Data Driven Approach for Drill Bit Monitoring

[1] Nishchal K. Verma, [1] Rahul K. Sevakula, [1] Sonal Dixit and [2] Al Salour
[1] Department of Electrical Engineering,
Indian Institute of Technology Kanpur, India
[2] The Boeing Company, St. Louis, MO, USA
E-Mail: {nishchal, srahulk, dsonal}@iitk.ac.in and al.salour@boeing.com

***Abstract* — Drill Bit Monitoring has become an important part of Automation in manufacturing industries, especially when product quality and efficiency are highly demanded. Conventional drill monitoring methods use imaging and process parameters like thrust, cutting force, torque, feed rate etc. for detecting presence of wear and tear in drill bits. This paper presents a study where various Pre-processing, Feature Extraction, Dimensionality Reduction and Classification strategies are used with a target to find the most accurate and time efficient set of strategies for vibration based drill bit monitoring. The entire fault recognition process has been made simple by developing and implementing all the selected strategies onto a smartphone application (App). The App is able to quickly perform the recognition process of recordings present on Cloud and internal storage. A case study has been performed on a Computerized Numerical Control (CNC) machine having drill bits of 9mm diameter in 4 states namely Healthy and three faulty states. The proposed model is able to correctly predict the drill bit state by analyzing a one second vibration recording with accuracy of 95.5%.**

Keywords — drill bit monitoring; condition monitoring; vibration analysis; tool wear monitoring; spectral analysis; SVM

I. INTRODUCTION

Machine Tool automation has great impact in reducing human efforts and also in improving precision of the work done. Tool wear monitoring forms an integral part of Machine Tool automation which also makes production line systems more reliable. Literature Survey [1] states that Drilling accounts for up to 50% of all machining operations in the United States of America; thus making Drilling process one of the most common machining processes in industries [2]. Due to its utter importance in machining operation, tool wear monitoring of cutting tools have been quite popular among researchers [3-6].

Literature study gives multiple investigations for drill bit wear detection based on acoustic, vibration, thrust, torque, power and current measurements. Patra [7] and Everson et al. [8] presented Tool wear monitoring systems using acoustic emission (AE) signature analysis. Patra's scheme used time and wavelet domain based features with back propagation algorithm based artificial neural network (ANN) for tool wear prediction. Everson's experiments demonstrated a relation of AE signals with hole size and lip height variation. However due to sensor mounting and noise attenuation issues, AE based methods are generally deemed to be slightly inaccurate [6]. Ertunc et al. [9] worked with cutting force signals namely thrust and torque using dynamometer to detect the drill wear. Among the four tested methods, HMM based approach was found to be most feasible and reliable solution. Cuppini et al. [10] derived a mathematical relation between wear and cutting power, and used this measure for detection of wear. Patra et al. [11] developed current signal based back propagation network to predict the wear on high speed steel (HSS) drill bit. During drilling, thrust and torque force causes vibration on the surface. Considering this, Wardany et al. [12] presented a threshold controlled based approach with vibration signatures to detect drill wear. Isaan [13] further presented a vibration based approach using harmonic wavelets, entropy and spectrum features with ANN for drill wear detection.

This paper presents a study of drill bit monitoring with accelerometer recordings by describing how the authors validated various pre-processing, feature extraction, dimensionality reduction and classification strategies before deciding the final strategy. After identifying the best strategy, a Smartphone application has been developed, which is able to recognize the presence of faults in the drill bit within 10 seconds. The contribution of this paper is that as compared to previous strategies, a much simpler and faster method has been presented and developed for convenience, with recognition accuracy of up to 95.5%.

The paper further proceeds as follows. Section II throws some light regarding drill bit monitoring. Section III gives details of the variations tested in preprocessing, feature extraction, dimensionality reduction and classification steps. Section IV presents results and a thorough analysis of the effectiveness of features, Principal Component Analysis (PCA) and classifiers. Section V talks about the model that was finally used in making real time drill bit monitoring system for Android based smartphone and finally Section VI concludes our presented work.

II. Drill Bit Monitoring

A typical drilling operation requires drilling machine, work piece, fixture and cutting tool. Fig. 1 shows typical geometry of a drill bit. It has a cone like structure consisting of chisel edge, cutting lips, web, flute, heels, body and shank. As soon as drill bit comes in contact with the work piece, it starts penetrating via chisel edge. The cutting edges then chips off the material during penetration in first stage, also known as penetration stage. At second level, as drill bit moves into the material, flute edges do similar work as cutting edges, but in a more refined manner which makes the drilled holes look clearer. This stage is known as steady stage.

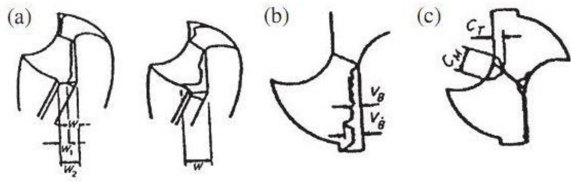
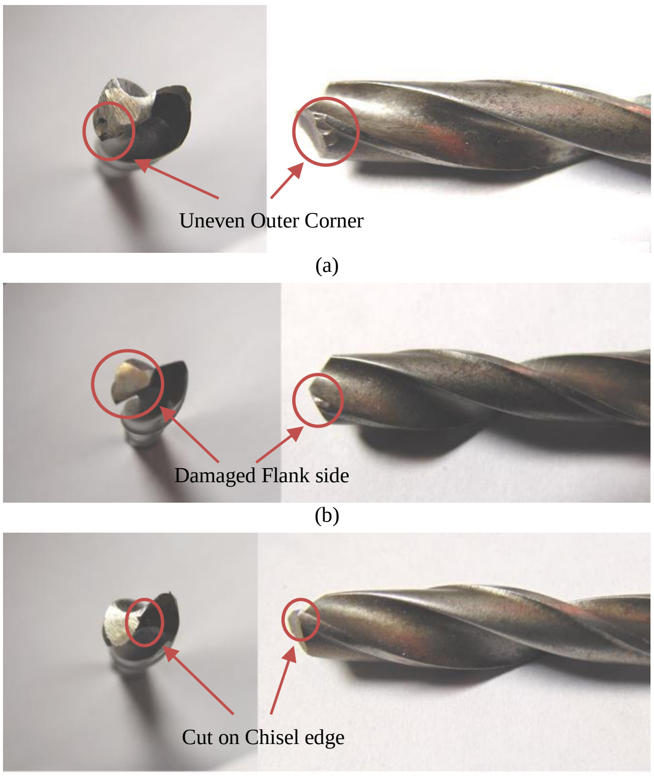


