B. TECH. PROJECT REPORT

On

Fault diagnosis of Centrifugal Pumps in Frequency Domain of Vibration Data Using SVM Algorithms

BY

Navneet Singh (130003023)

DISCIPLINE OF MECHANICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

November 2016

Fault diagnosis of Centrifugal Pumps in Frequency Domain of Vibration Data Using SVM Algorithms

A PROJECT REPORT

Submitted in partial fulfilment of the requirements for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

Mechanical Engineering

Submitted by:

Navneet Singh

Guided by:

Dr. Anand Parey,
Associate Professor,
Discipline of Mechanical Engineering,
Indian Institute of Technology, Indore.

INDIAN INSTITUTE OF TECHNOLOGY INDORE
November, 2016

CANDIDATE'S DECLARATION

I hereby declare that the project entitled **"Fault diagnosis of Centrifugal Pumps in Frequency Domain of Vibration Data Using SVM Algorithms"** submitted in partial fulfilment for the award of the degree of Bachelor of Technology in **Mechanical Engineering** completed under the supervision**, Dr. Anand Parey, Associate Professor, Discipline of Mechanical Engineering, IIT Indore** is an authentic work.

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

Navneet Singh
130003023
Discipline of Mechanical Engineering,
Indian Institute of Technology, Indore.

CERTIFICATE by BTP Guide

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

Dr. Anand Parey,

Associate Professor,

Discipline of Mechanical Engineering,

Indian Institute of technology, Indore

(Project Guide)

Preface

This report on “**Severity Assessment and Classification of Blockage of Centrifugal Pumps in Frequency Domain of Vibration Data Using SVM Algorithms”** is prepared under the guidance of **Dr. Anand Parey, Associate Professor, Discipline of Mechanical Engineering, Indian Institute of Technology, Indore.**

Through this report I have tried to give a detailed description of the automation methodology of vibration based condition monitoring, severity assessment and fault detection in centrifugal pumps using binary SVM classifier on frequency domain data.

I have tried to the best of our abilities and knowledge to explain the content in a lucid manner. I have also added tables and figures to make it more illustrative.

Navneet Singh,
B.Tech. IV Year,
Discipline of Mechanical Engineering,
IIT Indore.

Acknowledgements

I would like to thank my btp supervisor, **Dr. Anand Parey**, for his constant support in structuring the project and for his valuable feedback which helped me in the course of the project. He gave me the opportunity to discover and work in this domain. He guided me thoroughly and pulled me out of the craters of failures I faced all through the period.

I am also thankful to all my family members, friends and colleagues who have been a constant source of motivation. Finally, I offer sincere thanks to everyone else who knowingly or unknowingly helped me complete this project.

Navneet Singh,
B.Tech. IV Year,
Discipline of Mechanical Engineering,
IIT Indore.

Abstract

The present work proposes an automation methodology of the vibration based condition monitoring, fault detection and severity assessment in centrifugal pumps using SVM classifier based on frequency domain data. The inlet pipe blockage is artificially induced on the pump and is considered in steps of increasing severity. As the flow rate decreases with increasing blockage, recirculation and associated vapour bubble formation starts. The pump is run at different flow conditions and speeds. Energy is extracted from frequency domain data. Binary and multi-class classifications are proposed using Gaussian RBF kernel function of the SVM algorithm. The kernel input parameter (Y) is optimally chosen. A fault prediction performance is presented.

Table of Contents

List of Figures

Chapter 1:

Introduction

This chapter highlights the background and motivation for the project. The problem statement has been described of the project and the importance of results is also clearly portrayed. Towards the end, the objectives and expectations to solve the problem statement as far as possible were also stated.

1.1. Background

Centrifugal pumps find their applications in variety of fields starting right from households to heavy industrial applications. The obvious reasons for their choice are their simple design and cost effectiveness. They form crucial components to keep the flow of the process intact. Their breakdown may lead to a temporary stoppage of process flow or in extreme cases may lead to a complete stall of it. The attachments in the pumps become even more of a concern, when they affect the other attachment in line. Hence, early fault detection in the pumps and their improving monitoring is very essential. The future technology is moving towards improving the productivity/ efficiency of the industry, by minimizing human involvement and the maintenance. Maintenance costs are a major part of the total operating costs and depending on the specific industry, they can represent from 15% to 40% of costs of goods produced. Pumps that deal with unclean liquids, especially in the industrial and sewage applications, undergo a lot of clogging. When such obstruction to flow is created the flow rate drops and a secondary flow develops, called the recirculation flow. The separation of flow increases, vortex is formed which results in local pressure drop and thus formation of vapour bubbles.

The after effect of this is unwanted vibrations due to resulting flow instabilities. The online fault detection of centrifugal pumps has been popularly done using the vibration signals, motor current signal, fluid pressure and acoustic signal. The use of motor current for the fault diagnosis is found to be useful because it does not use any mechanical sensors. The faults like the cavitation, blockage, and impeller damage have been detected using the current signal. Acoustic signal on the other hand has been used for the detection of cavitation inception. Vibration signals have always been very versatile signatures, as they capture even the slightest change in the performance parameters of the system. Faults like flow instability, cavitation, impeller damages and bearing damages have been detected using vibration signals. Essential part of the automation in condition monitoring is the classification or faults. There are many machine learning algorithms available for this purpose but the popular ones, however, are neural networks, decision tree, fuzzy logic and support vector machine (SVM) algorithm. Neural networks, fuzzy logic, rough partially linearized neural networks have been extensively used for the fault classification. These algorithms are very versatile and highly helpful in the multiclass classification. The choice of the domain for the classification (time, frequency, time-frequency) and also the features extracted in the domain, play a big role in improving the efficiency of the classifier. The SVM algorithm is a relatively new classifier and there has been extensive research on this. Its application has also been talked about very much in the recent past. There are also many studies that compared the efficiencies of the SVM algorithm with more established neural networks. The efficiency of the SVM algorithm and the time taken by for the classification are found to be better than neural networks.

Taking into consideration the advantages offered by the SVM algorithm over the other classifiers, in the present paper, analysis of frequency domain data of the vibration signal using C-SVM algorithm is proposed. The main fault that would be considered is that of the blockage. Inlet pipe blockage is considered in steps of 0% (full flow/no fault), 16.7%, 33.3%, 50% and 66.6%.

Chapter 2:

Literature Review

The problem statement and the objectives mentioned in chapter 1 are real life problems pertaining to classification. Accuracy and efficient classifier is very important in many domains. This chapter focuses on the concepts of pump, cavitation, recirculation flow and many other.

2.1 Pumps:

A pump is a device that moves fluids (liquids or gases), or sometimes slurries, by mechanical action. Pumps can be classified into three major groups according to the method they use to move the fluid: *direct lift*, *displacement*, and *gravity* pumps.

