PREDICTION OF FLANK WEAR AND SURFACE ROUGHNESS BY RECURRENT NEURAL NETWORK IN TURNING PROCESS

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ABSTRACT: Tool wear and surface roughness plays a significant role for proper planning and control of machining parameters to maintain product quality in order to achieve sustainable manufacturing. The machining process is complex, thus it is very difficult to develop a comprehensive model. This study proposes an innovative model of flank wear and surface roughness prediction for turning of AISI 1040 steel based on a recurrent neural network (RNN). In this study, the flank wear and surface roughness was measured during turning at different cutting parameters. Full factorial experimental design applied aims to increase the confidence limit and reliability of the experimental data. The input variables for the proposed RNN network were cutting speed, feed rate, depth of cut and the homogeneity extracted from the surface texture images obtained by using grey level co-occurrence matrix. The result shows that the accuracy of the flank wear and surface roughness prediction using RNN can reach as high as 97.05% and 96.58%, respectively.

KEYWORDS: *Prediction; Tool Wear; Surface Roughness; Turning Process*

1.0 INTRODUCTION

Machining remains critically important as it is a fundamental industrial process in which metal is sculpted by removal of material that is expected to still be used in the next decades. In the context of machining, the cutting tool is always a key issue as it is well recognized that the quality of the surface finish and the dimensional accuracy are greatly influenced by tool condition. Tool failure constitutes 20% of CNC machine downtime which results in declining productivity [1]. Surface quality is considered as a major importance in manufacturing for a variety of reasons. Machined surface attributes are found to greatly influence friction, fatigue strength, corrosion resistance and tribological properties of machined components [2-3]. Therefore, monitoring the surface of machined components is necessary. Therefore, an efficient tool condition monitoring system is highly desirable for real-timely and accurately evaluating the wear status of cutting tools as well as the surface quality in order to forecast the schedule of the worn cutting tool replacement before the occurrence of damage and catastrophic failures.

Traditionally, the tool life is usually predicted based on the Taylor formula or the statistics and probability methods [4]. However, the models are deterministic, and unable to consider the underlying uncertainty in tool wear due to its stochastic behaviour. In recent decade, the use of multiple sensor signals such as cutting forces, vibration, acoustic emission and temperature for the effective monitoring of tool wear conditions have been widely studied [5-6], which provide crucial feedback information to the process control and tool wear prediction. The sensor signals captured from the machining process are usually required to be pre-processed for signal features which show high sensitivity to tool condition. Tool wear monitoring based on sensor signal usually works in three steps. The steps include (i) signal acquisition or choice of measurable sensor signal to be captured, (ii) feature extraction (e.g. mean, root mean square value) and (iii) feature estimation and classification as illustrated in Figure 1 [6]. The raw sensor signals are processed to extract significant features from the signal in the time domain or frequency domain, and to correlate the tool wear, or further fed into a model such as autoregression model, neural network to estimate the tool state. However, sensor signals are highly sensitive to the noise and easily disturbed. Tool wear monitoring has applied expensive sensing systems, for example, dynamometers and accelerometers as well as with expensive data acquisition hardware [7]. The installation of the devices also requires re-equipment of the machine structure, which is not suitable for production [5].