Fig.1 Different types of wear (a) Outer corner wear, (b) Flank wear, (c) Chisel wear. [14]



(a)

(b)

(c)

Fig. 2. Actual images of a Drill bit having following faults: (a) Outer Corner wear, (b) Flank wear, (c) Chisel wear [30]

As drilling continues, deformations due to physical and mechanical reactions begin to occur in the drill bit. In the case study presented here, four states of drill bit namely healthy state and three faulty states have been studied and analyzed. The three faults that have been studied here are as follows:

- Chisel wear: Drilling process starts as soon as chisel point penetrate into work piece. Due to high shear and stress, the temperature at chisel point gets raised and results into a blunted chisel edge as shown in Fig. 1(a).
- Flank Wear: Due to friction between the work piece and flank of drill bit, abrasive wear occurs. As shown in Fig. 1(b), v_b and v_b' flank surfaces get abrasive. This abrasion increases as cutting speed increases.
- Outer corner wear: Due to high impact forces and friction between drill bit and hole's inner head wall, the outer corner of the drill erodes or gets chipped off. This defect causes wear on one or both outer corners of the drill point as shown by points C_m and C_t in Fig 2(c).

III. Fault Recognition Model

For detection of faults, a supervised learning approach has been modeled and implemented. Supervised learning approach consists of two phases namely training phase and testing phase. Training phase includes development of robust model/s using pre-recorded training samples and in testing phase, the developed model is used for finding out the class that test samples belong to. In Training phase, firstly necessary training data are acquired to form a set of recordings to learn from. These recordings are pre-processed to improve its quality and later features i.e. signal characteristics are extracted from the same. Having a reduced set of important features can improve the generalization capability of classifiers. For this reason, dimensionality reduction techniques are used to learn/recognize the reduced set of features. Finally, a classifier is made to learn relationship between samples' reduced features and their respective class label. In Test phase, whenever a test recording arrives, the recording is first pre-processed, then features are extracted from it, then dimensionality is reduced based on earlier learning, and finally using the learnt classifier model, class/category of the test sample is recognized. Details for each step have been given below.

A. Data Acquisition

To capture the vibration signature of machine, uniaxial accelerometer, PCB 63001 was used. The sensor was mounted on the work piece and using NI data acquisition (DAQ) [15] system, analog vibration sensor signals were converted into sampled signals at a sampling rate of 32,768 Hz. NI DAQ system consists of NI 9234 Signal Processing unit in conjunction with NI 9172 chassis connected to a Desktop PC.

B. Preprocessing

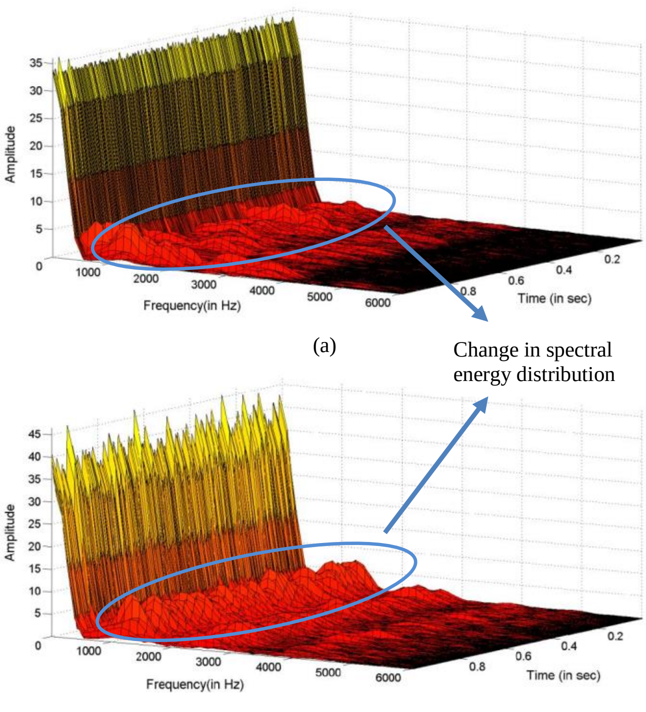
Various kinds of noise due to environmental conditions and sudden jerks may also become part of the recording. To reduce effects of such noise, recordings are preprocessed. In pre-processing, 4 steps were incorporated in a consecutive fashion, namely frequency filtering, clipping, smoothing and 0-1 scaling. Frequency filtering step has a low pass 20 order Butterworth filter with cut-off frequency of 12 kHz. Clipping step is used for making systems robust to sudden jerks. For clipping, the entire recording is divided into multiple overlapping windows, for e.g. in this experiment, each recording was divided into 8 overlapping windows having 8192 samples each. The window having least standard deviation was selected for further process. Such window with low standard deviation is expected to give the stable part of recording that is free from sudden jerks. The third step of smoothing is meant to smoothen the recording and reduce effects of outliers in the recording. A moving average filter has been used for the same. The fourth step is scaling where smoothed recording is scaled from 0 to 1 using max-min normalization.

