Condition Monitoring of Rotating Equipment Considering the Cause and Effects of Vibration: A Brief Review

Arka Sen^{1*}, Manik Chandra Majumder², Sumit Mukhopadhyay², Robin Kumar Biswas²

¹*² Mechanical Engineering Department, National Institute of Technology Durgapur, India. ²Condition Monitoring and Structural Analysis Group, Central Mechanical Engineering Research Institute, Durgapur, India.

ABSTRACT: This paper attempts to summarise and review the recent research and developments in diagnostics and prognostics of mechanical systems implementing Condition Monitoring with emphasis on models, algorithms and technologies for data processing and maintenance decision-making. Realising the increasing trend of using multiple sensors in condition monitoring, the authors also discuss different techniques for multiple sensor data fusion. The paper concludes with a brief discussion on current practices, possible future trends of Condition Monitoring with a brief outline on the novelty of the current research work.

Keywords: Condition monitoring, Vibration analysis, Rotating equipment, Fault detection and diagnosis, Signal Processing Techniques.

I. INTRODUCTION

Condition Monitoring of rotating equipment has been a very important aspect in the field of maintenance engineering. There are various types of condition monitoring techniques, namely: Vibration Analysis, Oil Debris Analysis, Ferrography, Temperature analysis. Among all these techniques, vibration analysis have gained much importance in the field of condition monitoring because of its accuracy in detecting faults its ability for proper diagnosis of the faults. Vibration-based condition monitoring (VCM) requires vibration measurement on each. Bearing pedestal using a number of vibration transducers and then signals processing forall the measured vibration data to identify fault(s). The Table 1 below summarises the condition monitoring techniques in brief with their merits and demerits:

| Serial No | Monitoring techniques | Application area | Strengths | Weaknesses |
|--------------|-----------------------------|--|---|--|
| 1 | Vibration analysis | Mass unbalance such as eccentric rotors, bent shafts, and misalignment. | Can be used for permanent as well as temporary monitoring with a break in between. | It is not suitable for small machines. |
| | | | More likely to point to the actual faulty component. | It is not significant for drives used in transport applications. |
| | | | Accurate signal processing techniques which can be applied to vibration signals to take out even very weak fault indications from | |
| | | | noise and other masking signals. | |
| 2 | Lubrication oil analysis | Application of wide range where lubricants themselves might come into contact with the environment | Lubricants to be considered for research oriented purpose. | Oil samples to be taken accurately |

Table 1: Comparison of different fault diagnosis techniques in condition monitoring

Condition Monitoring of Rotating Equipment considering the Cause and Effects of ...

| 2 | | | | |
|---|-------------|---------------------------|---------------------------------|-----------------------------|
| 3 | Current | Mass Shortened turns in | Sensitive to pattern changes in | The improper preload is |
| | signature | the low voltage stator | addition to the amplitude, | difficult |
| | analysis | winding, broken | making fault detection much | to detect |
| | | rotor bar, eccentricity | easier | |
| | | | | In spite of these |
| | | Mechanical faults such as | | monitoring techniques, the |
| | | bear box and load | | induction motors still face |
| | | oscillations | | unexpected failure. |
| 4 | Fourier | Broken rotor barStator | First speed | Lost time information |
| | transform | current | Suitable for varying load | |
| | | | condition | Not effective at lightly |
| | | Short winding | | loaded conditions |
| | | | Easy to implement | |
| | | Air gap eccentricity | | Poor frequency resolution |
| | | Load fault | | |
| 5 | Wavelet | Bearing faults | Light loads | Experts required |
| | transform | - | | |
| 6 | Temperature | Bearing faults | Results are very precious and | Thermal imaging cameras |
| | monitoring | | there is no need for complex | and related software are |
| | | | analysis | very expensive |
| | | | Lead times are shorter | Require expertise |

II. MATERIALS AND METHODS

This review paper is based on different fault detection and diagnosis techniques that have been used in Vibration Condition Monitoring (VCM). The vibration condition monitoring is basically divided into three parts:

A Condition Based Monitoring program consists of three key steps (see Figure. 1):

1. Data acquisition step (information collecting), to obtain data relevant to system health.

2. Data processing step (information handling), to handle and analyse the data or signals collected in step 1 for better understanding and interpretation of the data.