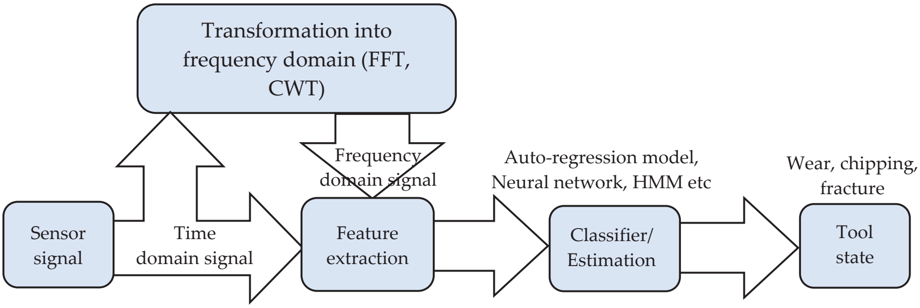


Figure 1: The framework of tool condition monitoring using indirect method

A wide range of Artificial Intelligence (AI)-based techniques have been employed to construct the correlation between the input (machining parameters, sensor signals) and the output (tool wear and surface roughness) of machining process as prediction of surface roughness and tool wear by means of AI-based approaches is more accurate in the comparison to those based on theoretical techniques [8]. Artificial neural networks (ANN) is the most popular AI models for predicting the wear of cutting tools and surface roughness in the past, because ANN can overcome the problems encountered in the machining process by its massive parallelization computing in solving complex nonlinear problems [9-11]. Pal and Chakraborty [12] apply back propagation neural network (BPNN) to estimate the surface roughness while the cutting speed, feed rate, depth of cut and cutting forces are considered as input of BPNN. Attanasio et al. [13] compare Response Surface Methodology (RSM) with ANN for tool wear prediction during turning of AISI 1045 steel rods, and found that ANN models outperform RSM in the prediction of flank wear. Addona et al. [14] estimate the tool wear in turning of Inconel 718, and it is achieved by using the ANN supervised training derived from investigational tool wear measurements. Mandal et al. [15] adopt BPNN for the flank wear prediction of zirconia toughened alumina (ZTA) inserted in turning of AISI 4340 steel. Machining parameters are chosen as input to the neural network model and flank wear of inserts corresponding to these conditions which are selected as the output of the network. Khan and Maity [16] develop a generalized regression neural network (GRNN) to estimate the surface roughness and tool wear during turning of titanium alloys by considering the cutting speed and machining duration as input variables.

The rapid development of machine vision and image processing methods is shown to be effectively used in tool wear and surface quality monitoring. A comprehensive review on applying image processing methods in tool condition monitoring has been reviewed in

[17]. The surface texture is also used to evaluate the cutting tool condition, as the cutting tool operates directly on the workpiece, and the machined surface carries valuable information about the machining process. The surface finish descriptors from the images of the freshly machined surface texture such as contrast and homogeneity, the number of polygons with zero cross moment and the total void area of the Voronoi diagram from the machined surface images with various techniques such as grey level co-occurrence matrix (GLCM), Voronoi tessellation and discrete wavelet transform are found to have high correlation with tool flank wear [18-20]. This paper attempts to develop an effective strategy to predict tool flank wear and surface roughness while turning of AISI 1040 carbon steel. In this proposed strategy, cutting parameters and homogeneity of machined surface texture are combined with measured tool flank wear and surface roughness data to create a prediction model using Recurrent Neural Network (RNN).

2.0 METHODOLOGY

2.1 Machining and Image Acquisition

The turning was conducted by using Harrisson Alpha 400 NC lathe machine In this experiment, TNMG 220408 MF, Sandvik Ltd carbide was used as the cutting tool material while AISI1040 carbon steel was used as the workpiece material. The experiments were established upon full factorial design of the cutting parameter. In this experiment, three factors, which were cutting speed, feed rate and depth of cut with three levels were used as listed in Table 1. Standard L_3 (3^3) orthogonal array was used as the fractional factorial design. A total of 27 sets of data were used to train and test the RNN model, and Table 1 tabulates the variables (cutting parameters) and the three levels of each variable, coded variable values -1, 0 and 1 which corresponded to the lowest, middle and highest of each variable. After finishing the turning process, the flank wear VB of the cutting tool was measured by using Nikon MM-60 toolmaker's microscope according to ISO 3685:1993. While average surface roughness, Ra was measured with a stylus type roughness profilometer Mitutoyo Surftest SJ400. The cut-off length was set up to 0.8 mm. Three measurements were taken, and the average for each combination of the cutting variables was determined.

