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Prediction of Tool Life based on Empirical Mode Decomposition and Gaussian Process Regression

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Abstract : *Tool wear is an important factor that affects the quality and tolerance of machined parts. Tool failure in the machine can lead to unscheduled downtime and damage to the workpiece. Having an accurate prediction of tool life is important for machining industries to maintain the machined surface quality and can onsequently reduce inspection costs and increase productivity. The development in sensor technology has made possible online and real-time tool life prediction. Forecasting the tool degradation process is an effective way to realize remaining useful life of cutting tool. For this purpose, a condition indicator is required that can reflect the severity of degradation in tool in a proper manner. The specialty of condition indicators is to provide accurate information regarding the condition of various components at different levels of damage (initial, heavy or growing). In this paper, the authors have proposed a hybrid technique combining Empirical mode decomposition (EMD), time domain features, Self-organizing map (SOM) and City block distance (CBD) to construct the degradation pattern for cutting tool where Gaussian mixture model (GMM) is used to compare degradation pattern. EMD and time domain feature together are employed to extract the fault features from the tool vibrations signals. The fault features are then used to train and test the SOM assessment model to achieve the health indicator for cutting tool. A Gaussian process regression (GPR) model is then constructed based on one-step ahead prediction strategy to predict the life of tool. The experimental results are validated to check the efficiency of the proposed approach.*

Keywords: *City block distance, Cutting parameters, Empirical mode decomposition , Self-organizing map, Gaussian process regression, Gaussian mixture model.*

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I. Introduction

In production industries, tool are playing important role for different machining operation. For more productivity of product, well machine tools are used to produce the good quality of product. The production of low cost and good quality of work pieces compose of various factors. According to the research study, we found that the cutting parameters are the main factors during machining in order to get the final job to be done. If the selection of parameters is not correct, it will cause shorter tool life. This will cause the impact of cost of production which could not compete to market effectively. The problem of achieving the optimum stage of the process parameters has attracted the attention of the researchers and practicing engineers for a very long time. Many researchers have inspected the effects of these cutting parameters on tool by the one-variable at a time approach. The present work takes into account at constant speed, feed rate and depth of cut and predicts the tool life of the material. There are limitations that can influence the manufacturing process, such tool wear and life, surface roughness, surface location error, and machining stability. When tool wear reaches a certain severity, increased cutting force, vibration and temperature can cause deteriorated surface integrity and dimensional error greater than tolerance, and lead to the end of tool life. Tool wear is definitely unpleasant because as it increases to a certain value, the tool needs to be changed. Hence replacement with a new tool results in process disruption and also results in increase in machining cost, which is the most undesirable consequence in the manufacturing field. Therefore, to achieve high quality machining performance, machining parameter selection and control are essential. This necessitates the development of reliable methodologies for tool life estimation. The objective of proposed model is to develop a data-driven prediction model for building an appropriate degradation pattern that could be used to detect accurately the cutting tool deterioration phenomena. To compare the result with some known and widely used degradation indicators. To develop an effective prediction model utilizing the healthy state values of the cutting tool degradation pattern and get the one-step ahead predicted values of the tool life. To develop a prediction model which can predict non-linear non stationery signals for a cutting tool used in machining operation.

II. Methodology

2.1 Empirical Mode Decomposition

Empirical mode decomposition method was fundamentally a part of Hilbert-Huang transformation [1] and was initially generated with an assumption that any signal comprises many simple modes of oscillations which are called Intrinsic Mode Functions (IMF). It is a key method for the analysis of non-linear non-stationary signals. It was developed by N-Huang. This method decomposes the signal into no. of functions with slightly different and varying phases and amplitudes.

