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An Intelligent Combined Method Based on Power Spectral Density, Decision Trees and Fuzzy Logic for Hydraulic Pumps Fault Diagnosis

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***Abstract*—**Recently, the issue of machine condition monitoring and fault diagnosis as a part of maintenance system became global due to the potential advantages to be gained from reduced maintenance costs, improved productivity and increased machine availability. The aim of this work is to investigate the effectiveness of a new fault diagnosis method based on power spectral density (PSD) of vibration signals in combination with decision trees and fuzzy inference system (FIS). To this end, a series of studies was conducted on an external gear hydraulic pump. After a test under normal condition, a number of different machine defect conditions were introduced for three working levels of pump speed (1000, 1500, and 2000 rpm), corresponding to (i) Journal-bearing with inner face wear (BIFW), (ii) Gear with tooth face wear (GTFW), and (iii) Journal-bearing with inner face wear plus Gear with tooth face wear (B&GW). The features of PSD values of vibration signal were extracted using descriptive statistical parameters. J48 algorithm is used as a feature selection procedure to select pertinent features from data set. The output of J48 algorithm was employed to produce the crisp if-then rule and membership function sets. The structure of FIS classifier was then defined based on the crisp sets. In order to evaluate the proposed PSD-J48-FIS model, the data sets obtained from vibration signals of the pump were used. Results showed that the total classification accuracy for 1000, 1500, and 2000 rpm conditions were 96.42%, 100%, and 96.42% respectively. The results indicate that the combined PSD-J48-FIS model has the potential for fault diagnosis of hydraulic pumps.

***Keywords*—**Power Spectral Density, Machine Condition Monitoring, Hydraulic Pump, Fuzzy Logic.

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I. INTRODUCTION

THE technique of early fault diagnosis is used to prevent serious damages in a mechanical system. Rotating machinery such as internal combustion engines, gearboxes, electromotor, pumps, and air compressors can have their vibration and acoustic emission signals monitored for early fault diagnosis [1]-[2].

Vibration analysis has been used in rotating machines fault diagnosis for decades. By measuring and analyzing the vibration of a machine, it is possible to determine both the nature and severity of the defect, and hence predict the machine's useful life or failure point [3]-[4]. In [4], it is claimed that vibration monitoring is the most reliable method of assessing the overall health of a rotor system. Machines have complex mechanical structures that oscillate and coupled parts of machines transmit these oscillations. This results in a machine related frequency spectrum that characterizes healthy machine behavior. When a mechanical part of the machine either wears or breaks up, a frequency component in the spectrum will change. In fact, each fault in a rotating machine produces vibrations with distinctive characteristics that can be measured and compared with reference ones in order to perform the fault detection and diagnosis [5].

Vibration is often measured with multiple sensors mounted on different parts of the machine. For each machine there are typically several vibration signals being analyzed in addition to some static parameters like load. The examination of data can be tedious and sensitive to errors. Also, fault related machine vibration is usually corrupted with structural machine vibration and noise from interfering machinery. Further, depending on the sensor position, large deviations on noise may occur in measurements. Stronger noise than the actual failure signal may lead to misrecognition of the useful information for diagnosis. Therefore, it is important that the noise be canceled from the measured signal as far as possible for sensitively identifying the failure type [6]-[8]. Furthermore, in the case of condition diagnosis of pump machinery, the knowledge for distinguishing failures is ambiguous because definite relationships between symptoms and fault types can not be easily identified. The main reasons can be explained as follows; (1) It is difficult to identify the symptom parameters for diagnosis by which all fault types can be distinguished perfectly. (2) In the early stages of a fault, effects of noise are so strong that the symptoms of a fault are not evident [9]. (3) The pumps dynamic responses, generated by a wide range of possible impulsive sources, are very complex [10].

The main advances in vibration analysis in recent years are the development in signal processing techniques, for vibration diagnostics of gearing systems [11]–[15] and bearing faults [16]–[18]. The analysis of vibration signals was often based on the Fast Fourier Transform (FFT) [19]-[21]. This approach suffers from some limitations. Among these limitations, the FFT is not efficient to describe the non-stationarities introduced by faults in the vibration signal. The second limitation and the most important one is the frequency resolution, which is the ability to distinguish the spectral responses to two or many harmonics. Another limitation is due to the windowing of data which appears during the FFT processing. In order to overcome these performance limitations inherent to the FFT approach, many modern spectral estimation techniques have been proposed during the last two decades [22]-[28]. Power spectral density (PSD) is one of those methods that is reported by several research works [29]-[31].

