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# Tool Wear Prediction Using Multiple Regression in Turning

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**Abstract:** Cutting tools are subjected to an extremely severe rubbing process. They are in metal-to-metal contact between the chip and work piece, under high stress and temperature. This situation causes the inconsistencies and unwanted effects on the workpiece and cutting tools such as flank wear. Flank wear may lead to the decrease of the accuracy of produced parts, finishing surface, and economics of cutting operation. The objective of the study is to extract feature from the vibration sensor signal based on different cutting conditions, then evaluate the accuracy of the tool wear monitoring method from the supervised learning technique after wavelet analysis. Experiments have been conducted for measuring tool wear based on the factorial design technique in a turning of AISI 1045 Steel using carbide insert. Then, the cutting conditions and statistical features from vibration signal in time domain and generated from the wavelet decomposition were used as the input of regression model corresponding to the output, flank wear for the tool wear prediction by using MATLAB. The tool wear prediction of Model V has 79.13% of accuracy in the correlation between cutting condition, vibration signal and flank wear which show that the vibration signal generated from the wavelet at higher frequency level is more sensitive to predict flank wear as the accuracy is increased compared to the vibration signal in time series.

**Keywords:** Feature extraction · Tool Wear · Regression Analysis · Vibration · Wavelet decomposition · Dry Turning

## 1. Introduction

Cutting tools are exposed to an extremely strong friction process. They are in metallic contact between the chip and the workpiece under high loads and temperatures. This situation leads to the inconsistencies and unwanted effects on the workpiece such as the existence of extreme stress and temperature gradients near the surface of the tool. This will lead to failure like abrasive wear, chipping, thermal cracking and fracture, which result can lead to scrapped parts, serious damage, and rework.

When a specific level of tool wear has been reached, increased cutting force, vibration, and temperature will lead to worsened surface integrity and dimension inaccuracy that is outside of tolerance. Therefore, the surface roughness of a machined component grows together with tool wear

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[1]. Any metal cutting process must take into account a cutting tool's condition since using worn tools results in higher expenses for machine tool failure, discarded parts, and unplanned downtime. The cutting edges of a tool gradually deteriorate during machining, which causes the tool to stop cutting effectively or even fail [2]. In machining, tool wear can lead to insufficient surface smoothness, excessive vibration, and energy used. This will cause the whole effectiveness or productivity decrease and increase the overall cost which include raw material, waste management, maintenance cost, and other resources.

In tool wear condition monitoring, there are two different monitoring methods: direct and indirect method [3]. Direct method usually measure the tool wear by optical microscope while indirect method apply the sensor signal to correlate the tool condition. The tool wear monitoring is necessary is because tool wear can adversely affect quality and productivity and reduces unscheduled downtime for tool changes and reworks of damaged parts the tool life. Worn tool can be replaced in time to avoid scrapped components and over production time with effective tool wear predicting system [4-5]. The objective of the study is to predict the tool wear based on the vibration signal using supervised learning technique. The extracted features from vibration signal by using wavelet transform will be used as input to estimate the tool flank wear.

## 2. Methodology

In this experiment work, the turning process was carried out on HAAS SL-20T CNC lathe machine. AISI 1045 carbon steel workpiece material were turned with carbide inserts TNMG160408PS from Kyocera in dry cutting condition. The cutting parameters involved in this study were cutting speed, feed rate, depth of cut and cutting time.

The experiment was performed by manipulating the value of cutting speed, feed rate and depth of cut during dry machining. Based on the experiment design, there were 27 possible combination of data set produced from three level of full factorial design and three factors of cutting parameter. Table 1 presented the setting of parameters that were involved in the experiment.

