Analytics in Tool Condition Monitoring

Submitted in the fulfilment of the requirements of the

R & D Project (ME 691)

by

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(2017)

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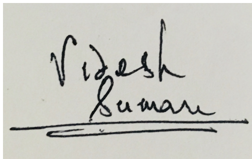

Date: 24/11/2017

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ACKNOWLEDGEMENT

I would like to express my gratitude to my guide Prof. Asim Tewari for his endless support, continuous motivation and valued guidance during the entire course of work. I would like to acknowledge the support provided for this work by National Centre for Aerospace Innovation and Research (NCAIR) at Indian Institute of Technology Bombay.

ABSTRACT

Increasing demands of process automation for un-manned manufacturing has attracted many researchers in the field of on-line monitoring of machining processes. In view of this, extensive research work is taking place world-wide in the area of on-line tool condition monitoring systems (TCMS). Large-scale machining, the contact between the cutting tool, workpiece, and the chips exert forces on the tool and make the state of the tool change, either bit by bit as tool wear or suddenly as tool breakage or fracture. Tool wear is the most undesirable characteristic of machining processes as it adversely affects the tool life, which is of foremost importance in metal cutting owing to its direct impact on the quality of the machined surface (workpiece), and its dimensional accuracy, and consequently, the economics of machining operations. Therefore, methods for cutting tool wear sensing are crucial in view of the optimum use of cutting tools. With an effective monitoring system, the damages to the machine tool, downtime and scrapped components can be avoided.

This report explores the area of data-driven techniques for Tool Condition Monitoring through an effective analysis on some literature data gathered for a ball-end milling process by Chen Zhang and Haiyan Zhang (2016) in their experiments.

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CHAPTER 1: INTRODUCTION TO TCM

1.1 Introduction

Tool wear is defined as the change of shape of the tool from its original shape during cutting in any machining process. Tool wears out due to various factors, viz. thermal, mechanical, abrasive and chemical, acting on the tool. Tool wear is a stochastic phenomenon depending on time, hence the time to fail for a tool varies significantly from tool to tool. If the machining process continues with the worn tool, then the dimensional accuracy, surface quality of the workpiece and even process stability will be deteriorated. Therefore, the estimation of tool wear is very important for improving machining quality and increasing productivity in machining process.
In order to obtain tool wear, many researchers have developed tool wear models through analytical modelling and experimental observation in the milling process. There are two types of model-based approaches to construct tool wear monitoring model in machining processes.

- **Direct Measurement:** In this method, the actual value of tool wear is measured directly through different methods (like laser or video based artificial vision systems) to observe the tool wear directly in real time. But very high cost and limited illumination have stopped this method from being deployed in the industry. Direct measurement techniques are used for research purposes to validate the proposed models and theories through experimentation.

- **Indirect Measurement:** In this method, the tool wear is predicted from various signals like *vibration, cutting force, acoustic emission, motor current* obtained from machining processes. The signals are obtained through signal processing steps, to maintain the sensitivity and robustness of its states. Many researchers have developed tool wear models through analytical modelling and experimental observation and can be used to monitor tool wear or breakage in machining process. Shi and Gindy [1] have shown that there are two types of model-based approaches to construct tool wear monitoring model in machining processes.
  - **Theoretical Quantitative Models:** such as differential equations, state space methods and finite element analysis, may be applied to develop such models. Unfortunately, these theoretical models for complex machining processes are difficult to obtain and in some situations are impossible or too expensive to derive. Moreover, the tool wear prediction results obtained from these models may not be desirable due to the disturbances, modelling errors and sensor noise since huge amount of sensory signals are available for training.
  - **Data Driven Techniques:** statistical modelling techniques can be developed to create highly efficient models since huge amount of sensory signals are available for training. In training stage, the corresponding models can adjust themselves adaptively to the data and once the training stage is accomplished, the models can predict tool wear to an acceptable level of accuracy even corresponding to data unused during the training stage through their generalisation ability. This method is less complicated and the most feasible for deployment in industries.

1.2 Motivation

As the Industry 4.0 Era (i.e., the Fourth Generation Industrial Revolution) builds, machines are becoming interconnected, forming IoT spaces in smart factories. "Smart production" is becoming the norm, in a world where intelligent machines, systems and networks are capable of independently exchanging and responding to information, to manage industrial production processes [2]. A key to building smart factories is to turn traditional machines into more intelligent ones.

The basis of this next generation manufacturing system is the ability to automate the monitoring, control and diagnosis the machining processes involved. Though, this idea of such systems is out of sight until a reliable and feasible method of estimating on-line tool wear is developed. Tool wear is arguably the most crucial limitation of any machine's productivity. Tool wear or breakage can cause unplanned downtime in industrial manufacturing, or harm the quality of product, eventually leading to less productivity and hence economic loss. The productivity loss can be curbed by replacing tools frequently, but this will lead to increase in the costs related to tools and regular manned monitoring. It has been observed that only 50-80% of the tool life is utilized due to this. It is estimated that the downtime due to breakage on an average machine tool is 7–20%. Hence, a smart tool condition monitoring technique is the need of the hour. Accurately predicting the tool wear may increase spindle speed by 10-50% hence increasing the productivity, also the machine downtime may be reduced resulting in reduction in machining cost by 10-40% which is huge.

The main goal of my research is to develop a method solely based on statistical methods and machine learning rather than any physical model to predict tool wear, eliminating the requirement of complex calculations, mathematics and assumption. The end model should be trained on the hyperspectral cutting data of *forces, vibrations, acoustic emissions* and *motor current* for different tools and cutting parameters (*depth of cut, feed rate, spindle speed, cutting length*), thus producing accurate tool wear predictions.

However, this report presents the related literature that has been studied and various models which have been tested upon some wear data acquired from the publication by Chen Zhang and Haiyan Zhang [3], as a part of the bigger goal to be achieved.