Any signal $f(t)$ as a function of time can be decomposed by EMD with following steps:

i. All the maxima and minima of the vibration signature are identified and connected by a cubic spline curve to form a envelop to the signal. This envelops covers-up the signal data.

ii. The mean of the upper and lower envelop curves and designated as $x^{'}(t)$.

iii. The difference between the signal $f(t)$ and $x^{'}(t)$ is taken as a component $c_1(t)$. If $c_1(t)$is an IMF, then it is a component of $f(t)$. If it not, the process will be repeated to find the first IMF.

iv. If after k iterations we get the first IMF, then

$$c_{1k}(t) = c_{1(k-1)}(t) - x^{'}_{(1k)}(t) \quad (1)$$

The process of accessing the IMF is called sifting process. It is controlled by the determination of limited standard deviation (D_s). This standard deviation is calculated with respect to two consecutive $c(t)$.

$$D_s = \sum_{t=0}^{T} \frac{(c_{(k-1)}(t) - c_{(k)}(t))}{c^2{}_{(k-1)}(t)} \quad (2)$$

Ideally D_s can be set for 0.2 to 0.3.

v. As $c_1(t)$ is considered, it should be removed from former $f(t)$ to get $r_1(t)$ which can be calculated are to be repeated. Similarly

$$\begin{cases} r_2(t) = r_1(t) - c_2(t) \\ \quad\quad . \\ \quad\quad . \\ \quad\quad . \\ \quad\quad . \\ r_n(t) = r_{n-1}(t) - c_n(t) \end{cases} \quad (3)$$

The process of decomposition will lasts up to the gain of a monotonic function $r_n(t)$.

So that no more IMF further can be obtained [1]. By summing up to the equations

$$f(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (4)$$

Thus n empirical mode and a residue are obtained from an original signal. This residue is the mean trend of the signal$f(t)$.

2.2 Self-Organizing Map (SOM)

SOM [2] consists of neurons which are arranged on a regular pattern of low dimensional grid system. The number of neurons varies up-to thousand. Each and every neuron represents the K-dimensional weight vectors. These vectors are also called as prototype and codebook vectors denoted as $n = [n_1 n_2 \dots\dots\dots . n_k]$, the value of k is decided by the dimensions of the input vectors which is same. SOM algorithm executes the topological preservation mapping.

It is an iterative method in which each iteration any one sample column or row vector is randomly selected from the input data set. In SOM, it has a provision of the changes in the organization and variation in the size of map units [3]. This data set undergoes a series of step by step calculations. The distance, specifically Euclidian distance between weight vectors and chosen vector is calculated. The closest weight vector is called as best matching unit (BMU).

$$\|\mathrm{x} - \mathrm{n_c}\| = \mathrm{min_1}\{\|\mathrm{x} - \mathrm{n_i}\|\} \quad (5)$$

where, the distant measured is $\|\ .\ \|$. When the identification of BMU is over, weight vectors for the BMU is updated and movement closer to the input occurs so as to obtain the best matching unit.

$$\mathrm{w_i}(\mathrm{t}+1) = \begin{cases} \mathrm{w_i}(\mathrm{t}+1) + \beta(\mathrm{t})\big(\mathrm{x}(\mathrm{t}) - \mathrm{w_i}(\mathrm{t})\big)\mathrm{i} \in \mathrm{N_c}(\mathrm{t}) \\ \quad\quad \mathrm{w_i}(\mathrm{t})\mathrm{i} \in \mathrm{R_c}(\mathrm{t}) - \mathrm{N_c}(\mathrm{t}) \end{cases} \quad (6)$$

$\mathrm{x_i}(\mathrm{t})$ is the input vector, $\mathrm{N_c}(\mathrm{t})$ is the non-increasing neighbourhood function and selected unit C and $0 < \beta(\mathrm{t}) < 1$ is learning rate. The adjustment of the weight vectors to the input depends on the learning rate $\beta(\mathrm{t})$ and training time.