Pumps operate by some mechanism (typically reciprocating or rotary), and consume energy to perform mechanical work by moving the fluid. Pumps operate via many energy sources, including manual operation, electricity, engines, or wind power, come in many sizes, from microscopic for use in medical applications to large industrial pumps.

Mechanical pumps serve in a wide range of applications such as pumping water from wells, aquarium filtering, pond filtering and aeration, in the car industry for water-cooling and fuel injection, in the energy industry for pumping oil and natural gas or for operating cooling towers. In the medical industry, pumps are used for biochemical processes in developing and manufacturing medicine, and as artificial replacements for body parts, in particular the artificial heart and penile prosthesis. There are many types of pumps:

- **Single stage pump -** When in a casing only one impeller is revolving then it is called single stage pump.
- **Double/ Multi stage pump -** When in a casing two or more than two impellers are revolving then it is called double/ multi stage pump.

In biology, many different types of chemical and bio-mechanical pumps have evolved, and bio mimicry is sometimes used in developing new types of mechanical pumps.

2.1.1 Applications of pumps:-

The basic purpose of a pump is to transfer fluid or liquid or gases or slurries from a low level to a higher level. In fluid systems, pumps are used to keep the fluid moving in a very useful way. When fluids move, they are frequently required to move upwards through the pipes. The pumps provide enough push to keep the fluid going upwards. Also, while fluids go through pipes, they encounter friction, like anything else. Pumps help to overcome this friction loss to keep everything moving. Pumps are widely used in variety of applications starting from homes to offices to school/colleges/hospitals/ to commercial complexes to industrial applications to aerospace. Pumps are used throughout society for a variety of purposes. Early applications include the use of the windmill or water mill to pump water. Today, the pump is used for irrigation, water supply, gasoline supply, air conditioning systems, refrigeration (usually called compressor), chemical movement, sewage movement, flood control, marine services, etc.

2.1.2 Types of Pumps

1. **Displacement Pumps**

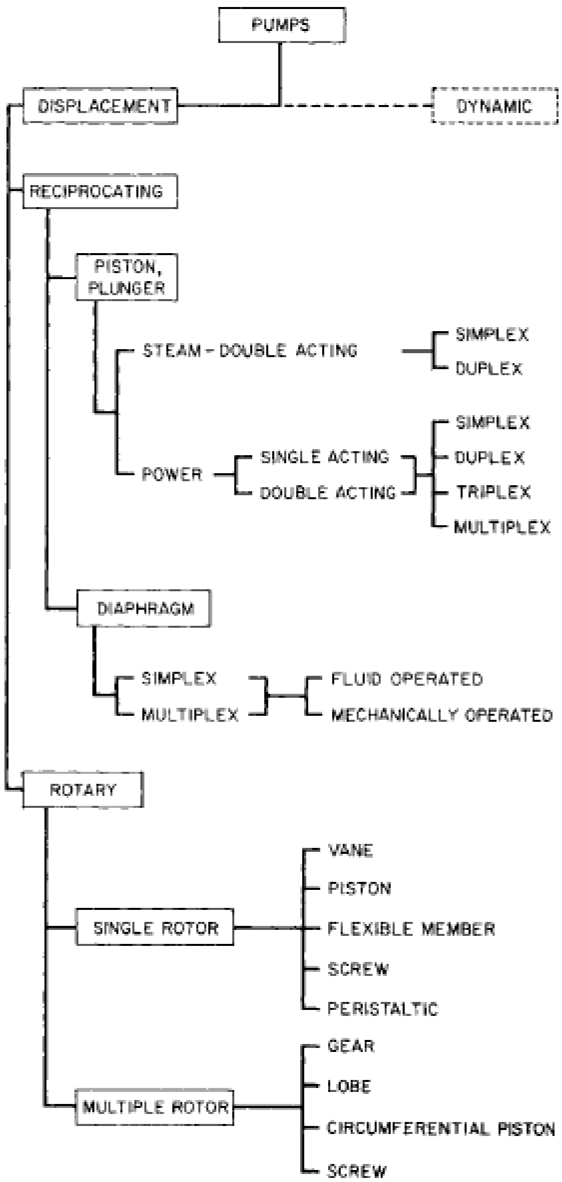


Figure 1-a: Types of Displacement Pumps

2. Dynamic Pumps

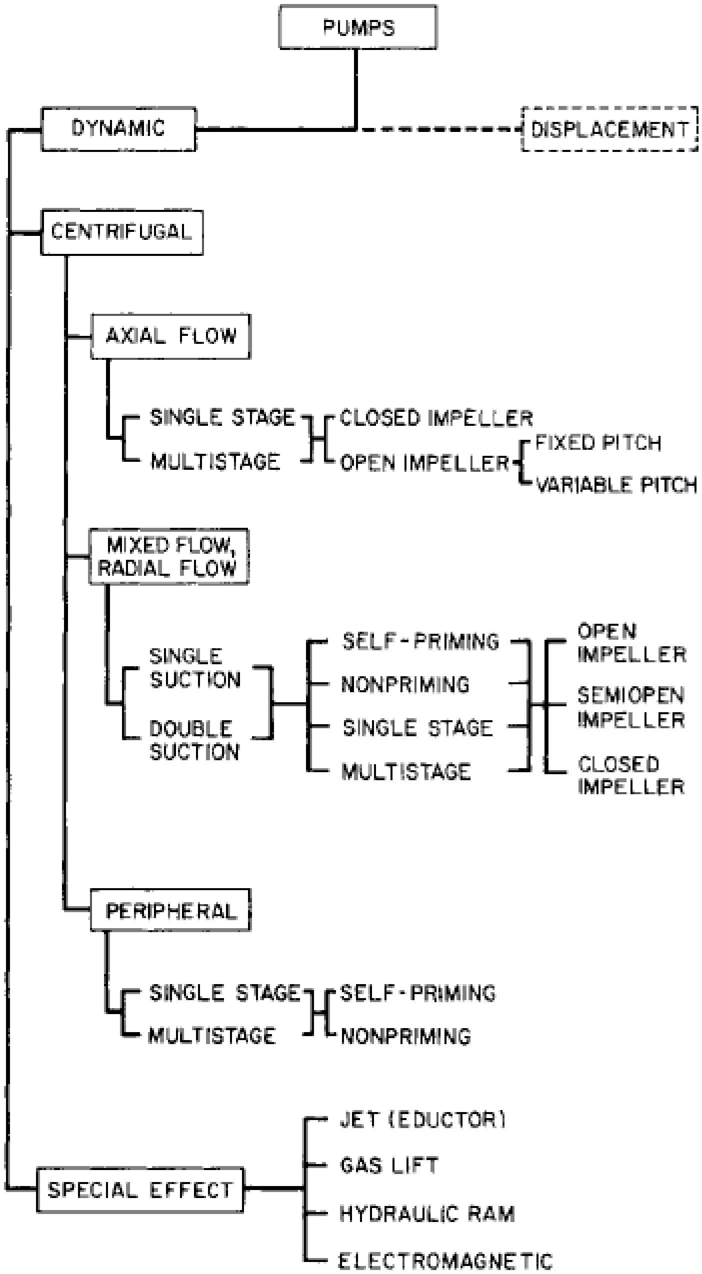


Figure 1-b: Types of Dynamic Pumps

2.1.3 Centrifugal Pumps

A centrifugal pump is a rotating machine in which flow and pressure are generated Dynamically. The inlet is not walled off from the outlet as is the case with positive displacement pumps, whether they are reciprocating or rotary in configuration. Rather, a centrifugal pump delivers useful energy to the fluid or "pumpage" largely through velocity changes that occur as this fluid flows through the impeller and the associated fixed passageways of the pump; that is, it is a "rotodynamic" pump. All impeller pumps are rotodynamic, including those with radial-flow, mixed-flow, and axial-flow impellers: the term "centrifugal pump" tends to encompass all rotodynamic pumps.

