FAULT DIAGNOSIS OF MONOBLOCK CENTRIFUGAL PUMP USING DISCRETE WAVELET FEATURES AND J48 ALGORITHM

V. Muralidharan¹, Hemantha kumar², V. Sugumaran³

¹Research Scholar, Karpagam University, Coimbatore, Tamilnadu, India. v_murali2@yahoo.co.in
²Birla Institute of Technology and Science - Pilani, K. K. Birla Goa Campus, Goa-403726, India. Email: hemantha@bits-goa.ac.in
³Department of Mechanical Engineering, VIT University, Chennai, Tamil Nadu, v_sugu@yahoo.com

ABSTRACT

Monoblock centrifugal pumps play an important role in variety of engineering applications such as food industry, waste water treatment plants, agriculture, oil & gas industry, paper & pulp industry etc., Condition monitoring of the various mechanical components of centrifugal pump becomes essential and which in turn increases the productivity and reduces the break downs. Vibration based continuous monitoring and analysis using machine learning approaches are gaining momentum. Particularly artificial neural networks, fuzzy logic were employed for continuous monitoring and fault diagnosis. This paper presents the use of J48 algorithm for fault diagnosis through discrete wavelet features extracted from vibration signals of good and faulty conditions of the components of centrifugal pump. The classification accuracies of different discrete wavelet families were calculated and compared to find the best wavelet for the fault diagnosis of the centrifugal pump.

Keywords: Mono-block centrifugal pump; J48 algorithm; Fault diagnosis; Discrete Wavelet Transforms (DWT)

1. INTRODUCTION

In a monoblock centrifugal pump, many a times very serious problems arise due to defective bearing, defect on the impeller and cavitation. Cavitation results in undesirable effects, such as deterioration of hydraulic performance (drop in head capacity and efficiency). Fault detection is achieved by comparing the signals of monoblock
centrifugal pump running under normal and faulty conditions. Vibration signals are widely used in condition monitoring of centrifugal pumps. The fault considered in this study are cavitation (CAV), impeller fault (FI), bearing fault (FB) and fault with bearing and impeller (FBI). For the measurement of the vibration levels for each condition, seismic or piezoelectric transducers along with data acquisition system is used to capture the vibration signals. From the vibration signal relevant features are extracted using Stationary Wavelet Transformations (SWT) and classification is done using J48 algorithm (A WEKA implementation of C4.5 algorithm) and the results are presented.

L. Alfayez, et al., (2005) proposed that acoustic emission has been applied for detecting incipient cavitation and determining the best efficiency point (BEP) of a centrifugal pump are based on net positive suction head (NPSH) and performance tests [1]. Sugumaran V et al., (2011) discussed that the importance of number of features using SVM and PSVM classifiers [2]. Radhika S et al., (2010) presented the piece wise wavelets for three phase induction motors and proved that it is an effective approach [3]. H. Q. Wang et al., (2007) presented a fault diagnosis method for a centrifugal pump with frequency domain symptom parameter by using wavelet transform (feature extraction), rough sets (rule generation) and fuzzy neural network (classification) to detect faults and distinguish fault types at early stages [4]. Huaqing wang et al., (2007) proposed the synthetic detection index with fuzzy neural network to evaluate the sensitivity of non dimensional symptom parameters for detecting faults in centrifugal pump [5]. S.Rajakaranakaran et al., (2008) developed a model for the fault detection of centrifugal pumping system using two different artificial neural network approaches, namely feed forward network with back propagation algorithm and binary adaptive resonance network (ART1). The performance of the developed back propagation and ART1 model was tested for a total of seven categories of faults in the centrifugal pumping system. Classification accuracy of 99.3% was achieved [6]. Jiangping want et al., (2006) used fuzzy logic principle as classifier with the features extracted from the vibration signals of the pump [7].

