ISSN 2250-3153

Proactive condition Monitoring Systems for Power Plants

Shameer V. Hameed[*], Shameer K. M[**]

[*] Department of Mechanical Engineering, S.C.M.S School of Engineering and Technology, karukutty-683582
[**] Research at Bharathiar University, Coimbatore

***Abstract-* Power** plant condition monitoring systems are pervasive around the industrial space of mechanical systems due to the ever-increasing demand for improved reliability and fail proof operation. Much of the downtime can be obviated with proactive maintenance by measuring vital machine parameters to discover imminent failures. The condition of the turbine and the generator are monitored using the characteristic signatures present in the Acoustic Emanations generated by the vibrating components of the reciprocating parts. The feeble noise of the malfunctioning components will not be detectable at the beginning stages as they are often buried in the noise floor and this creates a major challenge in prognostic reporting of the events that could lead to a catastrophic failure. In this paper an attempt is made to lift and isolate the fault signatures that are hidden behind the noise floor by utilizing Digital Signal Processing Source separation techniques, which is then compared with a pre-collected data base of the different fault stages of the turbine and generator that helps in prognostic report making which in turn eliminates the need of trained professionals for condition monitoring. Implementation of this prototype system will effectively reduce the downtime of power generation along with the elimination of expensive human professional. The collected acoustic data are simulated in MATLAB.

***Index Terms*-** Proactive condition monitoring, Noise floor, Classifier, Neural networks.

I. INTRODUCTION

Power plants productivity depends profoundly on turbines and generators. In order to maximize the power plant efficiency, the rotating parts of the turbines and generators should work with less downtime and maximum throughput. Rotating parts of the power plants passed through a series of subsequent stages before catastrophic failure occurs. The reciprocating parts of the generators produce acoustic emanations during it operations and it varies as it goes through different stages of its lifetime, which is being utilized for monitoring the moving parts of the power plant. Proactive monitoring systems continuously listen to the acoustic emanations of the interested bearings and shafts and helps in making prognostic report for taking necessary actions, which leads to fail proof operation of the plant.

The proposed system acquire signals from the power generating machine trains that often buried in the noise floor which is then separated and elevated from the noise using blind source separation, a digital signal processing technique. The source separated fault signals are classified in to corresponding class and the fault stage preceding to failure are identified that gives way for a mechanical engineer to prepare timely report for proactive maintenance. Based on the report the malfunctioning components of the plant can be identified at each stage before it stops and appropriate maintenance schedule can be prepared and carried out without affecting the overall productivity of the plant.

Power generation efficiency of a plant is an interesting problem and a lot of capital and human effort is spend on this for maximum fail proof operation. By the implementation of the prototype system human effort in diagnosing, the faulty stages are being reduced drastically. Automated monitoring helps in recognizing the malfunctioning parts at an earlier stage with great accuracy and to eliminate the expense in maintaining an expert engineer for the purpose.

II. METHODOLOGY

Acoustic emanations from the vibrating parts of the power plant machinery of monitoring interest are acquired, preprocessed and source separated from the background mixture using BSS a signal processing technique. The decomposed signal contains the independent acoustic sources from the entire vibrating components of the power plants being made utilized for the proactive monitoring. The source-separated signals, includes bearing noise, rotor, shaft, piston slap, turbine noise etc. are classified into corresponding class labels using an artificial neural network classifier with the help of pretrained database of the interested components. Classifier with prior knowledge of various fault stages of the components to be monitored categorizes each stage of a component from its normal operation to fault and the present stage of the monitoring component is indicated, which helps in preparing the prognostic report for scheduling the maintenance task that constructively brings down catastrophic failure and down times, resulting in improved performance and efficiency of the power plant. Block diagram of the prototype system is depicted in figure 1.