Knowledge-based techniques [32]-[33] become a suitable strategy towards automatic fault detection (AFD). Fuzzy logic is among the knowledge-based techniques to address the fault detection problem. Several researchers [34]-[37] have proposed fault detection and diagnosis approaches based on fuzzy system. Fuzzy system is a rule-based approach where the rule set is usually learned from an expert's experience or prior knowledge of the system. The process of fault detection can be seen as a classification problem and hence fuzzy system acts as a classifier to distinguish different faults according to its rules. The success of the fault detection process hence depends on the accuracy of the fuzzy rules. Typically, fuzzy rules are generated by intuition and expert's knowledge. However, for complex systems with large amount of redundant features, the derivation of fuzzy rules is tedious and inaccurate. Researchers have continuously tried to find efficient and effective methods to generate these fuzzy rules. Decision Trees have been proposed to solve the problem [38].

The subject of this research is to propose the new intelligent system for fault diagnosis in hydraulic pumps. The proposed approach consists of three stages. First, PSD of vibration signals is calculated because of its better performance in fault illustration rather than FFT method. Second the decision tree is performed as a feature selection tool to obtain the valuable features and to identify the structure of classifier in the next iterative step. Third, the Fuzzy logic classifier is used to diagnose the faults of hydraulic pump.

II. Material and Methods

A. Procedure for Development

In this research, the procedure consists of five stages as shown in Fig. 1: data acquisition, PSD creation, feature extraction, feature selection and classification model extraction, and fault diagnosis, which are specifically explained in the next sections. The summary role of each procedure is described as follows:

Data acquisition: this procedure is used to obtain the vibration signals. Furthermore, data processing is also carried out.

PSD creation: the power spectral density (PSD) of vibration signals are calculated by using specific formula.

Feature extraction: the most significant features are calculated by using statistical feature parameters from PSD values.

Feature selection and classification model extraction: the J48 algorithm is used as a decision tree to select the salient features from the whole feature set. In this section the data obtained from feature extraction procedure is split into two data sets: training data and testing data. Training data is employed to build the model whilst testing data is for validating the model.

Fault Diagnosis: Fuzzy logic inference system is used to diagnose the faults.

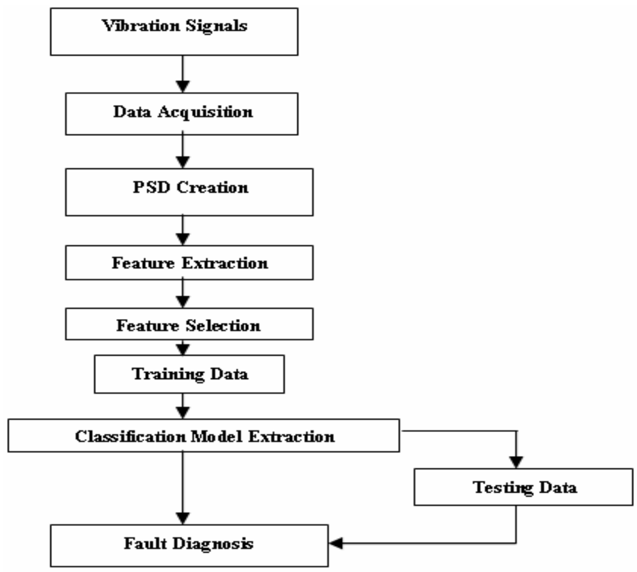


Fig. 1 Proposed system

B. Experimental Works and Data Acquisition

An external gear hydraulic pump that was mounted on an agricultural tractor as a main part of its steering hydraulic system was used to perform the experiments. This pump uses two rotating gears which un-mesh at the suction side of the pump to create voids which allow atmospheric pressure to force fluid into the pump. The spaces between the gear teeth transport the fluid along the outer perimeter of the housing to the discharge side, and then the gears re-mesh at the center to discharge the fluid. The gears are supported by Journal-bearings on both sides, which allow high discharge pressure capabilities. The motion of the motive gear is directly produced by tractor engine. SAE 15w40 oil was used as a hydraulic liquid. With the sensor mounted on body of gear housing of the pump, vibration signals were obtained for various fault conditions. The sensor used is a piezoelectric accelerometer (VMI-102 model) which was mounted on the flat surface using hand mounting technique because of aluminized substance of the gear housing of the pump (Fig. 2).

