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Rough set based rule learning and fuzzy classification of wavelet features for fault diagnosis of monoblock centrifugal pump ☆

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ABSTRACT

The fault diagnosis problem is conceived as a classification problem. In the present study, vibration signals are used for fault diagnosis of centrifugal pumps using wavelet analysis. Rough set theory is applied to generate the rules from the vibration signals. Based on the strength of the rules the faults are identified. The different faults considered for this study are: pump at good condition, cavitation, pump with faulty impeller, pump with faulty bearing and pump with both faulty bearing and impeller. However, the classification accuracy is based on the strength and number of rules generated using rough set theory. Wavelet features are computed using Discrete Wavelet Transform (DWT) from the vibration signals and rules are generated using rough sets and classified using fuzzy logic. The results are presented in the form of confusion matrix which shows the classification capability of wavelet features with rough set and fuzzy logic for fault diagnosis of monoblock centrifugal pump.

1. Introduction

Centrifugal pump is an integral part in engineering industries and it requires continuous monitoring to increase the availability of the pump. The pumps are the key elements in food industry, waste water treatment plants, agriculture, oil and gas industry, paper and pulp industry, etc. As bearing and impeller are the critical components in a centrifugal pump that directly affects the desired pump characteristics. Hence, defect with these components have been taken for analysis. In a monoblock centrifugal pump, defective bearing, defect on the impeller and cavitation cause number of serious problems such as abnormal noise, leakage, and high vibration. Machine condition monitoring system is a decision support tool, which is capable of identifying the failure of a machine and capable of predicting failure from its symptoms [1]. Comparative study between naïve bayes and bayes net algorithms is carried out for different faults in monoblock centrifugal pump and concluded that bayes net is an effective algorithm [2]. J48 algorithm was used on monoblock centrifugal pump and attained the overall classification accuracy close to 100% [3]. Vibration and acoustic emission (AE) signals are widely used in condition monitoring of rotating machines. Fault detection is possible by comparing the signals of a machine running in normal and faulty conditions. Artificial neural network (ANN), support vector machine (SVM) and fuzzy classifier are widely used as classification tools and reported in literature. Fast Fourier Transform (FFT) is the commonly used method in conventional condition monitoring, through frequency domain. The vibration can be measured with the help of piezo electric transducers. The measured vibration is compared with the threshold value in order to understand the

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severity. Interestingly, some conventional techniques would be used to know the pattern of the individual frequencies present in the signal. This process is a very complex process and it demands domain experience and expertise. These frequencies correspond to certain malfunction. By understanding these frequencies and their patterns, the analyst can identify the location, type of problem and the root cause as well. However, the influence of machine learning in fault diagnosis is more common as an alternative to conventional methods. It is largely due to increased availability of computational resources and development in algorithms. For complex systems involving many components, it is difficult to compute characteristic fault frequencies. Even if characteristic frequencies are available the vibration signals are highly non-stationary in nature, hence FFT based methods may not be well suited for continuous monitoring. However, machine learning algorithms can be considered as an alternate for such situations. In machine learning approach, the data acquisition system is used to capture the vibration signals [4]. From the vibration signal relevant features can be extracted and classified using a classifier. Therefore, the vibration signals have been acquired from the experimental setup and classifiers such as artificial neural network and support vector machines have been used for the purpose of classification. Time domain analysis has been performed in order to get good classification accuracy [5]. Continuous wavelet features were extracted for monoblock centrifugal pump and classification was carried out with decision tree algorithms give reasonable classification accuracy [6]. A new combined diagnostic system for triplex pump based on wavelet transform, fuzzy logic, neural network was proposed [7]. An attempt has been made to establish a comparative study between neural network and support vector machines for a condition monitoring problem [8]. However, this comparative statement may not generalize the relations. A model for the fault detection of centrifugal pumping system using two different artificial neural network (ANN) approaches, namely feed forward network with back propagation algorithm and binary adaptive resonance network (ART1) which could classify seven categories of faults in the centrifugal pumping system was presented [9]. A fault diagnosis method for a centrifugal pump by using wavelet transform for feature extraction, rough sets for rule generation and fuzzy neural network for classification to detect faults and distinguish fault types at early stages have been presented [10,11]. However, the main drawback of fuzzy neural network is poor capability of creating its own structure. A synthetic detection index with fuzzy neural network to evaluate the sensitivity of non dimensional symptom parameters for detecting faults in centrifugal pump is reported [12]. A mean correlation rule is proposed to evaluate the capability of each of the principal components (PC) in characterizing machine conditions and the most representative PCs are selected to classify the machine fault patterns. Then, a procedure that uses the low-dimensional PC representations for machine condition monitoring is proposed [13]. The use of decision tree for selecting best statistical features extracted from the vibration signals of the faulty gear box was presented. A rule set is formed from the extracted features and fed to a fuzzy classifier. The author also presented the usage of decision tree to generate the rules from the feature set. A fuzzy classifier is built and tested with representative data [14]. A novel rough set-based case-based reasoner to use in text categorization (TC) is presented with four main components: feature term extractor, document representor, case selector, and case retriever. They operate first reducing the number of feature terms in the documents using the rough set technique. Then, the number of documents is reduced using a new document selection approach based on the case-based reasoning (CBR) concepts of coverage and reachability. As a result, both number of feature terms and documents are reduced with only minimal loss of information. The experimental results demonstrate its effectiveness and accuracy as it significantly reduced feature terms and documents, important for improving the accuracy of TC, while preserving and even improving classification accuracy [15]. As presented in [16], when localized fault occurs in a bearing, the periodic impulsive feature of the vibration signal appears in time domain and the corresponding bearing characteristic frequencies (BCFs) emerge in frequency domain. However, in the early stage of bearing failures, the BCFs contain very little energy and are often overwhelmed by noise and higher-level macro-structural vibrations, an effective signal processing method would be necessary to remove such corrupting noise and interference. A new hybrid method based on optimal Morlet wavelet filter and autocorrelation enhancement was presented. Moreover, the proposed method can be conducted in an almost automatic way. The results obtained from simulated and practical experiments prove that the proposed method was very effective for bearing faults diagnosis [16].

