B. TECH. PROJECT REPORT

On

Fault Detection of Reciprocating Compressors using Artificial Neural Networks

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DISCIPLINE OF MECHANICAL ENGINEERING

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Fault Detection of Reciprocating Compressors using Artificial Neural Networks

A PROJECT REPORT

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in

MECHANICAL ENGINEERING

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INDIAN INSTITUTE OF TECHNOLOGY INDORE

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CANDIDATE'S DECLARATION

We hereby declare that the project entitled **"Fault Detection of Reciprocating Compressors using Artificial Neural Networks"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Mechanical Engineering' completed under the supervision of **Dr. Anand Parey,** IIT Indore is an authentic work.

Further, I/we declare that I/we have not submitted this work for the award of any other degree elsewhere.

Signature and name of the student(s) with date

CERTIFICATE by BTP Guide(s)

It is certified that the above statement made by the students is correct to the best of my/our knowledge.

Signature of BTP Guide(s) with dates and their designation

<u>Preface</u>

This report on "Fault Detection of Reciprocating Compressors using Artificial Neural Networks " is prepared under the guidance of Dr. Anand Parey.

An experimental investigation has been carried out to find the vibration signal characteristics of a reciprocating compressor when it worked under limited speed variation and different degrees of valve leakage. We have conducted experiments to obtain the raw vibration data. This acquired data was decomposed using empirical mode decomposition and then feature extraction was performed to obtain different features to be entered as input into the neural network model. Using a neural network, a model has been built which can be used further to classify unlabeled vibration data from reciprocating compressors with any degree of valve leakage.

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Dubakula Yeshwanth & Chetan Sharma

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Abstract

Reciprocating compressors are used in pressure based applications to achieve high-pressure ratio. An efficient detection of leakage in reciprocating compressors can facilitate the reduction of maintenance and reparation cost. This fault detection approach is based on the analysis of raw vibration signals obtained using a tri-axial accelerometer and Machine Fault Simulator. The acquired data was processed and condition indicators (CIs) such as RMS, Kurtosis, etc. were obtained and analyzed. The main idea is that the graphical representation of these indicators will show typical patterns depending on the fault state. The problem is to detect these patterns reliably. In the present study, the vibration signals were acquired under different levels of valve leakage under limited speed variation. The raw data was then decomposed into intrinsic mode functions(IMFs) using Empirical Mode Decomposition(EMD). This data was further used to train and test the Artificial Neural Networks(ANNs) model. Artificial Neural Networks (ANNs) are multi-layer inter connected nodes, similar to the broad network of neurons in the human brain. The trained and tested model, then, can be used for the differentiation between the signals collected from a healthy and a faulty compressor.

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Chapter 1

Introduction

1.1 Compressors:

Compressors are the mechanical devices designed to deliver gas at a pressure higher than the already existing pressure. Fluid enters the compressor through the suction valve. The fluid is then compressed by the piston in a cylinder. The compressed fluid, with a higher pressure, is then discharged through the discharge valve. Discharge valve is a passive valve and acts completely on the basis of pressure difference inside and outside the cylinder. There are different types of compressors. Rise in pressure, working pressures, specific speeds and mechanical designs form the basis of differentiation and classification.

1.2 Types of Compressors:

On the basis of the mechanism used to increase the pressure, compressors are broadly divided into two types:

1. Positive Displacement: These machines work by mechanically changing the volume of the working fluid. Reciprocating Compressors (RCs) are a type of positive displacement compressors. Reciprocating compressors come under this category.

2. Continuous Flow: These machines work by mechanically changing the velocity of the working fluid. These include centrifugal and axial flow compressors. Centrifugal compressors are dynamic machines in which the rapidly rotating impeller accelerates the gas. The process flow propagates from axial to radial into a stationary diffuser converting velocity to pressure. While, on the other hand, Axial compressors are dynamic machines in which the gas flow is accelerated in an axial and peripheral direction by the rotation of specially shaped blades.

1.3 Reciprocating Compressors:

Reciprocating Compressors (RCs) are positive-displacement machines in which the compressing and displacing element is a piston having a reciprocating motion within a cylinder. They are widely used in oil refineries, gas pipelines, chemical plants, natural gas processing plants and refrigeration plants. They can single acting or double acting. Efficient condition monitoring of reciprocating compressors is very essential. Condition Monitoring is a maintenance technique in which the health and condition of different parts of machines are checked by monitoring and measuring some signals and variables.

This report will mainly deal with Reciprocating Compressors.

1.4 Main types of faults in reciprocating compressors:

In a reciprocating compressor, the valves have the greatest effect on the operating performance of the machine, both from an efficiency standpoint and from a mechanical reliability standpoint. Compressor valves are devices placed in the cylinder to permit one-way flow of gas either into or out of the cylinder. There must be one or more valves for inlet and discharge in each compression chamber. A compressor valve regulates the cycle of operation in a compressor cylinder. Automatic compressor valves are pressure activated, and their normal movement is controlled by the compression cycle. The valves are opened solely by the difference in pressure across the valve; no mechanical device is used. They are mainly two types of valve faults:

1. Valve Leakage: This type of fault occurs when there is a leakage of the working fluid, either from the inlet valve or the discharge valve.
    - Cause: This type of fault occurs by the looseness in the valve or breaking of the discharge valve, intake pulsations or discharge pulsations might also be the reason for leakage of the valves.
    - Solution: Tightening of bolts can be used to remove looseness and solution of a broken valve is its replacement.
2. Valve Blockage This type of fault occurs when there is a blockage in the discharge valve and hence it's functioning is halted by that blockage which resists in the smooth flow of the working fluid.
    - Cause: This type of fault is mainly caused by the corrosive elements present in the working fluid which deposit at the discharge valve. Foreign material carryover or liquid slugs in the working fluid can also cause blockage in the discharge valve.
    - Solution: This can be avoided by keeping the blockage prone part clean using a compressed air blow. Replacement of discharge valve can also be done if the damage is beyond repair.

1.5 Valve Leakage:

Valve leakages in particular, are considered as the most common fault in RC. They account for 36% of the cases where the compressor needs to be shut down and 50% of the total cost of repair. Leakage within the valve allows high temperature gases to be pushed through the valve and accelerates valve system deterioration which eventually affects the efficiency of the compressor. Hence detection of leakages in the valves of a reciprocating compressor is very essential.

Hence, we will be be working on the valve leakage fault in reciprocating compressors.

1.6 Empirical Mode Decomposition:

Empirical Mode Decomposition (EMD) is a signal processing technique which can decompose and analyze the signals without an advance knowledge of the signals of interest. It is suitable for the analysis of nonlinear and non-stationary signals. It doesn't require information about the signal periodicity, linearity or about the behavior of the signal being stationary or non-stationary. It decomposes a multi-component signal into a finite number of mono-component signals which are called as intrinsic mode functions (IMFs).

These intrinsic mode functions (IMFs) are detected by calculating the mean value of the signals, which comprises of two envelopes interpolating the local maxima and local minima. The initial IMFs which have been calculated include the higher frequency components. So there exists a proper sequence because this decomposition process terminates, when a monotonic IMF (known as "Residual signal") has been observed. The decomposition is based on the assumptions:

(1) the signal has at least two extrema-one maxima and one minima;
(2) the characteristic time scale is defined by the time lapse between the extremes of the signal; and
(3) if the data is totally bereft of extrema and contains only inflection points, then it can be differentiated one or more times to obtain the extrema. Final result can be found by integration of the components.