III. SOURCE SEPARATION

Sensors attached to the interested parts of the power plant to be monitored, consists of an exotic ensemble of background noises emanating from all parts, that should be source separated for further classification and fault detection. Acoustic emissions from each parts of the machinery have a unique feature set that reveals its identity among the noise mixture are extracted, after the mixture being source separated. Separation of the interested signal sources were accomplished by component analysis for estimating the individual signals. The composite signal mixture

ISSN 2250-3153

observed from the sensors are decomposed into its independent components using statistical technique by applying linear transformations to co-ordinates for extracting the machine modeling signals below the noise floor. ICA method works on certain assumptions that the source components are independent and have non-Gaussian distributions

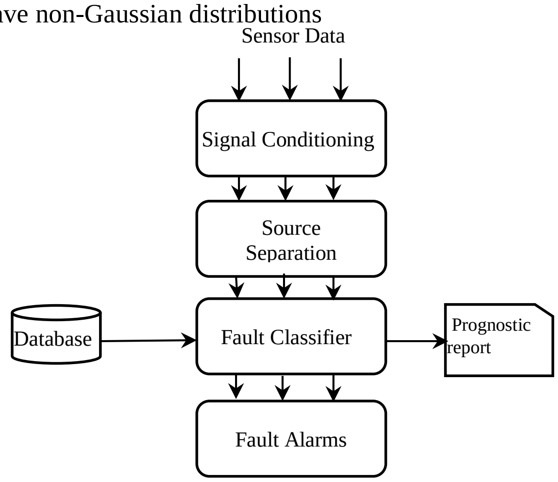

Figure 1. Block diagram of prototype system

. ICA decomposes the simultaneous signals from various sensors attached to the generator and power train assembly of the turbines of the power plant. The process of decomposition of these simultaneous independent signals starts with a signal pre-whitening stage followed by an optimization stage, which retrieves the independent source signals.[1],[5-7] ICA isolates and extracts the vital signals buried under the noise floor. The decomposed independent signals are feature extracted and then recognized with an artificial neural network classifier.

IV. Mel Frequency Feature Extraction

Among the set of spectral features generally used for acoustic feature extraction, Mel Frequency Cepstral Coefficients (MFCC) has a special position due to its simplicity and robustness. MFCC represents the signal as a sequence of compact Mel Frequency Spectral Coefficients or feature vectors, which could effectively reduce the computational complexity of the subsequent stages. The MFCC feature estimation process divides the incoming signal stream into finite width frames and a windowing function (Hamming window) is used to remove the effect of frame discontinuities. The frames are converted into frequency domain using a DFT function. The frequency domain frames are transformed into the mel pitch scale and the frequency scale-warping converts it into the cepstrum domain. By taking the inverse DFT of the converted scale, the signal is restored again into the time domain.The mathematical abstraction of the process can be described as follows:

The DFT of the input signal $x(n)$ is given by:

$$X(k) = \sum_{n=0}^{N-1} x(n) \exp\left(-\frac{j2\pi nk}{N}\right) \qquad (1)$$

$$k = 0,1,2, \dots \dots \dots N-1$$

Each Fourier Transform magnitude coefficient $X(k)$ is multiplied by a sequence of triangular gain filters and the results are accumulated. The Mel-frequency filter bank [132], [133] comprises of p filters with the energy in each band given by mj (j=1, 2,…,p), and is computed as:

$$m_j = \sum_{k=0}^{N-1} \left|X_{(k)}\right|^2 \; H_j(k) \qquad 0 \le j \le p \qquad (2)$$

where Hj (k) is the transfer function of jth filter. The Mel-frequency cepstrum is then the discrete cosine transform [55] of the p filter outputs and is represented as

$$c_i = \sqrt{\frac{2}{N}} \sum_{j=1}^{p} m_j \cos\left(\frac{\pi i j}{p}\right) \qquad (3)$$

Where ci is the ith MFCC coefficient.

A series of equal area triangular filters are designed to achieve the filtering process happens in ear preceded by the cepstral step where the mel frequency coefficients are converted back to time domain.