C. Feature Extraction

One of the most important tasks in analyzing signals is identification of some important signal characteristics which are capable of representing the signal in entirety, at least up to great extent. Such signal characteristics are termed as features here. Here features have been extracted using Statistical parameters in time domain, Fast Fourier Transform (FFT) coefficients, Discrete Cosine Transform (DCT) coefficients, Morlet Wavelet Transform coefficients and Wavelet Packet Transform node energies.

1) Time Domain : In general, signal is stored in the form of sampled signal values, showing how amplitude of the signal changes w.r.t time. Popular statistical parameters were used to extract 14 features in this domain and hence give a fair idea of the distribution and peakedness of data in signal. These 14 statistical parameters [16] inlcude non-parametric features namely absolute mean, root mean square, shape factor, crest factor and parametric features namely median, mean of peaks above upper quartile, variance, skewness, kurtosis, upper quartile, interquartile, negentropy found by approximation [17], Hjorth's complexity and Hjorth's mobility [18].

2) FFT and DCT : Spectral analysis has always been popular in vibration signal analysis [19]. For non-stationary signals, FFT gives an average picture of the signal energy distribution across frequency components. FFT gives both, phase and amplitude information of the signal. Before extracting features, spectogram plots of pre-processed signal samples from all four states were found using Short Time Fourier Transform (STFT). These plots have been shown in Fig. 3. Two inferences could be made from the figures. First



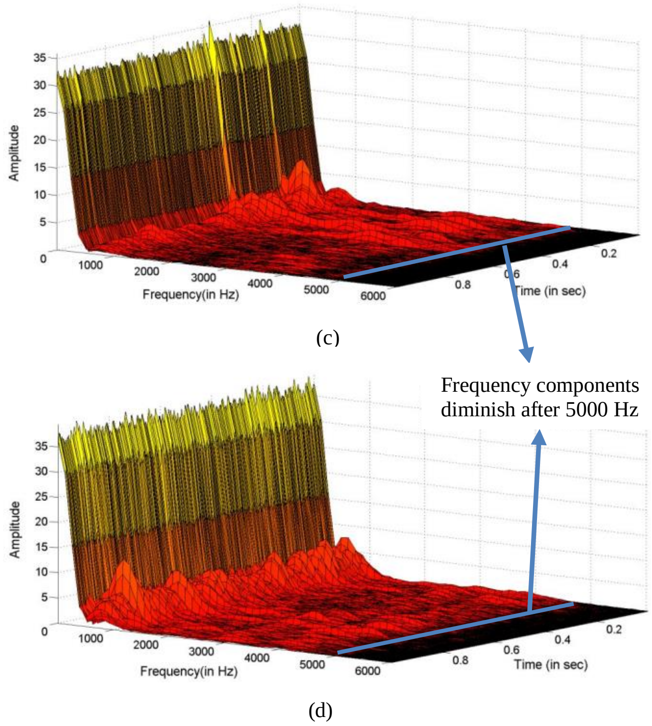


Fig. 3 Spectrogram Plots of Accelerometer Recordings while drilling is in Steady state and Drill bit is in following states - (a) Flank wear fault, (b) Chisel wear fault, (c) Outer Corner wear fault and (d) Healthy

is that there are clear differences in the four plots; thus showing that spectral analysis is sufficient to discriminate recordings of the four states. Second inference is that there are no significant frequency components after 5kHz. For this reason, only spectrum of 0-5kHz was considered while extracting features. After performing FFT, the obtained spectrum from 0-5Khz was divided into 14 equal segments, called bins. The ratio of individual bin energy to the total energy of all 14 bins gave 14 features in frequency domain

DCT transform represents signal into sum of small cosine functions with different frequencies. More than representing the signal in spectral domain, it is primarily used for compactly representing the signal with few DCT coefficients. As most of the energy is concentrated in earlier coeffecients itself, starting from the first DCT coefffecient, ceffecients upto which 99.5% energy is present, are considered while extracting features. The considered DCT coeffecients are divided into 14 equal bins. Similar to FFT features, ratio of individual bin energies to total energy were calculated to give 14 DCT features.

3) Morlet Wavelet Transform (MWT) : Every Wavelet Transform has a basis function termed as mother wavelet. When signal is convolved with the translated and scaled versions of mother wavelet, a variety of signal characteristics i.e. time-frequency information become prominent, observable and measurable. Due to its simplicity and similarity with periodic impulses, Morlet wavelet is well known for use in vibration signal analysis. Drill wear causes impulse variations in vibration recordings and are important to be captured for recognizing the drill bit's current state. MWT coeffecients have therefore been considered here for giving useful features.

$$y_{(a,b)} = e^{\frac{-b^2(t-b)^2}{a^2}} \cos\left(\frac{\pi(t-b)}{a}\right) \qquad (1)$$

Morlet wavelet is mathematically defined in (1). Two scales of Morlet wavelet have been considered here, one with a = 8 and other with a = 16. These values were decided by experimenting with various possible values and finding which pair amongst them gave best results. Signal is then convolved with both wavelets to give two sets of MWT coeffecients. From each set, 7 features have been extracted by finding the coeffecients' statistical parameters namely standard deviation, variance, skewness, kurtosis, sum of peaks, variance and zero crossing rate. In total, thus 14 features are got.