A comparative study has been made between decision tree – fuzzy and rough set – fuzzy classification algorithms for fault diagnosis of monoblock centrifugal pump using the vibration signal. The study reveals that rough-set fuzzy rules are better when compared to the other set. However, this study was carried out only for the particular data set considered at that particular speed and for the statistical features [17].

In this study, wavelet features are considered for the signal at different working conditions. A roller bearing was considered for the study and fuzzy logic was used to classify the faults in it. The application decision tree was well narrated in fault diagnosis domain and the results witness that it is good for real time applications [18,19]. However, there decision tree works based on the entropy functions. Therefore, one needs some other technique which also promises the same performance to substantiate the proposed approach. Hence, rough set based rule generation is used in this study and fuzzy logic is used to evaluate the rules and for classification.

The rest of the paper is organized as follows. In Section 2, the methodology followed is presented. The experimental setup and experimental procedure is described in Section 3. Section 4 presents feature extraction from the time domain signal. Section 5 describes the rule generation using rough set and the classification accuracy is tested and subsequently Section 6 presents the classification using fuzzy logic. Section 7 presents the result of an experiment. Conclusions are presented in Section 8 and followed by the references.

2. Methodology

The step by step procedure to be followed in sequence is presented in Fig. 1. First, the vibration data is acquired from the experimental setup using DAQ system. The features are then extracted using Discrete Wavelet Transforms (DWTs). Then, set of rules is framed using rough set and fed as an input to the fuzzy inference engine. Finally, the classification accuracy is achieved by means of confusion matrix there by the faults are segregated.

3. Experimental studies

The primary objective of this work is to find whether the monoblock centrifugal pump is in good condition or in faulty condition. If the pump is found to be in faulty condition, then it has to be segregated into cavitation, bearing fault, impeller fault, and both bearing, impeller fault together. This experimental study mainly focuses on the use of rough set theory for fault diagnosis of monoblock centrifugal pump. The monoblock centrifugal pump with sensor and data acquisition is discussed in the following topics under experimental setup and experimental procedure respectively.

3.1. Experimental setup

The motor of 2 hp capacity is fitted to drive the pump. A valve control system is provided to adjust the inlet and outlet valve. By adjusting the inlet valve of the pump, one can make the pressure drop between suction head and an eye of an impeller in order to simulate the cavitation phenomenon. To visualize this phenomenon, an acrylic pipe is fitted on the inlet pump. As discussed, piezo-electric accelerometer is used to measure the vibration signals. It is located at the inlet and is connected to the signal conditioning unit through the charge amplifier and an analogue to digital converter (ADC). Therefore, the signal is stored in the memory. Then the signal is processed from the memory and it is used to extract different features.