V. Defect Identification and classification

Fault identification of the interested bearing is based on the classification of input signals into its corresponding faulty stage with a classifier. Classifier identifies the component malfunctioning stages, by utilizing the prerecorded trained database. Artificial neural network classifiers are used for the defect identification task, as it acts as a basic background techniques for pattern recognition. Probabilistic neural networks (PNN) are a type of ANN which uses probabilistic approaches for the statistical inference of the fault stage identification. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. The fundamental processing element of a neural network is a neuron. This building block of human awareness encompasses a few general capabilities. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then outputs the final result.

PNN is a multilayer perceptron consisting of an input layer, output layer and intermediate layers, which perform activation function and weight adjustment for training the network for a particular output. PNN that is widely accepted as a classifier, proposed for the classification due to the advantage of faster training process compared to back propagation algorithms and its flexibility to add or remove training samples without extensive retraining. Probabilistic neural network is a computational simulation of a biological neural network, an implementation of a statistical algorithm called kernel discriminant analysis in which the operations are organized into a multilayered feed forward network with four layers such as Input layer, Pattern layer, Summation layer and Output layer. PNN offers a cost-effective and reliable approach to condition monitoring. Using artificial neural networks, collected data regarding the condition of the machinery can be classified and trained in order to generalize a method for data analysis at any time of the measurement. The general architecture of PNN is depicted in figure dddd

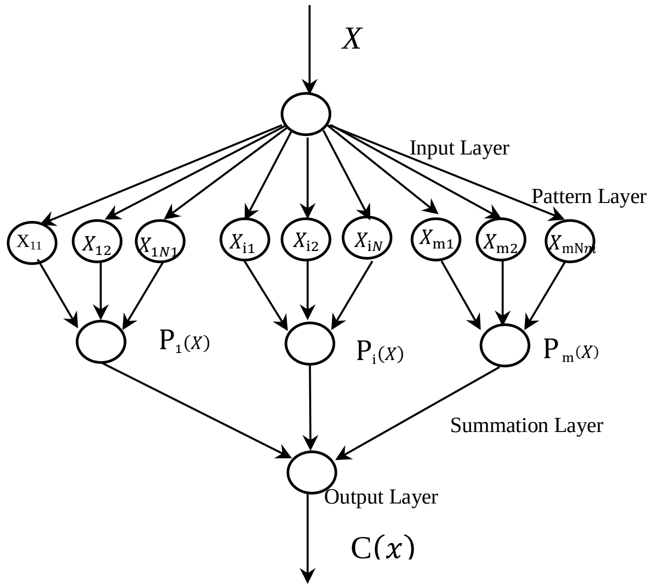

Figure 2. The general architecture of PNN

VI.PROGNOSTIC REPORT MAKING

To reduce repair costs and minimize losses in productivity, more manufacturing operations are turning from preventive maintenance (maintenance based on a fixed schedule) to proactive maintenance and predictive maintenance (maintenance based on objectively determined need) in order to protect their high-value assets. Condition monitoring of crankcase, hydraulic, motor bearings and gear lubricants plays an important role in the maintenance of equipment including heavy machinery and plant equipment .Prognostic report making includes the making of report after the testing phase; the report shows the actual stage of the bearing and this report help the maintenance engineer in charge to arrange the maintenance properly without sudden breakdown. relatively low failure rate of mechanical components compared to electrical components, failures of mechanical components in drive trains often create high repair costs and revenue loss due to long down times.

Two major issues concerning machine condition monitoring are machine fault diagnosis and prognosis. Diagnosis refers to the determination of the current "health" status or working condition of the machine being monitored, whereas prognosis refers to the prediction of the remaining service life in the machine. Reliable diagnosis and prognosis techniques not only reduce the risks of unexpected machine breakdowns, but also help in prolonging machine life. Due to these reasons, the current trend in the maintenance industry is increasingly shifted towards condition-based, preventative, and proactive maintenance

To avoid this sudden failure the prognostic report plays an important role. With the help of condition monitoring system the mechanical engineer in charge can understand the actual stage of the bearing as per the stored data, thereby preplan the maintenance considering the seriousness of the present condition of the bearings.