CHAPTER 2: LITERATURE REVIEW

2.1 Data Acquisition

The most efficient indirect tool condition sensing systems are based on *cutting forces*. All monitoring systems based on this principle utilize the fact that tool wear causes an increase in cutting force components, and tool breaks manifest themselves in the form of discontinuities or pulse-like changes in one or several cutting force components. Meanwhile, oscillations of cutting forces lead to *vibrations* of the machine structure, which change due to tool wear or breakage. Vibration sensors have the advantages of low costs and easy installation, and are widely used for TCM. Furthermore, cutting processes produce a large amount of *acoustic emission* (AE) waves, and tool breakage causes peaks in AE signals. This makes AE signal the cutting edge parameter for tool breakage detection.

2.1.1 Cutting Force:

The *cutting force* is the key machining process variables related to cutting performance. A significant amount of investigation has been conducted to monitor tool failure using cutting force signals, due to their high sensitivity and rapid response to changes under cutting conditions. Apart from the direct cutting force measurements with the table dynamometers, several indirect methods can also be applied to measure the cutting forces with the integrated devices in spindle structures. Firstly, cutting forces can be estimated from the deformations of flexible mechanical parts of the machining system by using strain gauges. This integrated rotating dynamometer (Fig. 1a) consists of a strain gauge based sensor that is mounted on a force sensing element which is then placed in the rotating tool holder. Alternatively, cutting forces can be derived from spindle vibrations by using displacement probes (Fig. 1b) or accelerometers. In their publication, Auchet st al. [4] had tried to determine the cutting forces as a function of the measured command voltages of the milling spindle's magnetic bearings. However, the major drawback of these indirect approaches is the poor frequency bandwidth.

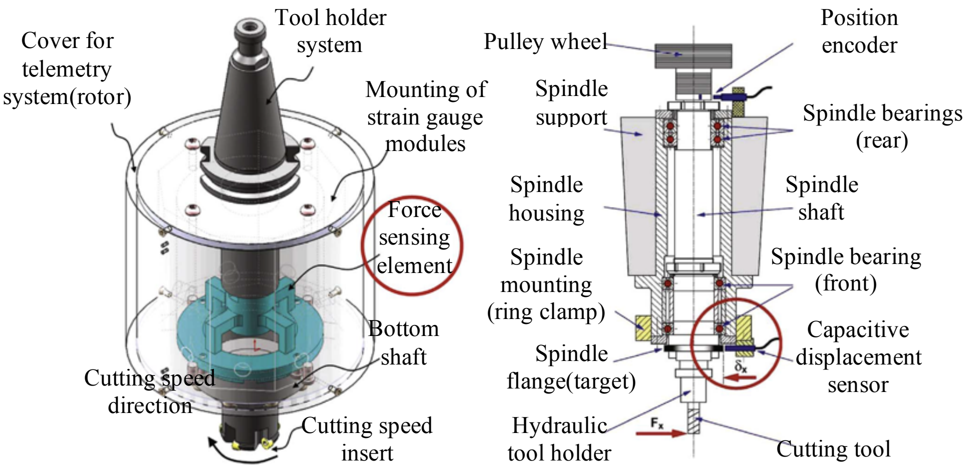

Figure 1: Integrated cutting force measurement system based on: (a) strain gauge, (b) displacement probe

Generally, piezoelectric crystals have a good compromise between stiffness and sensitivity. Piezoelectric force sensors can be embedded in a ring-like frame to form a piezoelectric force ring. An alternative method that has become attractive in recent years for cutting forces measurement is through spindle integrated force rings. The piezoelectric force rings possess various advantages and can be used for detecting anomalies that are related not only to the cutting process but also to the spindle itself, such as bearing condition and misalignment.

2.1.2 Vibrations:

The *vibration* signals, which respond quickly to changes of tool states in online monitoring, are widely used as one of major tool wear dependent variables. The most common vibration sensors that satisfy the requirements of applicability and reliability, the accelerometers are usually attached to spindle housing for vibration measurement. The acceleration signals can then be used to estimate tool wear states and detect tooth breakage in milling processes. The displacement sensor is another way to measure spindle vibration for monitoring tool wear. In short, the vibration signal is a very important component in multiple sensor fusion strategies, which can detect both tool wear and breakage effectively.

2.1.3 Acoustic Emissions:

The *acoustic emissions* can be summarized as the transient elastic energy released from materials undergoing deformation or fracture (workpiece). Energy contained in AE signals is strongly dependent on the rate of deformation, the applied stress and the volume of the material. A large number of sound/ acoustic signals are generated during the milling process. Boutros and Liang collected acoustic signals during the milling process by utilizing a microphone attached to the milling machine, identifying the tool state (i.e., sharp, worn, or broken) from the acoustic signals.

2.1.4 Motor Current/Power:

The major advantage of using *motor current/power* to detect tool conditions is that they do not require modification to the original tool structure or interruption to the cutting process. Furthermore, current signals are perfect sine waves in the process of feeding without cutting. Currents from both the spindle motor and the feed motor can be used for the analysis, however, here only spindle motor current has been studied so far. The spindle motor current is typically measured by Hall effect current sensors. Based on the correlation between tool wear and the spindle motor current, tool wear in milling process has been estimated. Besides tool wear, tool breakage can also be detected from a spindle motor current.

2.2 Data Processing

Once the data is collected from the sensors, then data processing is carried out for decision-making purposes. Various signal processing techniques in time, frequency and time-frequency domains have been developed to analyse and interpret measured data for feature extraction. Signals acquired from a machining centre in an industrial environment contain high levels of mechanical, electrical and acoustic noises. Hence appropriate signal processing is mandatory before extracting features. The number of features originating from one or more signals can be very large, and feature selection should be automatically carried out to eliminate redundant and interrelated features, yielding more accurate predictions.

