Fault Diagnosis of Roller Bearing using Vibration Signals Through ARMA Features and Tree Family Classifier

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Abstract **- Bearings are one of the critical and vital component in rotating machinery. In any way if it fails, to do its work then not only machine but also whole assembly line stops deriving cost may be extremely high .Hence fault diagnosis in early stages of damage is essential to prevent their failure and malfunctions during operation. In proposed paper, vibration signals obtained from bearing in good condition and faulty conditions are simulated for fault diagnosis. A machine learning approach can be used for fault diagnosis problems. It has three steps i.e. feature extraction, feature selection and feature classification. There are many features like time domain, statistical, histogram, ARMA (Autoregressive moving average feature) and wavelet features. Using ARMA features classifications are done using tree family classifier. The classification results for various tree family classifiers are recorded, tabulated and compared.**

Key words: Fault diagnosis; bearing; vibration signals; ARMA features; tree classifier

I. INTRODUCTION

Bearing is the rolling element which is mostly responsible for any failure in rotating machines. Hence fault diagnosis of bearing gets major attention. Fatigue cracking occurs due to localized defect. Vibration & acoustic signals are majorly used in condition monitoring. Fault diagnosis is done by comparing the signals which are obtained in good & faulty conditions. The faults are simulated in bearing.

In present study faults are classified as inner race fault (IRF), outer race fault (ORF) & inner & outer race fault (IORF). Basically fault diagnosis has been done by machine learning approach. It consists of three important stages i.e. feature extraction, feature selection & feature classification. In feature extraction process various features get extracted from all obtained data base. Particular important feature has been select in feature selection process & these selected features are classified by comparing with different algorithm. Proposed to this technique lot of work has been done previously. In feasibility study on diagnostic methods for detection of bearing faults at by A. Fernández, the comparison study has been done on the performance of fault diagnosis of ball bearing. Different kind of faults have been obtained in real time & signals of faults are been created in an early stages. Tekiner & Yesilyurt carried out experiment to obtain best suitable machining conditions. Heng & Nor presented study on application of sound pressure & vibration signals to detect defects in bearing using stastical parameters elimination method. Suguna Thanagasundram presented a fault detection tool using analysis from an autoregressive model pole trajectory in that combination of autoregressive (AR) modeling & pole related spectral decomposition has been done for vibration-based monitoring system. All these work reported using conventional techniques. There is need of automated intelligent fault diagnosis system. In present study, vibration signals are used for fault diagnosis for introduce machine learning process & automated intelligent fault diagnosis system. Vibration signals are get by using transducer .To extract useful features, ARMA features are used with tree classifier. This combination has been not tried before, hence contribution is made with 98% & result has been recorded.

II.METHODOLOGY:

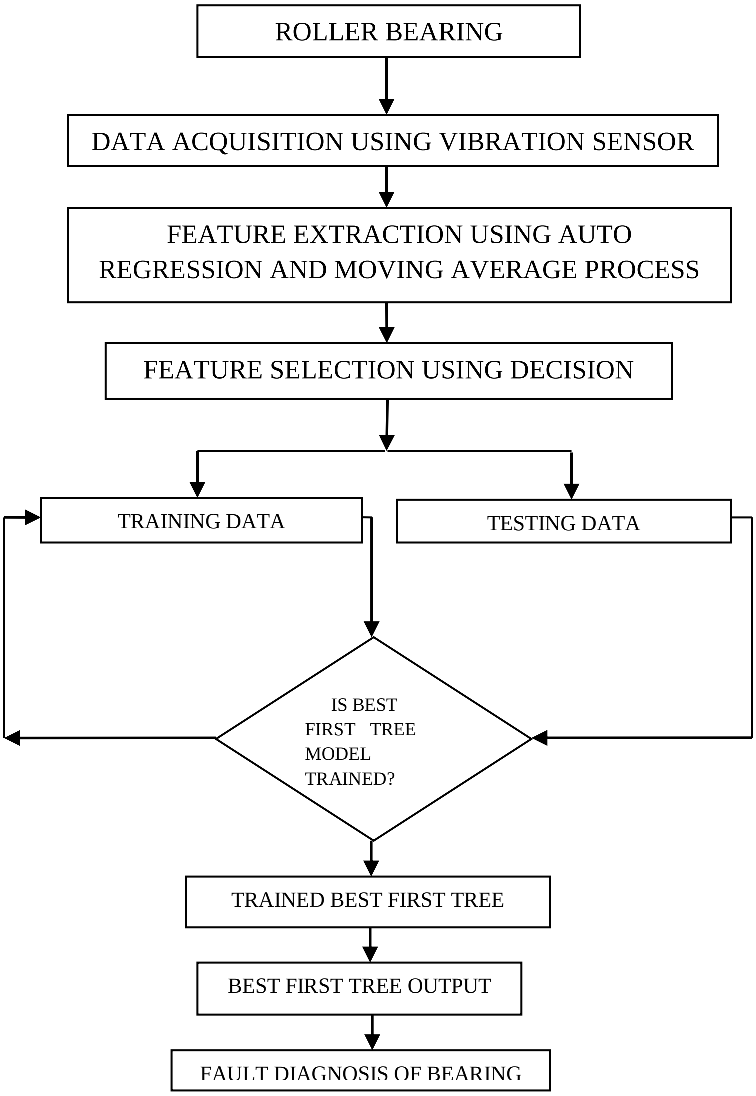

Fig. 1: Methodology flow charts

III. EXPERIMENTAL STUDIES

The ultimate goal of the study is to check whether bearing used in machine is good or faulty. If any case there is any fault in bearing then these faults are segregated in different cases like IRF, ORF, IORF, etc. In this paper the main concentration has been given on use of ARMA features to extract the different features which has been obtained by vibration signals and classified that features using tree classifier. An experimental study is described in to following sub section.

Fig. 2. Machine fault simulator setup.

IV .EXPERIMENTAL SETUP

The experiment setup the machine which is used for fault simulation having variable speed DC motor of 0.5Hp which has speed up to 3000 rpm. A shaft having short length and diameter 30mm is joined to the shaft of respective motor using flexible coupling; the main objective here is to avoid misalignment and vibration due to motor. The shaft has bearing support at its ends. The bearing which is near to the motor is selected as brand new since it is free from any fault.. In this experiment piezoelectric accelerometer is used which is mounted on the top of the bearing housing. The transducer is directly connected to the signal conditioning unit where signals are get through charge amplifier & analog-to-digital (ADC) converter. These signals are then stored in computer memory for feature extraction.

V. PROCEDURE

In the study of fault diagnosis of bearing four SK F6206 roller bearings were used. One among four bearing is in good condition, where as in all other bearings, the faults was created artificially using wire cut EDM process. The defect created on inner race is 0.525mm wide and 0.827mm. And 0.652 mm and 0.981mm deep on outer race. The vibration signals are taken by using accelerometer after initial running of bearing. The sample length of 8192 was chosen arbitrarily with 1200 Hz sampling frequency. In this fault diagnosis procedure, the vibration signals was acquired from the experimental setup with good conditioned roller bearing at different speeds of motor by using transducer. Then the above procedure was repeated for all other bearing with faulty condition.

VI. FEATURE EXTRACTION

Feature extraction is the process in which different features has been extracted from data which has been collected by transducer and stored in the computer's memory. In this study, ARMA features were extracted from the vibration signals. In the statistical analysis of time series, autoregressive–moving-average (ARMA) models provide a stationary stochastic process in terms of two polynomials, one for the auto-regression and the second for the moving average. Given a time series of data *Xt*, the ARMA model is a tool for understanding and, perhaps, predicting future values in this series. The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The model is usually then referred to as the ARMA (*p*,*q*) model where *p* is the order of the autoregressive part and *q* is the order of the moving average part.