3. Maintenance decision-making step (decision-making), to recommend efficient maintenance policies.

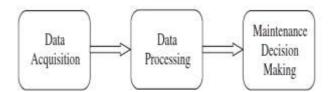


Figure 1: Three steps in Condition Based Monitoring Program

The existing methods for predicting rotating machinery failures can be grouped into the following three main categories:

1. Traditional reliability approaches—event data based prediction.

2. Prognostics approaches—condition data based prediction.

3. Integrated approaches—prediction based on both event and condition data.

Below listed are the various signal processing techniques used for faults detection and diagnosis. Also the prognosis or the prediction of futuristic machine degradation and life assessment procedures are discussed using Artificial Intelligence techniques.

3.1 Various Signal processing diagnosis and prognosis techniques are discussed below:

(i) Time domain analysis , Frequency Domain Analysis and Time Frequency Analysis

In the paper by **Jae Hong Suh** (4) used the vibration data from a gearbox as for the development of the Intelligent Diagnosis and Prognosis System by computing the wavelet coefficients using Morlet wavelet and

Artificial Neural network as classification/decision making tool. Peter W. Tse(7) and D.F Shia (8) designed exact wavelet analysis to enhance the robustness of vibration-based machine fault diagnosis using Genetic Algorithm to reveal the time and frequency properties of the inspected signal.B.Liu (13) proposed a method to select the wavelet packet basis for fault diagnosis of rotating machinery by dividing the signal vector space into two subspaces and represented them in different ways containing the transient components excited possibly by localized defects and the other contains the remaining components.H.X. Chen (14) suggested adaptive wavelet transform (AWT) to model vibration signal usingMorlet wavelet for diagnosis. The defect amplitudes and frequency component of the impulse vibration signal was extracted and displayed in the time-frequency plane. QiangMiao(19) in his paper, have introduced Hidden Markov Model based two-stage machine condition classification system based on wavelet modulus maxima. The modulus maxima distribution was used as the input sequence of the system. An adaptive algorithm was proposed and validated by three sets of real gearbox vibration data to classify two conditions: normal and failure. Rui Zhou (39)proposed redundant secondgeneration wavelet packet transform for fault diagnosis of rotating equipment.Because the length of the coefficients at each level was equal to the length of raw signal after decomposition, the wavelet packet coefficients was able to retain more faulty information. Cusido (40) combined wavelet and power spectral density techniques to give the power detail density as a fault factor which combines the time-frequency analysis of wavelet decomposition allowing a further fault factor estimation. Based on the good shift-invariance and reduced aliasing properties of Dual Tree Complex Wavelet Transform Yanxue Wang (41)incorporated DTCWT with NeighCoeff shrinkage showed better performance than Discreet Wavelet Transform and Second Generation Wavelet Transform based methods for faulty detection and diagnosis of rotating machinery. F. Al-Badour (45) in his research work studied the application the Wavelet Packet Transform, to fault detection in rotating machinery.Failure of FFT techniques in detecting faults from non-stationary signals was mentioned in his study.Lei Youa (46) proposed a new type of fault diagnosis system of rotating machinery vibration signal, which can measure the vibration acceleration and velocity signals accurately, and analyse the vibration severity and frequency division amplitude spectrum of vibration signal. Based on wavelet and correlation filtering, Shibin Wang (49) proposed a technique incorporating transient modeling and parameter identification for rotating machine fault feature detection by which both parameters of a single transient and the period between transients was identified from the vibration signal, and localized faults was detected based on the parameters, especially the period.Z.K Peng (53) in his research developed the time-frequency data fusion (TFDF) technique by incorporating the idea of data fusion technique and by combining the results produced by two or more different TFA methods i.e. Short Time Fourier Transform and Continuous Wavelet Transform. The TFDF technique was more accurate time-frequency presentation for the target signal than that of any individual TFA method.Md. Abdul Saleem (55) found the 'Deflected Shape of Shaft' (DSS) of a rotating machine for detecting unbalance in its rotating components using Fast Fourier Transform (FFT) method. B. Kiran Kumar (56) in his paper measured the vibration velocities at five different speeds using FFT (Fast Fourier Transform) at initial condition. Based on vibration readings, spectrum analysis and phase analysis was carried out to determine the cause of high vibrations and later by observing the spectrum, unbalance was identified. Bin Qiang Chen (60) proposed afast spatial-spectral ensemble kurtosis technique by incorporating discrete quasi-analytic wavelet tight frame(QAWTF) expansion methods were as the detection filters.Jun Wang (61) focussed on the improved time-scale representation by considering the non-linear property for effectively identifying rotating machine faults in the time-scale domain. He represented a new time-scale signature, called the Time Scale Manifold, by combining the Continuous Wavelet Transform and the non-linear manifold learning, for representing intrinsic machinery fault pattern, and explores the TSM ridge to identify the fault characteristic frequency. Qingbo He (62) combined the concepts of time-frequency manifold (TFM) and image template matching, and proposed a novel TFM correlation matching method to enhance identification of the periodic faults in a rotating machine. This method conducted the correlation matching of a vibration signal in the time-frequency domain by using the TFM with a short duration as a template.Dongju Chen (67) in his research work computed the frequency information for the spindle system, the results between the modal information of the spindle and the error frequency of the measured work piece surface which processed by wavelet transform and power spectral density was compared and the signal feature in the waviness which was consistent with the spindle unbalance frequency was extracted.Chen Bin Qiang (69) proposed a pseudo wavelet system (PWS) based on the filter constructing strategies of wavelet tight frames to address the deficiencies of discreet wavelet transform which was implemented via a specially devised shift-invariant filter bank structure that generated non-dvadic wavelet sub bands as well as dyadic ones. M. Lokesha (75) presented automatic detection and diagnosis of gear condition monitoring technique using Laplace and Morlet wavelet based enveloped power spectrum. The time and frequency domain features extracted from Laplace wavelet based wavelet transform are used as input to ANN for gear fault classification. Genetic algorithm was used to optimize the wavelet and ANN classification parameters. Shibin Wang (87) proposed a method based on transient modeling and parameter identification

