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Development of A Tool Condition Monitoring System for Flank Wear in Turning Process Using Machine Learning

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Abstract: Computer-numerical control (CNC) machining has become the norm in most manufacturing businesses. In order to maximize machining efficiency, prevent unintended damage, and maintain product quality all at once, tool wear measurement is essential. Wear on the tools is typically an inevitable side effect of machining. Because it endangers the machining process, flank wear, the most frequent type of tool wear, should be avoided. This study's objective is to fill this growing need by developing a system that can use machine learning to monitor tool condition during the turning process using MATLAB. The regression method with boosted decision trees and SVR with Gaussian kernels are applied to predict the flank wear based on the vibration signal and cutting parameters. This study found that the regression with boosted decision tree method has a lower mean average percentage error, 6.43%, while SVR is 10.11%. Plus, R-squared for regression is slightly better than SVR. It shows that the system successfully produced an accurate prediction of flank wear.

Keywords: Tool condition monitoring, flank wear, machine learning, CNC, turning process, SVR, regression

1. Introduction

A machining process is a process to remove some unwanted material, usually metal, to create parts for transportation, machines, and more. It is the process of removing material from a workpiece using power-driven machine tools to shape it into the desired design [1]. In current days, most industries have switched to computer numerical control (CNC) machining because the application of machining plays a big role as it involves time and money, which is a more cost-effective option than the conventional machining process [2]. CNC enables the machining process to be carried out with ease, with all the movements and operations of the mills, lathes, or other cutting machines being controlled by the computer. From all the evolution of machining comes a method for the tools that are being used in the machining process to be monitored using the computer with the help of a machine learning method to ensure that the process is at its top condition to get the job done. The new technology evolves as time goes on, as well as the application of these machines widens. The necessity of a method to always monitor the tools' wear also emerges.

Tool condition monitoring (TCM) is a key component of intelligent machining which is also known as machine learning (ML) and is critical during the simple or complicated metal manufacturing processes [3]. TCM is a valuable and beneficial method mainly being used in automated manufacturing processes as it shoot up the productivity by shrinking the downtime, prevents unwanted damage to the machining tool and maintaining the quality of the product [4]. TCMs helps in detecting accurately and instantaneously the condition of the tools if there are any abnormal conditions that might cause the desired product to be damaged. Tool wear measurement methods are classed as direct (intermittent or offline) and indirect (continuous or online) methods. Real time TCM is achieved by collecting various sensor signals such as

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vibration, cutting forces, acoustic emission and etc. Sensor signal in time domain, frequency domain and time-frequency domain have been proven can well characterize the tool condition. Extracted features from sensor signal in different domains such as mean, variance, root mean square, kurtosis, skewness and many more has been successfully correlate to the degree of tool wear [5-7]. As mainstream of data driven decision making, machine learning has been widely applied in TCM nowadays. Genetic algorithm [8], Markov models [9], Bayesian network [10], K-nearest neighbours [11] have shown their powerful data-mining ability in tool wear classification. However, the main limitation of these deep learning methods are long computational time and require extensive training datasets.

In this paper, a support vector regression and boosted decision tree regression based tool condition based on vibration sensor signal in turning process is presented. The vibration sensor signals were converted into time-frequency domain by wavelets and the features namely mean and standard deviation were extracted as input. The accuracy of the proposed TCM system is then validated.

2. Materials and Methods

2.1 Materials

The material that has been used in this study was AISI 1050 carbon steel with the dimensions of the material is 50 mm in diameter and 300 mm in length. The turning process was carried out using the DOOSAN LYNX 220L CNC lathe machine in a dry condition. Next, the turning process followed the setting of parameters prior to the run, which have a total of 27 combinations. For the cutting tool, a carbide insert with model named TNMG 160408 by Kyocera.

2.2 Methods

The proposed TCM based on sensor signal developed in Matlab is presented in Fig. 1. The process flow generally can be divided into three stages. The first stage is the experiment setup to collect data. In this stage, all the procedures to collect the raw data was carried out including the process of setting up the CNC machine for the turning process. The machining process will be running with parameters that have been set prior to the experiment. The second stage of the experiment is to develop the code to predict the tool condition. The coding for the TCM system is done by using MATLAB software with support machine regression and boosted decision tree regression is used to predict the flank wear. The last stage of the study is to validate the result to evaluate the accuracy of the proposed tool wear prediction.