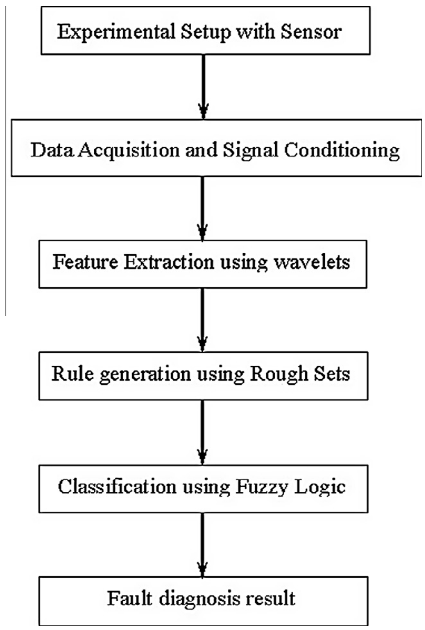

Fig. 1. Flow chart of monoblock centrifugal pump fault diagnosis system.

3.2. Experimental procedure

First, the pump was kept to rotate at a constant speed of 2880 rpm and vibration signals were measured from the monoblock centrifugal pump under normal conditions. Then a cavitation phenomenon was simulated by adjusting the inlet and outlet valves. Readings such as discharge, suction head and delivery head were calculated and tabulated. This experiment was repeated for different delivery heads. The vibration signal from accelerometer mounted on the pump inlet was taken. The sampling frequency was taken as 24 kHz and sample length was 1024 for all conditions of the pump. The sample length was chosen by considering the following points. After calculating the wavelet transforms it would be more effective when the number of samples is more. On the other hand, as the number of samples increases, the computation time increases. To strike a balance, sample length of around 1000 was chosen. In wavelet feature extraction techniques, the number of samples has to be 2^n. The nearest 2^n to 1000 is 1024; hence it was taken as sample length. 250 trials were taken for each monoblock centrifugal pump condition, and vibration signals were stored in the data files. Faults were introduced one at a time and the pump performance characteristic and vibration signals were taken.

3.2.1. Bearing fault

In this study, two KBC 6203 bearings were considered. Out of them, one was free from defects. The other one, in which a piece of metal of width 0.657 mm and a depth of 0.973 mm was machined in the outer race using electrical discharge machining (EDM) to simulate a defect. The size of the defect was noted in order to keep it under the control. At this condition, the performance characteristics of the pump under faulty bearing conditions were studied as explained for pump working under good condition. The vibration signals with faulty bearing were recorded keeping all other components in good condition.

3.2.2. Impeller defect

In the study two impellers of diameter 125 mm made up of cast iron were used. One impeller was a new impeller and was assumed to be free from defect. In the other impeller, defect was created by removing a small portion of metal through a machining process. The performance characteristic curves were studied for the pump under impeller defect.

3.2.3. Cavitation

The cavitation phenomenon was simulated by adjusting inlet and outlet valves. At suction head of 540 mm of Hg, there was abnormal noise, high vibration in the pump. Therefore, vapor bubbles were formed which can be seen in the acrylic pipe. At this condition, pump was allowed to rotate at set speed and the signals were taken and the performance characteristic curves were plotted for the pump under impeller defect.

4. Feature extraction

The vibration signals are very much used for computing wavelet transformations. Wavelet decomposition gives useful information about the signal. The decomposed signal has trend and detail parts. The detail part of the signal in each level is quantified and considered as feature vector. Feature V_1 is at first level decomposition (a1) and feature V_2 is at second level of decomposition (a2) and so on. 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 families considered for this study is given below:

1. Daubechies wavelet (db1, db2, db3, db4, db5, db6, db7, db8, db9, db10).
2. Coiflet (coif1, coif2, coif3, coif4, coif5).
3. Bi-orthogonal wavelet (bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8).
4. Reversed bi-orthogonal wavelet (rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.3, rbio3.5, rbio3.7, rbio3.9, rbio4.4, rbio5.5, rbio6.8).
5. Symlets (sym2, sym3, sym4, sym5, sym6, sym7, sym8).
6. Meyer wavelet.

The DWT of vibration signals were computed for different conditions of the pump. However, for the analysis here, eight levels are considered (from 'd1' to 'd8').

