeurons = 20;  % Adjust as desired
net = newfit(inputs,targets,numHiddenNeurons);
net.divideParam.trainRatio = 70/100;  % Adjust as desired
net.divideParam.valRatio = 15/100;  % Adjust as desired
net.divideParam.testRatio = 15/100;  % Adjust as desired
% Train and Apply Network
[net,tr] = train(net,inputs,targets);
outputs = sim(net,inputs);
pplotperf(tr)
plotfit(net,inputs,targets)
plotreression(targets,outputs)
```

Figure 3: MATLAB-M file

Figure 4: Flow chart of ANN Application
4. Results and discussions

The regression plot for training, testing and validating the model are summarized in Fig. 5. 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 0.97 or above.

![Figure 5: Plot of data regression (training, validation, testing)](image)

The final weights of the model are concluded in Table 3.

**Table 3. Final weights and bias of input layers to Hidden layers**

| Number of layer | Cutting speed | Feed rate | Depth of cut | Bias | Number of layer | Cutting speed | Feed rate | Depth of cut | Bias |
|-----------------|---------------|-----------|--------------|------|-----------------|---------------|-----------|--------------|------|
| 1               | 3.140         | -1.945    | 0.230        | -3.896 | 11              | 2.426         | 2.339     | 1.810        | 0.357 |
| 2               | 2.615         | 2.627     | -0.983       | -3.360 | 12              | 1.425         | 2.745     | 2.133        | 0.501 |
| 3               | 2.797         | 2.090     | -1.553       | -3.030 | 13              | 0.847         | -1.026    | -3.579       | 1.002 |
| 4               | 3.268         | -0.942    | 1.738        | -2.564 | 14              | -2.380       | -1.186    | 2.593        | -1.637 |
| 5               | -2.936        | -2.167    | 0.186        | 2.372  | 15              | 2.827         | 2.559     | 0.069        | 1.741 |
| 6               | 0.175         | -2.447    | 2.878        | -1.790 | 16              | -2.817       | 2.288     | 0.925        | -2.298 |
| 7               | 1.230         | 2.388     | -2.667       | -1.436 | 17              | 0.532         | -0.768    | -3.683       | 2.595 |
| 8               | 2.448         | -2.708    | 1.110        | -1.054 | 18              | -2.039       | -2.246    | -2.436       | -2.863 |
| 9               | 1.370         | 1.715     | -3.056       | -0.548 | 19              | -1.168       | 0.626     | 3.567        | -3.391 |
| 10              | -1.329        | 1.486     | 3.214        | 0.127  | 20              | 2.104         | -2.088    | -2.383       | 3.826 |

5. 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. Figure 4 shows the average deviation between the actual and the predicted values by the neural network models. The results show a high percentage of accuracy, 1.17% degree of variation from the original measured values.
6. Simulation
The effect of feed rate and depth of cut during high speed milling have been simulated by using the neural network model and the results were concluded in Figure 6 and Figure 7.

The results of the simulation show that

a. The effect of the depth of cut is higher than the feed rate in higher cutting speed (250 m/min)
b. Increasing the depth of cut will increase the flank wear.

c. Increasing the feed rate above 0.8 have a positive effect on the flank wear.

d. These results may due to

7. Conclusions

This study has been involved with the ANN technique to develop a new model to predict the values of temperature in the end milling machining operation. Twenty hidden layer has been used with feed forward back propagation hierarchical neural networks were designed with Matlab2009b Neural Network Toolbox. A new model is tested and validated.

This study has been involved with the ANN technique for development of models to predict the values of flank wear length in the end milling machining operation. Twenty hidden layer has been used with feed forward back propagation hierarchical neural networks were designed with Matlab2009b Neural Network Toolbox. The results show that the models are valid by using three inputs only; cutting speed, feed rate and depth of cut. The average deviations are 1.17 % for the flank wear length. This high correlation between the predicted and observed values indicated the validity of the models effect on the flank wear.

8. References

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