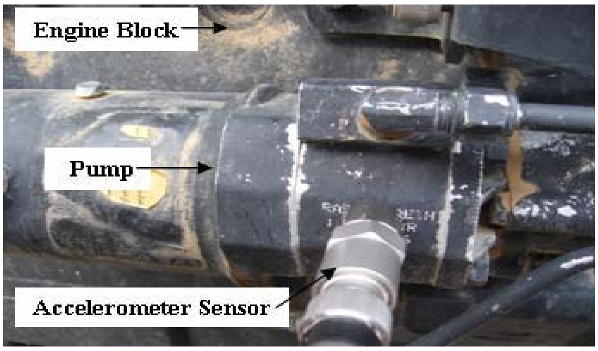


Fig. 2 Location of sensor on the body of pump

The accelerometer is connected to the signal-conditioning unit (X-Viber FFT analyzer), where the signal goes through the charge amplifier and an analogue-to-digital converter (ADC). The vibration signal in digital form is fed to the computer through a USB port. The software SpectraPro-4 that accompanies the signal-conditioning unit is used for recording the signals directly in the computer's secondary memory. The signal is then read from the memory and processed to extract the FFT [39] of vibration spectrum. The maximum frequency of the signal was 1 kHz, with 4010 sampled data and giving a measured time of 2.1 second.

Initially, the data were acquired from a healthy running pump. Then, data were measured from pump with faulty components that are described in Table I. Three working levels of pump speed (1000, 1500, and 2000 rpm) were considered as test conditions. Fig. 3 shows the used components and their cases.

TABLE I
PUMP FAULTS TAKEN INTO CONSIDERATION

Number	Fault type	Label of classification
1	Normal pump	GOOD
2	Journal-bearing with inner face wear	BIFW
3	Gear with tooth face wear	GTFW
4	Mixture of faults number 2 & 3	G&BW

C. PSD Creation

Power spectral density (PSD) function shows the strength of the variations (energy) as a function of frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are weak [40].

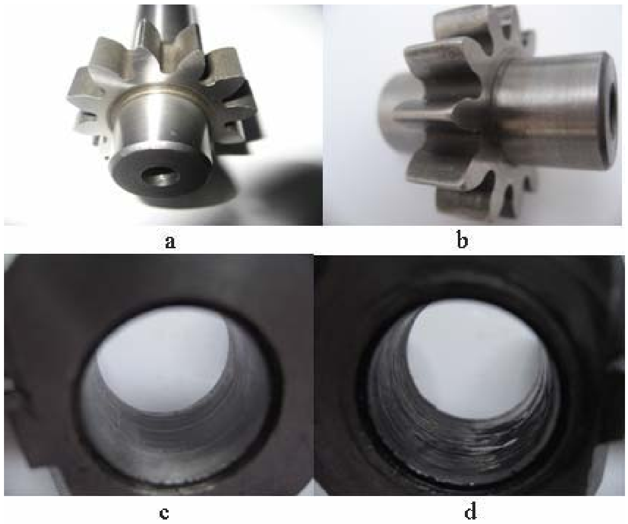


Fig. 3 a. View of good gear, b. View of gear with tooth face wear (GTFW), c. View of good journal-bearing, d. View of journal-bearing with inner face wear (BIFW)

The complex spectrum of a vibration x(t) in the time range (t_1, t_2) for any frequency f in the two-sided frequency domain (-F, +F) can be stated as (1) [41].

$$X(f) = \int_{f_1}^{f_2} x(t) e^{-2\pi i f t} \, dt \tag{1}$$

If x(t) is expressed in units of (m/s^2), X(f) is expressed in units of (m/s^2)/Hz. From the complex spectrum, the one-sided power spectral density can be computed in $(m/s^2)^2$/Hz as (2).

$$PSD(f) = \frac{2|X(f)|^2}{(t_2 - t_1)} \tag{2}$$

Where the factor 2 is due to adding the contributions from positive and negative frequencies.

The PSD divides up the total power of the vibration. To see this, we integrate it over its entire one-sided frequency domain (0, F):

$$\int_0^f PSD(f) df = \frac{\int_{f_1}^{f_2} |x(t)|^2 \, dt}{(t_2 - t_1)} \tag{3}$$

The result is precisely the average power of the vibration in the time range (t_1, t_2).

If FFT of vibration signal be used, PSD can be calculated directly in the frequency domain by following formula [41]-[42]:

$$PSD = \frac{G^2_{rms}}{f} \tag{4}$$

Where G_{rms} is the root-mean-square of acceleration in a certain frequency f.

D.Feature Extraction

The measured PSD values of signal were calculated to obtain the most significant features by feature extraction. The accuracy of feature extraction is of great importance since it directly affects the final diagnosis results. In this paper, the feature extraction using descriptive statistics from PSD values of vibration signals were used. Research works reported use of this method [43]-[46]. The parameters were Average, Standard deviation, Median, Sample variance, Kurtosis, Skewness, Minimum, Maximum, and Sum. These statistical features are explained below.