Mathematically,

$$X(t) = \sum_{n=1}^{N} IMF_n(t) + r_n(t)$$

Where, IMF_n(t) symbolizes the nth intrinsic mode function and r_n(t) symbolizes the residual component.

EMD is a better technique for processing of vibration signals than other primitive techniques such as Fourier Transform (FFT), Discrete wavelet analysis, etc.

1.7 Artificial Neural Networks:

Artificial Neural Networks (ANNs) are multi-layer inter-connected nodes, similar to the broad network of neurons in the human brain. ANNs are the interlinked congregation of individual information processing units known as nodes. A node receives inputs from its neighboring nodes, processes the information through an assigned activation function, and gives out an output, which is then transmitted to the next node.

A neural network consists of an input layer, one or more hidden layers, and an output layer. Each node in a layer is connected to every other node in the following layer. The network can be made deeper by increasing the number of hidden layers.

The strength of connection between any two nodes is known as weight between those nodes.

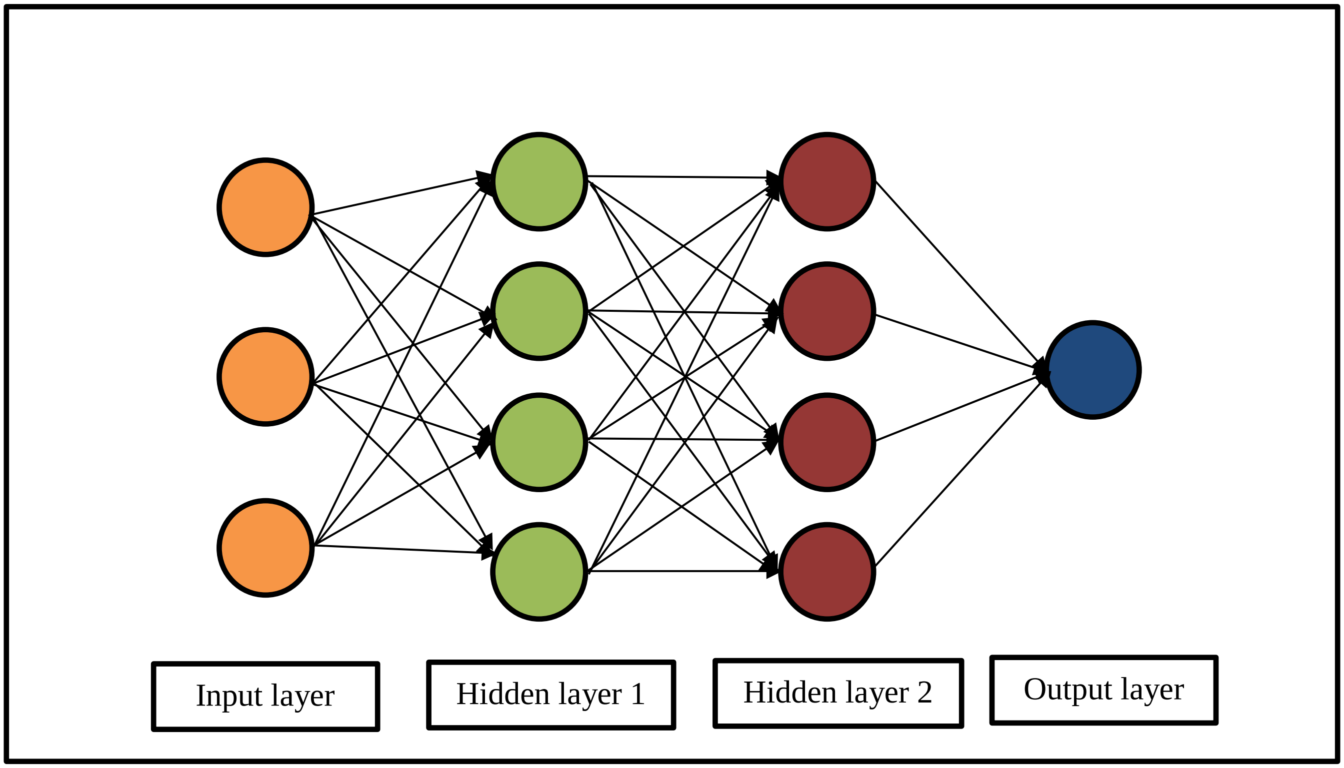

Fig. 1.1 Structure of ANN

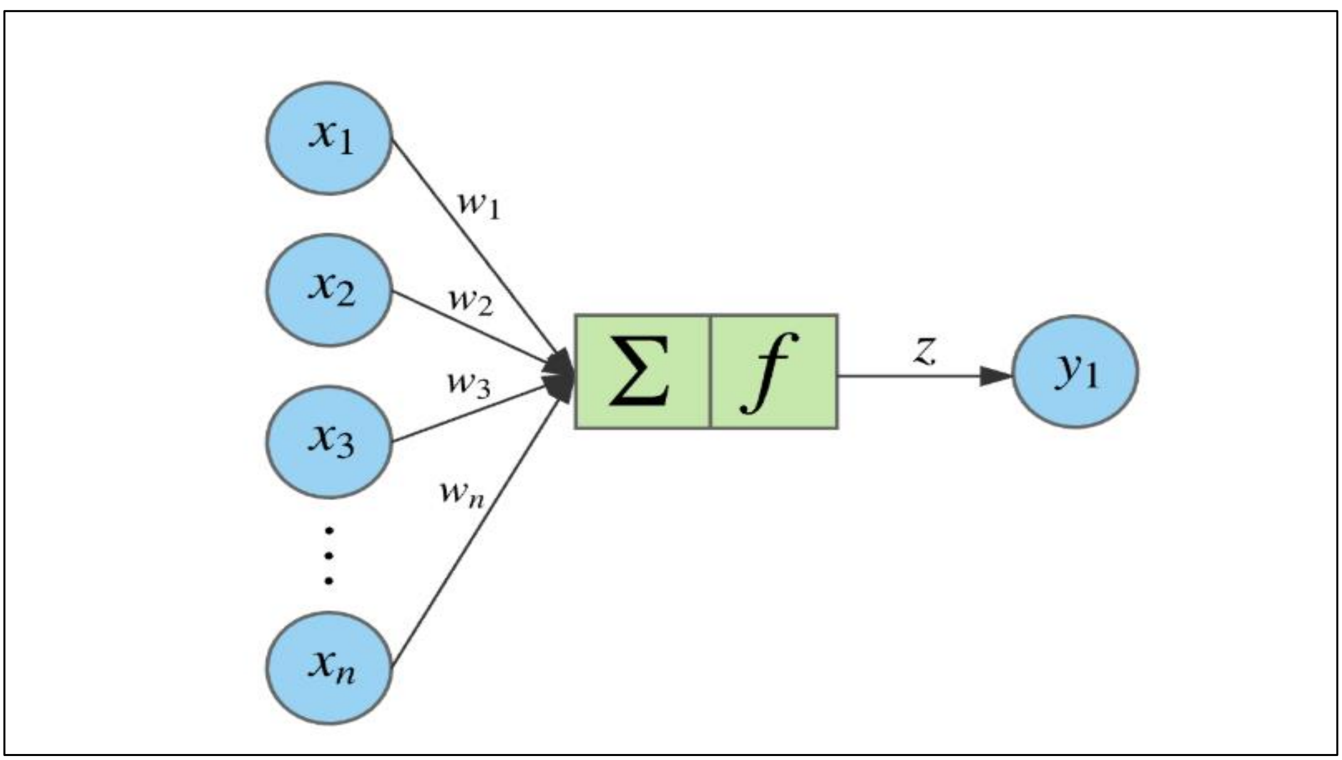

Fig. 1.2 Allocation of weights

A particular node calculates the weighted sum of its inputs and passes it to the activation function assigned to the layer. This output of the node is then further passed on to another node in the next layer as an input to that node. The information flows from left to right, and the final output is calculated by performing this process for all the nodes. Training this deep neural network means learning the weights associated with all the edges.