2.2.1 Segmentation:

Temporal *segmentation* is needed to extract the signal lobes during the time the tool is actually cutting the workpiece, since only these lobes contain information about tool wear condition. The first step in segmentation is the removal of incomplete lobes which may exist at either ends of a given raw signal sequence. This is then processed with low-pass filter to remove the high frequency noise from the measurements. In the next step the machining lobes are extracted by identifying the time points corresponding to engagement and disengagement of the cutting tool on the workpiece. Statistical change detection techniques can be applied to make this step robust against noisy peaks as was performed by Ghosh et al. [5] in their work.

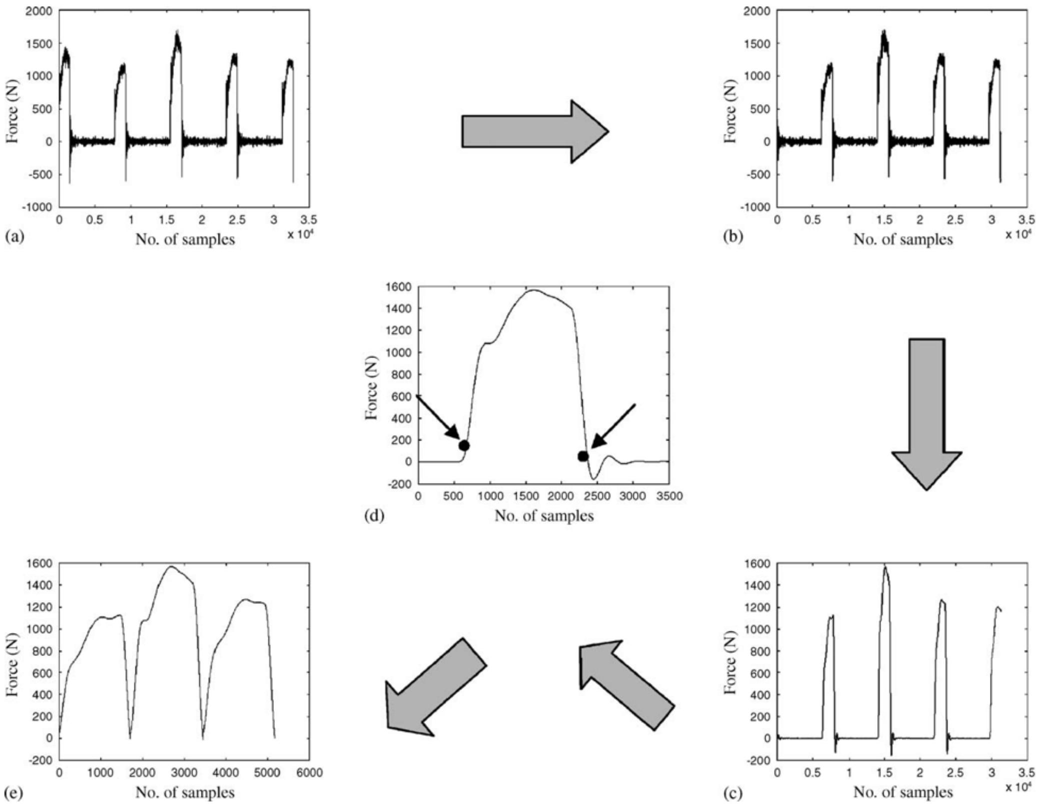

Figure 2: Signal processing modules: (a) raw signal, (b) chopped signal, (c) filtered signal, (d) entry and exit points and (e) segmented signal

2.2.2 Feature Extraction:

The number of features originating from one or more signals can be large, and feature selection should be automatically carried out to eliminate redundant and interrelated features, yielding more accurate predictions.

In their work, Ghosh et al. [5] selected only the simplest of the features to ensure feasibility of real-time implementation. Features (e.g. maxima, minima, peak-to-peak, mean, standard deviation, root-mean-square (RMS) values, and normalised ratios) were computed for each lobe and then averaged over segmented complete lobes. The feature vectors were composed of a set of these variables according to their efficacy in predicting the wear value. The features computed above were not suitable for direct usage in estimation of the tool wear. So to improve the overall estimation of the tool wear curve, the high frequency fluctuations in feature space were filtered out before training the predictive model. After features had been saved as datasets, each of the data vector, including the actual tool-wear value as observed under an optical microscope, was used as an exemplar for the supervised learning of the model.