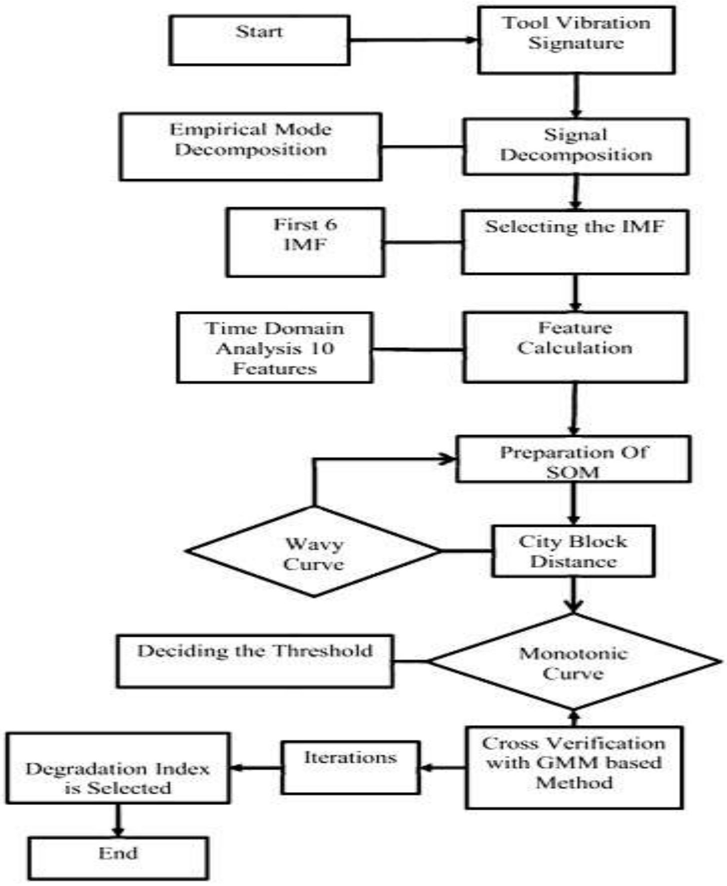

Fig. 1 Flow Chart of Degradation Assessment Model

2.3 Prediction Strategy of model

In time-series forecasting techniques, one-step-ahead or multi-step-ahead prediction is frequently used. One-step-ahead or multi-step-ahead prediction implies that the predictor utilizes the available observations to forecast one value or multiple values at the definite future time. The more the steps ahead is, the less reliable the forecasting operation is because the involved approaches in multistep prediction is associated with multiple one-step operations. [4]

2.3.1 One-step ahead prediction strategy

This technique utilizes the previous accurately known input values to predict future values. From the name it is clear that, this strategy is used to predict the succeeding value. In this prediction we assume that the inputs are accurately known. The one-step ahead prediction model is given by

$$\hat{y}[k|k-1] = G(q)u[k] + \hat{s}[k|k-1] \tag{7}$$

where, $\hat{y}[k|k-1]$ signifies the prediction y[k], given all the information upto k – 1.

2.4 Gaussian Process Regression

It is a non-parametric probabilistic approach for modelling and forecasting. Theoretical and practical developments of GPR over the last decades have made it a serious competitor for real supervised learning applications. A GPR is used to define a prior probability distributions over latent functions directly. It can be completely specified by its mean function and covariance function, written as $f(x) \sim GP(m(X), k(X, X'))$. The mean function encodes the central tendency of the function, and is often assumed to be zero. The covariance function encodes information about the shape and structure we expect the function to have. [5]

III. Experimental Setup

The vibrations signals have been achieved over the experimental setup shown in Fig. 2. It consists of a lathe machine in which turning operation have been carried for a mild steel rod using HSS tool. The data collection system consists of an accelerometer and data acquisition unit. A hub is attached over the tool post in which accelerometer have been attached so as to obtain the vibration signal of a cutting tool, where the accelerometer is connected to data acquisition unit to collect the vibration signal. A computer is also connected to display the vibration signal.