**Table 1: Setting of Parameters**

| No. | Parameter | Notation | Unit | Level | | |
|---|---|---|---|---|---|---|
| | | | | 1 (Low) | 2 (Medium) | 3 (High) |
| 1 | Cutting speed | Vc | m/min | 300 | 400 | 500 |
| 2 | Feed Rate | Fr | mm/rev | 0.3 | 0.4 | 0.5 |
| 3 | Depth of Cut | Dc | mm | 0.1 | 0.2 | 0.3 |

During machining process, the cutting vibration signal was collected by using Movipack vibration analyser (Stell MVI Technologies Group) with an accelerometer. After the dry turning operation is performed, the flank wear is measured by using Nikon MM-60 Toolmaker’s Microscope according to ISO 3685:1993. Flank wear was chosen because it is the indicator that used to define tool life and the cutting performance. The statistical features like mean, root mean square (RMS), variance and standard deviation were obtained from the time domain and frequency domain which extracted from wavelet analysis. The prediction of the tool wear is conducted by using MATLAB. The regression models are divided into 5 models based on different inputs as tabulated in Table 2. Input of Model I and II are based on the cutting condition and vibration signal data from time domain while Model III to V are according to cutting condition and vibration signal data from frequency domain.

**Table 2: Regression model with different input of variables**

| Regression Model | Input |
|---|---|
| **Model I** | Cutting speed, Feed rate, Depth of Cut |
| **Model II** | Cutting speed, Feed rate, Depth of Cut, Mean, Variance |
| **Model III** | Cutting speed, Feed rate, Depth of Cut, RMS, Variance, Standard Deviation from level 1 wavelet decomposition |
| **Model IV** | Cutting speed, Feed rate, Depth of Cut, RMS, Variance, Standard Deviation from level 2 wavelet decomposition |
| **Model V** | Cutting speed, Feed rate, Depth of Cut, RMS, Variance, Standard Deviation from level 3 wavelet decomposition |

## 3. Results and Discussion

Regression Model I considers the interactions among cutting speed, feed rate and depth of cut, according to Equation 1.

$$y = -7.6407 + 0.02144x_1 + 5.2778x_2 + 32.667x_3 \qquad \text{Eq. 1}$$

where, $x_1$ is cutting speed, $x_2$ is feed rate and $x_3$ is the depth of cut.

Meanwhile, Regression Model II has the additional of statistical features of vibration sensor signal such as mean and variance as input, according to Equation 4. The statistical features like RMS and standard deviation are not consider in Model II due to their p-value are higher than mean and variance. This is because the RMS and standard deviation are less significant compared to mean and variance in Model II. The predicted values of the Model I and Model II based on Equation 3 and Equation 2 were determined and have been tabulated in Table 3 as well as the absolute percentage error (APE) and mean absolute percentage error (MAPE).

$$\begin{aligned} y = -7.6407 + 0.028078x_1 + 4.0242x_2 + 31.408x_3 \\ -958.87x_4 + 0.000018501x_7 \end{aligned} \qquad \text{Eq. 2}$$

where, $x_1$ is cutting speed, $x_2$ is feed rate, $x_3$ is the depth of cut, $x_4$ is mean and $x_7$ is variance of vibration signal.