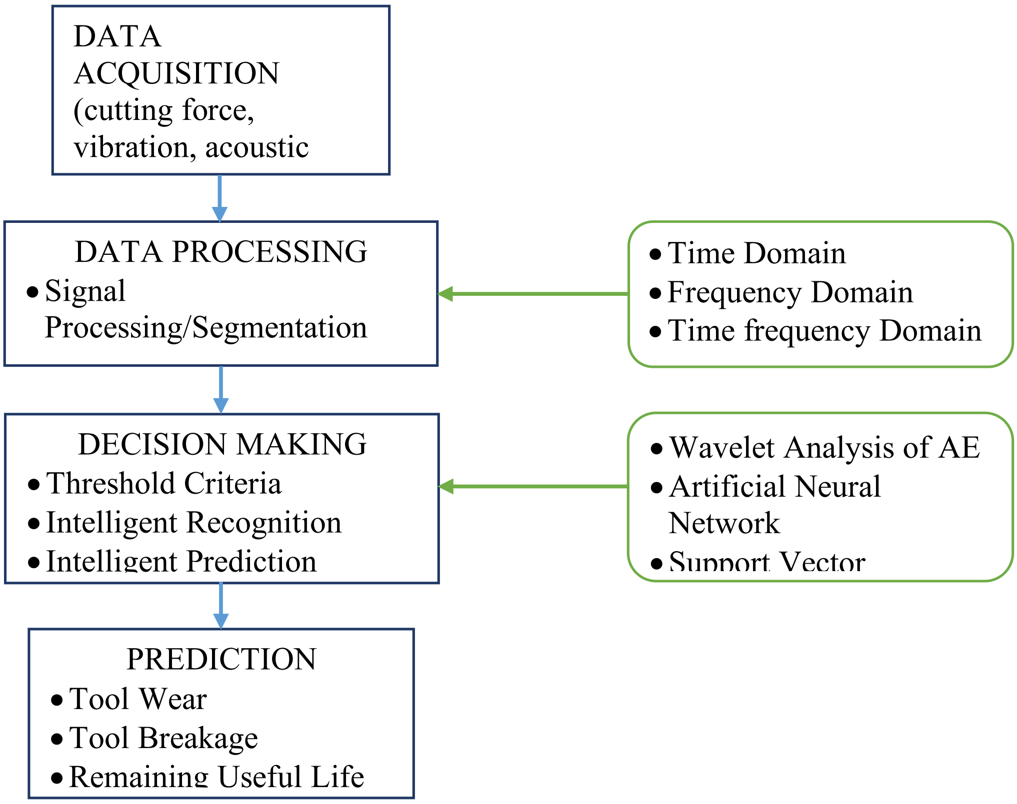

Figure 3: A schematic of the tool condition monitoring system

2.3 Decision Making

In addition to statistical analyses in the time or frequency domains, advanced signal processing methods have also been widely used to extract features that can reflect tool state. With the extracted features, tool states can be determined utilizing decision-making strategies based on various algorithms, such as *artificial neural networks* (ANN), *support vector machine*s (SVM), *hidden Markov models* (HMM), etc.

2.3.1 Thresholding:

The simplest methods for tool condition monitoring are based on threshold criteria. Tool failure can be detected when the monitored indexes are out of the pre-defined threshold value ranges. Various statistical indicators have been proposed with experimental verification, such as the energy magnitude at the tooth passing frequency, the average of the mean frequency, the sum of absolute values of digitally bandpass-filtered vibration signals. Marinescu and Axinte [6] analysed AE signals in the time-frequency domain for monitoring both tool malfunctions and workpiece surface anomalies in milling, while Cao et al. [7] used lifting wavelets to analyse AE signals in milling processes, with a threshold value set to indicate tool breakage. A review of wavelet transform in TCM can be found in [8]. For threshold-based TCM methods, however, a strong robustness of thresholds to varied cutting conditions and noise is needed to avoid missing or false alarms.

2.3.2 Intelligent Recognition:

With the application of AI techniques, decision-making systems can automatically recognize and classify tool conditions based on advance training with different types of samples (sharp, worn-out and broken edged tools). Then, these trained classifiers can be applied toonline identification of tool conditions.

ANN is a representation of the computational architecture of the human brain. ANNs have been widely used to classify the status of tools, due to their advantages of adaptive learning, self-organization and fault tolerance. However, there are some limitations in the application of ANNs for online TCM, such as the requirements of sufficient representative samples, the large diversity in training and the long computing time.

The SVM based on the statistical learning theory has also been widely used as a decision-making method. In comparison with ANNs, the SVM can support smaller samples and avoid overtraining in favour of the models with better generalization. The SVM has been combined with other algorithms, such as wavelets and genetic algorithms in the past, for better performance.

2.3.3 Intelligent Prediction:

Tool wear states and remaining useful life (RUL) can be predicted with data-driven methods. ANNs, fuzzy logic, regression models and SVM have been widely used to model the relationship between tool wear and measured data. In order to improve prediction accuracy, features from various signals have been fused and input into neural network models to estimate the average flank wear of a main cutting edge. However, tool condition prediction is more difficult than identification of tool state (wear or breakage). The accuracy of prediction depends on long-history data and accurate AI models, which still needs more investigation.

CHAPTER 3: MODEL ANALYSIS & VALIDATION

3.1 Experiment and Data

This study has been based on the experiments performed by Chen Zhang and Haiyan Zhang [3] to prepare tool wear data using a tool wear estimation method based on shape mapping.
These tool wear experiments were planned and conducted on a five-axis milling machining centre (MIKRON UCP710). Workpiece material of the tool wear experiments was stainless steel 1Cr18Ni9Ti, which is a difficult-to-cut material and has a wide application in industry. Aluminium alloy 6061 was selected as the mapped plate material compared with stainless steel 1Cr18Ni9Ti. Two different cemented carbide ball-end milling cutters were selected to estimate tool wear for stainless steel 1Cr18Ni9Ti.
According to the mechanical manuals and practical experience, parameters for machining stainless steel 1Cr18Ni9Ti, the ranges of cutting conditions chosen by them were

- 0.8 mm $\leq a_p \leq$ 2.0 mm,
- 80 mm/min $\leq f \leq$ 200 mm/min, and
- 800 rev/min $\leq n \leq$ 2000rev/min

After collecting the orthogonal experimental data, a series of mapping techniques were performed to measure the flank wear for each run of the experiment and a wear dataset of 32 entries were generated. This is labelled dataset where *flank wea*r has been mapped against *cutting depth, feed rate, spindle speed, cutting length* and *position,* 75% of which has been used for training the models and the other 25% for prediction.

Training Set (24 points):

Cutting Depth, a_p (mm)	Feed Rate, f (mm/min)	Spindle Speed, n (rpm)	Cutting Length, L (mm)	Position, h (mm)	Tool Wear (mm)
1.2	180	1600	360	0.7634	0.0189
1.5	150	1200	504	1.1511	0.0525
1.2	150	1000	576	0.7587	0.0440
1.2	100	1400	504	0.7587	0.0265
1.0	150	1600	504	1.1621	0.0194
1.2	120	1200	432	1.1511	0.0501
1.5	130	1600	432	0.7634	0.0215
1.5	150	1400	360	0.7634	0.0320
1.2	130	1400	504	0.7634	0.0244
1.5	150	1400	360	1.1621	0.0240
1.0	150	1600	504	0.7634	0.0331
1.2	180	1600	360	1.1621	0.0144
1.0	180	1400	432	1.1621	0.0152
1.2	150	1200	432	1.1621	0.0287