through Levenberg-Marquardt (LM) methodfor fault feature extraction of vibration signals. The double-side asymmetric model for the assigned problem was constructed based on parameterized Morlet wavelet, then the LM method was used to identify the parameters of the model. An iterative procedure was implemented to extract transients from the vibration signal, and eventually all extracted transients are represented in Time Frequency plane with satisfactory energy concentration, and there is no interference of cross- term among different transients. Y. Yang (88) proposed the procedure for procedure for the parameterized Time Frequency Analysis(TFA) to analyse the non-stationary vibration signal of varying-speed rotary machinery. The proposed method adopted the adaptive STFT to initialize the parameters estimation, and applied the spectrum concentration index to estimate the transform parameters. The estimated parameters are then used in component separation and parameterized TFA so the time-frequency features. AdrianD. Nembhard (89) discussed the transferability of the Individual Speed Individual Foundation (ISIF) and Multi Speed Individual Foundation (MSIF) techniques on a wider range of rotor related faults on different machines. A new Multi-Speed Multi-Foundation (MSMF) method which facilitates Fault Diagnosis by the direct comparison of vibration data from similarly configured machines with different dynamic characteristics operating at different steady-state speeds has also been proposed. Wei Li (91) in his paper used statistical feature extraction and evaluation method. The statistical features were sampled average of some conventional features, and these conventional features were obtained by analysing arbitrarily selected partitions of a given vibration signal with existing signal processing tools. According to the central limit theory, the obtained statistical feature vectors were close to normal distributions, and their means and variances could be estimated. The statistical features, the performance of ANN and SVM based fault classifiers was significantly improved. HocineBendjama(95) in his papers discussed fault diagnosis of rotating machinery using a combination between Wavelet Transform (WT) and Principal Component Analysis (PCA) methods. The WT was used to segregate the vibration signal of measurements data in different frequency bands. The obtained segregated levels were used as input parameters to the PCA method for fault detection and diagnosis.Phadatare H. P (96)in his paper describes how to calculate the nonlinear frequencies and resultant dynamic behaviour of high speed rotor bearing system with mass unbalance. Time history and FFT analysis were established for finding the fundamental frequencies for the rotating under variation of shaft diameter, effect of geometric nonlinearity and disk location while dynamic impact of mass unbalanced on the behaviour of rotor bearing system has been investigated using time history. Table 2 summarises the different Time Frequency methods used in condition monitoring.