Although the actual flow patterns within a centrifugal pump are three-dimensional and unsteady in varying degrees, it is fairly easy, on a one-dimensional, steady-flow basis, to make the connection between the basic energy transfer and performance relationships And the geometry or what is commonly termed the "hydraulic design" (more properly the "Fluid dynamical design") of impellers and stators or stationary passageways of these machines.
In fact, disciplined one-dimensional thinking and analysis enables one to deduce pump operational characteristics (for example, power and head versus flow rate) at both the optimum or design conditions and off-design conditions. This enables the designer and the user to judge whether a pump and the fluid system in which it is installed will operate smoothly or with instabilities. The user should then be able to understand the offerings of a pump manufacturer, and the designer should be able to provide a machine that optimally fits the user's requirements.

2.1.4 Defects in Centrifugal Pumps

Cavitation—the net positive suction head (NPSH) of the system is too low for the selected pump. Cavitation is the formation of vapour cavities in a liquid – i.e. small liquid-free zones ("bubbles" or "voids") – that are the consequence of forces acting upon the liquid. It usually occurs when a liquid is subjected to rapid changes of pressure that cause the formation of cavities where the pressure is relatively low. When subjected to higher pressure, the voids implode and can generate an intense shock wave. Cavitation is a significant cause of wear in some engineering contexts. Collapsing voids that implode near to a metal surface cause cyclic stress through repeated implosion. This result in surface fatigue of the metal causing a type of wear also called "cavitation". The most common examples of this kind of wear are to pump impellers, and bends where a sudden change in the direction of liquid occurs. Cavitation is usually divided into two classes of behaviour: inertial (or transient) cavitation and non-inertial cavitation. Inertial cavitation is the process where a void or bubble in a liquid rapidly collapses, producing a shock wave. Inertial cavitation occurs in nature in the strikes of mantis shrimps and pistol shrimps, as well as in the vascular tissues of plants. In man-made objects, it can occur in control valves, pumps, propellers and impellers. Non-inertial cavitation is the process in which a bubble in a fluid is forced to oscillate in size or shape due to some form of energy input, such as an acoustic field. Such cavitation is often employed in ultrasonic cleaning baths and can also be observed in pumps, propellers, etc. Since the shock waves formed by collapse of the voids are strong enough to cause significant damage to moving parts, cavitation is usually an undesirable phenomenon. It is very often specifically avoided in the design of machines such as turbines or propellers, and eliminating cavitation is a major field in the study of fluid dynamics. However, it is sometimes useful and does not cause damage when the bubbles collapse away from machinery, such as in super cavitation.

2.2 Recirculation Flow

Recirculation a potentially damaging flow reversal at the inlet or discharge tips of the impeller wings of the centrifugal pump, has long been a source of consternation to centrifugal pump designers and users. Until recently the pump industry had little recourse other than to cope with the effects of the recirculation after they had already begun wreaking havoc on the pumping system.

The pressure field produced in a centrifugal pump impeller at a flow corresponding to peak efficiency is more uniform and symmetrical than at any other flow. At flows less than that peak efficiency the pressure field become increasingly distorted until at some point the pressure gradient reverses and localized reversal of the flow takes place. This is the point of recirculation which can occur at the discharge or the suction of the impeller or at both of them.

2.2.1 Causes of Recirculation

Why does a reversal of flow occur at reduced flows? The answer to this question seems to be related to the fact that the pressure field not only increases from suction to discharge, but also that the total heat produced is the sum of the centrifugal head and the dynamic head. The centrifugal head for any given impeller diameter and speed is independent at the rate of flow The dynamic head, however is a function of the absolute velocity that is related to the rate of flow. At some point on the head capacity curve. The dynamic head will exceed the centrifugal head. At this point, the pressure gradient reverses and the flow is from the discharge to the suction of the impeller, because the pressure field is now not symmetrical. And because the vanes themselves distort the pressure field. the reverse or back flow takes place in the vicinity d the vane itself. The condition now exists where a small portion of the total flow has reversed its direction and the shear face between the two flows produces vortices that are “locked” into the vane system and rotate with it.

2.3 Classification:

In this section, the formulation of Binary class SVM is briefly discussed. The role of kernel function are also discussed.

2.3.1 Binary Class Support Vector Machines:

Binary SVMs are classifiers which discriminate data points of two categories. Each data object (or data point) is represented by an n-dimensional vector. Each of these data points belongs to only one of two classes. A linear classifier separates them with a hyper plane. For example, **Fig. 1** shows two groups of data and separating hyper planes that are lines in a two-dimensional space. There are many linear classifiers that correctly classify (or divide) the two groups of data. In order to achieve maximum separation between the two classes, SVM picks the hyper plane which has the largest margin.

We are given a training dataset of n points of the form

$(\vec{x}_1, y_1), \ldots, (\vec{x}_n, y_n)$ where y_i are either 1 or −1, each indicating the class to which the point $\vec{x}_i$ belongs. These hyper planes can be described by the equations

$$\vec{w} \cdot \vec{x} - b = 1 \text{ And } \vec{w} \cdot \vec{x} - b = -1.$$

Geometrically, the distance between these two hyper planes is $\frac{2}{\|\vec{w}\|}$. So to maximize the distance between the planes we want to minimize $\|\vec{w}\|$. As we also have to prevent data points from falling into the margin, we add the following constraint:

$$y_i(\vec{w} \cdot \vec{x}_i - b) \geq 1, \quad \text{for all } 1 \leq i \leq n.$$

We can put this together to get the optimization problem:

Minimize $\|\vec{w}\|$ subject to $y_i(\vec{w} \cdot \overrightarrow{x_i} - b) \geq 1,$ for i = 1,2,... n