Fansen kong et al., (2004) proposed a new combined diagnostic system for triplex pump based on wavelet transform, fuzzy logic, neural network. The developed diagnostic system consists of four parts. The first part was wavelet transform in which multiresolution analysis was employed. The second part was for asymptotic spectrum estimation of the characteristic variable. The third part was employed for characteristic variable fuzzified in simulating fuzzy inference using incomplete information. The fourth part was the neural network trained with fuzzified characteristic variable for triplex pump failure diagnosis [8]. Fa yuan et al., (2006) discussed the fault diagnosis based on support vector machine. It is binary tree classifier composed of several two class classifiers. The effectiveness of the method is verified by the application to the fault diagnosis for turbo rotor pump [9]. Sheng zhang et al., (2003) introduced a fault diagnosis system using fuzzy neural network based on the series of standard fault pattern pairings between fault symptoms and fault. Fuzzy neural networks were trained to memorize these standard pattern pairs and it adopts bidirectional association to produce 97.3% classification accuracy [10]. Therefore, the literature shows that not many researchers have reported the application of wavelets and J48 algorithm for fault diagnosis in spite of its scope and adaptability. Hence, there is a need for a detailed study on wavelets in association with J48 algorithm as a classifier for fault diagnosis of monoblock centrifugal pump.
1. EXPERIMENTAL STUDIES

The main idea of this study is to find whether the monoblock centrifugal pump is in good condition or in faulty condition by a systematic procedure following certain steps. If the pump is found to be in faulty condition then the next step is to segregate the faults into cavitation, bearing fault, impeller defect, bearing and impeller defect together.

1.1. Experimental setup description

The monoblock centrifugal pump is taken for this study. The motor (2HP) is used to drive the pump. Piezoelectric type accelerometer is used to measure the vibration signals. The accelerometer is mounted on the pump inlet using adhesive and connected to the signal conditioning unit where signal goes through the charge amplifier and an analog to digital converter (ADC) and the signal is stored in the memory. Then the signal is processed from the memory and it is used to extract the features.

2. Procedure

The pump was allowed to rotate at a speed of 2880 rpm at normal working condition and the vibration signals are measured. The sampling frequency of 24 KHz and sample length of 1024 were considered for all conditions of pump. The sample length was chosen arbitrarily to an extent; however, the following points were considered. After calculating the wavelet transforms it would be more meaningful when the number of sample is more. On the other hand, as the number of sample is increases, the computation time increases. To strike a balance, sample length of around 1,000 was chosen. The specification of the monoblock centrifugal pump is given as below.

<table>
<thead>
<tr>
<th>Specification of the pump under study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotational Speed</td>
</tr>
<tr>
<td>Current</td>
</tr>
<tr>
<td>Head</td>
</tr>
</tbody>
</table>

In the present study the following faults were simulated as described below.
- Cavitation – by intentionally closing the suction gate valve partially.
- Impeller fault – chipping to dislodge one material to simulate pitting.
- Bearing fault – a thin cut through wire cut EDM.
- Bearing and Impeller fault together.
- The faults were introduced one at a time and vibration signals were taken.
3. Feature extraction

The time domain signal can be used to perform fault diagnosis by analysing vibration signals obtained from the experiment. Discrete Wavelet Transform (DWT) has been widely used and provides the physical characteristics of time-frequency domain data. Wavelet analysis of vibration signals yields different descriptive parameters. Fairly a wide set of parameters were selected as the basis for the study. These features were extracted from vibration signals. The wavelet transformations are explained below. In this paper, DWT of different versions of different wavelet families have been considered. The list of wavelet families considered for this study are: Daubechies wavelet, Coiflet, Bi-Orthogonal wavelet, Reversed bi-Orthogonal wavelet, Symlets and Meyer wavelet.

Feature definition:

A careful perusal of the signal details under different conditions brings out that there are considerable changes in the average energy level of the signal details with respect to its conditions. Feature extraction constitutes computation of specific measures, which characterise the signal. The discrete wavelet transform (DWT) provides an effective method for generating features. The collection of all such features forms the feature vector. A feature vector is given by

\[ v^{dwt} = \left\{ v_1^{dwt}, v_2^{dwt}, ..., v_{12}^{dwt} \right\}^T \]  

(1)

A component in the feature vector is related to the individual resolutions by the following equation

\[ v_i^{dwt} = \frac{1}{n_i} \sum_{j=1}^{n_i} w_{i,j}^2, \quad i = 1, 2, ..., 12 \]  

(2)

where, \( n_i = 2^{12}, n_2 = 2^{11}, ..., n_{12} = 2^0 \).

\( v_i^{dwt} \) is the \( i \)th feature element in a DWT feature vector. \( n_i \) is the number of samples in an \( w_{i,j}^2 \) individual sub-band, \( w_{i,j}^2 \) is the \( j \)th detail coefficient (high frequency component) of the \( i \)th sub-band. The wavelets considered for the present investigation are Haar (db1), Daubechies, Symlets, Coiflets, Biorthogonal, Reverse Biorthogonal and Meyer (dmey). Each of them is considered in the DWT form.