VII.RESULTS AND DISCUSSIONS

A typical scenario of a bearing malfunction and its evolution through different states has been selected for evaluating the system performance and simulated in Mat lab. The ICA algorithms are able to separate these weak signals that are hidden below the noise floor. The component signals are assumed to have different origins and a priori knowledge is needed to identify the components to which these signals correspond. Supervised learning classifiers have the ability to incorporate a priori knowledge. Because of its ability to recognize subtle patterns in the input data even in presence of noise, PNN classifiers trained with exemplar data have been used to detect and categorize the fault signatures. The prognostic fault stages are enlisted in Table 1.

Table 1 .fault stages

FAULT STAGES	
Fault Stage	Fault Rigorousness
0	Normal functioning
1	Minor Defect
2	Attention required
3	Critical.

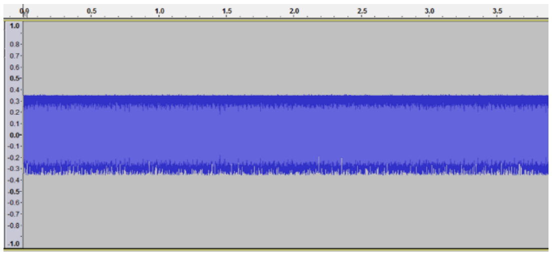

Figure 3. Bearing normal operation

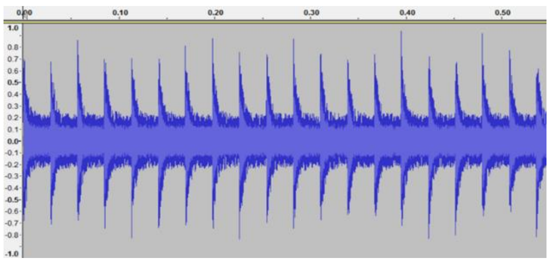

Figure 4. Bearing Stage-2 minor fault

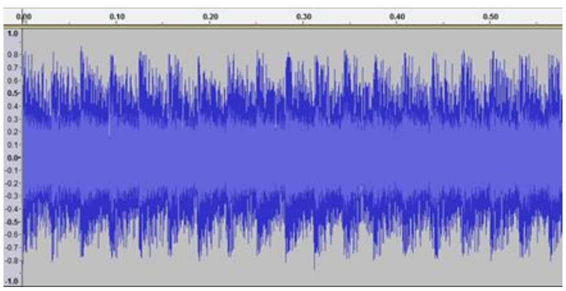

Figure 5. Bearing Stage-3 major fault

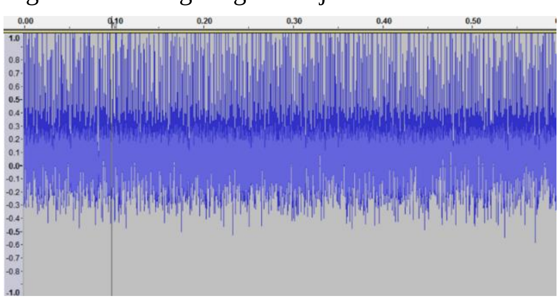

Figure 6. Bearing Stage-4 Faulty

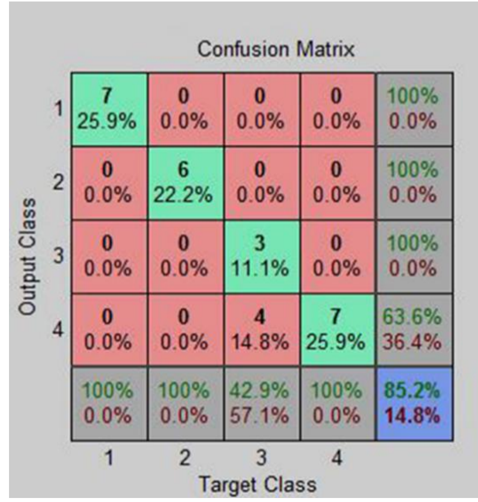

Figure 7.Classifier output

Acoustic signals from a bearing under its different stages of operation are plotted and demonstrated. The normal operation emits acoustics, which gradually varies during its course of operation until it reaches a stage where catastrophic failure occurs. The below shown waveforms gives the clear idea about the variation of sounds according to the conditions of the bearings, from which the sound is collected.