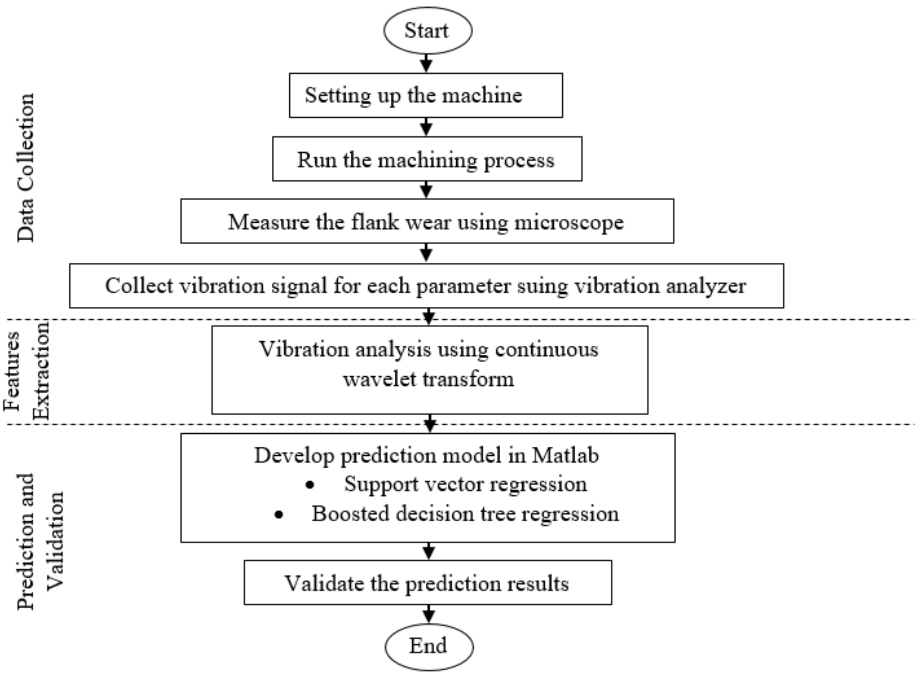


Fig. 1 - Flowchart of the study

2.3 Sensor Signal Acquisition

The vibration acquisition setup basically consists of a workpiece, a cutting tool, an accelerometer, and vibration analyzer. An accelerometer was located near the cutting insert. The piezoelectric accelerometer was used. The Movi-Pack vibration analyzer manufactured by Stell MVI Technologies Group was used as it is complete analyzer that comes with piezoelectric accelerometer.

2.4 Tool Wear Measurement

The flank wear produced by the turning process on the insert was measured using the Nikon-MM-60-Toolmaker's Microscope. The definition of flank wear was based on ISO 3685:1993.

2.5 Feature Extraction

In this study, vibration signals in the time domain begin as a series of digital values reflecting velocity before being converted to frequency-time domain using wavelet transform. Statistical parameters such as mean and standard deviation from the frequency-time domain were extracted to diagnose the condition of the cutting tool according to Equation 1 and Equation 2, respectively.

$$\text{Mean, } \mu = \frac{1}{n} \sum_{i=1}^{n} x_i \quad (1)$$

$$\text{Standard deviation, } \sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n-1}} \quad (2)$$

where n is the number of measurement and x_i is the value of coefficient.

2.6 Prediction of Tool Wear by Machine Learning

In this study, a regression method was used to predict flank wear of cutting tool from the experiment data obtained through the experiment of turning processes, and a vibration signals were collected during the machining process. The prediction of tool wear is done by the boosted decision tree and SVR with a Gaussian kernel in the TCMsThe coding for the TCMs was done in MATLAB software.

The code in Fig. 2 shows the first line of code is using the fitrsvm function from the Statistics and Machine Learning Toolbox in MATLAB to train a support vector machine (SVM) model. The second line uses the trained model to predict the dependent variable values for a new set of data (idxTest) and stores the predicted values in YFit. Meanwhile, Fig. 3 shows the fitensemble function was used in MATLAB to fit an ensemble model called "LSBoost" with 5 base learners. The "PredictorNames" and "ResponseName" options are being used to specify the input and output variable names. The learnRate option is set to 0.01, which controls the step size for the boosting algorithm.

```
Mdl = fitrsvm(idxTrn,'wear','Standardize',true,'KernelFunction','gaussian');
YFit = predict(Mdl,idxTest);
```

Fig. 2 - Coding for SVR with a Gaussian kernel using MATLAB

```
mdl = fitensemble(X(cvp.training,:),y(cvp.training,:),'LSBoost',500,t,...
    'PredictorNames',inputNames,'ResponseName',outputNames{1},'LearnRate',0.01);
```

Fig. 3 - Coding for Regression with boosted decision tree using MATLAB

2.7 Validation of the Result Finding

From the experimentation, all the data will run through a validation process where the accuracy and consistency of the result can be used for the discussion regarding the topic's objective. For the accuracy validation process, the data will be evaluated using absolute percentage error (APE) and mean absolute percentage error (MAPE). The formula for calculating these two are:

$$\text{APE} = \left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (3)$$

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (4)$$

where y_i is the actual value of data from experiment, $\hat{y}_i$ is the forecast value calculated by the developed system, N is number of times summation iteration happens.