1.Auto-regreesive model:

The notation AR(*p*) refers to the autoregressive model of order *p*. An autoregressive model is essentially an all-pole infinite impulse response filter with some additional interpretation placed on it.

2.Moving average model:

The notation MA(*q*) refers to the moving average model of order *q*.

For feature extraction using ARMA feature, programming in Mat lab is necessary. ARMA model contains following three functions:

I.ARBURG:

It generates all-pole filter coefficients that model an input data sequence using the Levinson-Durbin algorithm.

II.ARYULE:

It generates all-pole filter coefficients that model an input data sequence using an estimate of the autocorrelation function.

III.PYULEAR:

It estimates the PSD of an input signal vector using the Yule-Walker AR method.

All the signals which are obtained from transducer are collected & extracted into useful data files using a different algorithm which belongs to particular ARMA functions in Mat lab.

VII. FEATURE SELECTION USING DECISION TREE (J48 ALGORITHM)

In feature selection more efficiency value can be calculated by using J48 algorithm. The reason behind selection of particularly J48 algorithm is this algorithm gives maximum overall value which is taken in to consideration. The decision tree has the nodes in which the classes are been mentioned with the condition which are to be find. Decision tree is use to classify the different features that are been associated to this conditions in the leaf node manner so that classification of the condition is made easier. In the present study, order no. 7 has maximum value of correctly classified instances i.e. 95.5% (a2+a3+condition) where there are only two nodes are available i.e. a2 & a3. Hence at least for the feature selection process the study is limited up to only J48 algorithm, all other algorithms are tested in classification i.e. features classification, because research area is tree classifier itself.

VIII. FEATURE CLASSIFICATION

In this paper feature classification is done by using tree classifier. There are different algorithms are present in the tree classifier. This feature classification work has been done by studying all these algorithms comparatively. There are some algorithms which are used for comparative study like J48, decision stump, FT(functional tree), J48 graft, random tree, random forest, REP tree, LAD tree. Classification has been done using all these algorithms.

IX. RESULTS AND DISCUSSIONS

In this paper highest parameter value obtained using ARMA features are been classified with the help of Tree classifier. Here classification is been done by “Ten Fold Cross Validation” method. In this method, the values are been tested with the help of algorithm and also they are been obtained in the form of matrix formation. Where the values of both the Training data and the Validation data for which the best accuracy percentage is been carried out.

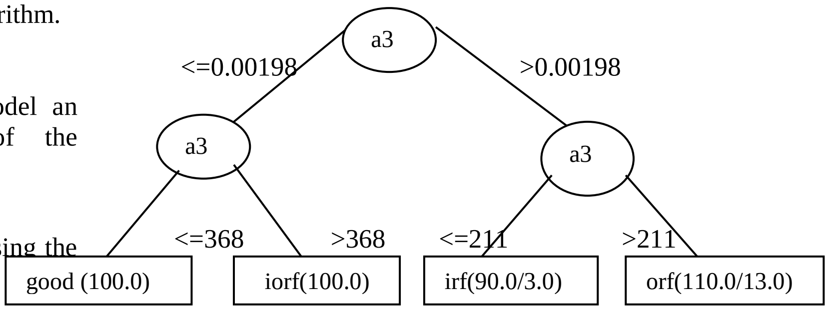

Fig 3 . J48 decision tree for ARMA features

As per research concern following results are obtained from different algorithms with consideration of condition & important nodes in decision tree:

TABLE I

Sr. no.	Algorithm name with a2+a3+condition	Result (%)
1	J48	96.25
2	Decision stump	49.5
3	FT(Functional tree)	98
4	J48 graft	96
5	Random tree	95.75
6	Random forest	97.5
7	REP tree	95
8	LAD tree	74.25

Hence as per the different algorithms FT(functional tree) gives highest possible result i.e. 98% among all other algorithms. As per this research FT gives more efficient result for the fault diagnosis of bearing using ARMA with tree classifier.