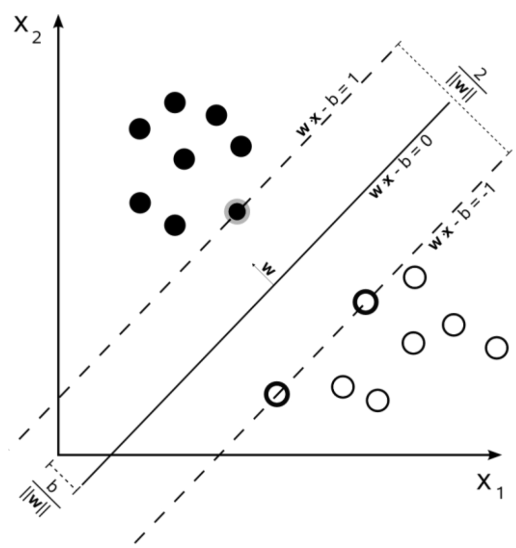


Figure 2: Binary Class classification using SVM

If the training data is not linearly separable, there is no straight hyper plane that can separate the classes. The process of finding classification functions using nonlinear SVMs consists of two steps. First, the input vectors are transformed into high-dimensional feature vectors using kernels where the training data can be linearly separated. Then, SVMs are used to find the hyper plane of maximal margin in the new feature space. The separating hyper plane becomes a linear function in the transformed feature space but a nonlinear function in the original input space. A kernel function is the one which satisfies the Mercer's theorem. In general a kernel can be defined as:

$$K(\mathbf{x}, \mathbf{x}') = \langle \psi(\mathbf{x}), \psi(\mathbf{x}') \rangle$$

where ψ is a function that projections vectors x into a new vector space. The kernel function computes the inner-product between two projected vectors. The choice of kernel functions and also kernel parameters has a great effect on the accuracy and time taken for the classification. The kernel is chosen based on the datasets. In this project, we choose a Gaussian RBF kernel defined as following:

$$K_{\mathrm{RBF}}(\mathbf{x}, \mathbf{x}') = \exp\left[-\gamma \|\mathbf{x} - \mathbf{x}'\|^2\right]$$

where γ is a parameter that sets the "spread" of the kernel.

After the optimization problem is solved, the SVM equations is as follows:

$$f(\mathbf{x}) = \sum_{i}^{N} \alpha_i y_i \exp\left(-||\mathbf{x} - \mathbf{x}_i||^2/2\sigma^2\right) + b$$

2.3.2 Feature Selection:

In this project we use energy as a feature for classification. When faults are induced, the value of energy increases thereby making the classification efficient. Energy measures the distribution of spectrum H(j), of a signal h(j), j=1,2..N. The spectrum is normalised as:

$$\mathbf{E(j)} = \sum_{i=1}^{100} \mathbf{H(i)2}$$

These energy values are used as datasets for training and testing the binary classifier.

Chapter 3

Experimental Procedure:

In this section, configuration of experimental set-up, procedure of the experimentation are described. A few initial observations while conducting the experiment are presented

3.1 Configuration

A Machine Fault Simulator (MFS) is used for the purpose of experimentation. Figure 3 shows the overview of the experimental setup. A healthy pump is installed on the fixed base of the MFS. The pump is driven by an induction motor, by a double-belt pulley drive. The speed of the motor may be altered. Modulating valves are provided for regulating the flow rate by varying the cross-section of the inlet/ outlet pipes.

One tri-axial accelerometer and one uni-axial accelerometer are used in this experiment. One of them is mounted on the pump casing and the second one is mounted at the bearing housing location. Forces get transmitted to the bearing on which the rotor shaft is supported, hence it is logical to expect the vibration signature at bearing location. It is observed that bubbles formed due to flow instabilities collapse at the casing. Water is circulated in a closed loop. The vibration data is acquired by using a Data Acquisition System (DAQ) and commercial software. For each pump fault condition, 30,000 non-overlapping data sets have been collected in 35s. Each data set has 300 samples in frequency domain.