Table 1: Variables and their levels

Variables	-1	0	1
Cutting speed (m/min)	100	150	200
Feed (mm/rev)	0.10	0.20	0.30
Depth of cut (mm)	1.00	1.25	1.50

Figure 2 shows the image acquisition setup which consist of Canon EOS 60D DSLR camera, lighting source, camera stand holder, block and computer. After each turning process with different data sets of cutting parameter; cutting speed, feed rate and depth of cut, the images of workpiece surface were captured by using the DSLR camera with the aid of lighting system. Then, the important features from the image were extracted using grey level co-occurrence matrix (GLCM) image processing technique in Matlab programme. These features were further used for predictive model.

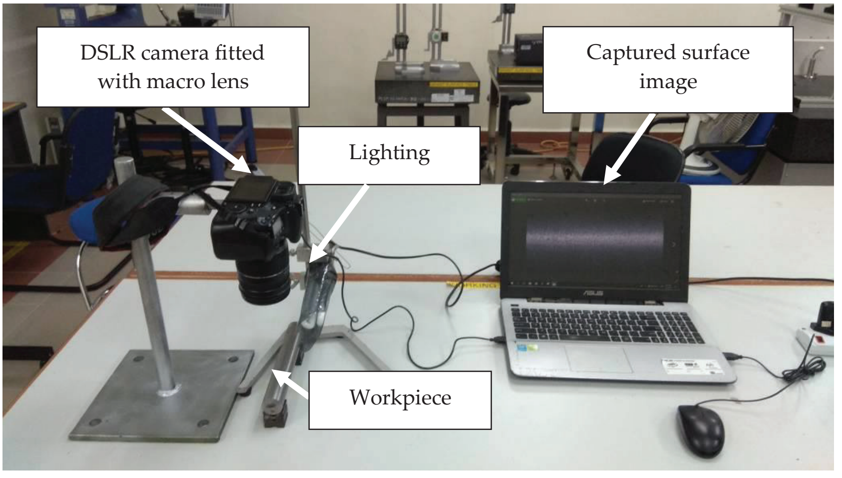
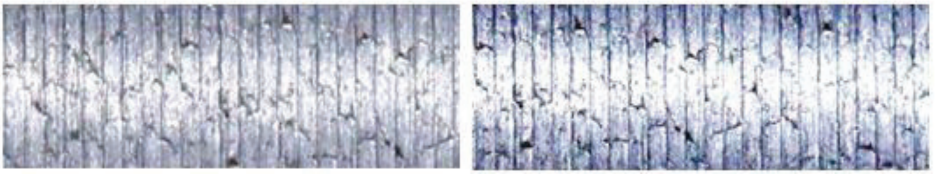


Figure 2: Image acquisition setup

2.2 Texture Feature Extraction

Before extracting the surface texture features, the images of surface texture were improved by using Contrast Limited Adoptive Histogram Equalization (CLAHE) technique. The image of machined surface after CLAHE technique provided better and clear contrast quality of image by redistributing the non-uniform grey level distribution uniformly, and equalized the histograms of distinct section of image which can be observed in the pre-processed image and its histogram as shown in Figure 3 and Figure 4, respectively.



(a) (b)