Average: It is the average of all signal point values in a given signal.

Standard deviation: This is a measure of the effective energy or power content of the vibration signal. The following formula was used for computation of standard deviation.

$$Stdv = \sqrt{\frac{n\sum x^2 - (\sum x)^2}{n(n-1)}} \tag{5}$$

Where n is the sample size.

Median: It is the number separating the higher half of signal point values from the lower half.

Skewness: Skewness characterizes the degree of asymmetry of a distribution around its mean. The below shown expression was used to calculate the skewness:

$$Skewness = \frac{n}{(n-1)(n-2)}\sum\left(\frac{x_i - \bar{x}}{s}\right)^3 \tag{6}$$

Where s is the sample standard deviation.

Kurtosis: Kurtosis indicates the flatness or the spikiness of the signal. The following formula was used for computation of Kurtosis:

$$Kurtosis = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i - \bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{7}$$

Sample variance: It is variance of the signal points and the following formula was used for computation of sample variance:

$$Variance = \frac{n\sum x^2 - (\sum x)^2}{n(n-1)} \tag{8}$$

Minimum value: It refers to the minimum signal point value in a given signal.

Maximum value: It refers to the maximum signal point value in a given signal.

Sum: It is the sum of the all signal point values in a given signal.

E. Feature Selection and Classification Model Extraction

A "divide-and-conquer" approach to the problem of learning from a set of independent instances leads naturally to a style of representation called a decision tree. A decision tree is a tree based knowledge representation methodology used to represent classification rules. 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. In a decision tree the top node is the best node for classification. The other features in the nodes of decision tree appear in descending order of importance. It is to be stressed here that only features that contribute to the classification appear in the decision tree and others do not. Features, which have less discriminating capability, can be consciously discarded by deciding on the threshold. This concept is made use for selecting good features.

In this research J48 algorithm (A WEKA implementation of c4.5 Algorithm) was used to construct decision trees [47]. Input to the algorithm was the set of statistical features extracted from PSD values of vibration signatures. The data sets of the features for each condition have 80 samples. In each operating condition, two-thirds of samples are employed for training process and the remaining samples for testing purposes. The detailed descriptions of those data sets are given in Table II. Based on the output of J48 algorithm, various statistical parameters are selected for the various conditions of the pump. Selected statistical features are used as membership functions and the values appearing between various nodes in the decision tree are used for generating the fuzzy rules to classify the various conditions of the pump under study.

TABLE II
DESCRIPTIONS OF DATA SETS IN EACH CONDITION

Label of classification	Number of training samples	Number of testing samples
GOOD	13	7
BIFW	13	7
GTFW	13	7
G&BW	13	7
Total Samples	52	28

F. Fault Diagnosis using Fuzzy Inference System

Fuzzy logic makes use of the knowledge of experts which is possible through its transformation into linguistic terms. Fuzzy logic is a rule-based system that successfully combines fuzzy set theory with the inference capability of human beings. As rules, linguistic terms are used and are modeled through membership functions that represent simulation of the comprehension of an expert. Membership functions give the scaled value of definite number values that are defined by linguistic labels. Rules are defined such as IF (condition) THEN (result). The conditions and results are linguistic terms that represent the input and output variables respectively. The rule base of the fuzzy logic classifier consists of many rules. A rule base is used to obtain a definite output value according to the input value.

The general fuzzy logic inference engine is given in Fig. 4. In the fuzzy logic inference engine, "x" is the input value, μ(x) is the fuzzified value, μ(u) is the result of the inference operation, and "u" is the output value. The fuzzifier unit converts crisp data in the input of the inference engine to the format of linguistic variables. The knowledge base represents two basic data: the database and the rule base. While the database includes definition of each system variable using the fuzzy set, the rule base covers inspection rules that are necessary to obtain a real output. The inference unit is a unit that performs fuzzy inference on fuzzy rules. This unit performs the operation resembling the way that people think. Finally, the defuzzification unit converts the fuzzy values obtained from the output of the inference unit to numerical values. This operation is called defuzzification [48].

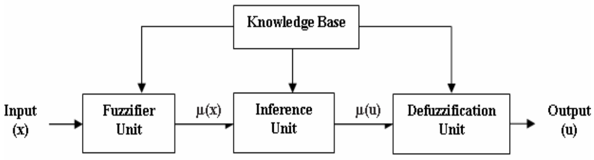


Fig. 4 Fuzzy inference engine

After defining membership functions and generating the "if-then" rules by J48 algorithm, the next step is to build the fuzzy inference engine. The fuzzy toolbox available in MATLAB 7.2 [49] was used for building fuzzy inference engine. Each rule was taken at a time and using membership functions and fuzzy operators the rules were entered.