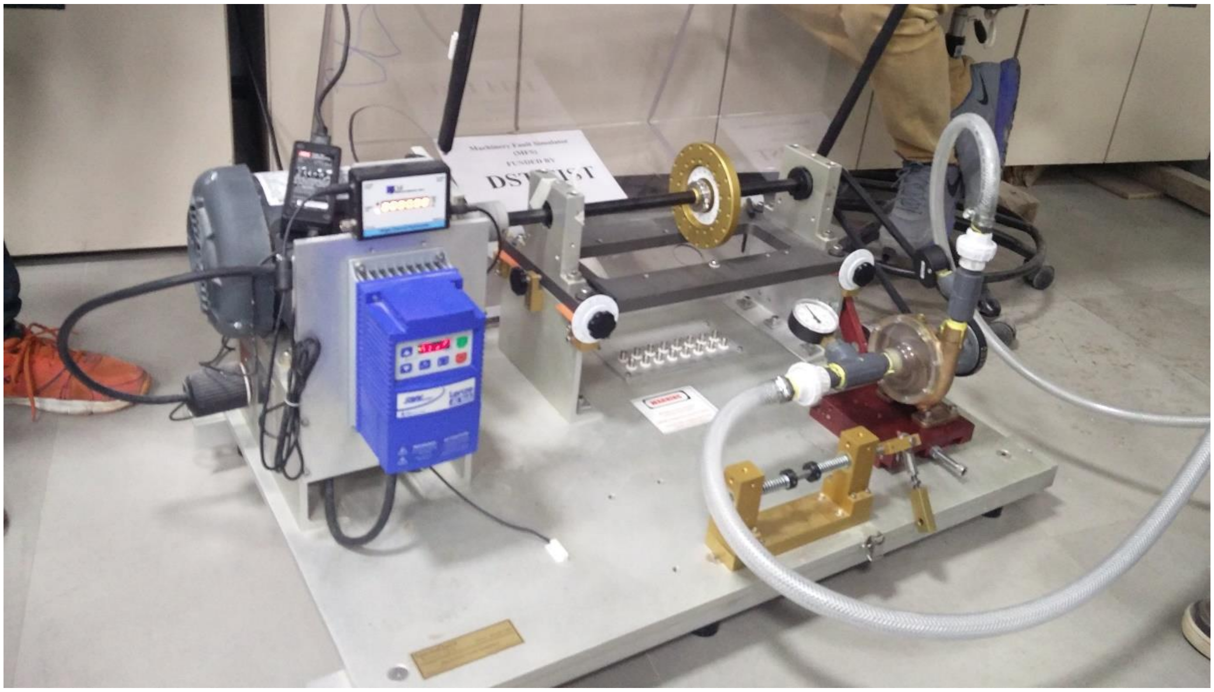


Figure 3: Experimental MFS setup

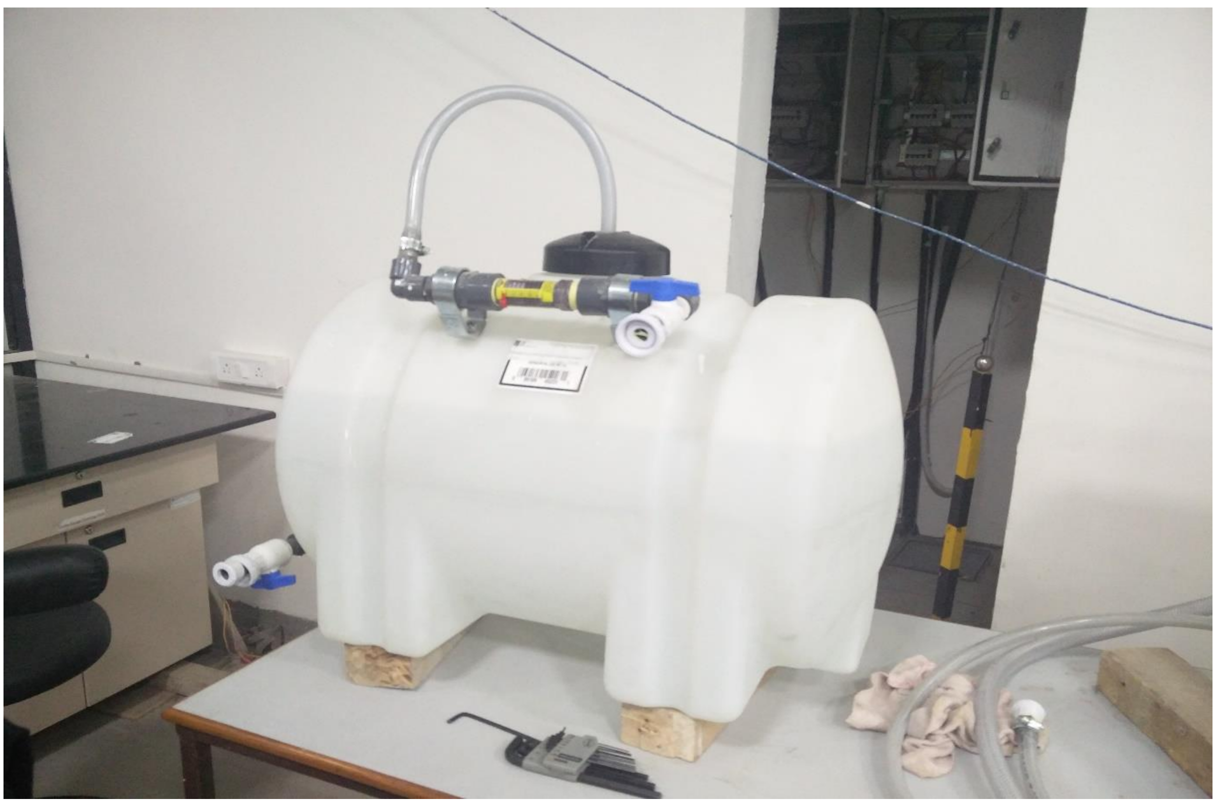


Figure 4: Water reservoir

Figure 5: Centrifugal Pump

Figure 6: Control Box

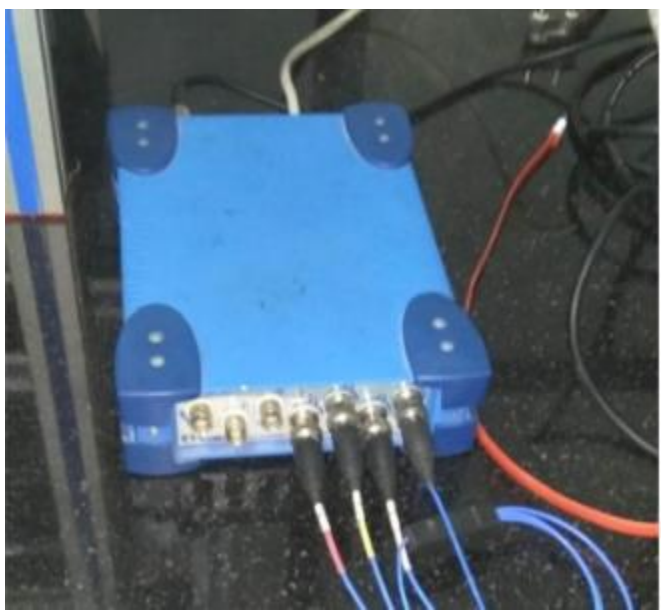


Figure 7: Analyzer

The speeds chosen for this experiment are 20, 25, 30, 35, 40, 45 and 50 Hz.
The following five different blockage conditions of the pump were taken for each specific speed.

1. **0% blockage of flow or full flow (BO):** This is a healthy condition of pump. In this case the flow is not restricted or the modulating valve is fully open. As practically visualized, there was flow instability. This is the benchmark condition for the binary classification.
2. **16.7% blockage or 5/6 of full flow (B1):** 16.7% of flow restriction was induced. No effect on the flow observed yet in this condition also. This suggests that it behaves more like a healthy pump.
3. **33.3% blockage or 2/3 of full flow (B2):** 33.3% of inlet area is blocked.In this case vibrations are found to increase. This might be due to excess blockage.
4. **50% blockage or 1/2 of full flow (B3):** There is half blockage. The transparent cover is covered with bubbles. The actual formation of bubbles already started somewhere between B2 and B3. There are no bubbles in the outlet hose
5. **66.6% blockage or 1/3 of full flow (B4):** 33.33% of area is available for the flow. The sound increased further. Bubble collapse at the wall of centrifugal pump housing was observed. Further, bubbles were seen in the outlet hose Pipe.

The rotatable knob facilitates in adjusting the blockage level. Increasing the blockage results in decrease in flow rate and separation of flow. Bubble formation resulted with increasing flow restriction. Hence, all the blockage levels are checked to sense the severity of intensity of bubble formation. Until B3 there is no evidence of bubble formation and it started between level B2 and B3.

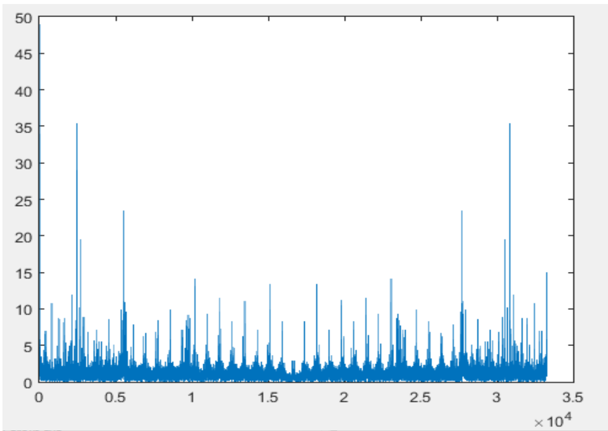
Chapter 4

Results and Observations:

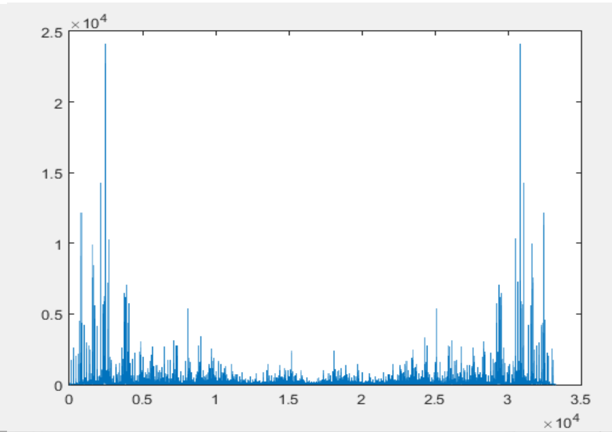
The data from the accelerometers is in time domain. It is converted to the frequency domain using fast Fourier Transform (FFT). The frequency domain data is very useful, if the severity of the fault condition needs to be found out. The frequency domain also gives information about the low frequency vibrations experienced, their severity and also the high frequency fault severity. In the present case, the FFT has been truncated at 10 kHz frequency. The frequency domain data by itself may not be useful to train the algorithm. Statistical features have always been able to capture the properties of the data, better than the raw data itself. Hence, useful features are extracted to conduct the fault classification using the SVM.

4.1 Selection of features and kernel parameters:

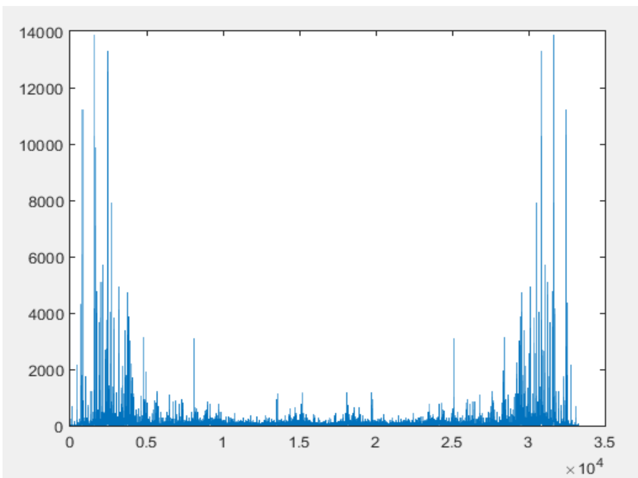
In this work, Energy is chosen as statistical feature. Many features such as like entropy, standard deviation, kurtosis, root mean square, etc. can also be used as features. The data is divided into training data and testing data. In the Present work 200 datasets have been taken for training and 100 datasets are taken for testing. The training data is used to train the OC-SVM algorithm. The SVM Gaussian RBF kernel parameters trial range is first given. Depending on the classification accuracy obtained and the value of kernel parameter at the maximum classification accuracy, a call has been taken to decide if that Parameter is Fault or not, and if it is suitable then the kernel parameter is further fine-tuned to obtain optimum result.



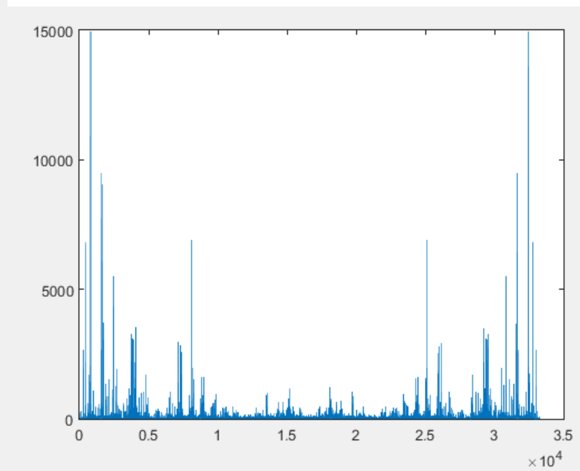
(a1)



(a2)



(a3)



(a4)

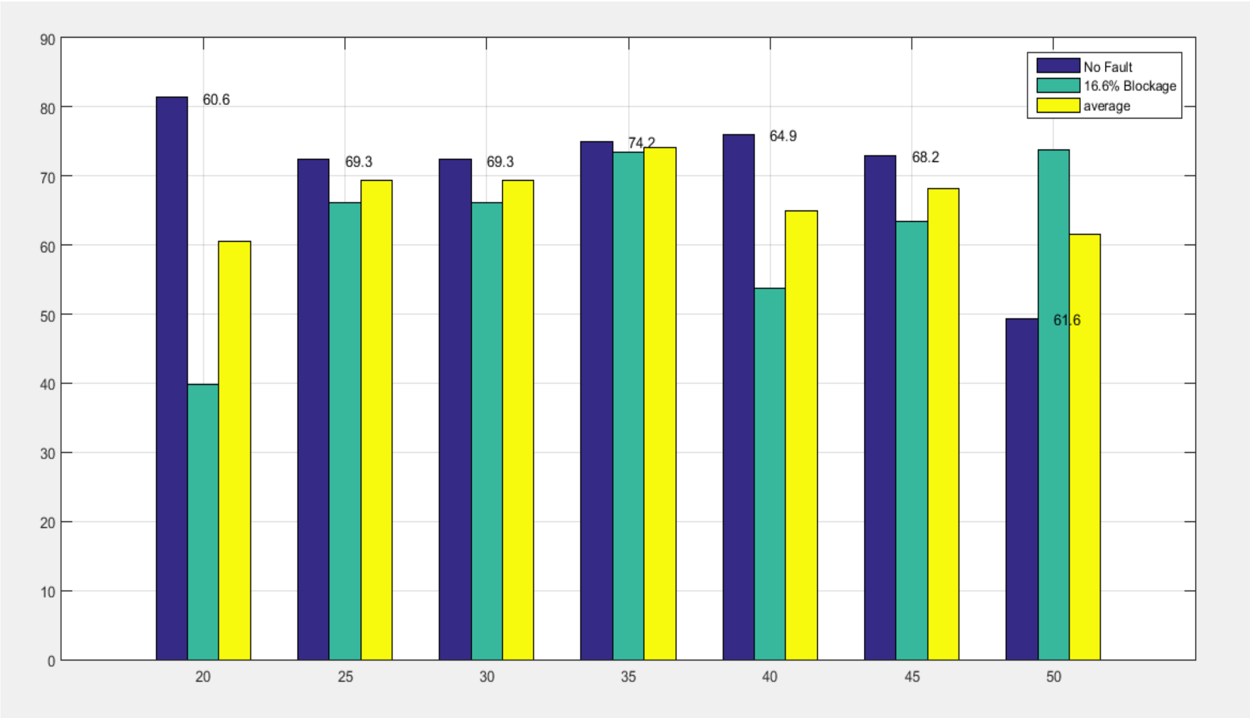
Figure 8 : (a1), (a2), (a3) shows the frequency vs acceleration for tri accelerometer at 50Hz in healthy condition i.e. 0% blockage at X,Y,Z directions respectively and (a4) shows for uni-axial accelerometer in X direction