For the consistency of the obtained data, the R-squared will be used to determine whether the proportion data can be evaluated and included in the discussion of this study. The formula for R-squared is as:

$$RSS = \sum_{i=1}^{n}\left(y_i - f(x_i)\right)^2 \quad (5)$$

where y_i is iteration value of the variable to be predicted and $f(x_i)$ is predicted value of y_i.

$$TSS = \sum_{i=1}^{n}(y_i - \bar{y})^2 \quad (6)$$

where y_i is value in a sample and $\bar{y}$ mean value of sample.

$$R^2 = 1 - \frac{RSS}{TSS} \quad (7)$$

where RSS is the sum of squares and TSS is the total sum of squares.

3. Results and Discussion

This section presents all the results and discussions that the research produced to accomplish the key goals and scopes.

3.1 Experiment Results

The features extracted from the time-frequency domain of vibration sensor signal namely mean and standard deviation as well as the corresponding flank wear for each experiment run are tabulated in Table 1. It can also be said that with the lower cutting speed and depth of cut, the flank wear is lower. Meanwhile, the flank wear is more likely to have higher value when the cutting speed and depth of cut is increased. The data in Table 1 comprised of 27 runs. 26 runs were applied for regression model and 1 data was used for testing the performance of regression model. This step was repeated until a total of 27 prediction results were obtained.

Table 1 - Result obtained from the experiment

Experiment Run	Cutting speed (m/min)	Feed rate (mm/rev)	Depth of cut (mm)	Mean	Standard deviation	Flank wear (μm)
1	300	0.3	0.1	3.30E-03	2.60E-03	1.60
2	300	0.4	0.1	3.10E-03	2.50E-03	3.40
3	300	0.5	0.1	3.50E-03	2.40E-03	4.00
4	400	0.3	0.2	5.50E-03	4.30E-03	4.80
5	400	0.4	0.2	6.40E-03	5.20E-03	5.30
6	400	0.5	0.2	7.80E-03	4.70E-03	5.80
7	300	0.3	0.2	4.70E-03	3.60E-03	6.10
8	300	0.4	0.2	4.50E-03	3.30E-03	6.50
9	300	0.5	0.2	4.80E-03	4.30E-03	6.60
10	400	0.3	0.1	3.60E-03	2.90E-03	7.00
11	400	0.4	0.1	4.90E-03	4.40E-03	7.50
12	400	0.5	0.1	5.20E-03	4.60E-03	8.50
13	500	0.3	0.1	4.50E-03	3.20E-03	9.50
14	500	0.4	0.1	5.00E-03	4.70E-03	11.00
15	500	0.5	0.1	4.80E-03	2.80E-03	11.60
16	500	0.3	0.2	4.80E-03	3.00E-03	11.90
17	500	0.4	0.2	4.20E-03	2.10E-03	12.20
18	500	0.5	0.2	4.50E-03	2.10E-03	12.50
19	500	0.3	0.3	4.80E-03	3.00E-03	12.70
20	500	0.4	0.3	3.70E-03	2.20E-03	13.00
21	500	0.5	0.3	4.00E-03	2.40E-03	13.10
22	300	0.3	0.3	5.90E-03	4.80E-03	13.40
23	300	0.4	0.3	6.30E-03	5.50E-03	13.60

24	300	0.5	0.3	7.10E-03	6.70E-03	13.70
25	400	0.3	0.3	6.70E-03	4.90E-03	14.10
26	400	0.4	0.3	5.90E-03	4.20E-03	14.50
27	400	0.5	0.3	6.60E-03	5.20E-03	14.80

3.2 Comparison of Predicted Flank Wear Obtained from SVR with Gaussian Kernel and Regression with Boosted Decision Tree

It can be seen in Table 2 that the prediction values were mostly very close to the experimental values for flank wear. Overall, the performances of the SVR with a Gaussian kernel function and boosted decision tree regression were outstanding for predicting flank wear. Both MAPEs are low, at 10.11% and 6.43%, respectively. The smaller the errors occurred; the more accuracy of the model performed. These numbers determine the accuracy of each method, which leads to the conclusion that the regression method has a lower value of MAPE, indicating that it has a lower error in predicting the new data and has higher accuracy than the SVR method [12]. The boosted decision tree regression method outperforms SVR with a higher average accuracy of 6.43%.