**Table 3: Regression result for Model I and Model II**

| Experimental Runs | Actual Flank Wear (μm) | Model I | | Model II | |
|---|---|---|---|---|---|
| | | Predicted Flank Wear (μm) | APE (%) | Predicted Flank Wear (μm) | APE (%) |
| **1** | 1.6 | 3.64 | 127.66 | 3.23 | 101.87 |
| **2** | 3.4 | 4.17 | 22.66 | 3.77 | 10.79 |
| **3** | 4 | 4.70 | 17.45 | 3.66 | 8.55 |
| **4** | 4.8 | 9.05 | 88.62 | 9.24 | 92.52 |
| **5** | 5.3 | 9.58 | 80.78 | 10.35 | 95.34 |
| **6** | 5.8 | 10.11 | 74.30 | 8.51 | 46.66 |
| **7** | 6.1 | 6.91 | 13.27 | 6.18 | 1.36 |
| **8** | 6.5 | 7.44 | 14.42 | 6.39 | 1.72 |
| **9** | 6.6 | 7.96 | 20.68 | 7.91 | 19.84 |
| **10** | 7 | 5.79 | 17.33 | 6.08 | 13.18 |
| **11** | 7.5 | 6.31 | 15.80 | 7.30 | 2.67 |
| **12** | 8.5 | 6.84 | 19.50 | 7.69 | 9.50 |
| **13** | 9.5 | 7.93 | 16.51 | 8.35 | 12.11 |
| **14** | 11 | 8.46 | 23.10 | 10.49 | 4.61 |
| **15** | 11.6 | 8.99 | 22.53 | 8.45 | 27.12 |
| **16** | 11.9 | 11.20 | 5.90 | 10.97 | 7.85 |
| **17** | 12.2 | 11.73 | 3.89 | 11.10 | 9.03 |
| **18** | 12.5 | 12.25 | 1.97 | 11.21 | 10.29 |
| **19** | 12.7 | 14.46 | 13.90 | 14.10 | 11.05 |
| **20** | 13 | 14.99 | 15.33 | 15.15 | 16.51 |
| **21** | 13.1 | 15.52 | 18.48 | 15.11 | 15.35 |
| **22** | 13.4 | 10.18 | 24.06 | 10.08 | 24.79 |
| **23** | 13.6 | 10.70 | 21.30 | 11.39 | 16.23 |
| **24** | 13.7 | 11.23 | 18.02 | 13.73 | 0.21 |
| **25** | 14.1 | 12.32 | 12.62 | 12.25 | 13.13 |
| **26** | 14.5 | 12.85 | 11.39 | 12.31 | 15.12 |
| **27** | 14.8 | 13.38 | 9.62 | 13.70 | 7.40 |
| **MAPE (%)** | | - | 27.08 | - | 22.03 |

Figure 1 and Figure 2 illustrated the actual flank wear versus predicted flank wear in Model I and II based on Table 3. Model I has 27.08% of error while Model II has 22.03% of error based on MAPE result. The $R^2$ value for Model I was lower than Model II which stated only 0.68. A low R-squared is usually a bad signal for a predictive model. The results indicated that addition of vibration signal improved the accuracy of flank wear prediction in multiple linear regression model. Similar result is found by Xu et al [6], there is differences between the wear prediction results of milling cutter and the wear prediction results with an addition of single sensor signal. Most of the predicted flank wear in Model II are close to actual flank wear, although there are some predicted flank wear deviate with the actual flank wear. This is because each of the data have different number of error or absolute percentage error due to the arrangement of the cutting conditions. Sometimes the variables of cutting condition increased or decreased significantly and cause the results have small and huge errors.