Figure 3: Turned surface: (a) before and (b) after pre-processing

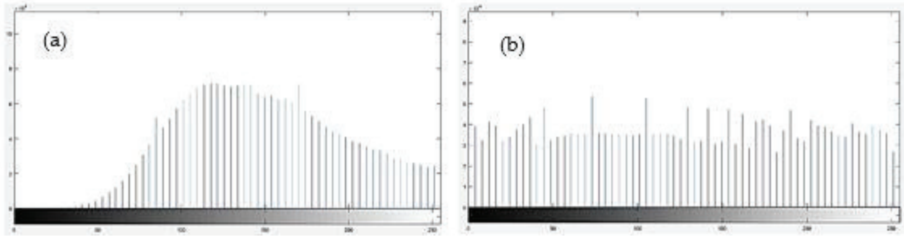


Figure 4: Histogram of turned surface: (a) before and (b) after pre-processing

Grey-level co-occurrence matrix (GLCM) is one of the most popular and widely applied techniques in surface texture analysis as it has the ability to extract the second order statistical texture features from an image [20]. GLCM allows provision of information regarding the relative occurrence of pixel intensities within a pair of pixels in a particular spacing and direction of an image. The number shown in element (i,j) of the GLCM P(i,j) refers to the probability by which pixel intensity i and pixel intensity j co-occur for a given distance d and orientation, θ. GLCM technique has been successfully applied for evaluating the surface texture in machining operation in the past [19-22]. Homogeneity of a GLCM measured the closeness of the distribution of elements in the GLCM to its diagonal in a surface texture image used in this study to interpret the tool condition, as given in Equation (1) such as

$$\text{Homogeneity} = \sum_{i}\sum_{j}\frac{P(i,j)}{1+|i\ j|} \tag{1}$$

2.3 Recurrent Neural Network

RNN model is ideally suitable for computations that unfold over time since the capability of the network to use both the present and recent past memory inputs to predict the output data. In this study, the Recurrent Neural Network (RNN) model was built to predict the tool wear and surface roughness under various cutting conditions. The training was performed in order to achieve the best net to estimate the flank wear and surface roughness. Initially, the inputs to the net, the number of hidden layers, the neurons on each hidden layer should be defined and taken into account in the feedback connection from the output of the hidden layer to the input [23]. The proposed RNN has the following structure: 4-X-1 which indicates that it has 4 inputs (cutting speed, feed rate, depth of cut and the homogeneity extracted from the images of machined surface texture), 1 output (surface roughness or tool wear) and 1 hidden layer with X neurons. These four net inputs have been selected as input as these features have high impact on the tool wear and surface roughness. This X is a value which was determined during the training process. The structure of RNN model was fixed by using 'trial and error' method to find the structure that gave the best prediction accuracy. The RNN model was developed by using language in MATLAB. Then, the extracted features, homogeneity from the machine surface images and cutting parameters were fed into the RNN model. Sets of input data were used to train and test the RNN model in order for the network to learn the patterns present in the data set.

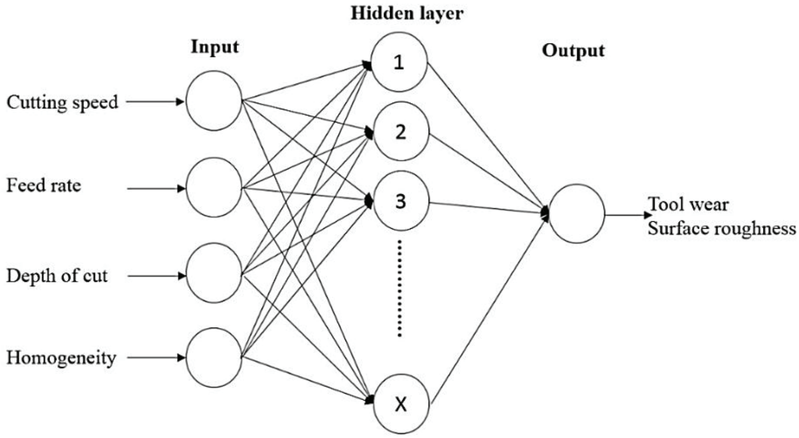


Figure 5: Schematic diagram of RNN network

3.0 RESULTS AND DISCUSSION

In this study, the experimental data comprised of 27 trials, of which 26 trials were applied for training the network and 1 data was used for testing the performance of the trained network. After completing the network training stage, it was tested with the experimental data beyond the training data set. This step was repeated until a total of 27 prediction results were obtained. The accuracy of the RNN models in prediction the degree of flank wear and the surface roughness were determined by the performance measure of determination coefficient (R^2) and mean absolute percentage error (MAPE) that is calculating using the following equations:

$$R^2 = 1 - \frac{\sum_i (P_i - A_i)^2}{\sum_i A_i^2} \quad (2)$$

$$\text{MAPE} = \frac{1}{N}\left|\frac{P_i - A_i}{A_i}\right| \times 100\% \tag{3}$$

where P_i represents the predicted value for flank wear and surface roughness by RNN, A_i is value for flank wear and surface roughness obtained from the experiment, N is the total number of experiment trials. The results found that a 4-10-1 network was optimal for the application. Figure 6 and Figure 7 illustrate the scatter diagrams of the predicted values and experimental values of flank wear and surface roughness of 27 of testing dataset using RNN model, respectively. In Figure 6 and Figure 7, it was observed that the correlation between the actual and predicted values of flank wear and surface roughness followed the 45^0 line very closely. In other words, the predicted values were not far from actual measurement values obtained from the experiment. The correlation coefficient, R^2 value for tool wear prediction in 4-10-1 RNN model was 0.9988 and the R^2 value for surface roughness was 0.9985. Thus, it can be concluded that the model had a very good relationship and fit which indicates that the proposed 4-10-1 Recurrent Neural Network model was capable in prediction of tool wear and surface roughness accurately.

The measured and predicted values of tool flank wear and surface roughness along the percentage error are tabulated in Table 2. The finding shows that the predicted results by RNN model are consistent with the experimental results for both flank wear and surface roughness. It can be seen in Table 2 that the prediction values were very close to the experimental values for tool flank wear and surface roughness. The prediction result of flank wear, the minimum error of prediction was 0.30%, the maximum error was 5.81% and the average error was 2.96%. On the other hand, the minimum prediction error of surface roughness was 0.03%, maximum error was 8.35% and the average error of predicted surface roughness value was approximately 3.42%. It indicates that the RNN prediction model has the ability to predict the tool wear and surface roughness with accuracy of 97.04% and 96.58%, respectively. Comparisons between the predictions of tool wear and surface roughness by using both RNN and the feed-forward propagation neural network were also performed. The MAPEs between the experimental and the predicted values were 6.58%for VB and 21.46% for Ra. The results showed that predictions with RNN outperform the prediction resulted from ANN models. The present findings seem to be consistent with other research which found RNN model has a higher prediction accuracy [24].