Table 2 - Precision accuracy for SVR and Regression

Experiment run	Actual wear (μm)	SVR with Gaussian kernel		Regression with Boosted Decision Tree	
		Predicted wear (μm)	APE (%)	Predicted wear (μm)	APE (%)
1	1.60	3.42	113.87	1.62	1.25
2	3.40	3.91	14.96	3.61	6.09
3	4.00	4.51	12.76	3.75	6.33
4	4.80	5.31	10.62	3.85	19.81
5	5.30	5.81	9.63	6.63	25.19
6	5.80	6.31	8.79	6.71	15.69
7	6.10	6.61	8.35	5.84	4.24
8	6.50	7.01	7.84	5.95	8.51
9	6.60	7.11	7.71	6.46	2.08
10	7.00	7.51	7.28	5.90	15.72
11	7.50	8.01	6.80	7.44	0.79
12	8.50	9.01	5.99	7.55	11.23
13	9.50	9.80	3.12	10.38	9.30
14	11.00	10.49	4.64	10.68	2.91
15	11.60	11.09	4.40	11.66	0.54
16	11.90	11.39	4.28	11.34	4.73
17	12.20	11.69	4.19	11.75	3.68
18	12.50	11.99	4.07	11.94	4.50
19	12.70	12.19	4.01	13.32	4.92
20	13.00	12.49	3.93	12.28	5.50
21	13.10	12.59	3.88	13.55	3.42
22	13.40	12.89	3.80	13.41	0.07
23	13.60	13.09	3.74	13.50	0.74
24	13.70	13.19	3.72	13.49	1.56

25	14.10	13.59	3.61	13.46	4.52
26	14.50	13.99	3.51	14.22	1.92
27	14.80	14.29	3.44	13.56	8.39
MAPE (%)			**10.11**		**6.43**

From the result of the prediction of flank wear, two graphs as shown in Fig. 4 and Fig. 5 illustrate the predicted and actual flank wear. Some of the predicted flank wear data by boosted decision tree regression in Fig. 5 can see to be very close or approximate with the actual flank wear data even in the graph, with only a slight difference in terms of the numerical data compared to the predicted flank wear by SVR as shown in Fig. 4.