1.2	130	1400	504	1.1621	0.0282
1.8	150	1400	432	0.7587	0.0542
1.5	120	1400	576	0.7587	0.0577
1.8	150	1400	432	1.0000	0.0427
1.8	100	1200	576	1.1511	0.0105
1.0	130	1200	360	1.1621	0.0206
1.5	180	1200	504	1.1621	0.0408
1.5	150	1200	504	0.7587	0.0504
1.5	180	1200	504	0.7634	0.0390
1.5	130	1600	432	0.9615	0.0243

Test Set (8 points):

Cutting Depth, a_p (mm)	Feed Rate, f (mm/min)	Spindle Speed, n (rpm)	Cutting Length, L (mm)	Position, h (mm)	Tool Wear (mm)
1.5	100	1000	432	1.1511	0.0473
1.2	150	1200	432	0.7634	0.0378
1.5	130	1600	432	1.1621	0.0185
1.2	120	1200	432	0.7587	0.0400
1.0	180	1400	432	0.7634	0.0254
1.2	150	1200	432	0.9615	0.0396
1.5	100	1000	432	0.7587	0.0371
1.8	120	1000	504	1.1511	0.0254

3.2 Predictive Models

Statistical models on Linear Regression, k-Nearest Neighbours, ANN and SVM have been deployed to estimate the tool wear and hence, determine the relative validity of these models on comparing their RMSE values.

After plotting the correlation matrix for all the variables, it was found that there was no strong correlation between any two variables. Hence, all the other variables have been used to train the models for tool wear prediction.

All of these feature vectors had been *centred* and *scaled* before training the model which was further followed by 10-fold repeated cross-validation for best prediction results on the test set.

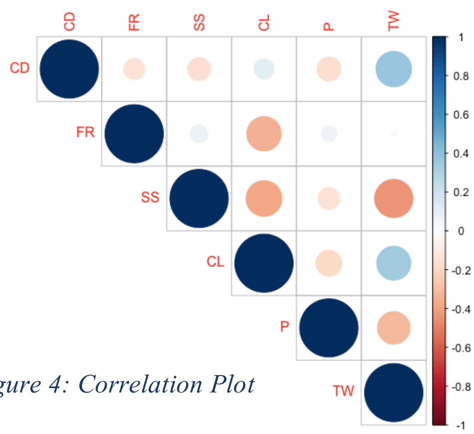

Figure 4: Correlation Plot

3.2.1 Linear Regression:

Simple linear regression is a very straightforward approach for predicting a quantitative response y based on a single predictor variable X. It assumes a linear relationship between the predictor X and response variable y.

This relationship can be written mathematically as:

$$y \ = \ + \theta_1 X \ + \ e$$

In the above equation, there are two unknown constants θ_0 and θ_1, which are known as intercept and slope respectively. The most common approach to estimate θ_0 and θ_1 involves minimizing the least square criterion. Let $\hat{y}_i = \theta_0 + \ \theta_1 X_i$ be the prediction value of Y for i^{th} value of predictor variable X. Then $e_i = y_i - \ \hat{y}_i$ represents the i_{th} residual.

Residual Sum of Squares is defined as:

$$RSS = e_1^2 + e_2^2 + \cdots + e_n^2$$

The least square approach estimates θ_0 and θ_1 such that it minimizes the RSS. By involving some calculus, we can estimate that to minimize RSS, θ_0 and θ_1 must be:

$$\theta_1 \ = \ \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

$$\theta_0 \ = \ \bar{y} \ - \ \theta_1 \bar{y}$$

In *multiple linear regression*, each predictor variable is given a different slope. Suppose there are k number of independent predictor variables; the multiple linear regression model will be:

$$Y \ = \ \theta_0 \ + \theta_1 X_1 + \theta_2 X_2 \ + \cdots + \ \theta_k X_k + e$$

θ_j shows the effect on y as a result of one unit increase in X_j. Let $\hat{y}_i = \widehat{\theta_0} \ + \ \sum_{i=1}^{k} \widehat{\theta_0}\, X_i$ be the predicted value of y, the parameters are estimated through least square method. $\widehat{\theta_i}$ is selected to minimize the residual sum of squares, $RSS \ = \ (y_i - \widehat{y_i})^2$. The estimate of these coefficients is in complicated form; hence they're not being presented here. The 'lm' function of the CARET package in R directly finds the coefficients and relation dependent variable and the predictor variables.

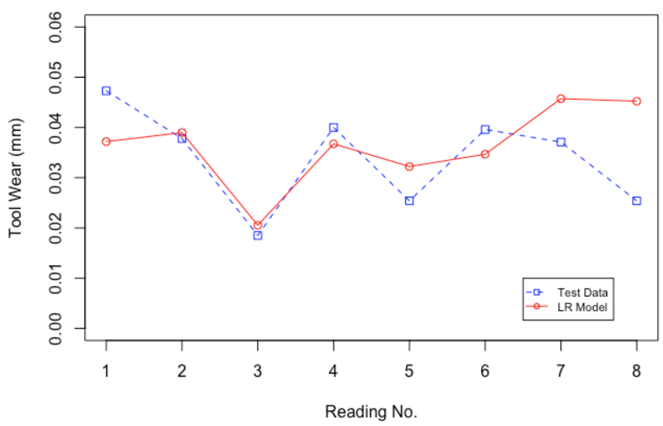

Figure 5: Prediction using linear regression

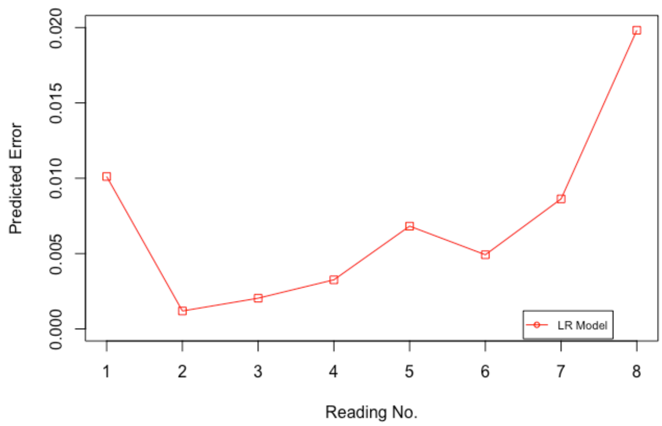

Figure 6: Error plot of linear regression

The above plot shows the prediction using all 5 parameters as predictor variables, though the plot doesn't give positive prediction results at all. The error curve is quite poor since even the tool wear values are of the order of 10^{-2} mm. The RMSE of this model is **0.00906 mm**.