| Sl No | Methods | Resolution | Interference term | Speed |
|-------|--|---|---------------------------------|------------------------|
| 1 | Continuous wavelet Transform (CWT) | Good frequency resolution and lowtime resolution for low-frequencycomponents; low frequency resolution and good time resolutionfor high- frequency components | No | Fast |
| 2 | Short-Time Fourier Transform (STFT) | Dependent on window function, good time or frequency resolution | No | Slower than CWT |
| 3 | Wigner–Ville distribution (WVD) | Good time and frequency resolution | Severe interference terms | Slower than STFT |

| Table 2. Comparison | of the performance | s of the different Ti | me Frequency methods |
|---------------------|--------------------|-----------------------|----------------------|
| rable 2. Comparison | of the periormance | s of the unferent 1 h | me frequency memous |

(ii) Support vector Mechanism

Sheng-Fa Yuan (18) in his paper have proposed a multiclass Support Vector Mechanism (SVM) algorithm and used it in the fault diagnosis for turbo pump rotor test bed. In his paper SVM binary tree classifier composed of several two-class classifiers organised by fault priority were used which was simple and hadvery less repeated training amount. Qiao Hu (21) in his paper described a fault diagnosis method based on improved wavelet packet transform (IWPT) and support vector mechanism where abiorthogonal wavelet with impact property was constructed via lifting scheme, and with the constructed wavelet the wavelet package transform was performed. Then, through Hilbert envelope spectrum analysis of wavelet package coefficients of the mostsalient frequency band, the faulty characteristic frequencies were determined. **Guang-Ming Xian** (33) in his paper proposed a new intelligent method for the fault diagnosis of the rotating machinery based on wavelet packet analysis (WPA) and hybrid support machine (hybrid SVM). In this paper, a 1-v-r multi-class support vector machine was presented. This paper describes a new approach using WPA for extraction of features from vibration signals of the rotating

machinery in time-frequency domain and hybrid SVM to classify the patterns inherent in the features extracted through the WPA of different fault types. Karim Salahshoor (35) proposed new FDD methodology his paper based on the fusion of two powerful Fault Detection and Diagnosis systems, implemented via anANFIS and SVM classifiers. The proposed FDD system has been tailored and adapted for an industrial steam turbine system, faced with a set of 12 major faulty conditions together with its healthy operation. Huo-Ching Sun (44) in his paperused the SVM is used to construct the vibration fault diagnosis model. The proposed approach was utilized to classify the faults of STGS according to the fault vibration signals. A total of 78 input/output databases are generated in this study; 60 samples are used for training and the others are provided for testing. M. Saimurugan (48) used the c-SVC and nu-SVC models of support vector machine (SVM) with four kernel functions for classification of faults using statistical features extracted from vibration signals under good and faulty conditions of rotational mechanical system. Decision tree algorithm was used to select the prominent features. These features were given as inputs for training and testing the c-SVC and nu-SVC model of SVM and their fault classification accuracies were compared.Van Tung Tran (51) proposed a method for Remaining Useful Life (RUL) based on Auto Regressive Moving Average (ARMA) identification model, Cox's Proportional Hazard Model (PHM) and Support Vector Mechanism (SVM) combined together. In the first stage, only the normal operating condition of machine was used to create ARMA model for recognizing the dynamic system behaviour. The differences between identification model and behaviour of system was calculated, and the degradation index was generated to indicate the machine status and determine the failure limit. In the second stage, the Cox's proportional hazard model was built to estimate the survival function of the system once the degradation index is higher than the failure limit. In the last stage, support vector machine association with timeseries techniques was utilized to forecast the Remaining Useful Life of the machine.Ning Li (58) used redundant second generation wavelet package transform (RSGWPT), neighbourhood roughest (NRS) and support vector machine (SVM)on faulty detection, attribute reduction and pattern classification.RSGWPT was utilized to extract faulty feature parameters from the statistical characteristics of wavelet package coefficients to constitute feature vectors, and then made the attribute reduction by NRS method to obtain the key features. In the end these key features were provided as the input into SVM to accomplish faulty pattern classification.Jinglong Chen (65) proposed a method for incorporating improved adaptive redundant lifting multi wavelet (IARLM) with Hilbert transform demodulation analysis which was applied to compound faults detection for the simulation experiment, rolling element bearing test bench and traveling unit of electric locomotive.AfroozPurarjomandlangrudi (76) in his study, proposed a data mining approach using a machine learning technique called anomaly detection (AD). This method employs classification techniques to discriminate between defect examples. Two features, kurtosis and Non-Gaussianity Score (NGS), were extracted to develop anomaly detection algorithm. Finally, the application of anomaly detection was compared with one of the popular methods called Support Vector Machine (SVM) to investigate the sensitivity and accuracy of this approach. Rajeswari.C (80) proposed a new intelligent methodology in bearing condition diagnosis analysis to predict the status of rolling bearing based on vibration signals by multi class support vector machine (MSVM), a classification algorithm. Wavelet packet transform (WPT) was used for signal processing and standard statistical feature extraction process. WenliaoDu (85) proposed a novel method based on wavelet leaders multifractal features for rolling element bearing fault diagnosis. The multifractal features, were combined with scaling exponents, multifractal spectrum, and log cumulants, and were utilized to classify various fault types and severities of rolling element bearing, and the classification performance of each type features and their combinations were evaluated by using SVMs. Eight wavelet packet energy features were introduced to train the SVMs together with multifractal features.