For Binary classification, the results are as follows:

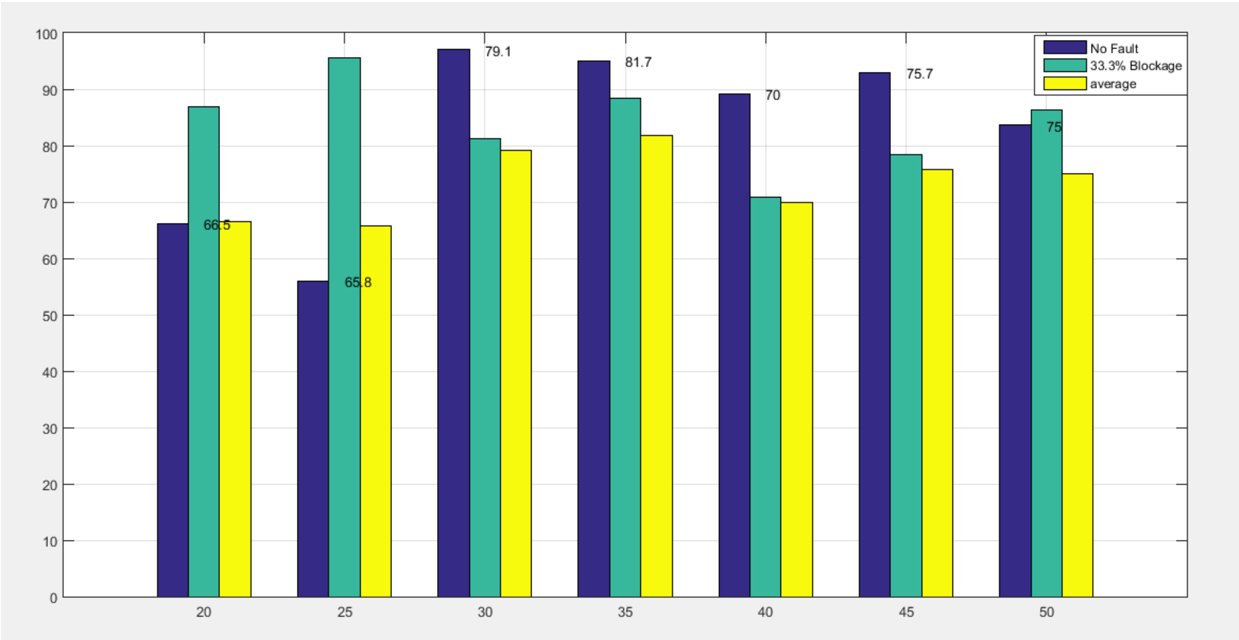
1. For 16.6% blockage the average classification accuracy over all the speeds has been found **64.8%**. The low classification accuracy may be attributed to the close behavior of the fault and no fault.

2. For 33.3% blockage the average classification accuracy over all the speeds has been found **74.2%**. The classification accuracy improved gradually with the amount the blockage.
3. For 50% blockage the average classification accuracy over all the speeds has been found **79.3%**
4. For 16.6% blockage the average classification accuracy over all the speeds has been found **90.2%**. This may indicate the clear distinction between fault and no fault

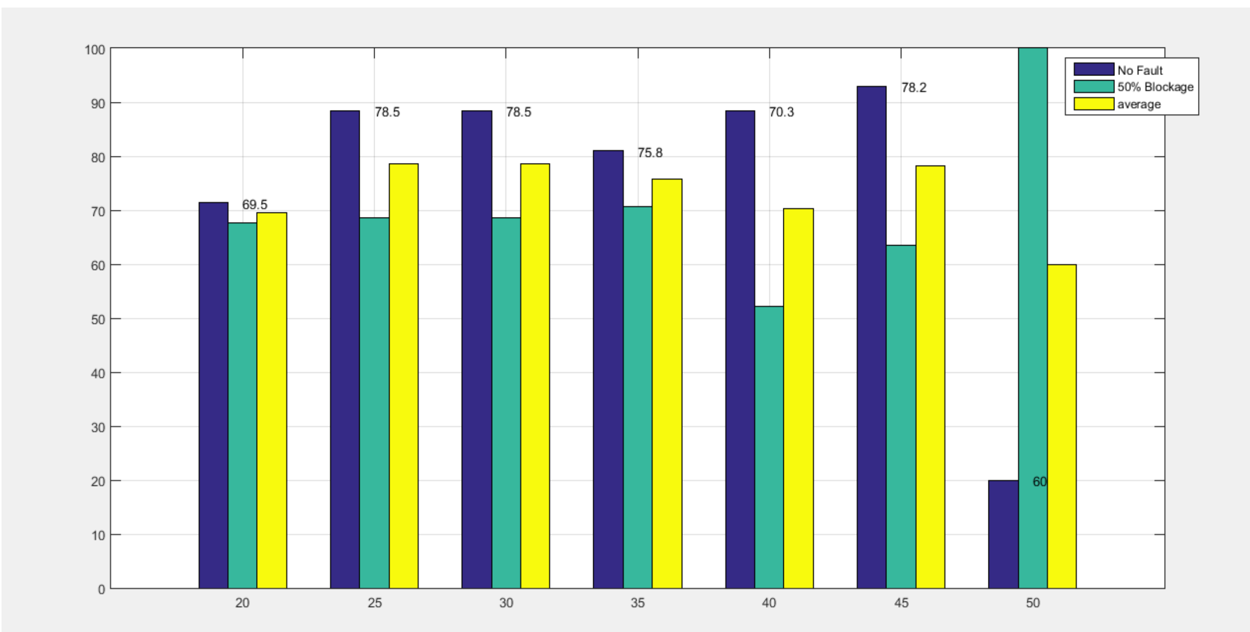
From these results, we can incur that B3 and B4 seem more serious than B1 and B2. Figure 9 below shows the change in average classification accuracy over the speed range for each fault.