4) Wavelet Packet Transform (WPT) : WPT is considered an important tool while studying non stationary signals [21]. It is fast to compute and works on a similar principle as in Discrete Wavelet Transform (DWT). Whereas decomposition in DWT generally occurs only with approaximation coeffecients, in WPT they occur on both sides i.e. with approximation coeffecients as well as with detailed coeffecients. The transform can be considered as a series of low pass and high filters at many scales to give approximation and detailed coefficients at each level. When decomposition occurs upto l level, it can be seen as a balanced binary tree of l levels and $2^{l+1}-1$ nodes, with each node containing either approximation coeffecients or detailed coeffecients. As level increseses, time resoltion gets poorer while frequency resolution gets better. For extracting features, WPT coeffecients are found upto 3rd level. Not considering the topmost node, a total of 14 nodes with coeffecients are found. Calculating the node energies of all 14 nodes gives 14 features.

D. Dimensionality Reduction

As known from the Curse of Dimensionality issue, having more features with less training samples is very bad from generalization point of view. The situation worsens when many of the features are redundant in information. To avoid this situation, two ways were used to reduce the number of features. Firstly domain/transform wise features were individually used to see if features from a single transform are sufficient for the recognition process. Apart from that, Principal Component Analysis, a well-known dimensionality reduction technique was tested separately. PCA works on the principle of transforming correlated feature space to an orthogonal uncorrelated space and then choose those basis functions which have maximum variance. More details regarding PCA can be found in [22].

E. Classification

After getting the reduced set of features, for learning relationship between features and the respective class labels, a classifier is built over the training samples. Three well known classifiers namely Support Vector Machine (SVM), Bayes Classifier and Artificial Neural Network have been tested here.

1) Support Vector Machine: SVM [23] is a very popular binary classifier which performs extremely well with less training data. In a linearly separable case, SVM finds the hyper-plane which separates the two classes with maximal margin. Maximal margin ensures lower VC dimension; hence higher generalization i.e. better performance on test samples. On similar concept, solutions for non linearly separable cases and non separable cases are also found. In this paper, C-SVM with RBF kernel is used. The parameters namely C and γ were found with crossvalidation based performance checks while varying C and γ through various possible values, also known as grid search method. The pair of (C , γ) giving best crossvalidation performance value was finally used for building the SVM classifier.

2) Bayes Classifiers: Bayes classifier [24] is a probablistic classifier based on Bayes theorem which assumes all the features to be linearly independent. Using prior information of individual classes and likelihood of samples, the classifier for a test sample computes posteriori probability of each class using (2). The class having maximum posteriori probability then becomes the assigned class of the sample. When priori probabilities and likelihood are not available, the same are learned from training samples. Priori probability is based on deductive reasoning and not on past beahavior, whereas posteriori probability is given by accounting relevant evidence and background.

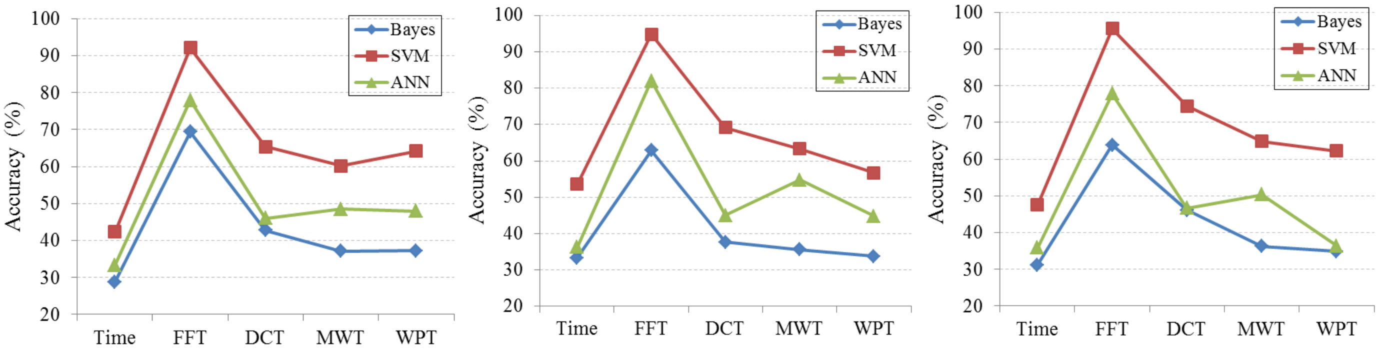
$$P\left(c_i \middle| \mathbf{x}_w, \mathbf{X}\right) = \frac{p\left(\mathbf{x}_w \middle| c_i, \mathbf{X}\right) P\left(c_i \middle| \mathbf{X}\right)}{\sum_{c'=1}^{L} p\left(\mathbf{x}_w \middle| c', \mathbf{X}\right) P\left(c' \middle| \mathbf{X}\right)} \qquad (2)$$

In (2), c_i refers to the class under consideration for finding posteriori probability and L refers to the number of classes. $\mathbf{X}$ refers to training data used for getting prior information and $\mathbf{x}_w$ refers to the test sample under consideration. Bayes classifier acts as an important benchmark in classification and works best for large training data.