Mathematically, the equation for a particular node can be written as follows:

$$z = f(b + x \cdot w) = f\left(b + \sum_{i=1}^{n} x_i w_i\right)$$

$$x \in d_{1\times n},\ w \in d_{n\times 1},\ b \in d_{1\times 1},\ z \in d_{1\times 1}$$

The weighted sum of the inputs is entered into the activation function. It can be shown as a vector dot product, where *n* is the number of inputs for the node.

Bias term has been omitted for simplicity in the above formula. Bias is a constant input to the each node and always has a fixed value. In most cases, bias has value 1.It allows to adjust the output of the activation function to the left or right. It also allows us to train the model when all the input features are null.

The above equation is written as follows with the *bias* term included:

$$z = f(x \cdot w) = f\left(\sum_{i=1}^{n} x_i w_i\right)$$

$$x \in d_{1\times n},\ w \in d_{n\times 1},\ z \in d_{1\times 1}$$

The process described until now is called *feed forward propagation,* meaning given an input and assigned weights how the output is calculated. After the completion of training, only the forward pass is run to make prediction. But before that, training the model to properly learn the weights is required, and the training procedure works as follows:

- Weights are assigned randomly to all the nodes.
- For every training example, forward propagation is done using these assigned weights, and output of each node is calculated as described above. The final output is the value of the node in the output layer.

- The final output from the last node is compared to the actual expected value from the training data, and error is measured using a *loss function.*
- Finally, a *backwards pass* is performed from right to left and the error is propagated to each node using *backpropagation*. Each weight's contribution to the error is computed, and the weights are adjusted accordingly using *gradient descent*. The error gradients are propagated back beginning from the rightmost layer.

Backpropagation is a vital part of ANN model training. It basically optimizes all the weights of the model and minimizes the loss function and assigns negligible weights to the nodes causing error in the output.

1.8. Literature Review

Several papers have been published about valve fault detection in reciprocating compressors. A.A. Khostov et al. presented a mathematical model of piston compressor and developed a representative database of test signals for each defect identified by the mathematical model. By construction of spectra for each mode (IMFs) obtained by empirical mode decomposition, suitable features for vibro-diagnostics were assessed. [9]. Kurt Pichler, Andrea Schrems et al. presented a fault detection method suitable for steady-state load conditions. Vibration data was transformed to a high-dimensional metric vector space of spectrogram data and the distance from a reference was measured. Larger distances indicated a faulty compressor. [29]

Rajeev Namdeo et al. applied a single layered functional link network (FLN) for pattern recognition of pressure signal which is used to find the location of leakage. The percentage of leakage was predicted using back propagation algorithm by simulating leakage in suction and discharge valves. [5]. Yih-Hwang Lin et al. developed an automated system using time-frequency analysis and the probability neural network (PNN) for condition classification of a RC. The method provided excellent classification accuracy with 7 seeded faults but applying their approach to extended test scenarios with higher number of seeded faults did not lead to satisfactory validation results. [27]

Vikas Sharma did a performance evaluation of empirical mode decomposition (EMD) and variational mode decomposition (VMD) to diagnose valve leakage in a RC under limited speed variation. FFT analysis along with RMS and kurtosis were evaluated post decomposition. The characteristics frequencies were clearly exhibited by VMD and the responses of kurtosis were also better with VMD. Overall VMD was found to better than EMD. [1]. Yang Liu proposed an effective and robust fault diagnosis method combining Local Mean Decomposition (LMD) and the Stack Denoising Autoencoder (SDAE). Firstly, the vibration signal is decomposed by LMD and reconstructed using the cross-correlation criterion and noise is reduced by constructing the virtual noise channel. Then, the de-noised signal is input into the trained SDAE model to learn the fault features. [10]

Salah M. Ali, K.H. Hui et al. proposed an automated fault detection method using support vector machine (SVM) and AE parameters which attempted to reduce human intervention in the process. Valve functioning was identified by acquiring AE signals and analyzing their waveforms. SVM model was devised for training and testing samples and then validated using randomly separated validation samples. Accuracy of the model was found to be a very good 98%. [20]. Houxi Cui, Laibin Zhang et al. proposed a fault diagnosis method for compressor valve fault diagnosis using information entropy to analyse signal characteristics and support vector machines (SVM) for fault classification. [6]. M. Ahmed, S. Abdusslam et al. developed a signal classifier using vibration signals with the help of probability neural network and SVM and compared their performance. It was found that the PNN performed better than the SVM when diagnosing both single fault and multiple faults using features extracted from the frequency domain while SVM did much better than the PNN in the diagnosis of multiple faults when using features extracted from the time-domain. The use of features extracted from the time-domain was found to be having a consistently higher success rate. [8]. Kurt Pichler, Edwin Lughofer et al. presented a method for detecting cracked or broken valves in RCs under varying load conditions. The patterns obtained by time frequency analysis of the vibration data were detected reliably by making a detour through the two dimensional auto correlation which reduces the noise and emphasizes the pattern. Classification was then done using support vector machines (SVM) and logistic regression. [2]Salah M. Ali, K.H. Hui et al. proposed a AI model based on acoustic emission and artificial neural networks (ANN) for valve fault detection in reciprocating compressors. AE signals were acquired under several operational conditions including healthy and faulty valves. ANN model was then developed with the healthy-faulty data using ANN tool box available in MATLAB. [4.]Y. Wang, A. Gao et al. presented an experimental study on diagnosis of various faults in reciprocating compressors with acoustic emission technology and simulated valve motion. Based on the characteristics of the measured AE signals and simulated valve motions of normal and failed valves, different types of valves were diagnosed. [7]

1.9 Scope of Dissertation:

1. Fault detection in reciprocating compressors is very necessary in order to save a big amount of maintenance cost and human effort.
2. The most common method used for fault detection and condition monitoring of rotating machinery was found to be vibration analysis.
3. Signal processing techniques such as LMD, EMD and VMD were widely used for effective results.
4. Different SVM and ANN models have shown successful performances in the fault detection and diagnosis in industries such as gearbox, machinery parts, compressors, wind and gas turbines and steel plates.

Chapter 2

Fault Diagnosis of Reciprocating Compressors Using Artificial Neural Networks

2.1 Introduction

The main objective of this study is to detect valve leakage in a single stage reciprocating compressor with the help of empirical mode decomposition (EMD) and artificial neural networks (ANNs). Firstly, vibration signals are acquired from the compressor under three different conditions of the valve - healthy, half-open and full-open. The acquired signals are then decomposed into intrinsic mode functions (IMFs) using empirical mode decomposition (EMD). RMS, kurtosis, crest factor and other factors of IMF1 are evaluated and the best ones are fed as inputs to ANN model for training and testing. Finally, the accuracies achieved in classification of the three simulated valve faults are noted.