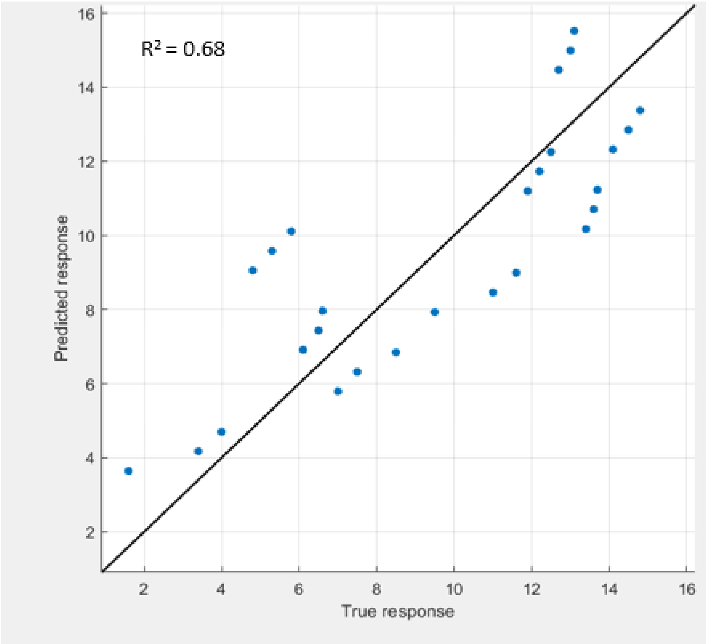


**Figure 1: Predicted versus actual flank wear of Model I**

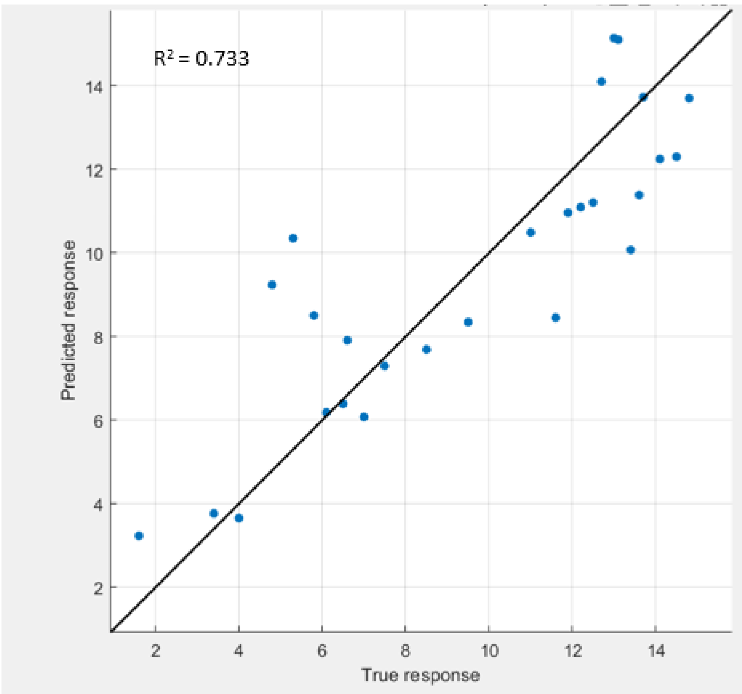


**Figure 2: Predicted versus actual flank wear of Model II**

Furthermore, Model III has the input variables of cutting speed, feed rate, depth of cut, RMS, variance and standard deviation. These statistical feature inputs are extracted from the level 1 wavelet decomposition of vibration signal and analysed with the flank wear (output). The equation of this model is presented in Equation 3:

$$\begin{aligned} \mathrm{y} = &-21.128 + 0.021343x_1 + 6.6601x_2 + 28.639x_3 \\ &+13.802x_5 + 18.493x_6 - 17.286x_7 \end{aligned} \qquad \text{Eq. 3}$$

Model IV and Model V have also been developed with the input variables same as Model III. However, the inputs are extracted from the result of level 2 wavelet decomposition for Model IV and the result of level 3 wavelet decomposition for Model V. Both Model IV and Model V have been represented by Equation 4 and 5 respectively. The regression results of Model III to Model V are displayed in Table 4.

$$\begin{aligned} \mathrm{y} = &-27.092 + 0.19915x_1 + 8.1372x_2 + 26.99x_3 \\ &+2.0318x_5 + 39.33x_6 - 20.094x_7 \end{aligned} \qquad \text{Eq. 4}$$

$$\begin{aligned} \mathrm{y} = &-22.847 + 0.021137x_1 + 10.379x_2 + 26.872x_3 \\ &+14.284x_5 + 14.717x_6 - 13.274x_7 \end{aligned} \qquad \text{Eq. 5}$$

where, $x_1$ is cutting speed, $x_2$ is feed rate, $x_3$ is the depth of cut, $x_5$ is RMS, $x_6$ is standard deviation and $x_7$ is variance.

From Table 4, it can be observed that Model III, IV and V have the MAPE with the percentage of 22.29%, 20.03% and 20.87% respectively, Model IV has the highest accuracy compared with Model III and Model V. This shows that the RMS, variance, standard deviation of continuous wavelet transform (CWT) coefficient at higher scale are sensitive to tool flank wear which can be potentially used as an important indicator for predicting flank wear. The large CWT coefficient at higher scales band (low frequencies) is due to the long wavelengths of the waviness of the workpiece profile caused by tool chipping.

On the other hand, Figure 3 to Figure 5 show the actual flank wear and predicted flank wear in Model III to V based on Table 4. By observing Figure 3 to Figure 5, it can be discovered that the correlation coefficient, $R^2$ value for Model III to Model V were stated as 0.74, 0.758 and 0.767 respectively. As a comparison, the results from Model III to Model V have higher R2 than Model I and Model II, which means that Model III to Model V have better relationship and fit model and the predictor can forecast the value of the response variable more precise.