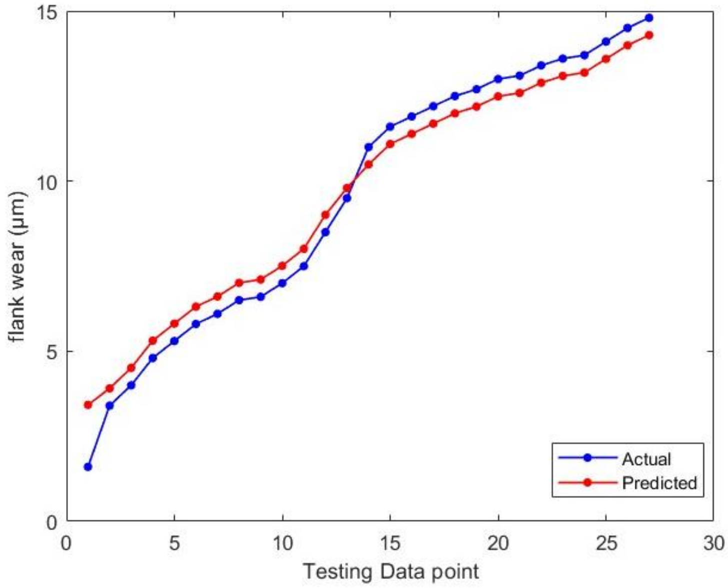


Fig. 4 - Predicted flank wear vs actual flank wear using SVR

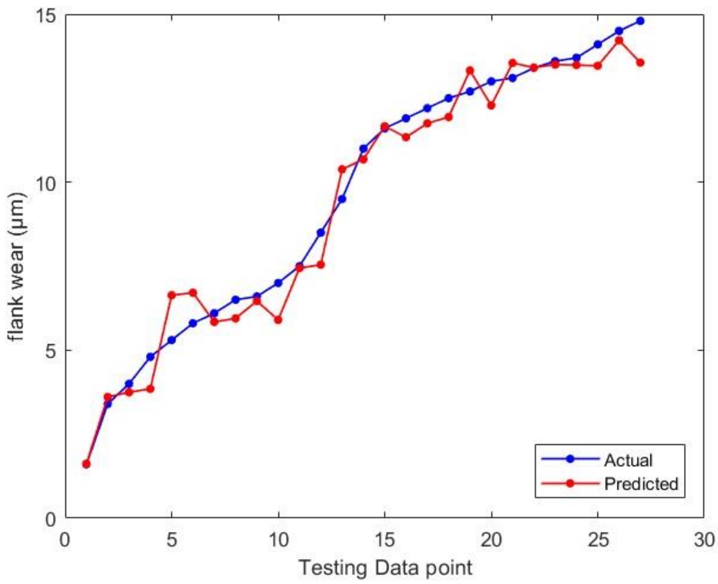


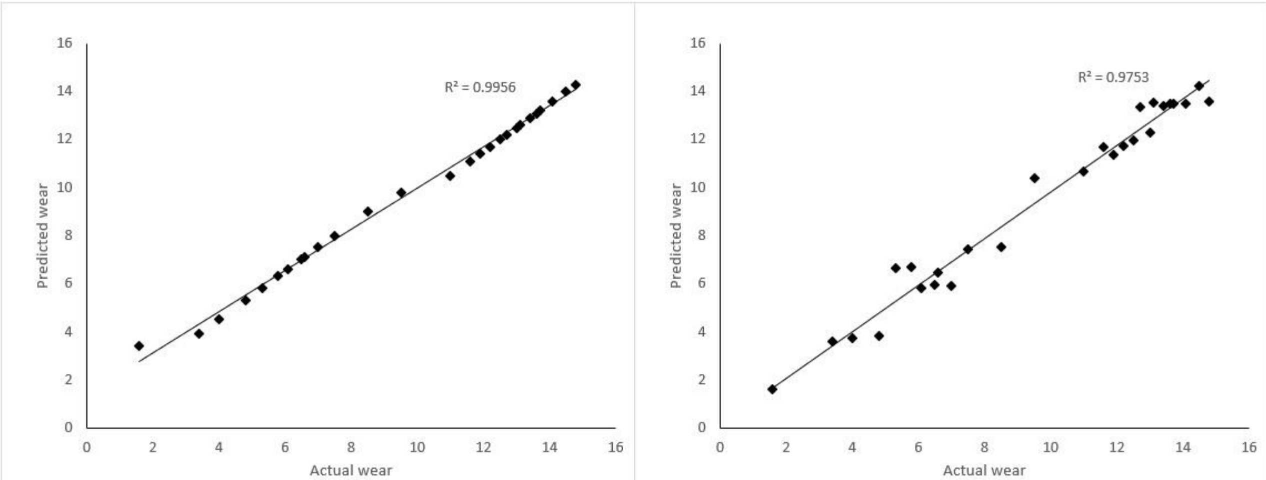
Fig. 5 - Predicted flank wear vs actual flank wear using Regression

The consistency of the TCMs in predicting the new data set can be demonstrated by using the R-squared formula in Equation 5, Equation 6 and Equation 7. From the equations, the value of R-squared for both methods can be seen in Table 3. For a better field of vision on the R-squared, a graph has been plotted for each of the methods used in the TCMs. For the SVR with Gaussian kernel, the graph of R-squared is shown in Fig. 6(a) while Fig. 6(b) shows the graph of R-squared for regression with boosted decision tree.

Both results show perfect graphs, in which the correlation between the actual and predicted values of flank wear followed the 45-degree line very closely. In other words, the predicted values were not far from the actual measurement values obtained from the experiment. The correlation coefficient R-squared values for both graphs were high, which were 0.9753 for SVR with a Gaussian kernel and 0.9956 for regression with a boosted decision tree. In short, the higher the R-squared value, the more precisely the predictor can forecast the value of the response variable. Thus, it can be concluded that the SVR and boosted decision tree regression had a very good relationship and fit, which indicates that the proposed SVR model and regression model could predict tool flank wear accurately.

Table 3 - Value of R-squared for TCMs

Value of R-squared	
SVR with Gaussian kernel	**Regression with boosted decision tree**
0.9753	0.9956



(a) (b)

Fig. 6 – R - squared for (a) boosted decision tree regression; (b) SVR regression

4. Conclusion

Throughout this study, it may be inferred that the research aim, which is the development of TCMs using the machine learning method for turning processes has been successfully achieved. The conclusions can be drawn. First, the development of a tool condition monitoring system for flank wear in the turning process has been successful. Second, in TCMs, the SVR with a Gaussian kernel and Regression with a boosted decision tree are good at predicting flank wear. Both have a lower MAPE value, with only regression having a lower value of MAPE than SVR, at 6.43% and 10.11%, respectively. Regression was also preferred over SVR because it had a slightly higher R-squared value, 0.9956 versus 0.9753, respectively. Last, the significance of accuracy and the consistency of the developed system demonstrate that the system is truly reliable for determining flank wear.

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