2.2 Experimental Setup

The experiment is performed using a device called machinery fault simulator (MFS) which is one of the best tools available for learning machinery fault diagnosis. It is shown in Fig.1 along with all the components used for performing the experiment. The test rig comprises of an AC motor, a single stage, single-piston half-horsepower reciprocating compressor which is driven by a power transmitting belt drive from the main shaft. The test rig is further equipped with two optical tachometers, one for the main shaft speed and the other one for the compressor flywheel speed. The motor is connected to a variable frequency drive, known as motor speed controller to control the speed of the motor and to achieve speed variation. A tri-axial accelerometer is mounted on the top of the compressor to acquire vibration signals. The accelerometer is connected to the data acquisition system using a connecting wire and it is connected to a laptop using a cable. NV gate software is used for recording the vibration signals. The air flow in the compressor is controlled by connecting an air tank to the compressor using an air tube. Both the suction and discharge valves are finger type valves (shown in Fig.2). The severity of the valve leakage is simulated with the help of a screw as shown in Fig.3

Parameter	Measurement
Bore Diameter	50.9 mm
Stroke Length	38.0 mm
Lift of valve	6.10 mm
Area of discharge valve	145.1 mm^2

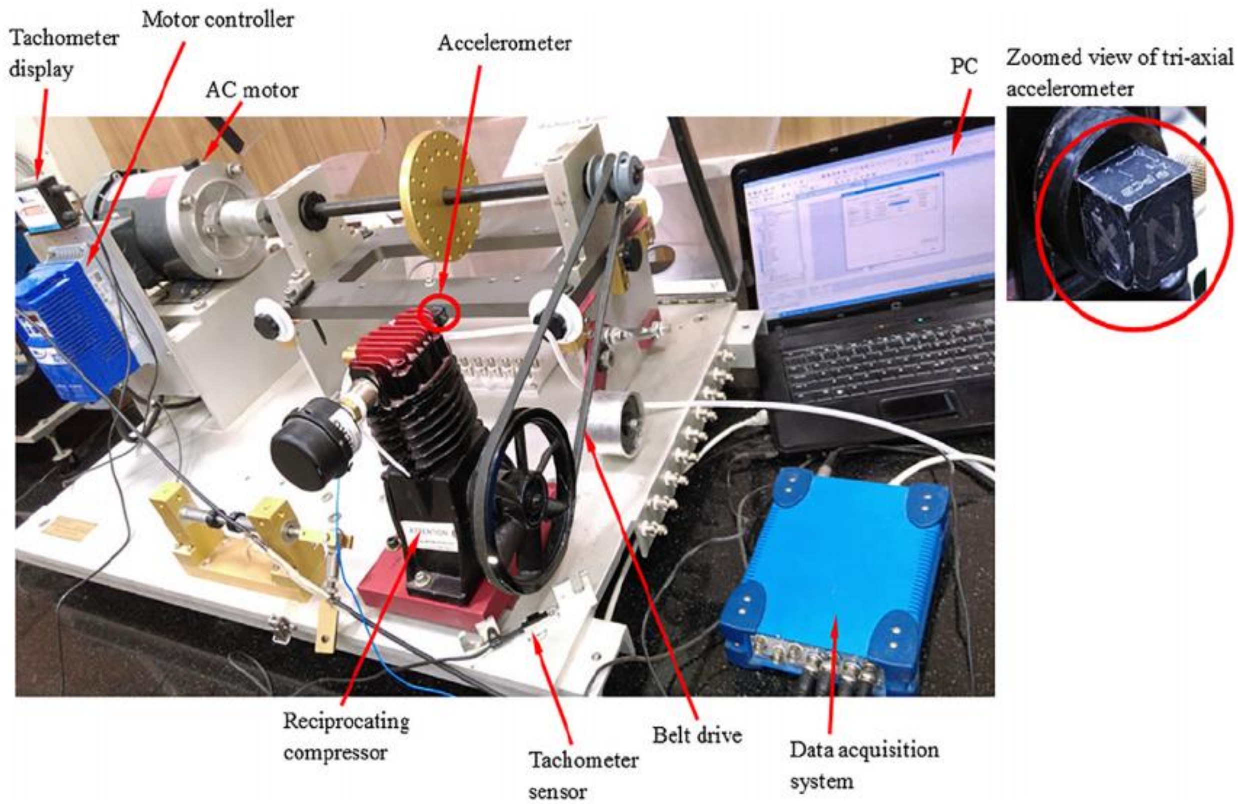

Fig. 2.1 Experimental Setup

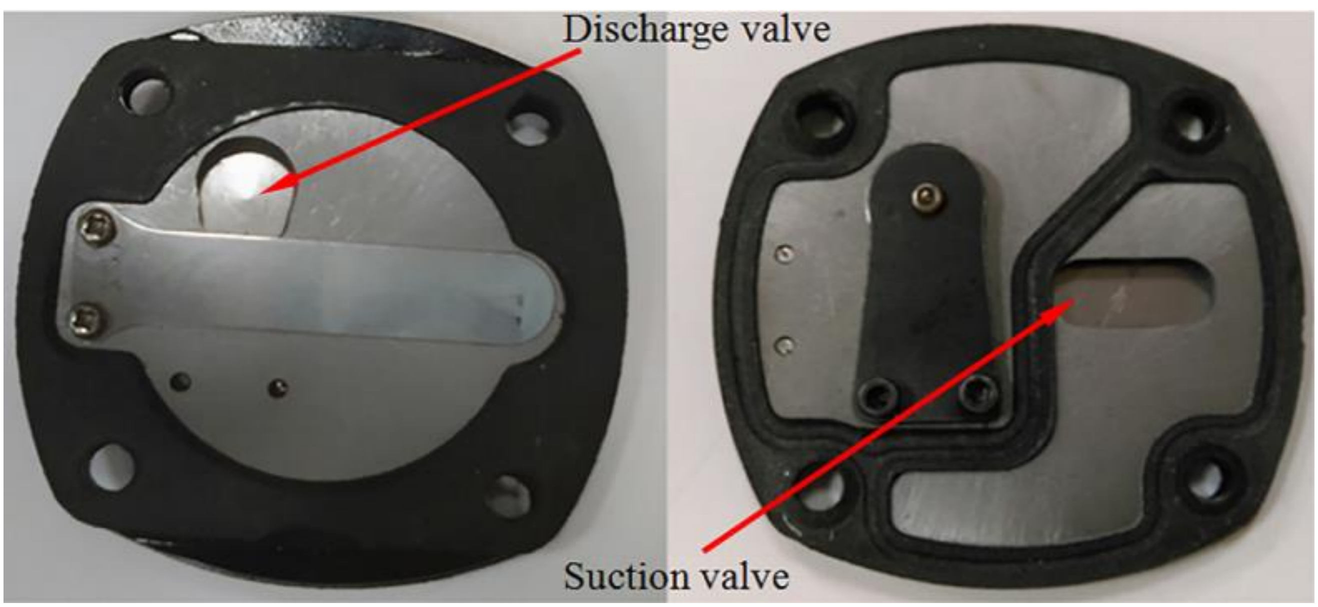

Fig. 2.2 Discharge and Suction Valves

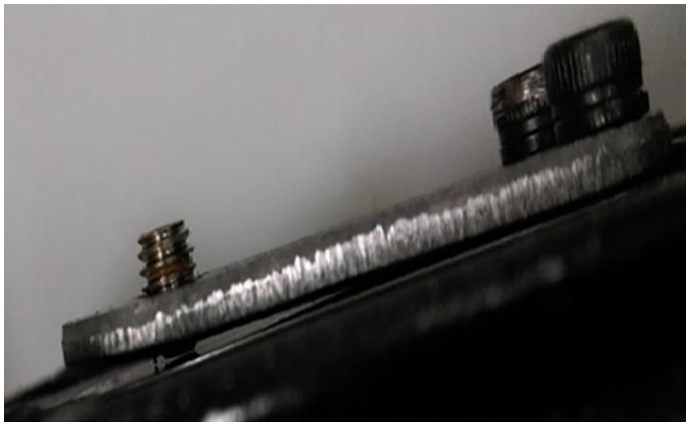

Fig 2.3 No Leak

Fig 2.4 Half-Open

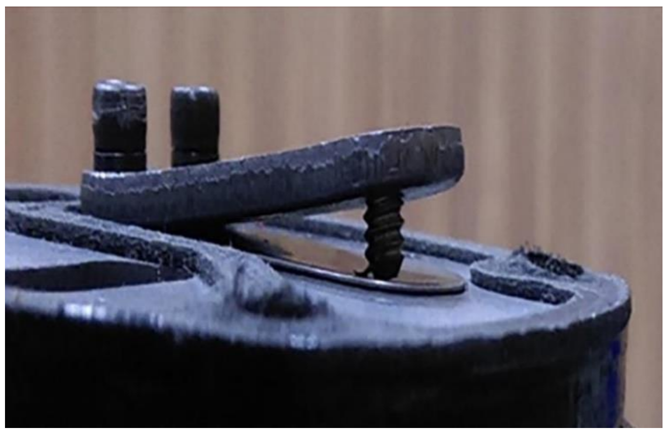

Fig. 2.5 Full-Open

2.3 Experimental Procedure:

Tests have been carried out at room temperature and atmospheric pressure in this investigation. Two parameters: limited speed variation and degree of valve leakage are present in the experimental investigation. The vibrations are recorded with 10 data sets for each arrangement.

The accelerometer (ACC301) used in the present investigation is having a sensitivity of 10.57mV/(m/s2).

During experiments, three trial runs have been conducted to check the working of the accelerometer. The run time is considered and the belt is checked for cases of overheating.

The sampling frequency for MATLAB Operations is kept at 6400 Hz. The speed is varied within the speed range (2200-2300). The RPM of RC was varied in the limit of 500-530 RPM. The velocity ratio of drive is calculated to be 4.4.

2.4 Raw Vibration Data Acquisition:

The raw vibration data acquired is in time domain. The data was acquired at a constant rotational speed of reciprocating compressor varying only the degree of valve leakage. Five different sets of measurements were performed at five different sets of constant rotational speed. The data was acquired for all three orthogonal directions viz. X, Y and Z. Given below is the pictorial representation of the acquired raw vibrational signal:

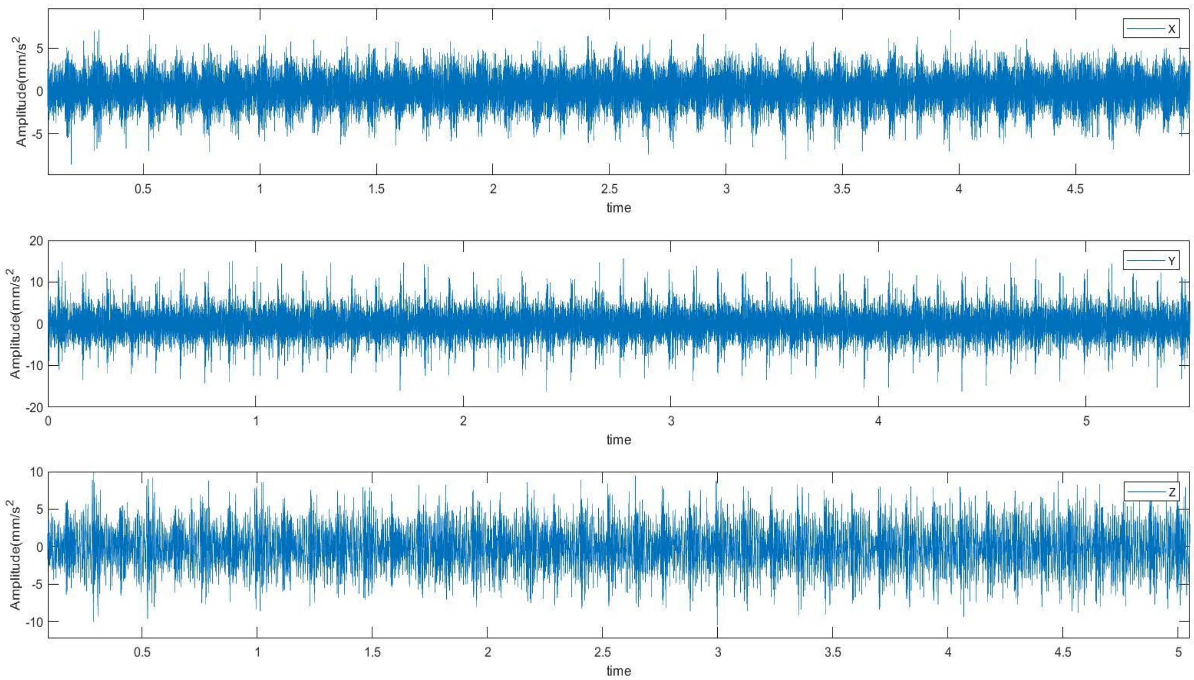

Fig. 2.6 Raw Vibration Signals

The signals in the X & Z direction were not found to be much relevant and considerable due to their less amplitude. Therefore, only the signals of Y axis have been considered for further analysis. Further results have been discussed in next section.

Chapter 3

Results and Discussions

3.1 Decomposition using EMD:

The signals of Y-axis were further processed using EMD to decompose them into Intrinsic Mode Functions called IMFs. The process was performed using MATLAB. The raw vibration signal was decomposed into 10 IMFs and a monotonic function known as "residuum".

The sample decomposed signal for healthy compressor (no leakage condition) were obtained as follows:

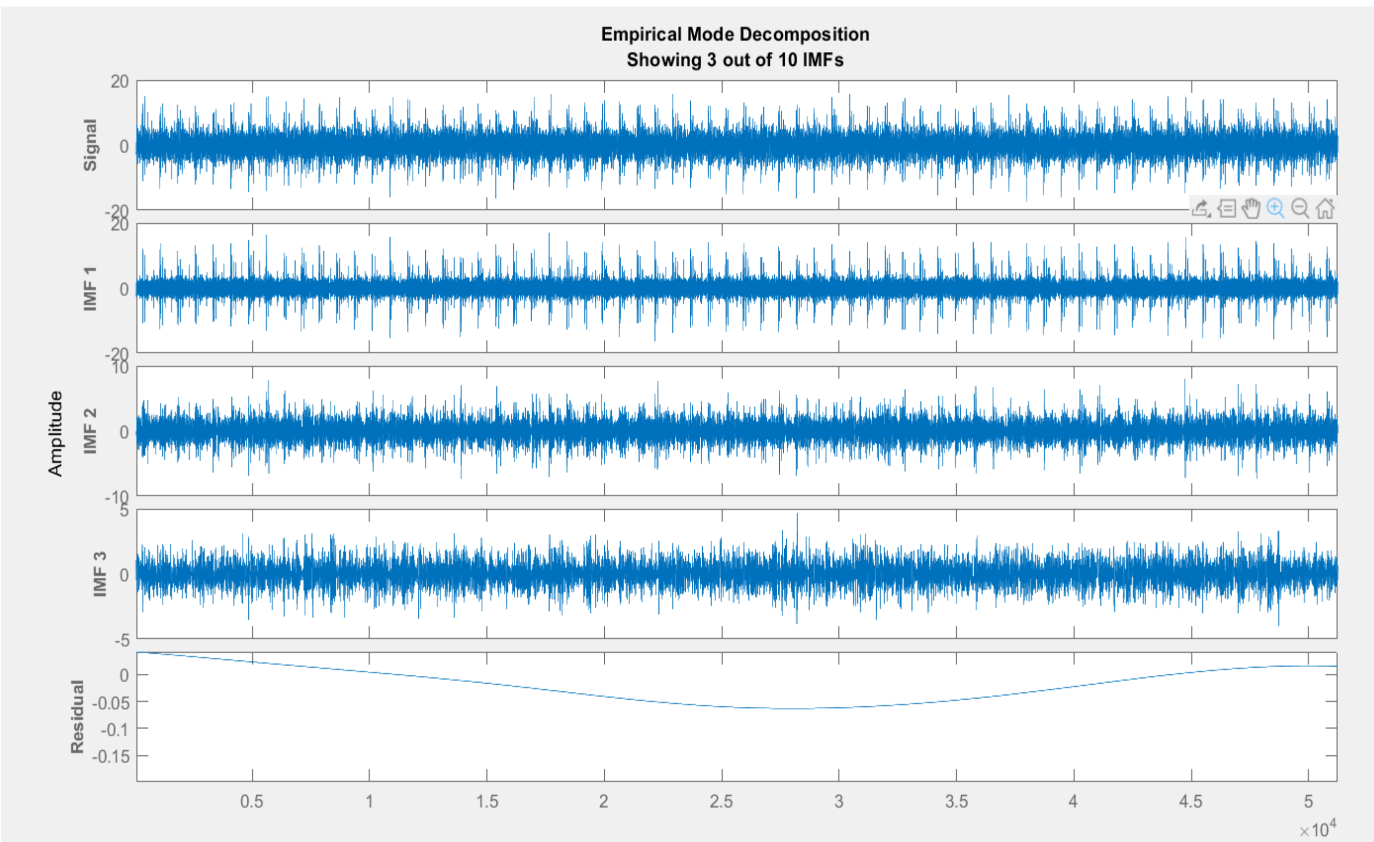

Fig. 3.1 Empirical Mode Decomposition

In above picture, only 3 out of 10 IMFs have been shown. As IMFs maintain a hierarchy in high frequency components, usually highest IMF contains the most relevant information. Hence, IMF1 has been considered for further feature extraction and classification process.

3.2 Feature Extraction:

The data or signals input into a model contain a lot of irrelevant information and sometimes noise, too. Therefore, to focus on the useful information and disregard the other things, feature extraction is a vital part of any fault detection process.

The following features were extracted from the IMF1 signal and analyzed:

- Root Mean Square(RMS)
- Kurtosis
- Crest Factor
- Shape factor, and
- Impulse Factor.

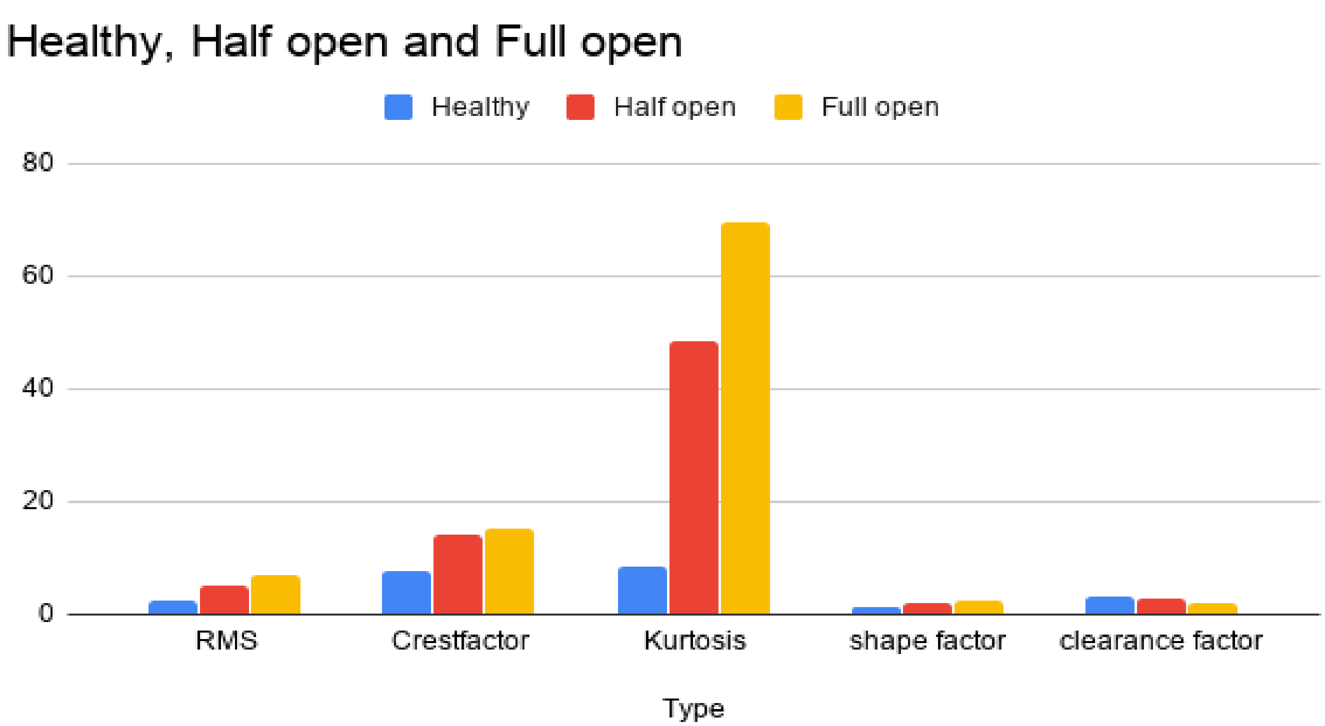

Fig. 3.2 Feature Extraction from IMF1

These parameters were used as input for the the artificial neural network algorithm.

Out of these only below three proved to be efficient:

- Root Mean Square: The Root Mean Squared values signifies the energy content within a signal w.r.t. time.
- Crest Factor: This is calculated to highlight the presence of small number of high-amplitude peaks, such as those caused by some kind of fault, leakage or blockage.
- Kurtosis: It is the fourth order normalized moment of a given signal and provides a measure of the peakedness of the signal, i.e. the number and amplitude of peaks present in the signal.

3.3 Artificial Neural Network Model:

The artificial neural network made by us was used for solving the problem of multi-class classification of different states of valve leakage viz. no leakage, half open, full open.

The code has been written in python language using TensorFlow framework and Keras library.