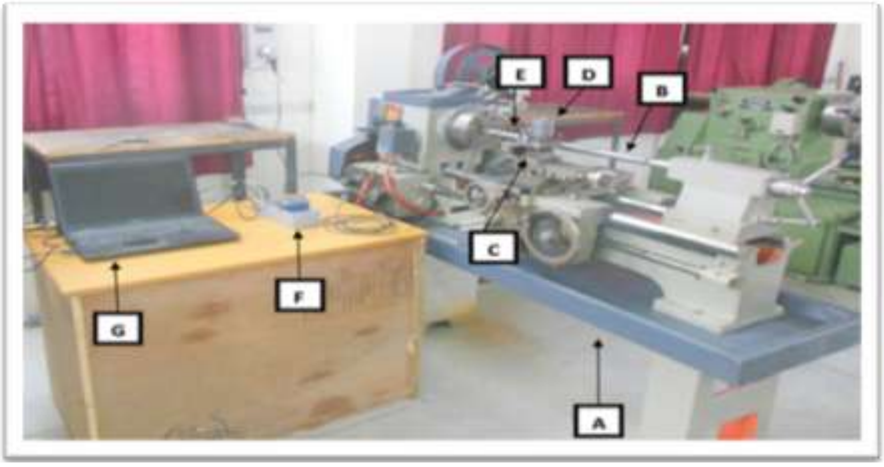

Fig. 2 Experimental setup (A) Lathe Machine, (B) Mild Steel, (3) High Speed Steel Cutting Tool, (4) Hub, (5) Accelerometer, (6) Data Acquisition System, (7) Computer.

In this experiment, turning operation of mild steel rod of 25 mm diameter have been carried out using HSS tool The process parameters such as cutting speed, feed and depth of cut have been kept constant throughout the experiment till the tool gets degrade. The data regarding cutting tool and cutting parameter is described in Table 4.1. Start and stop time are recorded for the analysis purpose. The vibration signals are extracted from the test with the help of PCB 608A11 piezoelectric ICP. Accelerometers are connected on the hub which is mounted on the tool post and Data Acquisition system NI cDAQ-9234 with a computer programmed in NI LabVIEW software.

Table 4.1 Details of the cutting tool and cutting parameter

Mild Steel Rod	25 mm
Cutting Tool	HSS
Cutting Speed	180 rpm
Feed	0.05 mm/rev
Depth of cut	0.1 mm

IV. Result Of Proposed Model

With the aim of predicting the life of the tool, vibration signals obtained after performing experiment have been analysed and combination of EMD, SOM and CBD are applied to find out the degradation Finally prediction result obtained by applying one step ahead prediction strategy and GPR.

The cutting tool vibration signals during whole life span is shown in Fig. 3. It can be realized that no clear picture about the cutting tool condition is observed by simply looking at the vibration signals. Thus, they need to be processed appropriately to retrieve the tool degradation pattern. The sequence of steps shown in Fig. 2 is applied on the acquired vibration signals. Fig. 4 shows the IMFs obtained after EMD of a cutting tool signal sample acquired under healthy conditions. According to this 6 IMFs were obtained after EMD of the signal. The initial 500 feature vectors are utilized. Next, the trained SOM model in which CBD is added is exploited to achieve the DI curve that is shown in Fig 5. It is observed from the Fig. 5 that at 525 inspection point, the DI curve drops and has last negative value of 0.02474, after this point the value starts to increase (positive value) and indicating that the slight degradation in bearing has begun at 526 inspection point. Between the time-steps of 526 and 721, the DI curve keeps on fluctuating. Beyond the 721-step, the DI curve continues to rise and the tool progresses rapidly from severe degradation phase to failure. Thus, it can be seen that the proposed DI can effectively track the progression of degradation in cutting tool.