3.2.2 k-Nearest Neighbours:

For a given predictor value X_i, k^{th} nearest neighbour (kNN) regression, at specified k, first looks for the k training observations nearest to X_i, represented by N_i. It then estimates $f(X_i)$ using the average of all the training responses in N_i.

$$f(X_i) = \frac{1}{k}\sum_{j\in N_i} y_j$$

One striking observation that can be made here is that after a point as the k is increased the prediction starts becoming more and more generalised thus losing its effectiveness and under-fitting the test data. This model was trained for different values of k, and the RMSE was the least for $k = 7$. Hence, the final model used had been trained with $k = 7$, the RMSE was found to be **0.00918 mm**, which is again very poor as far as prediction is concerned.

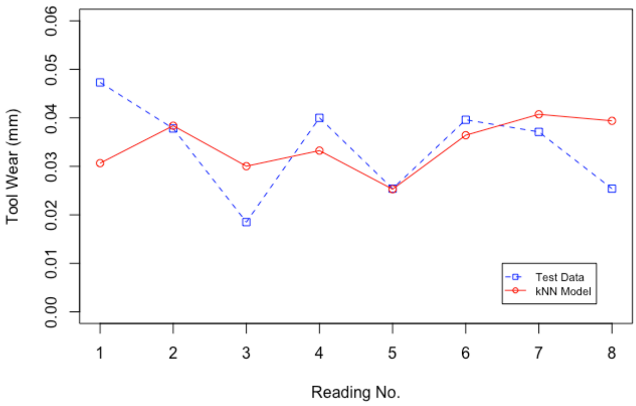

Figure 7: Prediction using kNN

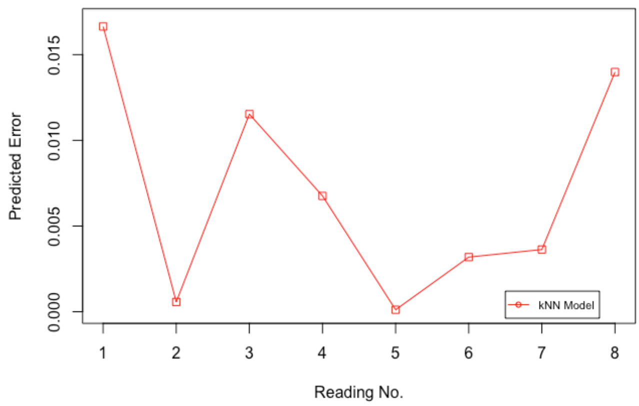

Figure 8: Error plot of kNN

3.2.3 Artificial Neural Networks:

After observing the two regression models, more sophisticated algorithms (ANN, SVM) of predictive analysis were looked into. An Artificial Neural Network (ANN) is a data preparing worldview that is enlivened by the way natural sensory systems, for example, the brain, process data. The key component of this worldview is the novel structure of the data processing framework. It is

made out of countless interconnected processing components (neurons) working as one to tackle particular issue. ANNs, similar to individuals, learn by illustration. An ANN is designed for a particular application through a learning procedure. Learning in biological frameworks includes acclimation to the synaptic associations that exist between neurons. This is valid for ANNs too.

Artificial neural networks use artificial neurons for data processing. An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the predictive mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the predictive mode, when a taught input pattern is detected at the input, its associated output becomes the current output.

If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not.

This model has been developed using the backpropagation algorithm with a single hidden layer of 8 neurons (least RMSE value during training), and all 5 parameters used up as the input layer. The diagram below show the topology of the ANN used for analysis.

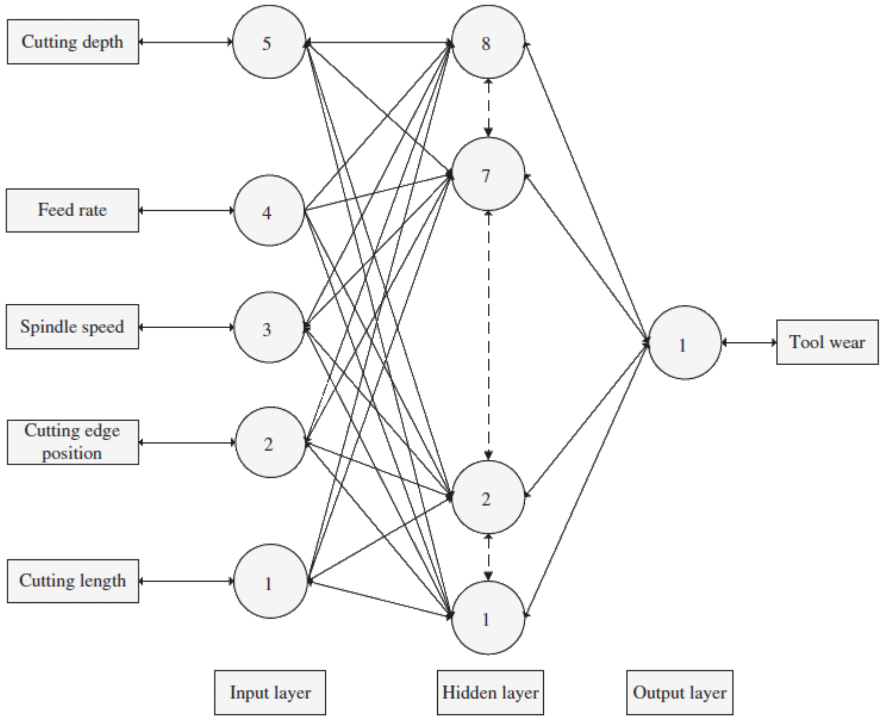

Figure 9: ANN structure used for TCM analysis

This model was trained on the same dataset and showed slightly improved accuracy than the previous two models with an RMSE of **0.00856 mm**.