(iii) Empirical Mode Decomposition and Hilbert Transform

Michael Feldman (15) developed a new technique based on Hilbert Transform for vibration separation. Estimation of the varying frequency of the largest energy vibration component was effected by low pass filtration of the instantaneous frequency of the vibration. Synchronous envelope demodulation is performed by multiplying the composition by a sine and Hilbert projection waves, which are phase locked to the current component. **Q.Gao (27)** in his paper described an empirical mode decomposition (EMD) based approach for rotating machine fault diagnosis. Combined mode function (CMF) increased the precision of EMD when the signal was over-decomposed. **Yaguo Lei (31)** in his paper proposed a new method based on ensemble empirical mode decomposition (EEMD) to diagnose rotating machinery faults. Two vibration signals from a rub-impact fault in a power generator and an early rub-impact fault in a heavy oil catalytic cracking machine set were analysed using the proposed method to diagnose the faults. **XinXiong (52)** used Hilbert Huang Transform with a fourth-order spectral analysis tool named Kurtogram, which was developed to extract high-frequency features from several kinds of faulty signals, where the Kurtogramwas applied to locate the non-stationary intra-

inter- wave modulation components in the original signals and produce more monochromatic Intrinsic Mode Functions.Dongvang Dou (54) proposed a new method for intelligent fault identification of rotating machinery based on the empirical mode decomposition (EMD), dimensionless parameters, fault decision table (FDT), MLEM2 rule induction algorithm and Improved Rule Matching Strategy (IRMS) was proposed in this paper.G.F. Bin (57) proposed a new approach based on wavelet packet decomposition (WPD) and empirical mode decomposition (EMD) which were combined to extract fault feature frequency and also neural networking was used for rotating machinery yearly fault diagnosis. Acquisition signals with fault frequency feature were decomposed into a series of narrow bandwidth using Wavelet Packet Distribution method for de-noising, then, the intrinsic mode functions (IMFs), which usually denoted the features of corresponding frequency bandwidth was obtained by applying EMD method. Hao Wang (83) proposed a method of fault diagnosis for nonstationary fault signals of rotating machinery by ensemble empirical mode decomposition (EEMD) time frequency energy and a self-organizing map (SOM) neural network. The method uses EEMD to decompose the fault signal, obtaining a Hilbert-Huang transform time-frequency spectrum based on all the intrinsic mode functions. In order to achieve accurate diagnosis for rotating machinery automatically a faultdiagnosis strategy based on rotor dynamics and computational intelligence was proposed by Junhong Zhang (90). In this paper Time-frequency characteristics was calculated through improved EMD as well as statistical parameters of the signal in time- and frequency-domains were extracted as fault features. Then, fuzzy support vector machine (FSVM) technique was used to optimize multi-population genetic algorithm and identify the state of the system automatically.

(iv) Spectral Kurtosis Technique:

Jerome Antoni (13) in his paper have highlighted how the Spectral Kurtosis (SK) Technique wasused in the vibration-based condition monitoring of rotating machines with respect to classical kurtosis analysis. The high sensitivity of the SK for detecting and characterising incipient faults that produce impulse-like signals were used. In his paper he had highlighted SK as a detection tool that precisely points out in which frequency band(s) the fault shows the best contrast from background noise and also suggested using SK as a basis for designing detection filters that can extract the mechanical signature of the fault in rotating machinery.