Fig 3. To fig 6 shows the waveforms of different condition of bearings. Fig 7 shows the classifier output, which gives the clear idea about the classification done by the classifier. The output also shows the success rate of the classifier. From this output the maintenance engineer can prepare the prognostic report and thus help to plan the preventive maintenance accurately to avoid sudden failure of the plant.

VI. CONCLUSION

The prototype system shows the effectiveness of ANN in condition monitoring of power plant machineries. By using this method we can detect the fault much faster and helps to take necessary steps for maintenance, thereby reducing the downtime significantly. Implementation of this prototype system in DSP as hardware in power plants helps in real time proactive maintenance.

VII. ACKNOWLEDGMENT

The authors gratefully acknowledge the Department of Mechanical Engineering, S.C.M.S School of Engineering and Technology for extending all the facilities for carrying out this work.

REFERENCES

[1] Suraj Kamal. "Performance Improvement of Proactive Condition Monitoring Systems for Marine Machinery",Accoustic society of india december 2012.

[2] M. Samhouri a,*, A. Al-Ghandoor a, S. Alhaj Ali a, I. Hinti b, W. Massad "An Intelligent Machine Condition Monitoring System Using time based analysis"Jordan Journal of Mechanical and Industrial Engineering Dec 2009

[3] D. Mba1 & Raj B.K.N. Rao "Development of Acoustic Emission Technology for Condition Monitoring and Diagnosis of Rotating Machines; Bearings, Pumps, Gearboxes, Engines and Rotating Structures" The shock and vibration digest -2006.

[4] Amani Raad , Fan Zhang , Ménad Sidahmed "Acoustic Emission for Gear Fault detection" A Promising Tool.Surveillance 5 CETIM Senlis.Oct 2004.

[5] Hyvärinen and Erkki Oja. "Independent component analysis: algorithms and applications", Neural Networks Volume 13, Issues 4-5, June 2000

[6] S.H. Ghaffari, F. Ismail and F. Golnaraghi; Canada "Bearing Prognosis based on Chaotic Indicators, Wavelet Index and Adaptive Neuro-Fuzzy Inference System" ,COMADEM international ,Volume 11, Number 4, October 2008

[7] R.I. Raja Hamzah and D. Mba; Malaysia and UK "Observing the Lubricant Regime of Spur Gears with Acoustic Emissions Technology",COMADEM international ,Volume 12, Number 1, January 2009

[8] M.S. Patil, J. Mathew and P.K. RajendraKumar; India: "Application of Statistical Moments and Spectral Analysis in Condition Monitoring of Rolling Element Bearings",COMADEM international, Volume 12, Number 1, January 2009

[9] J. Rafieea,_, F. Arvania, A. Harifib, M.H. Sadeghi" Intelligent condition monitoring of a gearbox using artificial neural network "Elsevier 2006.

[10] Abhinay V. Dube, L.S.Dhamande, P.G.Kulkarni" Vibration Based Condition Assessment Of Rolling element Bearings With Localized Defects" International Journal Of Scientific & Technology Research Volume 2, Issue 4, April 2013

[11] Yong-Han Kim a, Andy C C Tan a, Joseph Mathew and Bo-Suk Yang" Condition Monitoring Of Low Speed Bearings: A Comparative Study Of The Ultrasound Technique Versus Vibration Measurements"WCEAM 2006.

[12] Hamid Asgari1, XiaoQi Chen2, Raazesh Sainudiin" Applications of Artificial Neural Networks (ANNs) to Rotating Equipment "Third conference on rotating equipment in oil & power industries,Nov 2011

AUTHORS

First Author – Shameer V. Hameed, B.Tech , Department of Mechanical Engineering, S.C.M.S School of Engineering and Technology, saajan.hameed@gmail.com.
Second Author – Shameer K. M., M. Tech, Bharathiar University, Coimbatore.