III. Results and Discussions

A. PSD-Frequency Diagrams

Fig. 5 shows the samples of PSD-Frequency diagram of vibration signals acquired for various experimental conditions of the pump. According to this Fig., it is obvious that in each working speed of pump, the maximum value of PSD is increased by increasing the severity of pump faults.

B. Decision Trees

The outcomes of J48 algorithm are shown in Figs. 6 to 8. Decision trees show the relation between features and the condition of the pump. Tracing a branch from the root node leads to a condition of the pump and decoding the information available in a branch in the form of "if-then" statement gives the rules for classification using fuzzy for various conditions of pump. Hence the usefulness of the decision tree in forming the rules for fuzzy classification is established. The top node of decision tree is the best node for classification [45]. The other features appear in the nodes of decision tree in descending order of importance. It is to be stressed here that only features that contribute to the classification appear in the decision tree and others do not. The level of contribution is not the same and all statistical features are not equally important.

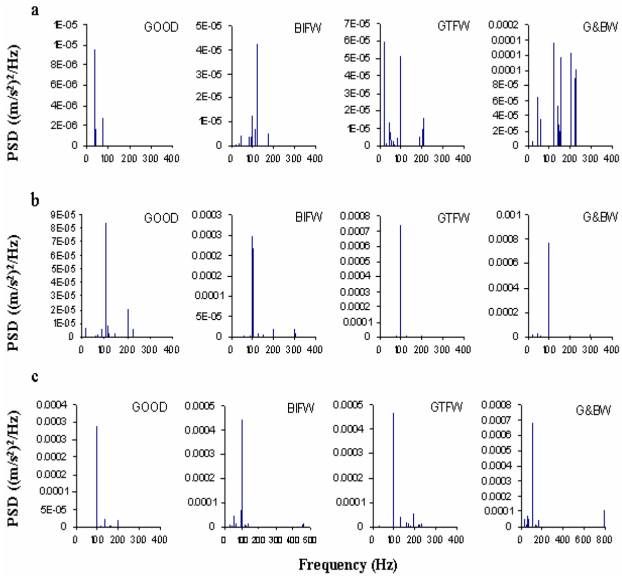


Fig. 5 PSD- Frequency diagrams of pump in a. 1000 rpm, b. 1500 rpm, and c. 2000 rpm

The level of contribution by individual feature is given by a statistical measure within the parenthesis in the decision tree. The first number in the parenthesis indicates the number of data points that can be classified using that feature set. The second number indicates the number of samples against this action. If the first number is very small compared to the total number of samples, then the corresponding features can be considered as outliers and hence ignored. Features that have less discriminating capability can be consciously discarded by deciding on the threshold. This concept is used in selecting good features. The algorithm identifies the good features for the purpose of classification from the given training data set and thus reduces the domain knowledge required to select good features for pattern classification problem.