**Table 4: Regression result based on statistical feature after wavelet analysis**

| Experimental Runs | Actual Flank Wear (µm) | Model III | | Model IV | | Model V | |
|---|---|---|---|---|---|---|---|
| | | Predicted Flank Wear (µm) | APE (%) | Predicted Flank Wear (µm) | APE (%) | Predicted Flank Wear (µm) | APE (%) |
| **1** | 1.6 | 2.32 | 45.13 | 2.50 | 55.98 | 2.39 | 49.66 |
| **2** | 3.4 | 2.22 | 34.68 | 3.44 | 1.25 | 2.06 | 39.47 |
| **3** | 4 | 4.72 | 18.06 | 4.41 | 10.25 | 3.88 | 3.09 |
| **4** | 4.8 | 10.21 | 112.64 | 8.97 | 86.96 | 9.82 | 104.49 |
| **5** | 5.3 | 9.18 | 73.24 | 8.79 | 65.82 | 6.05 | 14.12 |
| **6** | 5.8 | 7.97 | 37.35 | 6.05 | 4.26 | 9.37 | 61.52 |
| **7** | 6.1 | 7.58 | 24.33 | 7.45 | 22.20 | 7.80 | 27.94 |
| **8** | 6.5 | 8.08 | 24.38 | 8.11 | 24.72 | 8.21 | 26.37 |
| **9** | 6.6 | 8.68 | 31.52 | 9.38 | 42.10 | 9.40 | 42.48 |
| **10** | 7 | 4.66 | 33.48 | 4.52 | 35.49 | 5.58 | 20.33 |
| **11** | 7.5 | 7.24 | 3.48 | 7.51 | 0.11 | 7.90 | 5.34 |
| **12** | 8.5 | 8.02 | 5.59 | 8.78 | 3.31 | 7.01 | 17.55 |
| **13** | 9.5 | 8.62 | 9.25 | 8.70 | 8.43 | 9.23 | 2.86 |
| **14** | 11 | 9.15 | 16.80 | 8.45 | 23.20 | 9.93 | 9.72 |
| **15** | 11.6 | 9.17 | 20.92 | 9.26 | 20.16 | 9.15 | 21.09 |
| **16** | 11.9 | 11.69 | 1.76 | 11.93 | 0.25 | 11.78 | 0.99 |
| **17** | 12.2 | 11.50 | 5.76 | 11.40 | 6.54 | 11.36 | 6.85 |
| **18** | 12.5 | 12.75 | 1.97 | 12.71 | 1.65 | 11.87 | 5.05 |
| **19** | 12.7 | 13.82 | 8.85 | 14.61 | 15.03 | 13.18 | 3.79 |
| **20** | 13 | 13.57 | 4.42 | 14.43 | 10.98 | 14.12 | 8.65 |
| **21** | 13.1 | 14.29 | 9.07 | 15.15 | 15.68 | 15.10 | 15.27 |
| **22** | 13.4 | 9.82 | 26.74 | 10.70 | 20.13 | 10.03 | 25.16 |
| **23** | 13.6 | 11.49 | 15.52 | 10.71 | 21.28 | 11.45 | 15.82 |
| **24** | 13.7 | 11.05 | 19.38 | 11.34 | 17.22 | 11.91 | 13.10 |
| **25** | 14.1 | 12.82 | 9.08 | 12.49 | 11.43 | 12.61 | 10.58 |
| **26** | 14.5 | 13.68 | 5.66 | 12.64 | 12.81 | 13.29 | 8.34 |
| **27** | 14.8 | 14.40 | 2.73 | 14.29 | 3.44 | 14.24 | 3.80 |
| **MAPE (%)** | | - | 22.29 | - | 20.03 | - | 20.87 |