4. Decision tree

Data mining techniques are being increasingly used in many modern organizations to retrieve valuable knowledge structures from databases, including vibration data. An important knowledge structure that can result from data mining activities is the decision tree (DT) that is used for the classification of future events. Decision trees are typically built recursively, following a top-down approach. The acronym TDIDT, which stands for Top-Down Induction on Decision Trees, refers to this kind of algorithm. A standard tree induced with C5.0 (or possibly ID3 or C4.5) consists of a number of branches, one root, a number of nodes and a number of leaves. One branch is a chain of nodes from root to a
leaf; and each node involves one attribute. The occurrence of an attribute in a tree provides the information about the importance of the associated attribute. J48 algorithm (a WEKA implementation of C4.5 algorithm) is a widely used one to construct decision trees. Decision tree algorithm (J48) has two phases: building and pruning. The building phase is also called as the ‘growing phase’.

5. Results and discussion

The experimental studies have been carried out for good condition and various fault conditions of the pump as discussed in Section. 2. The results (classification accuracies) obtained from J48 classifier using wavelet features of various wavelet families shall be better explained in this manner. As a first step the classification accuracy is found for different versions of the wavelet family. In the similar fashion, the efficiencies of different versions of all the mentioned wavelet families are computed and the best one from all the families were picked up and plotted as histogram chart (Refer Fig.1.)

![Fig. 1. Graph between Best versions of different wavelet family Vs Classification Accuracy (%)](image)

![Fig.2. Performance of different versions of rbio family.](image)
From the Fig1 and Fig.2, best version of different families were picked up from each of the chart and compared among those best versions of different wavelet families and found the overall best wavelet family and the best version of that family. The confusion comes in picking up the best when two versions of the wavelet family gives the same classification accuracies. In such cases, any version shall be taken arbitrarily. But, the least version is taken up in this study as the computation effort and level of complexity increases when the version of the family increases. The waveform of the wavelets become more complex when the version increases which in turn increases the computation time and required resources. In this manner, the versions db2 (99.76%), coif2 (99.76%), bior2.2 (99.6), rbio1.5 (99.84%), sym2 (99.68%) and dmey (97.04%) have been picked up. All the best versions of different wavelet families were compared and overall best wavelet and the wavelet family was found. From Fig. 2, one can clearly say that the best wavelet from the chart is rbio1.5 and the classification accuracy achieved is 99.84% which is very close to 100%. The results of the wavelet rbio1.5 can be illustrated in better way using the confusion matrix as shown in Fig 3.

--- Confusion Matrix ---

```
250 0 0 0 0 | a = Good
1 249 0 0 0 | b = Cavitation
0 0 249 0 1 | c = FI
0 0 0 250 0 | d = FB
0 0 0 0 250 | e = FBI
```

Fig. 3 Confusion Matrix for rbio1.5 wavelet

From the confusion matrix (Refer Fig.3), one can understand that 250 samples were considered for each condition of the pump. All the diagonal elements of the confusion matrix represent the number of correctly classified data points and the non-diagonal elements represent the incorrectly classified data points. In this fashion the classification accuracies are found and compared for various types of wavelets of different families. In this case, all the good condition data points have been correctly classified and the same is the case with bearing fault data points and fault with both bearing and impeller. However, there were two misclassifications between pump with cavitation effect and fault impeller conditions and hence efficiency was calculated to be 99.84%. The results obtained are specific to this particular dataset. Classification accuracy of 99.84% does not assure similar performance for all feature datasets. However one can expect classification accuracy close to 100%. In general the classification accuracy is very high. Hence the rbio1.5 wavelet is very much suited for fault diagnosis of centrifugal pumps.

6. CONCLUSION

This paper deals with vibration based fault diagnosis of monoblock centrifugal pump. Five classical states viz., normal, cavitation, bearing fault, impeller fault, impeller and bearing fault together, are simulated on monoblock centrifugal pump. Set of features have been extracted using different wavelets and classified using J48 algorithm. From the
results and discussion, one can confidently say that feature extraction using wavelets as well as J48 algorithm for classification are good candidates for practical applications of fault diagnosis of monoblock centrifugal pump. The classification accuracy achieved was 99.84% for the representative data samples. However, the results can be fine tuned by conducting more experiments for a larger volume of data samples.

8. REFERENCES