3) Artificial Neural Network: Artificial Neural Network (ANN) is an extremely powerful tool for learning very complex feature-feature and feature/s-class relationships. ANN started by mimicing biological neural network and is generally based on adaptive neurodynamics structure. It is typically defined by three types of parameters : a) different layers of neurons having interconnection pattern, b) learning techniques involved for the updation of interconnection weights and c) conversion of neuron's weighted input to its output by an activation function. Number of neurons in input layer and output layer is equal to number of input features and number of output classes respectively. The network may contain single or multiple hidden layers. As single hidden layer suffices for most purposes, only single hidden layer network has been considered here. There is no proven best criteria to determine the number of neurons in hidden layer. It is either found by empirical formulations like crossvalidation checks or by experience based thumbrules, for eg. [25] recommends number of hidden neurons should fall in between the input and output layer size and [26] suggests that the number should not be more than the size of input layer, etc. In the case study presented here, number of hidden neurons have been equated to the mean of input layer number and output layer number of neurons. As mentioned earlier, ANNs are extremely powerful and flexible; due to which they are also known as arbitrary function approximator i.e. they can fit any function. This flexibility though makes it prone to overfitting and may largely provide suboptimal results. To avoid such situations, it is encouraged to have more training data with good variety.

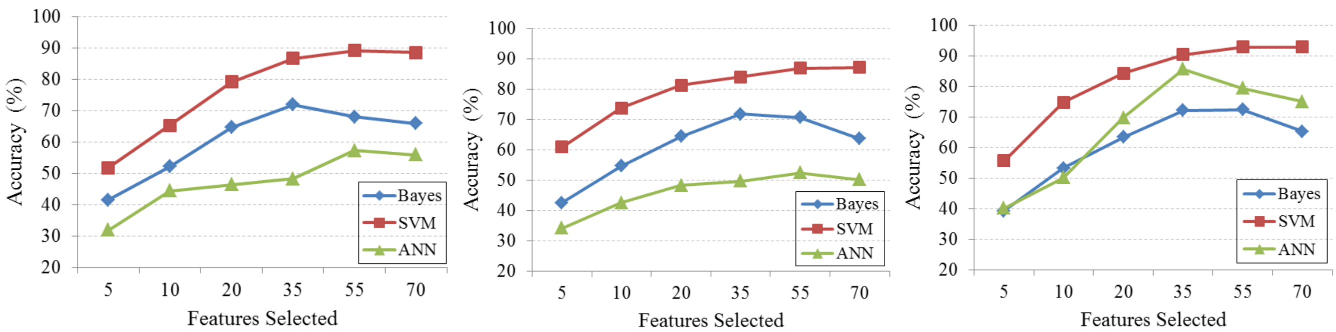
IV. Case Study, Results and Discussions

The entire experimentation was performed with 3-Axis CNC EMCO Concept Mill 105. HSS twist drill bit of diameter 9 mm was used for drilling holes in the work piece made of Mild steel. The target of the case study was to make a state recognition system that is able to accurately recognize 4 drill bit states namely Healthy state, Flank wear state, Chisel wear state and Outer corner wear state. For extensive experimentation, given a drill bit state, for each pair of varying feed rates and cutting speed combinations, a single vibration recording of 8 seconds was taken [30]. Feed rate was varied as 4 mm/min, 8 mm/min and 12 mm/min, and Cutting speed was varied as 160rpm, 170rpm, 180rpm, 190rpm and 200rpm; giving a total of 15 combination pairs. To increase training samples, the 8 second recording was then divided into 8 one second recordings. Thus for each state, 15x8 = 120 recordings were taken i.e. a total of 480 recordings for 4 states. Additionally, for analyzing fault recognition capability in steady stage and penetration stage of drilling, separate sets of 480 recordings were taken for both stages.



(a) (b) (c)

Fig. 4. Performance plot with Domain wise Features for (a) Steady State, (b) Penetration State and (c) Both Steady state and Penetration state combined



(a) (b) (c)

Fig. 5. Performance plots with PCA for (a) Steady State, (b) Penetration State and (c) Both Steady state and Penetration state

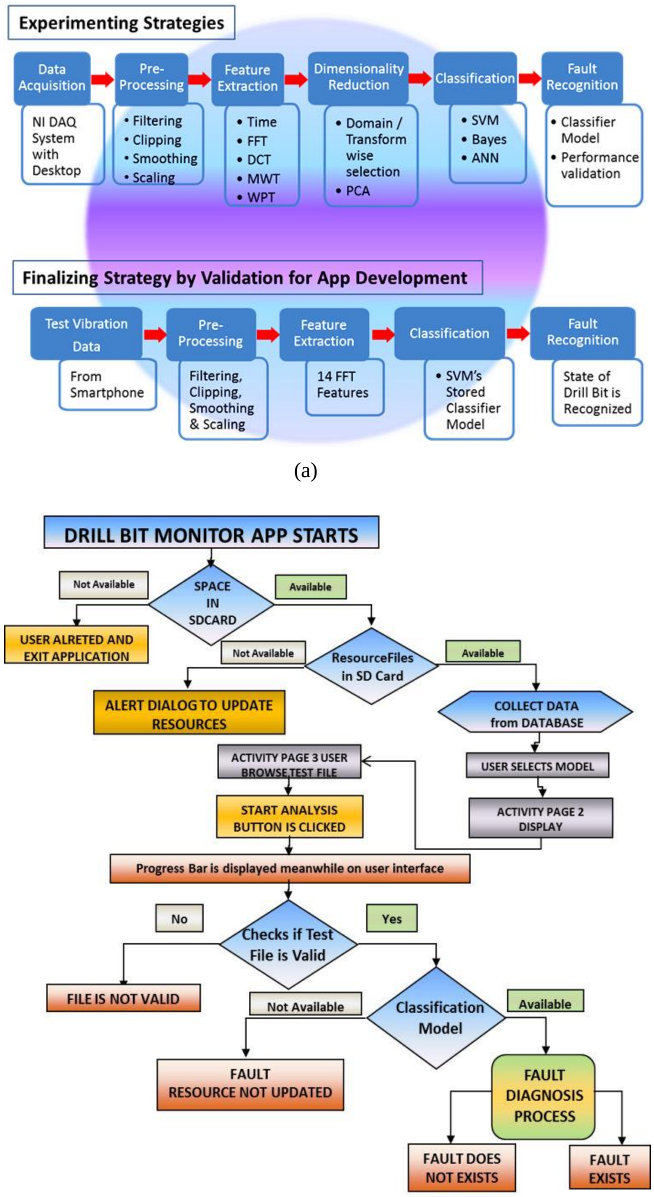
Overall 6 experiments were performed whose results are shown by 6 plots given in Figures 4 and 5. The three classifiers namely Bayes, SVM and ANN have been tested separately and their results are shown by three separate performance plots in all figures. In all experiments, average of 4 fold cross validation classification accuracies was used as the performance measure and forms the Y axis of result plots. Contrary to Bayes classifier and SVM, ANN produces different results every time it is run, as the minima it reaches during optimization depends on the random starting point. For this reason, while generating results with ANN, the classifier was tested thrice and average of the three outcomes was noted to make plots. Also as mentioned earlier, 8 recordings of 1 second were taken for each pair of feed rate and cutting speed in each drill bit state. While forming the 4 folds, care was taken such that in each fold, 6 of every set of 8 recordings became part of training set and remaining 2 became part of testing set. This was done to ensure that sufficient and similar variety in training and test datasets is always present.