The code sequence involved following steps:

1. Importing different libraries and loading the dataset:

```
#Processing
import numpy as np
import pandas as pd
from scipy.stats import kurtosis

#Def RMS
def rms(x):
  return np.sqrt(x.dot(x)/x.size)

def cf(x):
  return np.divide(np.amax(np.absolute(x)), rms(x))

#Read Healthy Data
H1 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_1_healty_comp_36-9---8-50Hz.xlsx', header=None)
H2 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_2_healty_comp_36-9---8-50Hz.xlsx', header=None)
H3 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_3_healty_comp_36-9---8-50Hz.xlsx', header=None)
H4 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_4_healty_comp_36-9---8-50Hz.xlsx', header=None)
H5 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_5_healty_comp_36-9---8-50Hz.xlsx', header=None)
H1 = H1.to_numpy()
H2 = H2.to_numpy()
H3 = H3.to_numpy()
H4 = H4.to_numpy()
H5 = H5.to_numpy()
H = np.concatenate((H1[:,0], H2[:,0], H3[:,0], H4[:,0], H5[:,0]))
print('Healthy Data Loaded.')

#Processing Healthy Data
a = H.shape[0]//500
X_h = np.zeros((a,4))
for b in range(a):
  X_h[b,0] = rms(H[b*500:(b+1)*500])
  X_h[b,1] = kurtosis(H[b*500:(b+1)*500])
  X_h[b,2] = cf(H[b*500:(b+1)*500])
print('Healthy Data Processed.')
```

This code shows the command to import different libraries to process the data and loading and processing of healthy dataset i.e. for no leakage condition.

Similarly, the datasets for half-open and full-open condition were loaded and processed.

```
#Read Half Open Data
ho1 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_1_defect_comp_36-9---8-50Hz-HALFopen.xlsx')
ho2 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_2_defect_comp_36-9---8-50Hz-HALFopen.xlsx')
ho3 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_3_defect_comp_36-9---8-50Hz-HALFopen.xlsx')
ho4 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_4_defect_comp_36-9---8-50Hz-HALFopen.xlsx')
ho5 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_5_defect_comp_36-9---8-50Hz-HALFopen.xlsx')
ho1 = ho1.to_numpy()
ho2 = ho2.to_numpy()
ho3 = ho3.to_numpy()
ho4 = ho4.to_numpy()
ho5 = ho5.to_numpy()

HO = np.concatenate((ho1[:,0], ho2[:,0], ho3[:,0], ho4[:,0], ho5[:,0]))
print('Half Open Data Loaded.')

#Processing Half Open Data
c = HO.shape[0]//500
X_ho = np.zeros((c,4))
for d in range(c):
  X_ho[d,0] = rms(HO[d*500:(d+1)*500])
  X_ho[d,1] = kurtosis(HO[d*500:(d+1)*500])
  X_ho[d,2] = cf(HO[d*500:(d+1)*500])
X_ho[:,-1] = 1
print('Processed Half Open Data.')
```

```
#Loading Full Open Data
fo1 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_1_defect_comp_36-9---8-50Hz-fullopen.xlsx')
fo2 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_2_defect_comp_36-9---8-50Hz-fullopen.xlsx')
fo3 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_3_defect_comp_36-9---8-50Hz-fullopen.xlsx')
fo4 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_4_defect_comp_36-9---8-50Hz-fullopen.xlsx')
fo5 = pd.read_excel('/content/drive/My Drive/BTP/NewIMFsEndSem/Meas_5_defect_comp_36-9---8-50Hz-fullopen.xlsx')
fo1 = fo1.to_numpy()
fo2 = fo2.to_numpy()
fo3 = fo3.to_numpy()
fo4 = fo4.to_numpy()
fo5 = fo5.to_numpy()

FO = np.concatenate((fo1[:,0], fo2[:,0], fo3[:,0], fo4[:,0], fo5[:,0]))
print('Full open Data Loaded.')

#Processing Full Open Data
e = FO.shape[0]//500
X_fo = np.zeros((e,4))
for f in range(e):
  X_fo[f,0] = rms(FO[f*500:(f+1)*500])
  X_fo[f,1] = kurtosis(FO[f*500:(f+1)*500])
  X_fo[f,2] = cf(FO[f*500:(f+1)*500])
X_fo[:,-1] = 2
print('Processed Full Open Data.')
```

1. Labelling the training data:

   The input training data was labeled to train the model defining different states of the reciprocating compressor condition. The no valve leakage condition was labeled as 0. Half-open and full-open conditions were labeled as 1 & 2, respectively.

2. Calculating and plotting different features:

   The features were calculated after the datasets have been processed as follows:

```
#Plot RMS
import matplotlib.pyplot as plt
y = list(range(1672))

dh0 = pd.DataFrame(X_h[:,0]).sample(n=1672)
dho0 = pd.DataFrame(X_ho[:,0]).sample(n=1672)
dfo0 = pd.DataFrame(X_fo[:,0]).sample(n=1672)
dh1 = pd.DataFrame(X_h[:,1]).sample(n=1672)
dho1 = pd.DataFrame(X_ho[:,1]).sample(n=1672)
dfo1 = pd.DataFrame(X_fo[:,1]).sample(n=1672)
dh2 = pd.DataFrame(X_h[:,2]).sample(n=1672)
dho2 = pd.DataFrame(X_ho[:,2]).sample(n=1672)
dfo2 = pd.DataFrame(X_fo[:,2]).sample(n=1672)

plt.figure(1)
plt.scatter(y, dh0, label='Healthy', color='green', s=2)
plt.scatter(y, dho0, label='Half Open', color='red', s=2)
plt.scatter(y, dfo0, label='Full Open', color='blue', s=2)
plt.xlabel('Data-Points')
plt.ylabel('RMS value of acquired signal')
plt.legend(loc='upper right')
plt.figure(2)
plt.scatter(y, dh1, label='Healthy', color='green', s=2)
plt.scatter(y, dho1, label='Half Open', color='red', s=2)
plt.scatter(y, dfo1, label='Full Open', color='blue', s=2)
plt.xlabel('Data-Points')
plt.ylabel('Kurtosis value of acquired signal')
plt.legend(loc='upper right')
plt.figure(3)
plt.scatter(y, dh2, label='Healthy', color='green', s=2)
plt.scatter(y, dho2, label='Half Open', color='red', s=2)
plt.scatter(y, dfo2, label='Full Open', color='blue', s=2)
plt.xlabel('Data-Points')
plt.ylabel('Crest Factor value of acquired signal')
plt.legend(loc='upper right')
plt.show()
```

The pictorial representation of the RMS, Kurtosis and Crest Factor values obtained after dividing the heavy data into sets of 500 points each is shown below.