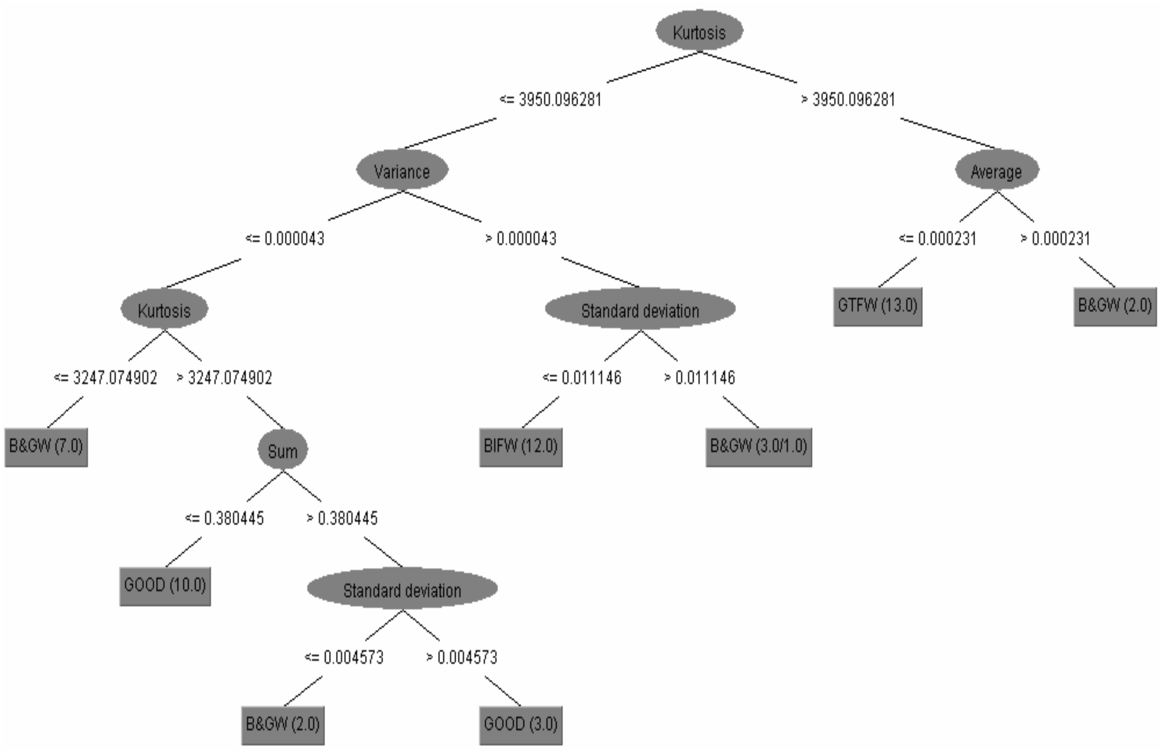


Fig. 6 Decision tree from J48 algorithm for 1000 rpm condition

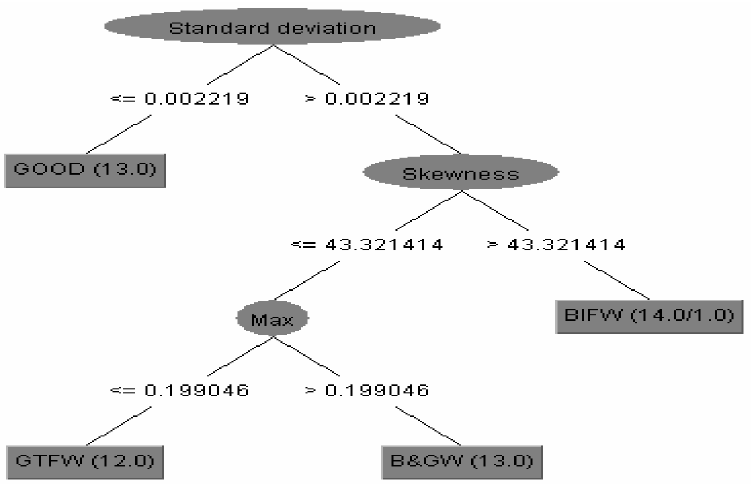


Fig. 7 Decision tree from J48 algorithm for 1500 rpm condition

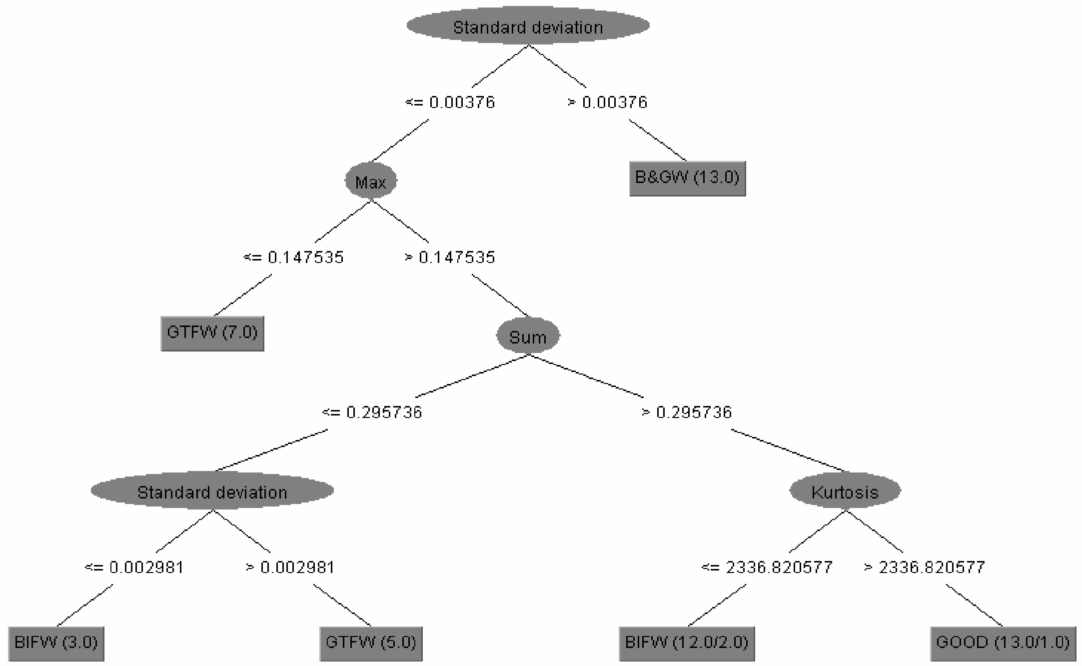


Fig. 8 Decision tree from J48 algorithm for 2000 rpm condition

C. Membership Functions

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Observing the values of the feature, based on which the branches of the decision tree are created for different conditions of the pump, MFs for the corresponding features are defined.