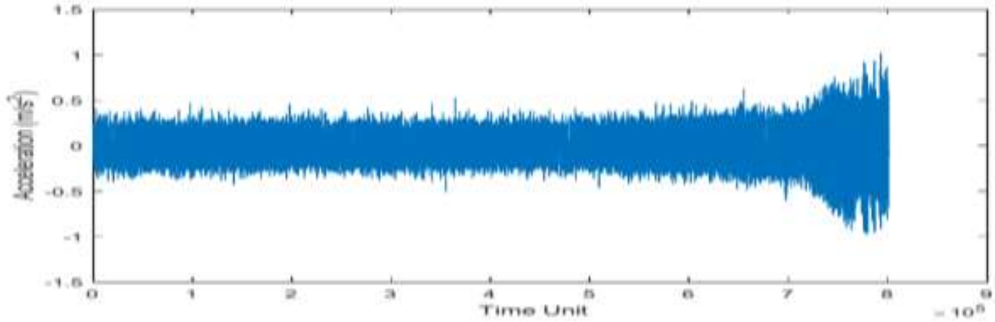

Fig. 3 Cutting Tool Vibration Signals

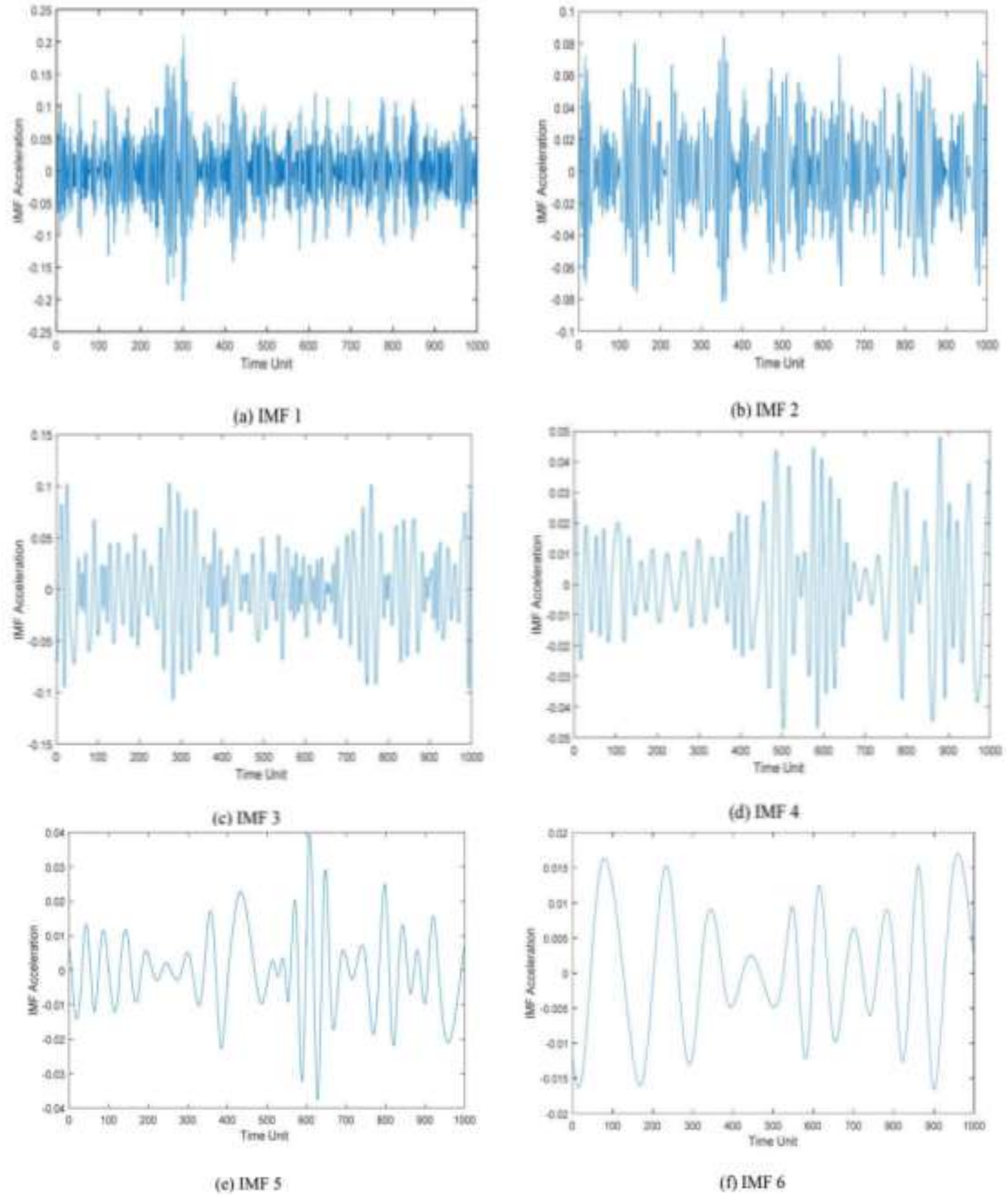

Fig. 4 (a) to (6) IMFs of Vibration Signals

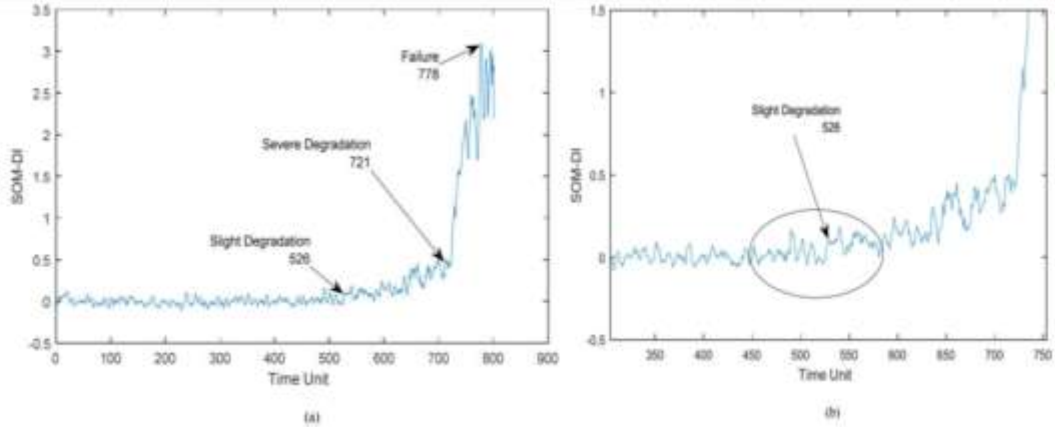

Fig. 5 DI curve as a degradation indicator based on SOM (a) Over complete life (b) Expanded view

From Fig. 5 it is clear that the tool slight degradation starts at 526 inspection point so in order to calculate the effectiveness of proposed model, is compared with Gaussian mixture model (GMM). Degradation pattern obtained from GMM model is shown in Fig. 6. It is found that in GMM slight degradation of tool starts at 529 inspection point.

When we aim for predicting the degradation state of cutting tools, the first step is to split the data into training and testing set. Training set is utilized to train the prediction model based on GPR. One step ahead prediction technique is adopted for forecasting purpose. This technique inhibits strong advantages as compared to multi step prediction strategy. We prepared a GPR based model and the results of training and validation can be observed in Fig. 7 and 8. In this model, we perform the training for a set of 500 data sample i.e. for a healthy range and testing is perform for the remaining data sample. The training set result is shown in Fig. 7. It is very clear that the predicted values lie within the limits decided by the maxima and minima values of original signal with considerable fluctuations. A model is prepared for one step ahead prediction in which several iteration have been done to find the accurate result. The testing sets are then supplied to this models which give the entire life prediction in one advance step by utilizing the required original data. The results of the prediction for next 200 steps can be observed in Fig. 8. The prediction error can be calculated with the help of parameter root mean square error. [7]

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i - y_i^*\right)}{N}} \qquad (8)$$

where, y_i and y_i^* are the original and predicted values of the SOM-DI. The error so obtained is minute with 0.23 value. As observed from Fig. 8 the model gives accurate result for monotonic data trend which clearly depicts the original value and predicted value.