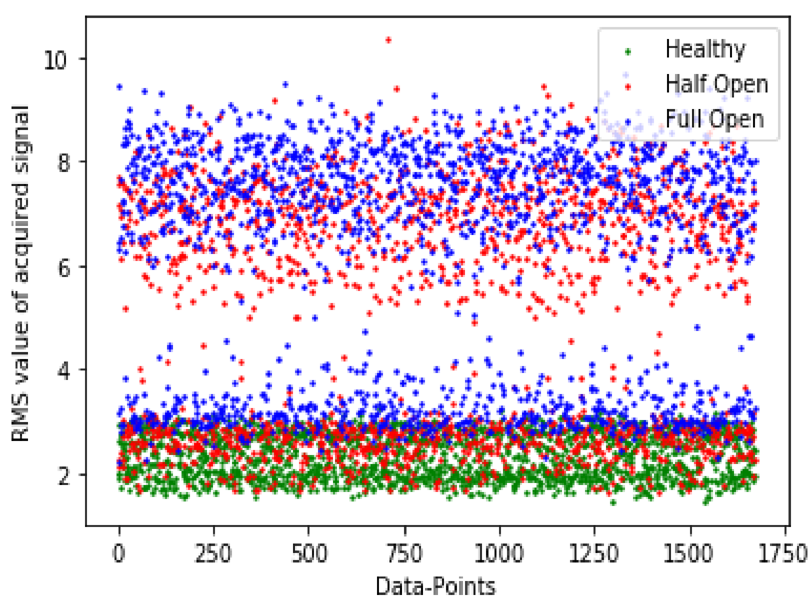

Fig. 3.3 Pictorial representation of RMS data-points and their value

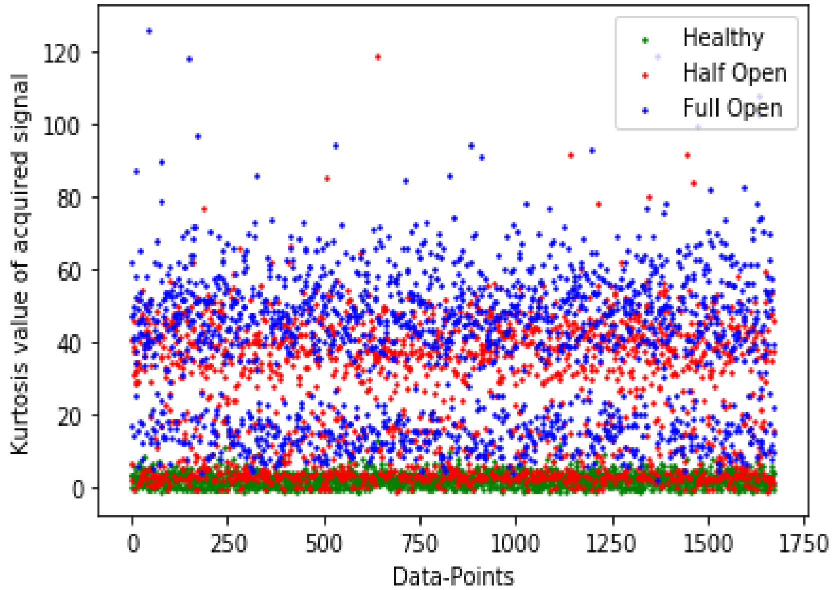

Fig. 3.4 Pictorial representation of kurtosis data-points and their value

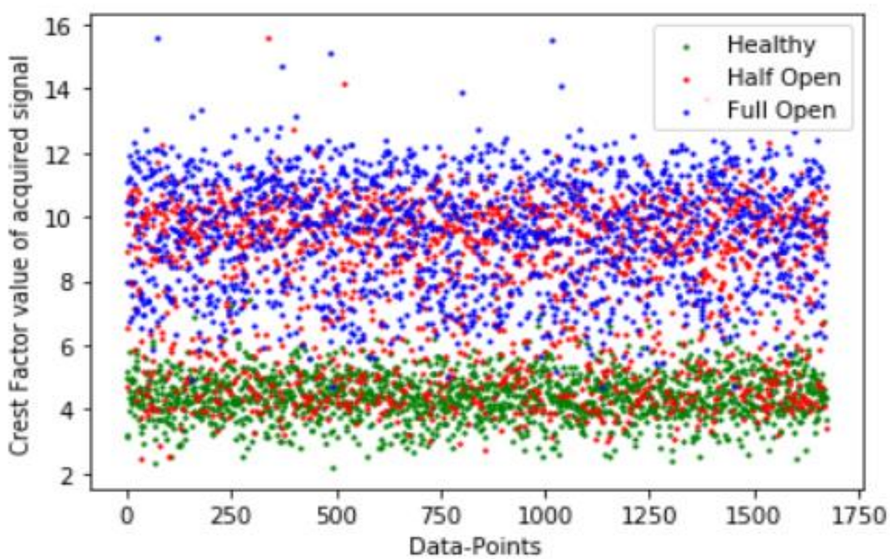

Fig. 3.5 Pictorial representation of crest-factor data-points and their value

3. Neural Network:

   The neural network used has 4 layers: input layer, 2 hidden layers and an output layer. The input layer has 3 nodes with input parameters- RMS, Kurtosis and crest factor values. The first hidden layer has 6 nodes and the activation function assigned to this hidden layer was "relu". ReLU stands for Rectified Linear Unit. Mathematically, it is defined as y = max(0, x).It is the most widely used activation function in ANNs.The second hidden layer has 10 nodes and same activation function. The Output layer has 3 nodes and the activation function assigned to this layer was 'Sigmoid'.
   It is a activation function of form **f(x) = 1 / 1 + exp(-x) .**

This has range between 0 and 1. And hence it is the most widely used activation function for probabilistic classification problems. The 3 output nodes had a condition assigned for each three levels of the valve leakage possible. One-hot encoding was used for the output layer.

The number of epochs used were 135. Each epoch had 16 batches.

The code written was as follows:

```
[ ] #Neural Network

    from keras.models import Sequential
    from keras.layers import Dense
    from sklearn import preprocessing
    from sklearn.preprocessing import LabelEncoder
    from keras.utils import np_utils
    from sklearn.model_selection import train_test_split

    seed = 7
    np.random.seed(seed)

    data = pd.read_csv('/content/drive/My Drive/BTP/endsemData_500.csv')
    data = data.to_numpy()
    X = data[:,:-1]
    Y = data[:,-1]

    encoder = LabelEncoder()
    encoder.fit(Y)
    Y = encoder.transform(Y)
    Y = np_utils.to_categorical(Y)

    (X_train, X_test, Y_train, Y_test) = train_test_split(X, Y, test_size=0.15, shuffle=True)

    model = Sequential()
    model.add(Dense(6, input_dim=3, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(10, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(3, kernel_initializer='uniform', activation='sigmoid'))
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    model.fit(X_train, Y_train, validation_split=0.20, epochs=135, batch_size=16, verbose=1)

    scores = model.evaluate(X_train, Y_train, batch_size=8, verbose=0)
    print('Train Accuracy is: %.2f%%' % (scores[1]*100))

    scores = model.evaluate(X_test, Y_test, batch_size=8, verbose=0)
    print('Test Accuracy is: %.2f%%' % (scores[1]*100))
```

The data was divided into 85% as training data and 15% as testing data.

The training and testing accuracy obtained were **71.69%** and **71.60%,** respectively. 135 epochs were found to be giving best accuracy, increasing or decreasing the number of epochs both resulted in lower accuracy.

Increasing the number of hidden layers increases the accuracy but it causes *overfitting.* Overfitting the data means the system gives high accuracies on the training data but when run on unlabeled data, results obtained are very unreliable.

Chapter 4

CONCLUSIONS AND SCOPE FOR FUTURE WORK

4.1 Conclusions:

In our study, EMD has been used to process the non-stationary vibration signals under different conditions of the valve leakage of RC under limited speed variation. Condition Indicators like RMS and kurtosis when used directly on raw vibration signals, failed to characterize the level of a leak present in the signal. Hence they were used on IMFs obtained through EMD for better results. The main objective of the study is to build an ANN model which can classify different degrees of leakage in a reciprocating compressor. The trained model is efficient with close to 70% accuracy and the following conclusions can be deduced from our observations:

1. Features such as RMS, Kurtosis and Crest factor were found to be giving highest accuracy.
2. The energy level of the vibration signals increases with increase in the degree of the leakge.
3. Increase in the number of hidden layers for higher accuracy results in *overfitting.*
4.

4.2 Scope for Future Work:

1. Laser based sensors can be used instead of accelerometer to acquire vibration signals more accurately.
2. Better signal processing techniques like Variational Mode Decomposition(VMD) can be used instead of EMD which give more accurate performance.
3. Using sequential models can help improve efficiency of the model.
4. A similar model can be built using deep learning algorithm techniques which can improve the accuracy obtained.
5. The quality of vibrations also depend on the work place where the signals are acquired.

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