1) 1000 RPM Condition

From Fig. 6 we can see that average, kurtosis, variance, standard deviation, and sum play a decisive role in classifying the various pump faults for this condition. This output of the decision tree is used to design the MFs for fuzzy classifier as shown in Fig. 9. In the present study, trapezoidal MF is used. The selection of this MF is to some extent arbitrary. However, the following points were considered while selecting MF. Observing the values of the feature, based on which the branches of the decision tree is created, the MFs for all five features are defined for average, kurtosis, sum, variance, and standard deviation respectively.

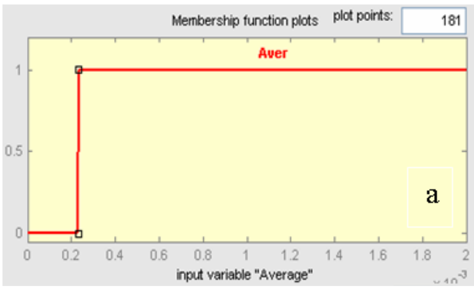
From Fig. 6 it is obvious that 0.000231 is a threshold for membership value of average. Up to this threshold value the MF generates the value "0" and afterwards it increases linearly (assumption). The trapezoidal MF suits this phenomenon and hence it was selected to map each point in the input space to a membership value (Fig. 9_a). To review, the threshold values are given by decision tree and the slope is defined by the user through heuristics. The threshold value (0.000231) is defined based on the representative training dataset. If average value is less than or equal to 0.000231, a MF which is defined on a 0–1 scale gives a value of 0 which means that it is not an average. If threshold value is greater than 0.000231, the MF generates a value of 1. Similarly MFs for other features are designed accordingly and shown in Fig. 9_b-e. There are four possible outcomes from a fuzzy classifier namely: Good, BIFW, GTFW and B&GW. Hence, four MFs are defined with equal range and shown in Fig. 10.

2) 1500 RPM Condition

See Fig. 11.

3) 2000 RPM Condition

See Fig. 12.



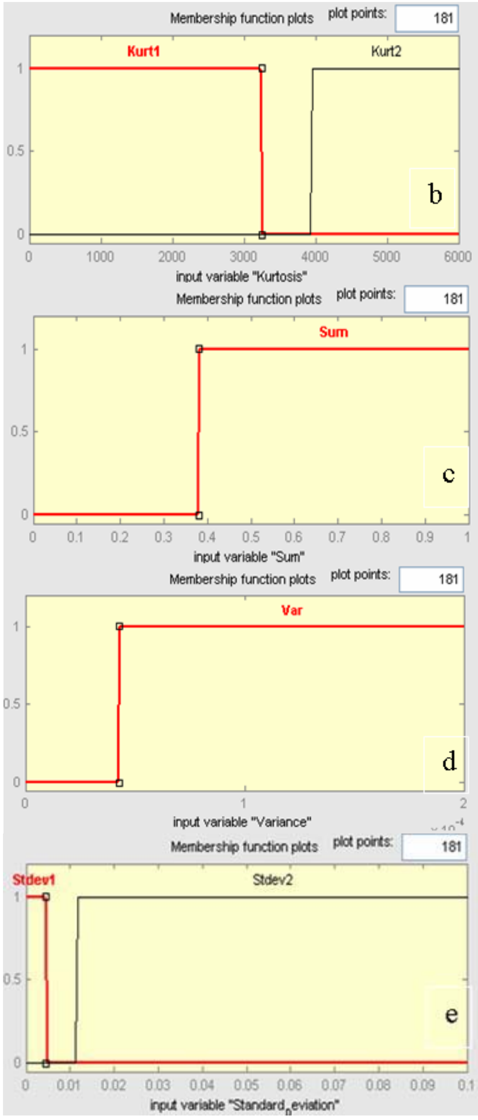


Fig. 9 MF for a. "Average", b. "Kurtosis", c. "Sum", d. "Variance", and e. " Standard Deviation"