4.1. Feature definition

A careful perusal of the signal details under different conditions brings out the fact 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 characterize 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

$$v^{dwt} = \left\{v_1^{dwt}, v_1^{dwt}, \ldots, v_1^{dwt}\right\}^T \tag{1}$$

v_i^{dwt} a component in the feature vector is related to the individual resolutions by the following equation

$$v_i^{dwt} = \frac{1}{ni}\sum_{j=1}^{ni} w_{i,j}^2, \quad i = 1, 2, \ldots, 12 \qquad n_1 = 2^{12}, \quad n_2 = 2^{11}, \ldots, n_{12} = 2^0 \tag{2}$$

where v_i^{dwt} is the ith feature element in a DWT feature vector. n_i is the number of samples in an $w_{i,j}^2$ individual sub-band, is the jth detail coefficient (high frequency component) of the ith 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.

5. Rough set theory

The process of identifying and segregating into different categories is called as classification. Rough set theory basically deals with automatic generation of the rules for classification of universe of objects. Very huge volume of data acquired from the data acquisition system or by human expertise may represent a vague knowledge. By visual inspection of the data points, it is highly impossible to classify the objects into defined categories and hence a tool which performs the task is looked for. Rough set theory provides the means to discern and classify objects in data sets of this type. In rough set theory knowledge is represented in information systems. Information system means that the data is represented in rows and columns, in which each row represents the sample for the particular condition and the each column represents the variable or feature that is capable of discriminating between the classes.

An information system, Λ, is defined as;

$$\Lambda = (U, A)$$

U = on empty finite set of objects called the universe, A = non empty finite set of attributes such that α: $U \to V$ for every $\alpha \in A$ and V is the value set of α.

The fundamental concept of rough set theory is indiscernibility, which is mainly used to define the equivalence classes for the objects. For example, consider a subset of attributes $B \subseteq A$, each subset defines an equivalence relation $IND_A(B)$ called an indiscernibility relation. This indiscernibility relation can be defined as

$$IND_A(B) = \{(x, x') \in U^2 | \forall \alpha \in B, \alpha(x) = \alpha(x')\}$$

where x and x' are objects in A.

In the above equation, B represents the segregation of pool of objects into sets such that a single object in a set cannot be classified by using only the attributes of B. The sets with which the partition happens is called an equivalence classes. In order to classify the data points into different classes, one more column of variable is added into the information system. Now, the information system becomes decision systems.

$$\Lambda = (U, A \cup \{d\})$$

d is the decision attribute.

The elements of A are called conditional attributes or conditions. The decision is not necessarily constant on the equivalence classes. That is, for two objects belonging to the same equivalence class, the value of the decision attributes may be different. In this case, the decision system is inconsistent (non-deterministic). If a unique classification can be made for all the equivalence classes, the system is consistent (deterministic). The decision attribute

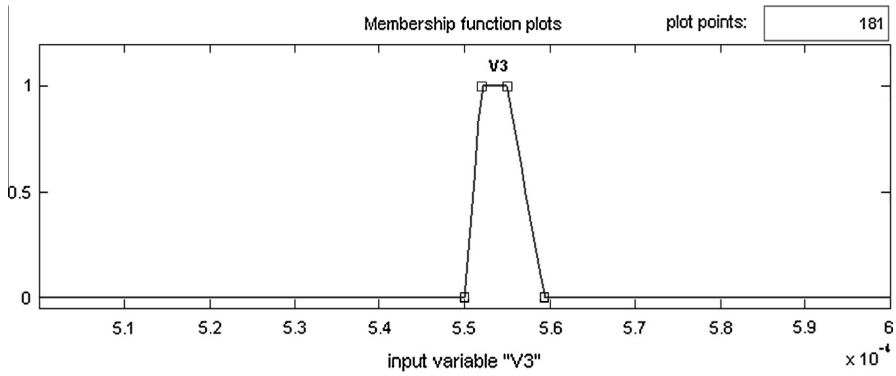

Fig. 2. Membership function for feature 'V_3'.

is introduced in the information system. This decision attribute states the good and different faulty conditions of the centrifugal pump.