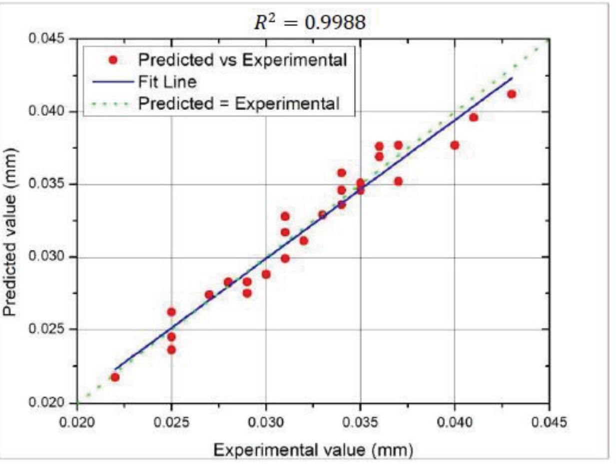


Figure 6: Predicted vs. experimental for flank wear

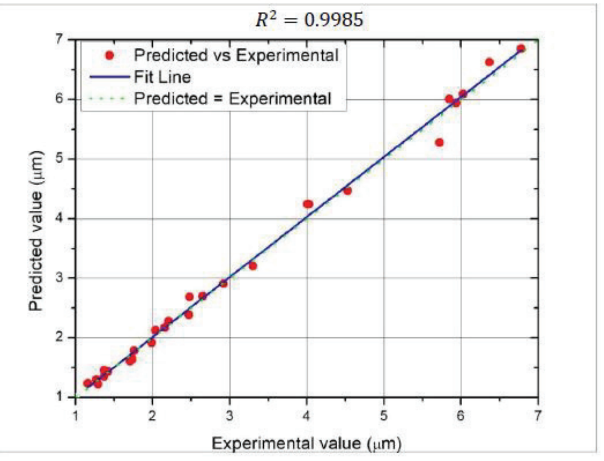


Figure 7: Predicted vs. experimental for surface roughness

Table 2: The RNN predictions for the flank wear and surface roughness value vs. experimental values

Trial No	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Flank wear VB (mm)			Roughness Ra		
				Actual	Predicted	APE (%)	Actual	Predicted	APE (%)
1	-1	1	-1	0.022	0.022	0.91	1.71	1.609	5.91
2	-1	-1	-1	0.025	0.025	2.00	2.92	2.908	0.42
3	-1	0	-1	0.027	0.027	1.48	5.94	5.942	0.03
4	0	1	-1	0.028	0.028	1.07	1.37	1.351	1.36
5	0	-1	-1	0.031	0.030	3.55	2.65	2.697	1.78
6	0	0	-1	0.035	0.035	0.57	5.85	6.009	2.71
7	1	1	-1	0.033	0.033	0.30	1.29	1.217	5.65
8	1	-1	-1	0.034	0.035	1.76	2.47	2.386	3.41
9	1	0	-1	0.04	0.038	5.75	5.72	5.280	7.69
10	-1	1	0	0.025	0.024	5.60	1.74	1.641	5.68
11	-1	-1	0	0.025	0.026	4.80	3.3	3.203	2.95
12	-1	0	0	0.028	0.028	0.71	4.53	4.476	1.20
13	0	1	0	0.029	0.028	2.41	1.42	1.435	1.08
14	0	-1	0	0.032	0.031	2.81	2.16	2.167	0.34
15	0	0	0	0.035	0.035	1.14	4.03	4.246	5.37
16	1	1	0	0.034	0.036	5.29	1.27	1.299	2.28
17	1	-1	0	0.036	0.037	2.50	2.04	2.122	4.01
18	1	0	0	0.041	0.040	3.41	4.01	4.242	5.79
19	-1	1	1	0.029	0.028	5.17	1.76	1.784	1.34
20	-1	-1	1	0.03	0.029	4.00	2.48	2.687	8.35
21	-1	0	1	0.031	0.032	2.26	6.78	6.850	1.03
22	0	1	1	0.031	0.033	5.81	1.37	1.452	5.96
23	0	-1	1	0.034	0.034	1.18	2.21	2.275	2.95
24	0	0	1	0.036	0.038	4.44	6.37	6.627	4.04
25	1	1	1	0.037	0.035	4.86	1.16	1.235	6.46
26	1	-1	1	0.037	0.038	1.89	1.99	1.918	3.62
27	1	0	1	0.043	0.041	4.19	6.03	6.094	1.05
					MAPE	2.96		MAPE	3.42

4.0 CONCLUSION

Tool wear and surface roughness prediction using RNN intelligent model has been successfully developed. The developed RNN model is shown to be effective in tool flank wear and roughness of surface prediction from cutting parameters and homogeneity features of surface texture. The findings from this study reveal that the prediction error for the tool flank wear and surface roughness are 2.96% and 3.42%, respectively. In other words, the accuracy of the flank wear and surface roughness prediction using RNN can reach as high as 97.04% and 96.58%, respectively, when validated with the measurement using a tool maker's microscope and stylus instrument. A good agreement between experimentally measured results and predicted values by

RNN was found for all quality characteristics considered in this study. The outcomes from the results can be used for prediction of cutting tool condition and the surface quality of machined part. Thus the tool can be monitored to avoid the breakage during machining based on tool wear state.

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