(v) Decision Tree and Regression Tree techniques:

Bo-Suk Yang (11) describes the development of a vibration diagnostics expert system, VIBEX, which enables operators of rotating machinery to solve vibration problems, when they cannot access the expert's knowledge using a decision tree method. **Van Tung Tran (23)** in his paper proposed a method to predict the future conditions of machines based on one-step-ahead prediction of time-series forecasting techniques and regression trees. Using 10 cross-validations to find the optimum tree size and an embedded dimension of 6, the results give a prediction error of 1.43% with peak acceleration data, and 6% with the enveloped acceleration data.

(vi) Principal component analysis:

Qingbo He (28) used low-dimensional principal component (PC) representations from the statistical features of the measured signals to characterize and hence, monitor machine conditions. The PC representations were automatically extracted using the principal component analysis (PCA) technique from the time- and frequency-domains statistical features of the measured signals. The proposed MCR effectively evaluated the capability of each of the PC representations for characterizing machine condition.

(vii)Artificial Neural Network and Fuzzy Logic:

YazhaoQiu(10) presented a fuzzy approach for the analysis of unbalanced nonlinear rotor systems involving uncertain parameters.Jiangping Wang (16) investigated the use of basic fuzzylogic principle as a fault diagnostic technique forfive-plunger pump. Fuzzy logic was used to classify frequency spectra according to the likely fault condition which they represent.Javier Sanz (20) in his paper used a combination of the capability of wavelet transform (WT) to treat transient signals with the ability of auto-associative neural networks to extract features of data sets in an unsupervised mode. Pattern recognition procedures based on neural approaches were used to compare Discreet Wavelet Transform coefficients obtained from undamaged and damaged gear vibration signals.Yaguo Lei (22) in his paper, proposed a novel method for intelligent fault diagnosis of rotating machinery based on statistics analysis, empirical mode decomposition (EMD), the

improved distance evaluation technique, adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithms (GAs). Multiple ANFIS combination with GAs was adopted to construct a more reliable and intelligent fault diagnosis system of rotating machinery. Six salient feature sets were selected input into the multiple ANFIS combination with genetic algorithms (GAs) to identify different abnormal cases. Yaguo Lei (25) proposed statistical analysis method combined with adaptive neuro-fuzzy inference system (ANFIS) for fault diagnosis. The approach consists of three stages. First, different features, including time-domain statistical characteristics, frequency-domain statistical characteristics and empirical mode decomposition (EMD) energy entropies, were extracted to acquire more fault characteristic information. Second, an improved distance evaluation technique was proposed, and with it, the most superior features were selected from the original feature set. Finally, the most superior features were fed into ANFIS to identify different abnormal cases. S. Rajakarunakaran (26) considered a centrifugal pumping rotary system for his research. Where the fault detection model was developed by using two different artificial neural network approaches, namely feed forward network with back propagation algorithm and binary adaptive resonance network (ART1). Totally 7 categories of faults including 20 faults from the centrifugal pumping system were considered in the developed model. Enrico Zio (29) in his paper developed a NeuroFuzzy approach for pattern classification. Empirical FKB was developed on the basis of the available training data, the algorithm optimally modifies the fuzzy input partitioning interface. During the model parameters optimisation process, the enforcing of such constraints induces both the improvement of the classification performance and the preservation of the intelligibility of the model. J. Rafiee (30) presented a gear fault identification system using genetic algorithm (GA) and researched on the type of gear failures of a complex gearbox system using artificial neural networks (ANNs). Three parameters were recognized to be optimized using GA i.e. Daubechies wavelet function order, decomposition level, and number of neurons in hidden layer of ANN. The Feature vector was also obtained from optimized standard deviation of wavelet packet coefficients acquired from DB11 at fourth level of decomposition following a piecewise cubic Hermite interpolation for synchronizing. Gang Niu (37) proposed a data-fusion strategy where vibration signals were collected, trendfeatures were extracted, normalized and sent into neural network for feature-level fusion. The data de-noising was conducted containing smoothing and wavelet decomposition to reduce the fluctuation and pick out trend information. The processed information was used for autonomic health degradation monitoring and data-driven prognostics where the remaining useful life of operating machine with its uncertainty interval were assessed. Karim Salahshoor (42) presented an innovative data-driven Fault Detection and Diagnosis methodology on the basis of a distributed configuration of three adaptive Neuro-fuzzy inference system (ANFIS) classifiers for an industrial 440MW Power plant steam turbine with once-through Benson Type boiler.IlyesKhelf (64) accurate identified the defects in rotating machines, using the combination of pattern recognition and non-destructive testing techniques such as vibration analysis and its indicators. Indicators selection was used to improve diagnosis performances by the help of a hybrid approach using several selection criteria and different classifiers. DimitriosKateris (77) in his paper presented the architecture of a diagnostic system for extended faults in bearings based on neural networks which highlighted the combined use of kurtosis and the line integral of the acceleration signal. Unbalance faults were identified through a data driven approach applied to a rotor dynamic test rig fitted with multiple discs by R.B. Walker (84). The process of automating the localization was achieved by using an artificial neural network (ANN).Sub synchronous nonlinear features in the frequency domain were identified and studied as a method to identify the location of the unbalance faults, particularly in situations where sensors cannot be placed properly.