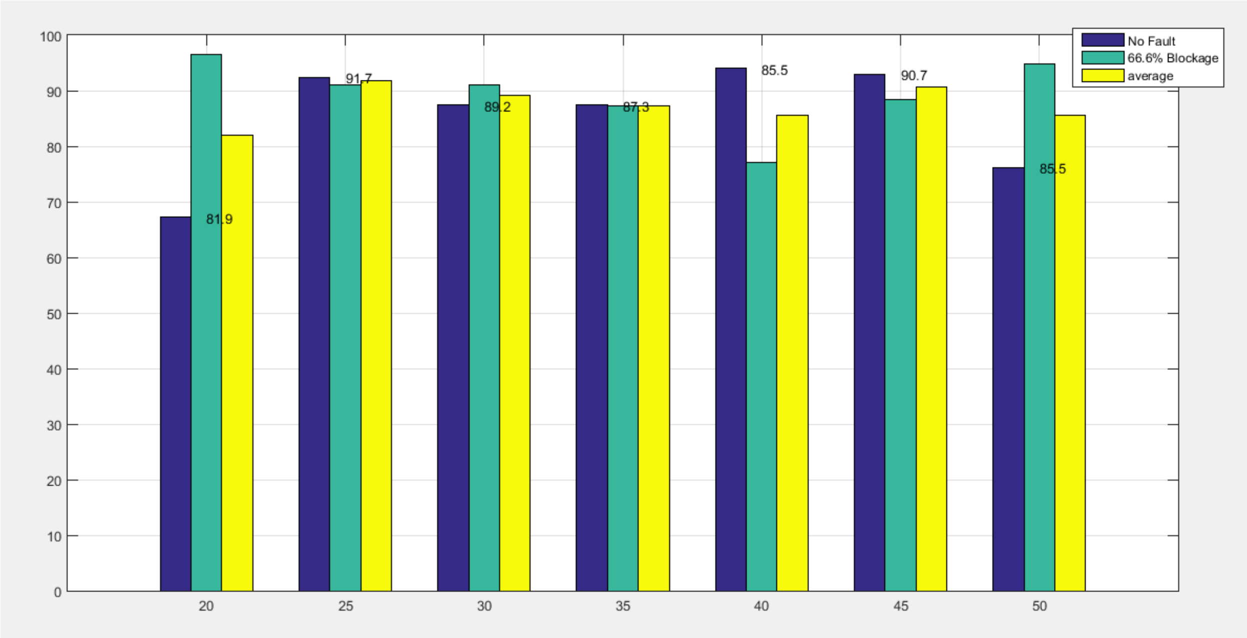
(a)


No Fault
33.3% Blockage
average
66.5
65.8
79.1
81.7
70
75.7
75

(b)


No Fault
50% Blockage
average
69.5
78.5
78.5
75.8
70.3
78.2
60

(c)



(d)

Figure 9: Binary classification of faults with respect to no faulty condition, speed (Hz) versus percentage classification accuracy, (a) Binary classification for B1 and B0 (b) Binary classification for B2 and B0 (c) Binary classification for B3 and B0 (d) Binary classification for B4 and B0

Chapter 5:

Conclusion:

In this report an attempt has been made to study the binary classification of blockage faults in centrifugal pumps. The faults are induced artificially on a healthy pump. B0, B1, B2, B3 and B4 faults are considered. Frequency domain of the vibration signal is used. Energy is found to capture the tendency of the frequency signature pertaining to each fault very well. OC-SVM algorithm is used for the binary class classifications. The Gaussian RBF kernel is used to map the input space to feature space. The SVM parameters and kernel parameters are parametrically chosen. The proposed frequency domain fault classification using SVM algorithm may be useful to identify the inception of blockage, and thus the fault severity can be curbed at very beginning itself, which may help to prevent the system a failure. The binary class classification is found to be very efficient in fault classification and diagnosis in the frequency domain of vibration signal.

5.1 Scope for Future Work

Since flow recirculation and the associated bubble formation and their dynamics is unsteady, transient phenomenon, time coupled with frequency (time-frequency) domain would be carrying more intricate information about the flow instability due to blockage. Hence the present work may be extended using Wavelet transform in time-frequency domain. Further, we can also use a multi class classifier for classification with each fault representing a separate label. Other statistical features such as entropy, standard deviation, total mean root square, etc. for better results.

References:

1. Harihara, P. P., & Parlos, A. G. (2008) Sensorless detection of impeller cracks in motor driven centrifugal pumps. ASME 2008 International Mechanical Engineering Congress and Exposition, 17-23.

2. Hellmann, D. H. (2002) early fault detection-an overview. World Pumps, 428, 54-57

3. Widodo, A., & Yang, B. S. (2007) Support vector machine in machine condition monitoring and fault diagnosis. Mechanical Systems and Signal Processing, 21(6), 2560-2574

4. Tabar, M. T. S., Hojjat Majidi, C., & Poursharifi, Z. (2011) Investigation of recirculation effects on the formation of vapor bubbles in centrifugal pump blades. World Academy of Science, 49, 883-888.

5. Perovic, S., Unsworth, P. J., & Higham, E. H. (2001) Fuzzy logic system to detect pump faults from motor current spectra. Industry Applications Conference, 2001. IEEE 1, 274-280.

6. Alfayez, L., Mba, D., & Dyson, G. (2005) The application of acoustic emission for detecting incipient cavitation and the best efficiency point of a 60kW centrifugal pump: case study. Non-destructive Testing & International, 38(5), 354-358.

7. Mba, D., & Rao R. B. K. N. (2006) Development of acoustic emission technology for condition monitoring and diagnosis of rotating machines: bearings, pumps, gearboxes, engines, and rotating structures. The Shock and Vibration Digest, 38(1), 3-16.

8. Luo, Y., Yuan, S., Yuan, J., Lu, J. (2014). Research on Characteristic of the Vibration Digest, 38(1), 3-16. Vibration Spectral Entropy for Centrifugal Pump. Advances in Mechanical Engineering, 6, 698938.

9. Abdulkarem, W., Amuthakkannan, R., & Al-Raheem, K. F. (2014) Centrifugal pump impeller crack detection using vibration analysis. Online proceedings of International Institute of Engg.

10. Zouari, R., Sieg-Zieba, S., & Sidahmed, M. (2004) Fault detection systems for Centrifugal Pumps Using Neural networks neuro-fuzzy techniques, surveillance, 5, 11-13

11. Wang, H. Q., & Chen, P. (2007) Fault diagnosis of centrifugal Pumps using symptom parameters in frequency domain. Agricultural Engineering International: The CIGR E Journal, 1682-1130.

12. Farokhzad, S. (2013) Vibration Based Fault Detection of Centrifugal Pump by - Fast Fourier Transform and Adaptive Neuro-Fuzzy Inference System. Journal of Mechanical Engineering and Technology, Bowen publications.

13. Azadeh, A., Saberi, M., Kazem, A., Ebrahimipour, V., Nourmohammadzadeh A., & Saberi, Z. (2013) A flexible algorithm for fault diagnosis in a centrifugal pump with corrupted data and noise based on ANN and support vector machine with hyper-parameters optimization. Applied Soft Computing, 13(3), 1478-1485.

14. Samanta, B., Al-Balushi, K. R., & Al-Araimi, S. A. (2003) Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection. Engineering Applications of Artificial Intelligence, 16(7), 657-665.

15. Hsu, C. W., & Lin, C. 3. (2002) A comparison of methods for multi-class support vector machines. Neural Networks, IEEE Transactions on, 13(2), 415-425.

16. Eshleman, R. L. (1999) Basic Machinery Vibrations, Vibration Institute Press, Suite, UK.

17. Chudina, M. (2003). Noise as an indicator of cavitation in a centrifugal pump. Acoustical Physics, 49(4), 463-474.

18. Chang, C. C., & Lin, C. 3. (2011) LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology (TIST), 2(3), 27.