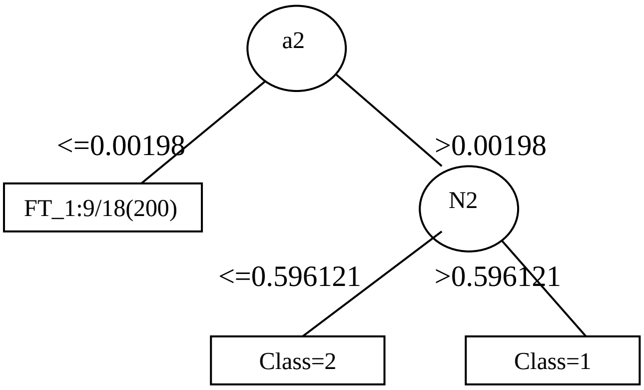

Fig 4. Tree for FT

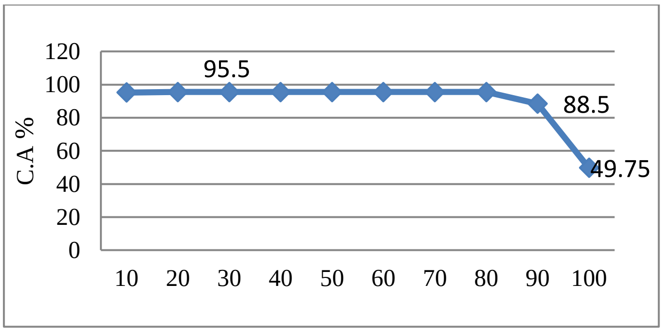

Fig 5. Classification % Vs Minimum no. of objects

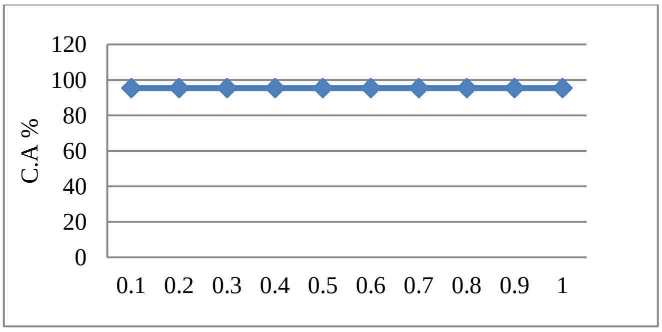

Fig 6. Classification % Vs No. of instances

The confusion matrix is been derived for the best value of percentage .In this classification we have to choose confidence factor and minimum number of objects to give best value of percentage.

a	b	c	d	→ classified as
99	0	1	0	a = good
0	94	6	0	b = irf
0	0	100	0	c = orf
1	0	0	99	d = iorf

Fig 7. Confusion matrix

The diagonal elements in the confusion matrix show the number of correctly classified instances. In the first row, the first element shows the number of data points belonging to 'good' class.The second element shows the number of data points belonging to 'good' class but misclassified as irf (inner race fault). The third element shows the number of data points misclassified as orf (outer race faults) and so on.

X. CONCLUSION:

Fault diagnosis is one of the best methods for detecting the faults created in the machinery. In this paper fault diagnosis of roller bearing has been studied & carried out using ARMA features with tree classifier. During this diagnosis different fault conditions are considered like irf, orf and iorf. In this research work different results are obtained from different classifiers but best suitable results has been considered i.e. functional tree (FT) with 98% result. Likewise using different features and classifiers more good results can be obtain. There is wide scope for fault diagnosis in the research area for analysis of different faults in any machinery. Fault diagnosis of bearing is important field of research & condition monitoring of rotating machines. Now-a-days machine learning process should have to develop in the industries that can help to reduce the cost of maintenance of any machinery in greater extent

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