In first set of three experiments, domain wise features were selected for dimensionality reduction i.e. 14 features from a single domain/transform were used at a time for fault recognition. Their results for Steady stage and Penetration stage recordings are shown in Fig 4(a) and 4(b). A third case was also taken where both Steady stage and Penetration stage data were mixed and used for training and testing. The purpose of this third case was to check if the two stages had any strong dissimilarities which if true could give bad performance with algorithms. The results of third case are shown in Fig. 4(c). In the plots, the five domains/transforms' features namely Time, FFT, DCT, MWT and WPT have been shown separately in X axis. A separate set of three experiments were performed while using PCA for dimensionality reduction.. Similar to Fig. 4, Fig 5(a) shows results for Steady stage recordings, Fig. 5(b) shows results for Penetration stage recordings and Fig. 5(c) shows the results when both Steady stage and Penetration stage recordings were mixed together. In Figure 5, X axes represent the number of features that PCA was made to reduce. Multiple inferences can be made by analyzing the results. First important inference would be that in all cases, SVM performed better than the other two classifiers. Also among the five domains/transforms considered here, FFT features have significantly outperformed others with all three classifiers. This shows that spectral analysis is most powerful for drill bit monitoring with vibration data. A significant jump can be seen in Bayes classifier after applying PCA. This reconfirms the statement that Bayes classifier works well with linearly independent and uncorrelated features. Another important observation would be that when Steady stage and Penetration stage data were mixed for training and testing, the performance still seemed to be fine; in fact for some cases it was better than individual stages' recordings. This means there are no significant dissimilarities to disrupt data. The reason for improvement in results in some cases would be because when both stages' recordings are combined, training data would be larger and would have slightly more variety, which is good from generalization perspective. Also there is no clear inference as to which stage recordings perform better, as none of them seem to outperform other in most cases. Best performance amongst all cases was found to be 95.52% when FFT features were used along with SVM while both stages' recordings were mixed. From that perspective, domain wise dimensionality reduction fared better than PCA. Thus for final implementation in smartphone, the flow planned to be used was Pre-processing stage followed by Feature extraction stage for extracting FFT features and SVM classifier modeled with both stages' recordings. Summary of model development and operation phase is shown in Fig. 6(a).

V. SMARTPHONE APP DEVELOPMENT

For allowing easy and regular check on drill bit's health, a smartphone application named "*Drill Bit Monitor*" has been developed on Android platform. By using either wired or wireless accelerometers, vibration data could be collected on a PC, which in turn would allow the data to be accessed on Cloud. For development of the Smartphone App, Eclipse IDE (Indigo version 3.7.2) with Android Development Tool (ADT) 22.0.3 plugin was used. This plugin provides support for development and debugging of App via simulation on Android Virtual Device Emulator. For implementation, external libraries namely *apache commons math* and *LIBSVM* libraries were also used. For deploying the application, user should install the installable named *DrillBitMonitor.apk* onto smartphone and store the *Resource Files* folder in SDcard. This folder contains database of all models/make of Drill Bits and the respective states which the App would support for fault recognition. The Resource File has information about drill model no., type and number of states for which it can be tested.

The App consists of five activity pages namely Drill Bit Input page , Confirmation page, Data Input page, Processing page and Results page. Snapshots of four activity pages running on a smartphone have been shown in Fig. 7. Flow chart presenting summary of the App's workflow is shown in Fig. 6(b). The App first takes input from user and collects information about drill bit and its model from *Resource Files* folder in SDcard. Second page shows stored information about the Drill Bit make and also asks user for confirmation that whether he/she wishes to go ahead for testing. After confirming the inputs, user proceeds to third



(a)

(b)

Fig. 6. (a) Summary Flow of Work, (b) Underlying Flow Chart of Smartphone App

page where he/she is asked to browse the input test file that he/she wishes to test. While browsing, the user can select files from either Cloud or internal phone memory or Phone's SDcard. After selecting the file, user selects the fault he/she wants to check for and then clicks the "*Start Analysis*" button. The user proceeds to a Processing page where a progress bar appears on the interface. While progress bar runs in front end, all processes needed during testing phase are run in back end i.e. pre-processing of recording, extraction of FFT features and classification using SVM with needed SVM model/s stored in *Resource Files* database folder. The entire processing in a smartphone with 1.5 Ghz dual core Krait processor, on average took little less than 10 seconds to compute. The user then proceeds to the Results page where based on classification result, determined drill bit state is presented.