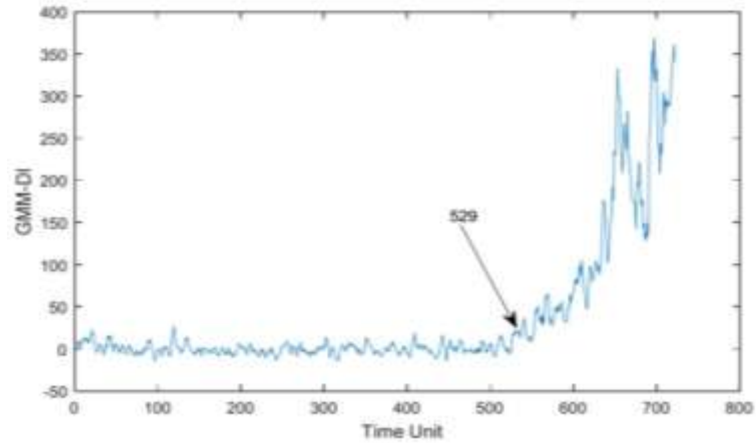

Fig. 6 DI curve as a Degradation Model based on GMM

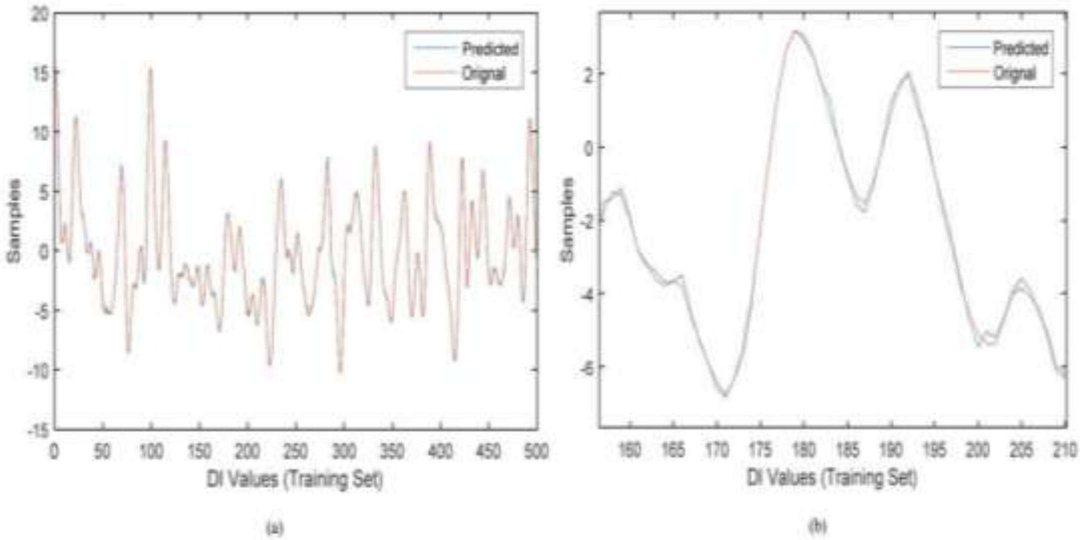

Fig. 7 (a) GPR based Result for Training Set (b) Expanded view of (a)

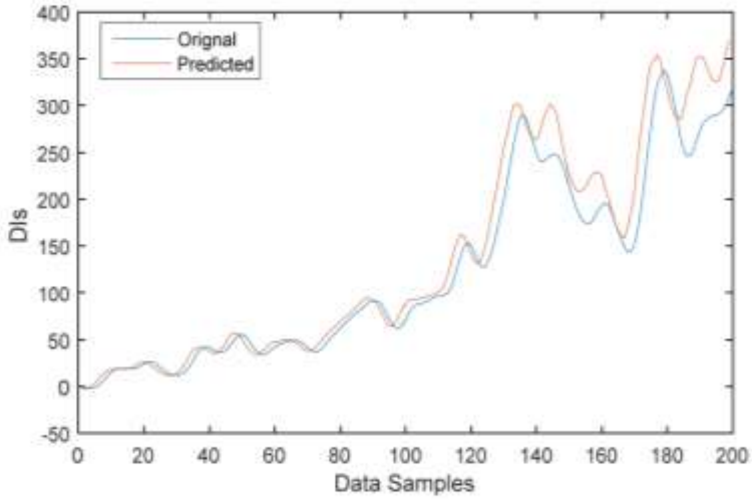

Fig. 8 GPR based Prediction Results for Testing Set

V. Conclusion

Moreover, with a definite range of the DI, proper thresholds can be imparted to the slight, severe and failure states of the tool. Based on the above discussions, the conclusions drawn from this report are as follows: Prediction of tool life is crucial to the uninterrupted operation machining operation.

i. Remaining useful life and degradation tracking estimation are the two objectives in prediction of tool life.
ii. The fault feature extraction plays an important role in predicting the tool degradation phases.
iii. The combination of EMD, SOM and CBD is capable to obtain an effective index for tracking the evolution of degradation in tool.
iv. One step ahead prediction technique based on GPR is validated on the generated DI which is found to be effective and has ability to forecast the degradation state with minimum error. This ability of model is crucial for the advance knowledge of remaining useful life of tool.

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