In order to classify an object based only on the equivalence class to which it belongs, the concept of set approximation is used. Given information system $\mathcal{A} = (U, A)$, and a subset of attributes $B \subseteq A$, to approximate a set of objects, X, using only the information contained in B.

$$\underline{B}X = \{x[x]_B \subseteq X\}; \quad \text{where } \underline{B}X - \text{Lower approximation of } X$$

$$\overline{B}X = \{x[x]_B \cap X \neq 0\}; \quad \text{where } \overline{B}X - \text{Upper approximation of } X$$

The lower approximation is the set containing all objects for which the equivalence class corresponding to the object is a subset of the set. The upper approximation is the set containing the objects for which the intersection of the objects equivalence class and the set to be approximated is not the empty set. This set contains all objects which possibly belong to the set X. Then the boundary region is defined.

$$BN_B(X) = \overline{B}X - \underline{B}X$$

This set contains the object that cannot be classified as definitely inside X or definitely outside X. In most of the cases not all of the knowledge in an information system is necessary to divide the objects into class. In these cases, it is possible to reduce the knowledge. Reducing the knowledge results in reducts. A reduct is a minimal set of attributes $B \subset A$ such that,

$$IND_A(B) = IND_A(A)$$

A discernibility matrix of $\mathcal{A}$ is a symmetric n x n matrix with entries

$$C_{ij} = \alpha \in A \geqslant |\alpha(x_i) \neq \alpha(x_j) \quad \text{for } i, j = 1, \ldots, n$$

The entries for each object are thus the attributes that are needed in order to discern object I from object j. Next step is to find out the rules derived from the rough set by following the above procedure. The rule given below is for rbio1.5.

Rule 1: If $V_3 > 0.000552$ and $V_4 \leqslant 0.0114$ then good.
Rule 2: If $V_3 > 0.000552$ and $V_4 > 0.0114$ then cavitation.
Rule 3: If $V_3 \leqslant 0.000552$ and $V_4 \leqslant 0.00203$ and $V_7 \leqslant 0.0015$ then FI.
Rule 4: If $V_3 \leqslant 0.000552$ and $V_4 > 0.00203$ then FB.
Rule 5: If $V_3 \leqslant 0.000552$ and $V_4 \leqslant 0.00203$ and $V_7 > 0.0015$ then FBI.

Similarly, the rules were found using rough set for all the wavelet families as described in Section 3. Only the

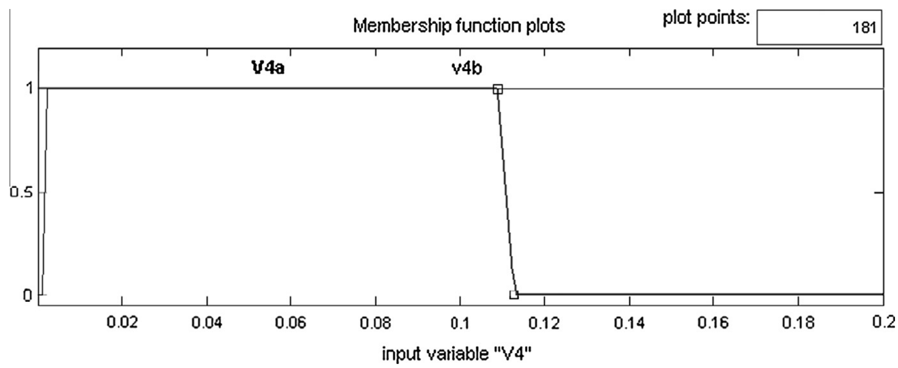

Fig. 3. Membership function for feature 'V_4'.

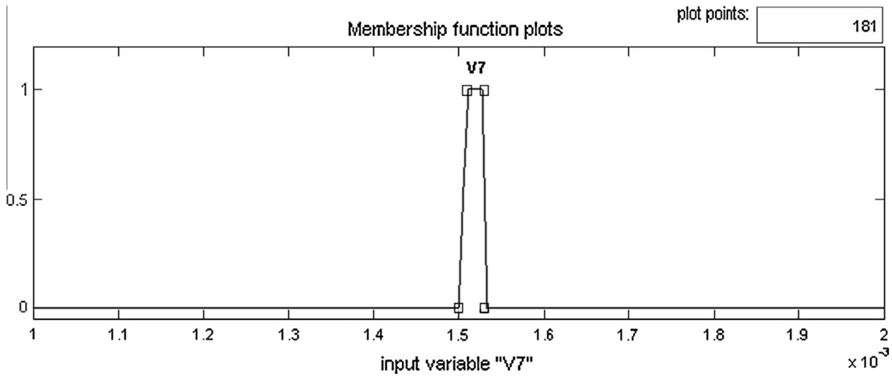

Fig. 4. Membership function for feature 'V_7'.