(viii) Use of Genetic Algorithm and simulated annealing method:

HelioFiori de Castro (36) in his paper discussed the identification of parameters in rotary systems, namely, the unbalance magnitude, phase and position in the rotor system. These parameters were identified by measuring the orbits in the hydrodynamic bearings. The oil film forces were evaluated in the different positions of the orbit of the journal and were applied to the shaft model. The use of Genetic Algorithm along with simulated annealing methods was used for the purpose of fault diagnosis.

(ix) Sequential Monte Carlo Method:

WahyuCaesarendra (38) in his paper proposed a prognosis algorithm applied in a real dynamic system known Sequential Monte Carlo method (also known as a particle filter) for predicting the future conditions of vibration amplitude (posterior state) which was based on actual data (prior state).Qinming Liu (50) proposed a prognostic method based on hidden semi-Markov model (HSMM) by using Sequential Monte

Carlo (SMC) method which was further based on joint probability distribution to recognize the health states of equipment and its health state change point was proposed in this paper.

(x) Motor Current Signature Analysis (MCSA):

Mohamed Salah (63) suggested that spectral analysis of the axial stray flux could be used as an alternative solution to cover effectiveness limitation of the traditional stator current technique. The proposed technique of motor current signature analysis (MCSA) had the advantage to use only one low- cost sensor (simple search coil) which was placed outside the machine housing. Furthermore, the derived data was effortlessly processed by means of the classical Fast Fourier Transform where any prior knowledge of the machine parameters was not required. **HamdiTaplak** (71) performed the experimental analyses of a direct coupled rotor-bearing system to investigate the undue vibration characteristics. Overall vibration level trend analysis for each bearing was accomplished in a regular period to calculate the fault parameters. Spectrum and related vibration trend graphs for running speed were obtained by using the calculated maximum fault values, and they were also used to make a decision about possible undue vibration sources in system.

(xi) Local Mean Decomposition Method :

To extract the significant fault features, a vibration analysis method based on hybrid techniques was proposed by**Linfeng Deng (66)** in this paper. The raw signals weredecomposed into a few product functions (PFs) using local mean decomposition (LMD) method and the instantaneous frequency and amplitude were also calculated. Subsequently, Fourier transform was performed on the derived PFs, and then, according to the spectra features, the useful PFs were selected to reconstruct the purified vibration signals. In the end all the different fault features were fused together to illustrate the operating state of the machinery.

(xii) Composite Spectrum technique:

Keri Elbhbah (68) presented the concept of the Coherent Composite Spectrum analysis which was applied to a laboratory test rig where different faults were simulated; healthy and three faulty cases named misalignment, crack shaft, and shaft rub. A single composite spectrum for a machine was used by means of data fusion in the frequency domain to bypass the analysis of vibration spectrum measured at each bearing pedestal in the machine for the fault(s) diagnosis. Jyoti K. Sinha (70) used the concept of fusion of the data from all sensors in the frequency domain to get a composite spectrum for a machine and then the computation of the higher order spectra (HOS) so that the vibration data is managed efficiently and able to detect fault uniquely. AkiluYunusa-Kaltungo (78) compared the proposed poly-Coherent Composite Spectrum (pCCS) method with the earlier composite spectrum (CS) method for faults diagnosis in rotating machines, using experimental data from a rotating rig.In his present study, a combined information of amplitude and phase from all locations was achieved, which provided a more accurate representation of the entire machine dynamics.

(xiii) Ferrography:

R. K. Biswas (72) proposed the use of vibration analysis, Fourier transform infrared technique (FTIR) and image processing of the ferrogram techniques for quantitative assessment of the deterioration.