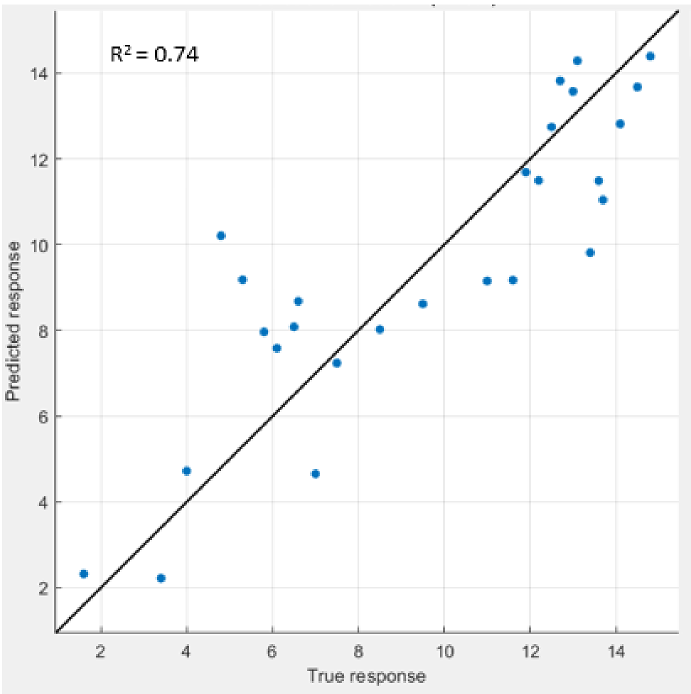


**Figure 3: Predicted versus actual flank wear of Model III**

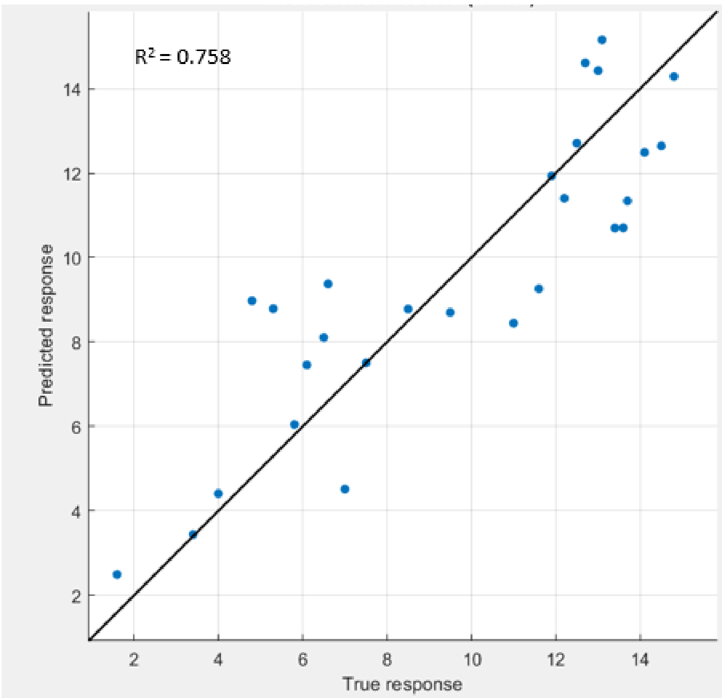


**Figure 4: Predicted versus actual flank wear of Model IV**

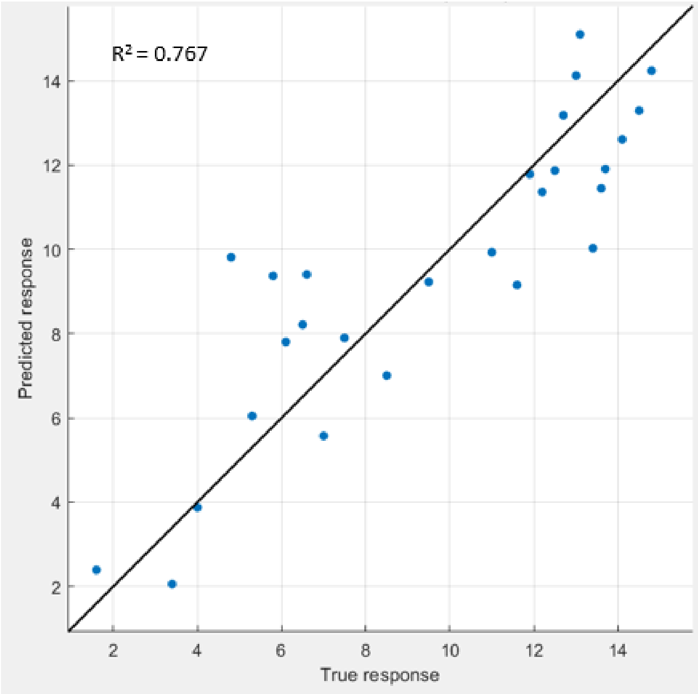


**Figure 5: Predicted versus actual flank wear of Model V**

Figure 6 presents the summary of regression's performance among five models in terms of R-squared and accuracy. According to Figure 6, Model V had the highest coefficient of determination, $R^2$ which has the value of 0.767. Although Model V has the highest $R^2$, but Model IV has the lowest mean absolute percentage error (MAPE) which achieved accuracy of approximately to 80%. Regression Model III to V are based on the frequency domain data and have higher $R^2$ and lower MAPE compared to Model I and II which the extracted features of vibration are based on time series as input. The coefficient of determination is a calculation that reveals how much of the variation in the response variable a regression model can explain. A higher R-squared indicates that more variability is explained by the regression model. In another word, the greater the R-squared, the better the regression model fits the data [3]. Although regression analysis is able to dig out the multiple linear relationship of tool wear, but each model has different predictive performance of tool wear [6].