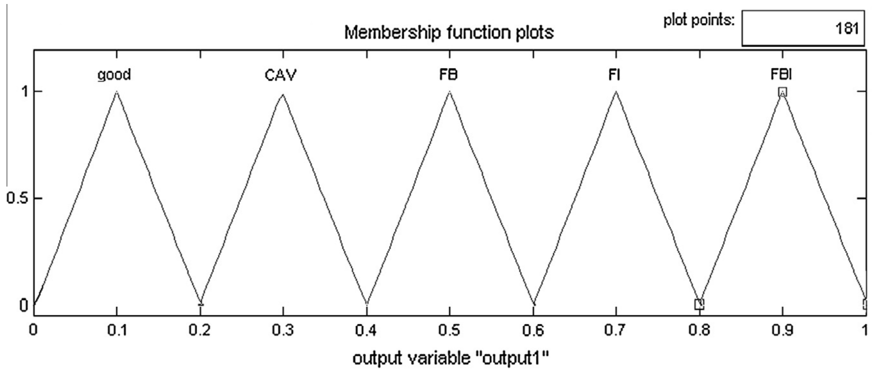

Fig. 5. Membership function for output.

representative rules are given above. These rules are sufficient to use the fuzzy inference classifier.

6. Fuzzy classifier

Fuzzy logic finds applications in variety of domains. It is proven to be much cheaper, stronger and reliable than most of the classification algorithms. Specifically, fuzzy logic is most used when the input data is not crisp in nature and it gives vague information. For the problem under study, the fault with bearing and impeller will not happen suddenly. It comes gradually. In that case, there is no threshold value (crisp data) based on which the decision on the condition of the bearing, impeller—whether bearing or impeller is now good or faulty—can be taken. The problems of this kind can be modeled using fuzzy classifier more closely. The point of Fuzzy logic is to map the input space to output space with the help of set of '*if–then*' statements called rules. The rules which were derived using rough-set algorithm are the inputs to build a fuzzy inference engine using membership functions.

The membership functions are the one which defines how each input space is mapped into a membership value (or degree of membership) between 0 and 1. From the rules generated using rough set algorithm, one can understand that there are three features namely V_3, V_4 and V_7 contributed for classification of faults. There are five possible outcomes namely good, cavitation, faulty bearing, faulty impeller and faulty bearing, impeller together. Figs. 2–4 show the corresponding trapezoidal membership functions for the inputs and Fig. 5 shows the triangular membership function for the outputs.

7. Results and discussion

The experimental studies have been carried out for good condition and various fault conditions of the pump as discussed in Section. 3. After having implemented the fuzzy algorithm to all versions of all wavelet family, it is found that '*rbio1.5*' was the best performing one. The results for the same are presented in the form of confusion matrix.

Interpretation:

- Discrete Wavelet Transform is used to extract the wavelet features as discussed in Section 3.1 namely V_1, V_2, $V_3, \ldots, V_8$. Out of these eight features only three features such as V_3, V_4 and V_7 were used for deriving the rules using rough set. The other features such as V_1, V_2, $V5$, $V6$ and V_8 were eliminated at the outset due to their imperceptible contribution to the classification.
- All the rules obtained from rough set in the form of 'if–then' are inputted to fuzzy inference classifier. Ref. [17] for detailed procedure. A representative data

Table 1
Confusion matrix for rbio1.5.

	Good	Cavitation	FI	FB	FBI
Good	250	0	0	0	0
Cavitation	1	249	0	0	0
FI	0	0	249	0	1
FB	0	0	0	250	0
FBI	0	0	0	0	250

set consisting of 250 trials is used to evaluate the fuzzy model and the results are presented in Table 1 in the form of confusion matrix.

- Observing the confusion matrix, three classes have been correctly classified and the remaining two classes have exactly one misclassification in each. It is quite within the tolerance range and hence *rbio1.5* can be considered as a good tool for this problem and can be recommended for the real time applications.

8. Conclusion

This paper deals with vibration based fault diagnosis of monoblock centrifugal pump. Five classical states viz. normal, cavitation, bearing fault, impeller fault, and impeller, bearing fault together, are simulated on monoblock centrifugal pump. Set of features have been extracted using different wavelets and classified using fuzzy logic algorithm (99.84%). From the results and discussion as discussed above one can confidently say that feature extraction using discrete wavelets, rule generation using rough set, and classification through algorithm for classification are good candidates for practical applications of fault diagnosis of monoblock centrifugal pump. However, the results obtained are only for the representative data points. For classification, only trapezoidal membership function is used for fuzzy engine in this study and other functions may also perform equally well. If proved that these results are consistent, then they can be considered as a guideline for real time applications. One can generalize the results by conducting similar experiments for various working conditions of the pump.

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