(xiv) Least Angle Regression (LAR) Technique

IoannisChatzisavvas (92) usedmulti-fault identification method which was applied for identification of single and double unbalance of a simple rotor-bearing system. The proposed method provided a more natural solution to the complicated problem caused from the limited number of measuring positions, especially in cases where a machine is operated under constant speed.

III. CONTRIBUTION OF CURRENT WORK AND NOVELTY OF THE RESEARCH

Considering the main cause of machine vibration as unbalance, a test rig for experimental validation of the model based identification technique has been built. Schematic representation of the experimental set been shown in the figures below.

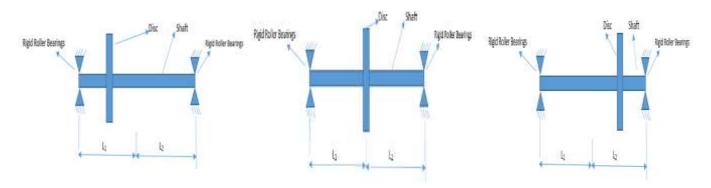


Figure 2:Schematic representation of the experimental set up (no fault case)

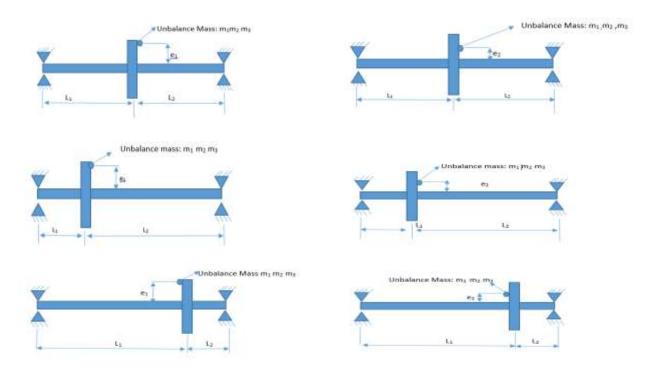


Figure3:Schematic representation of the experimental set up (faulty case)

The experimental verification for the Unbalance Identification of mass on a shaft with single plane and two eccentricities has been performed on a Machine Fault Simulator provided at Central mechanical Engineering Research Institute (CSIR-CMERI) located at Durgapur.

A rigid shaft considered to be massless is mounted between two roller bearings. The distance between the two bearings is L_1+L_2 , which is 60cm. This shaft is connected to a Variable Frequency Drive (VFD) motor by a flexible coupling. To measure the vibration in X-Direction and Y-Direction at the two bearings, four accelerometers are connected; two in each bearing. The weight of the disc is 653 gram (M₁). The position of the disc is varied in three different locations: (i) 15 cm from left bearing (ii) 30cm from left bearing which is the mid position on the shaft (iii) 45 cm from left bearing. Initially no unbalance mass was attached in order to get the no fault readings. Three unbalance masses of 8 gram (m₁), 12 gram (m₂) and 16 gram (m₃) are attached subsequently to the disc at eccentricities 6.85cm (e₁) and 4.85cm (e₂) separately one by one. Then the shaft is rotated at rpm 300, 600, 900, 1200 and 1500; and simultaneously the vibration readings and their phase shift values for x and y-direction at the two bearings have been noted down. Mathematical modelling of the system was done with help of Lagrangian Dynamics and Bond Graph for simulation in order to determine the natural frequencies and mode shapes of the vibrating system. Decision Tree Method has been used for identification and to determine the location of the fault in the vibrating system. Artificial Neural Networking and Fuzzy Logic techniques were used to determine the machine health condition. Also the plane and the mass of unbalance has been determined using Artificial Neural networking and is validated using simulation of mathematical model and experimental results which is the novelty of the research.

IV. CONCLUSION

In this paper, we have attempted to summarise recent research and development in machinery fault diagnostics and prognostics implementing Condition Monitoring. Various techniques, models and algorithms have been reviewed following the three main steps of a Condition Monitoring program, namely data acquisition, data processing and maintenance decision-making, with emphasis on the last two steps. Different techniques for multiple sensor data fusion have also been discussed. Also the scope of the current work and its novelty has been discussed which covers the modeling, simulation, experimentation, signal analysis and the computational prognosis techniques to determine the machine health condition index.

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