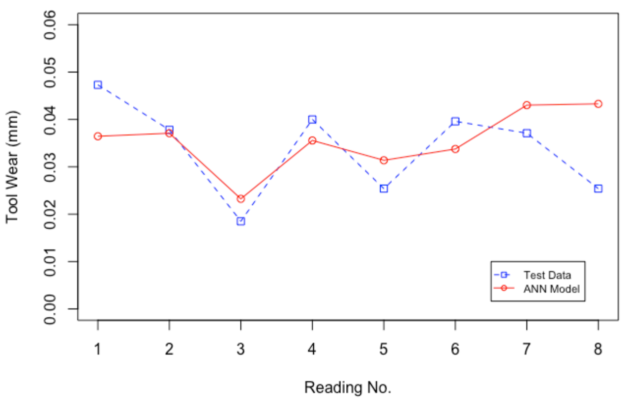

Figure 10: Prediction using ANN

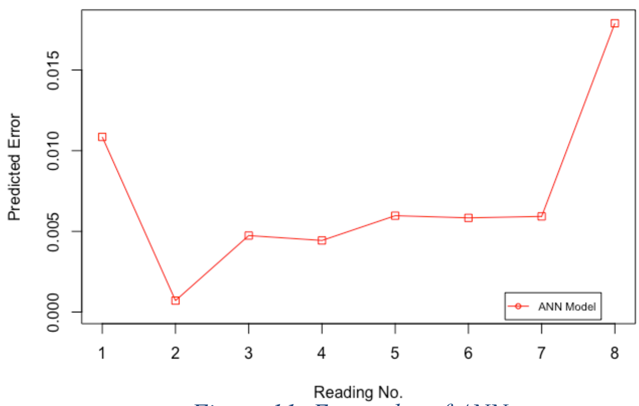

Figure 11: Error plot of ANN

3.2.4 Support Vector Machines:

Support Vector Machines (SVM) are very specific class of algorithms, characterized by usage of kernels, absence of local minima, sparseness of the solution and capacity control obtained by acting on the margin, or on number of support vectors, etc. They are particularly valuable for little training data. One of the key advantages of using SVM over other regression techniques is that it doesn't respond to outliers.
LS-SVMs are reformulations to standard SVMs which lead to solving linear systems. LS-SVM is closely related to regularisation networks and Gaussian processes but additionally emphasises and exploits primal– dual interpretations. The main advantage of LS-SVM is that LS-SVM training only requires the solution for a set of linear equations instead of the long and computationally difficult quadratic programming problem involved in standard SVM. The basic concept of SVM regression is to map nonlinearly the original data x into a higher dimensional feature space and to solve a linear regression problem in this feature space.
The final LS-SVM equation looks something like this:

$$y = \sum_{i=1}^{n} \hat{\alpha}_i K(x, x_i) + \hat{b}$$

where α is the Lagrange multiplier, $K(x, x_i)$ is the kernel function (Radial Basis Function in this case) and b is the bias term.

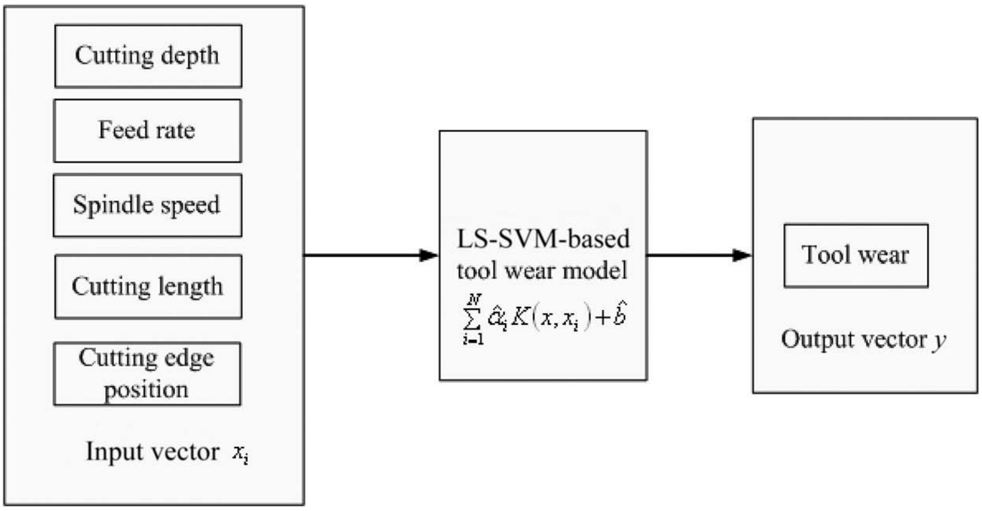

Figure 12: LS-SVM based tool wear predicting structure

Training of LS-SVM model plays a significant role in designing the direct LS-SVM-based prediction. The accuracy of prediction depends on the selection of different kernel function and experimental data normalisation through tuning. Radial Bias Function (RBF) was selected as the kernel function of LS-SVM based model for its high efficiency and more compact supported kernel.

For comparison, two SVM models have been plotted – one (Model B) of which was just trained without being tuned explicitly, while Model A was tuned to the best possible results. The optimum values of *cost* (regularization) and *gamma* came out to be 3.47 and 0.03 for the given set of training data respectively.