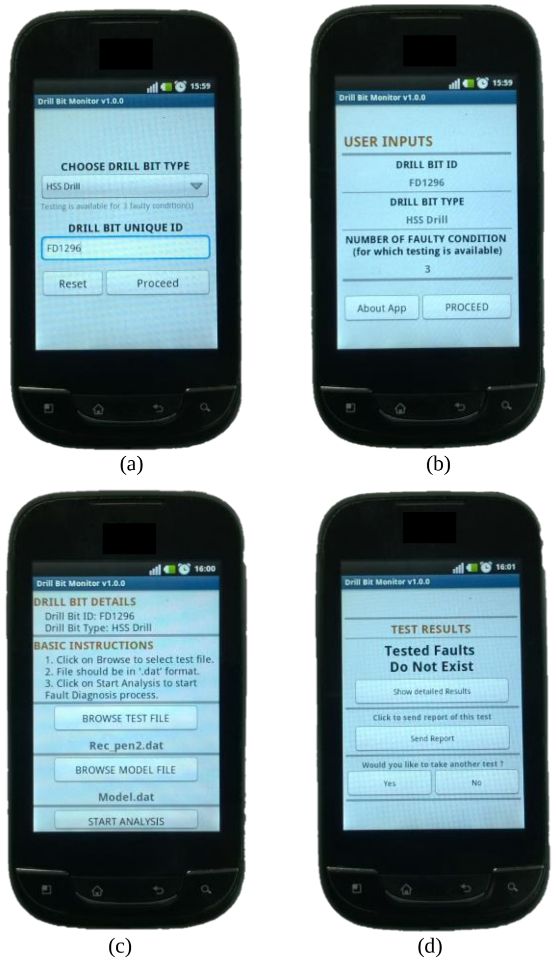


Fig. 7 Android App for Drill Bit Monitoring. (a) Drill Bit Input page, (b) Confirmation page, (c) Data Input page, (d) Results page

VI. Conclusions

An efficient strategy for drill bit monitoring has been presented in this paper. The strategy for test data had following steps: pre-processing with four steps namely filtering, clipping, smoothing and scaling, followed by feature extraction of FFT features and classification with SVM classifier using RBF kernel. This strategy was decided by experimenting with features from five domains/transforms, two dimensionality reduction methods and three classification methods. The final strategy was implemented as a Smartphone Application. The App allows users to recognize the state of drill bit recordings present on Cloud in less than ten seconds and with accuracy up to 95.52%. Future work would be to arrange setup that allows smartphones to directly collect vibration data from sensor/s present on machine/s.

Acknowledgment

Authors express sincere gratitude to The Boeing Company, USA, for sponsoring this research work at IIT Kanpur.

References

[1] Furness R.J., Tsao T.C, Rankin J. S., Muth M. J. and Manes K. W., "Torque Control for a Form Tool Drilling Operation", *IEEE Trans. Control Syst. Tech.*, vol. 7, pp. 22–30, 1999.

[2] Brinksmeier E., "Prediction of Tool Fracture in Drilling", *CIRP Annals-Manufacturing Technology*, vol. 39, no. 1, pp. 97-100, 1990.

[3] Byrne G., Dornfeld D., Inasaki I., Ketteler G., König W., and Teti R., "Tool condition monitoring (TCM)—The Status of Research and Industrial Application", *CIRP Annals-Manufacturing Technology*, vol. 44, no. 2, pp. 541-567, 1995.

[4] Dimla S. and Dimla E., "Sensor Signals for Tool-Wear Monitoring in Metal Cutting Operations—a Review of Methods", *International Journal of Machine Tools and Manufacture*, vol. 40, no. 8. pp. 1073-1098, 2000.

[5] Liang, Steven Y., Hecker R. L. and Landers R. G., "Machining Process Monitoring and Control: The State–of–the–Art", International Mechanical Engineering Congress and Exposition, American Society of Mechanical Engineers, 2002.

[6] Jantunen E., "A Summary of Methods Applied to Tool Condition Monitoring in Drilling", *International Journal of Machine Tools and Manufacture*, vol. 42, no. 9, pp. 997-1010, 2002.

[7] Patra K., "Acoustic Emission based Tool Condition Monitoring System in Drilling", Proceedings of the World Congress on Engineering, 2011, vol. 3, pp. 6-8.

[8] Everson C. E., and Cheraghi S.H., "The Application of Acoustic Emission for Precision Drilling Process Monitoring", *International Journal of Machine Tools and Manufacture*, vol. 39, no. 3, pp. 371-387, 1999.

[9] Ertunc, Metin H. and Oysu C., "Drill Wear Monitoring using Cutting Force Signals", *Mechatronics*, vol. 14, no. 5, pp. 533-548, 2004.

[10] Cuppini D., D'errico G. and Rutelli G., "Tool Wear Monitoring based on Cutting Power Measurement Wear", *International Journal on the Science and Technology of Friction, Lubrication and Wear*, vol. 139, pp. 303–311, 1990

[11] Patra K., Pal S.K. and Bhattacharyya K., "Artificial neural network based prediction of drill flank wear from motor current signals", *Applied Soft Computing*, vol. 7, no. 3, pp. 929-935, 2002.