For Model I and II which based on time series data, Model I has the accuracy of 72.92%. The accuracy of Model II improved to 77.97% compared to Model I due to the addition of the vibration statistical features. Model II also has higher $R^2$ than Model I. Model III to Model V are based on vibration statistical feature after wavelet analysis and have higher accuracy than Model I which based on cutting parameters in time domain. This is because vibration signals have higher phase level frequency and become more sensitive corresponding to flank wear after wavelet decomposition into detail coefficients. Wavelet analysis of original signal can avoid the influence of redundant information the model training and also reduces the dimensionality of the original signal [6].

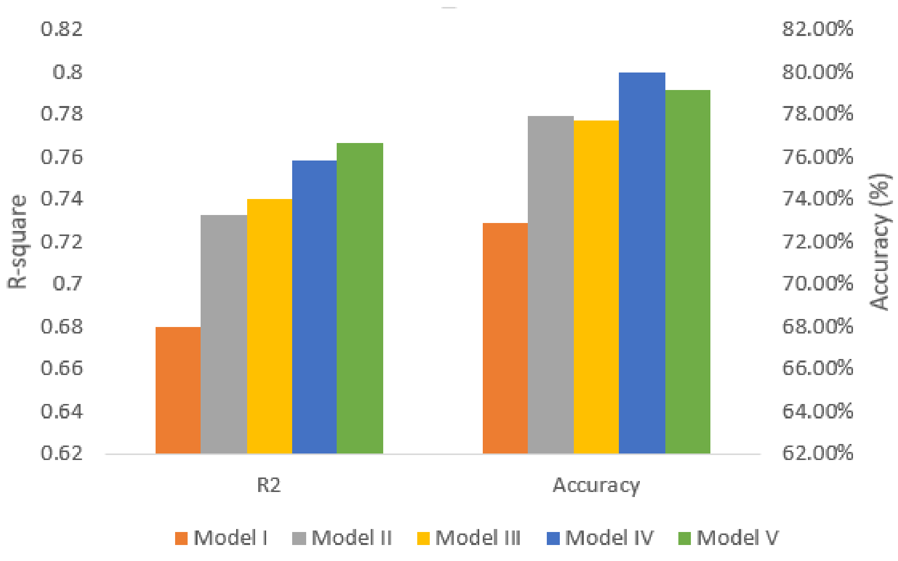


**Figure 6: Regression summary**

## 4. Conclusion

The study draws the following conclusion:

i. The statistical features from vibration signal in time domain and wavelet coefficients in frequency domain were successfully extracted.
ii. Multiple regression model to predict the flank wear based on the cutting conditions and statistical features from vibration signal have been successfully developed
iii. The statistical features (RMS, variance and standard deviation) of CWT coefficients of vibration signal at higher scale (lower frequency) are useful to correlate the flank wear.


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