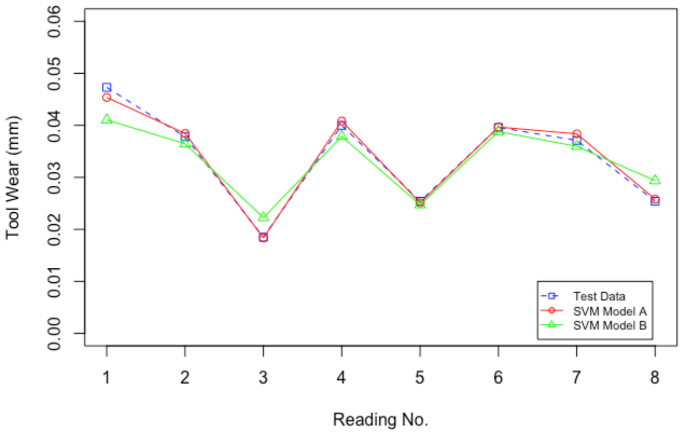

Figure 13: Prediction using SVM

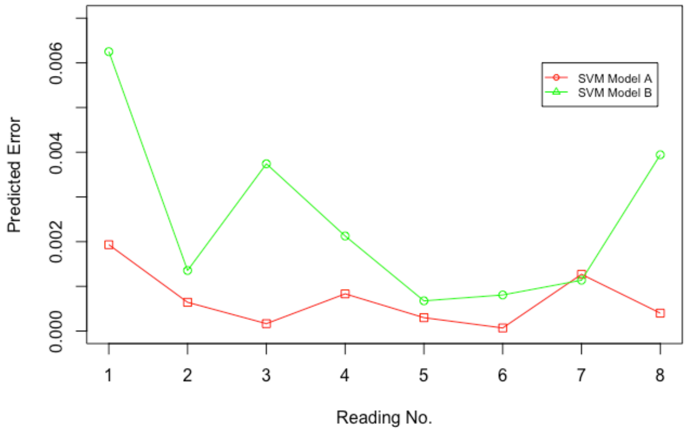

Figure 14: Error plots for SVM

The plots (for both the models) seem to capture the actual trends pretty well when compared to the labelled vector, though the tuned Model A seems even more accurate and hits the lowest scores on the prediction error scale for each wear state with an RMSE value of **0.000917 mm** only, almost $1/10^{th}$ of the other models. The RMSE value for the un-tuned Model B was **0.00311 mm.**

CHAPTER 4: INFERENCE

4.1 Model Comparison

The plot below shows the comparison among the above mentioned techniques, linear regression and kNN can be seen to perform very poorly, while ANN performs slightly better but still doesn't give satisfactory results. On the other hand, SVM performs a lot better than the other methods giving promising predictions owing to the small number of data points.

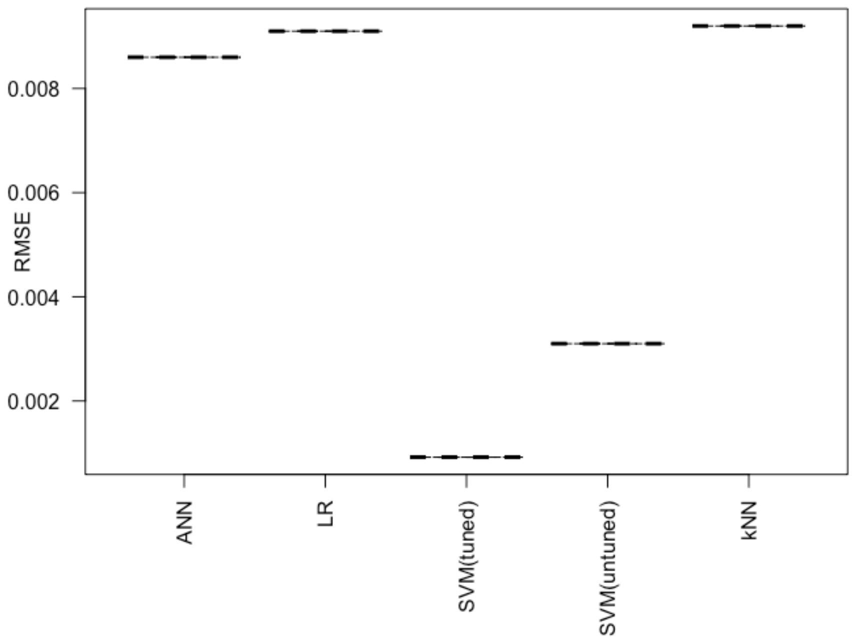

Figure 13: Comparison of all the model types used

4.2 Conclusion

LS-SVM was excellent in predicting the tool wear even with such small amount of data collected. Even the ANN model gave futile results. Some more techniques could be tried to this analysis though it's not required as the SVM results are quite satisfactory.

With the right quality of multi-variable data spanning over the features of *cutting forces, vibrations, acoustic emissions* and *motor current*; a much more in-depth analysis could be possible. Different types of signal processing, feature extraction techniques along with machine learning algorithms can be implemented to study the aspects of TCM more effectively.

CHAPTER 5: FUTURE WORK

- By varying the cutting parameters of spindle speed, feed rate, depth of cut and cutting length, the following data to be collected:
    - Forces in 3 orthogonal axes by the Kistler 9255C piezoelectric dynamometer
    - Vibrations in 3 orthogonal axes by the MPU 6050 accelerometer
    - Acoustic Emissions by a microphone
    - Spindle motor current by a Hall effect current sensor
- Appropriate segmentation, signal processing and feature extraction techniques to be applied to these signals before they can be used for analysis.
- Sensor fusion using an appropriate predictive algorithm for improved and robust estimates since this estimator would have had a lot of training on different types of parameters (hyperspectral data collected) before it would actually have to predict.
- If the model seems to work well, this idea could be used to make online TCM systems with sensors intact, that would predict the tool wear states online – a beginning to the Industry 4.0 Era!

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