[12] Wardany E., Gao T.L.D. and Elbestawi M.A. "Tool condition monitoring in drilling using vibration signature analysis", *International Journal of Machine Tools and Manufacture*, vol. 36, no. 6, pp. 687-711, 1996

[13] Abu-Mahfouz and Issam. "Drilling Wear Detection and Classification using Vibration Signals and Artificial Neural Network", *International Journal of Machine Tools and Manufacture*, vol. 43, no. 7, pp. 707-720, 2003.

[14] Kanai M. and Kanda Y., "Statistical characteristics of drill wear and drill life for the standardized performance tests" *Annals of CIRP*, vol. 27, no. 1, pp. 61-66, 1978.

[15] Verma N.K., Jagnaatham K., Bhairat A, Shukla T. and Subramanian T., "Statistical Approach for finding Sensitive Positions for Condition Based Monitoring of Reciprocating Air Compressors", IEEE Control & System Graduate Research Colloquium, 2011, pp.10-14.

[16] Sheskin D. J., “Handbook of Parametric and Nonparametric Statistical Procedures”, CRC Press, 2003.

[17] Jones M.C. and Sibson R., “What is Projection Pursuit ?”, *Journal of the Royal Statistical Society, Ser. A*, vol. 150, no. 1, pp. 1-37, 1987.

[18] Vidaurre C., Krämer N., Blankertz, B. and Schlögl A., “Time Domain Parameters as a Feature for EEG-based Brain Computer Interfaces”, *Neural Networks*, vol. 22, no. 9, pp. 1313-1319, 2009.

[19] S. L. Marple, Digital Spectral Analysis with Applications, 1987 : Prentice-Hall

[20] Qingbo H., Kong F. and Yan R., "Subspace-based Gearbox Condition Monitoring by Kernel Principal Component Analysis", *Mechanical Systems and Signal Processing* , vol. 21, no. 4, pp. 1755-1772, 2007.

[21] Xiaoli Li., "On-line Detection of the Breakage of Small Diameter Drills using Current Signature Wavelet Transform", *International Journal of Machine Tools and Manufacture*, vol. 39, no. 1, pp. 157-164, 1999.

[22] Jolliffe I.T., Principal Component Analysis. New York: Springer-Verlag, 1986.

[23] Vapnik V. and Naumovich V., “Statistical learning theory” New York: Wiley, vol. 2 ,1998.

[24] Meyer E. and Tuthill T., “Bayesian Classification of Ultrasound Signals using Wavelet Coefficients”, IEEE National Aerospace and Electronics Conference, 1995, pp. 240–243.

[25] Masri, S. F., Smyth A. W., Chassiakos A. G., Caughey T. K. and Hunter N. F., "Application of Neural Networks for Detection of Changes in Nonlinear Systems", *Journal of Engineering Mechanics*, vol. 126, no. 7, pp. 666-676, 2000.

[26] Goumas S.K., Zervakis M.E. and Stavrakakis G.S., "Classification of Washing Machines Vibration Signals using Discrete Wavelet Analysis for Feature Extraction", *IEEE Transactions on Instrumentation and Measurement*, vol. 51, no. 3, pp. 497-508, 2002.

[27] Google Android Developers, Android Developer Guide, http://developer.android.com/guide/topics/fundamental.html

[28] Commons Math Developers, Apache Commons Math, Release 2.2 Available: http://commons.apache.org/math

[29] Chang C.C. and Lin C.J., “LIBSVM : a library for support vector machines”, *ACM Transactions on Intelligent Systems and Technology*, vol. 2, no. 3, pp. 27-27, May 2011.

[30] Kumar A., Ramkumar J., Verma N. K. and Dixit S., "Detection and Classification for Faults in Drilling Process using Vibration Analysis", IEEE Prognostics and Health Management, June 2014, pp. 1-6.

AUTHORS BIOGRAPHY

Nishchal K Verma (M’05 & SM’13) received his Ph.D. from IIT Delhi, India, in 2007 in Electrical Engineering. He is currently an Associate Professor with the Department of Electrical Engineering, IIT Kanpur, India. He is Editor of IETE Technical Review, an Associate Editor of Transactions of the Institute of Measurement and Control, UK and Editorial board member for several reputed journals and conferences. His research interests include Big Data, Internet of Things, Intelligent Data Mining Algorithms, Diagnosis and Prognosis of Rotating Machines, Computer Vision and Computational Intelligence.

Rahul Kumar Sevakula (M’12) was born on October 31, 1987. He received B.Tech. degree from National Institute of Technology Warangal in 2009. He is currently a doctoral student at Electrical Engineering Dept. of IIT Kanpur and also the Student Head of IEEE U.P. Section Chapter, Computational Intelligence Society. His research interests include Machine Learning Algorithms, Fuzzy Systems, Intelligent Informatics and Health monitoring.

Sonal Dixit (M’13) was born in India on July 31, 1989. She received her B.E. in Computer Science from RGPV University of in 2009 and Masters in Computer Science from Banasthali University in 2011. She is currently a doctoral student at IIT Kanpur and Secretary of IEEE U.P. Section Chapter, Computational Intelligence Society. Her research interests fall mainly in the field of Machine Learning, Intelligent Informatics, Natural Language Processing and Condition based Monitoring of Rotary Machines.

Al Salour is a Technical Fellow at The Boeing Company’s research & technology organization. Al is leading the manufacturing technologies for equipment and process health monitoring as well as automated identification. In these areas he has developed methods and procedures to collect performance data from machine tools and robotic systems and report them in real time to the operation users. He has installed multiple systems to initiate automated manufacturing transactions and alert notifications for quick actions and has focused on eliminating non-value added tasks. Dr. Salour is the Chairman of the Intelligent Maintenance Systems (IMS) industrial advisory board supported by four universities and 60 member companies.