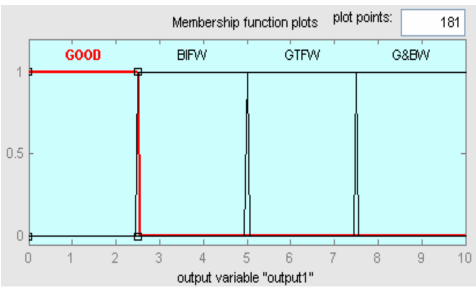


Fig. 10 MF for output ("Output1")

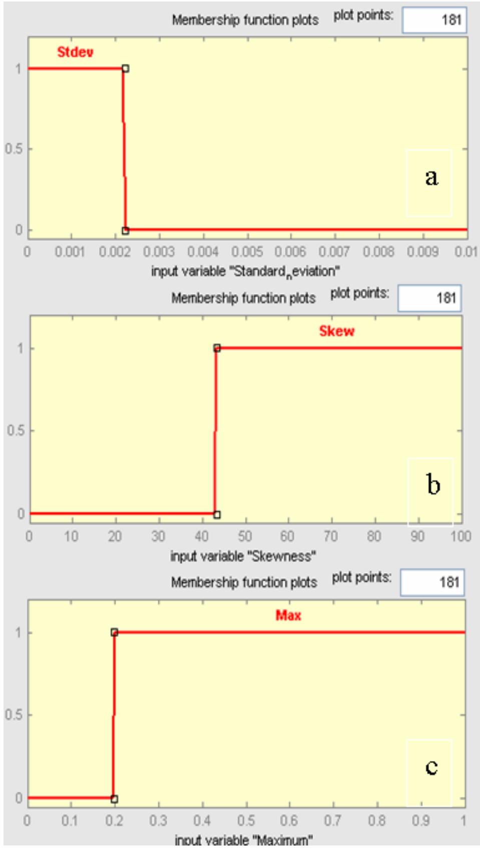
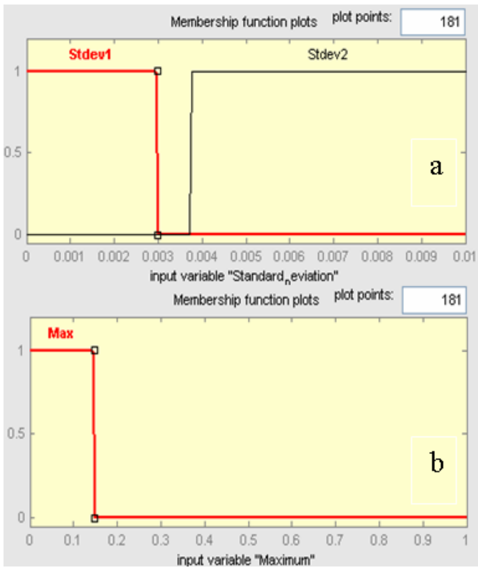


Fig. 11 MF for a. "Standard Deviation ", b. "Skewness ", and c. "Maximum"



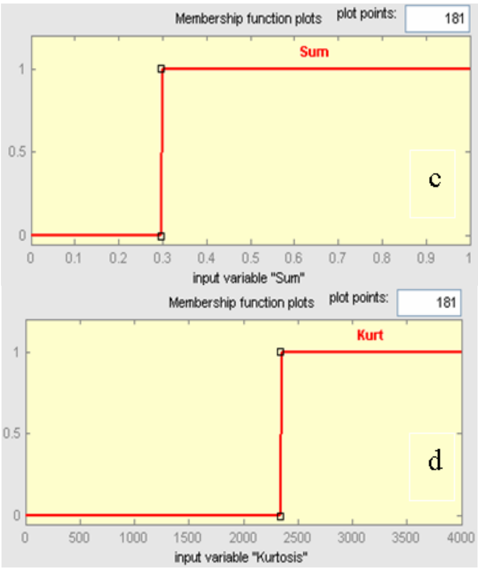


Fig. 12 MF for a. "Standard Deviation", b. "Maximum", c. "Sum", and d. "Kurtosis"

D.Fuzzy Rules

Using Figs. 6-8, fuzzy rules were designed with "If-Then" statements. All rules are evaluated in parallel, and the order of the rules is unimportant.

1) Rules Designed for 1000 RPM Condition

1. If (Kurtosis is Kurt2) and (Average is Aver) then (Output1 is B&GW)
2. If (Kurtosis is Kurt2) and (Average is not Aver) then (Output1 is GTFW)
3. If (Kurtosis is not Kurt2) and (Variance is Var) and (Standard Deviation is Stdev2) then (Output1 is B&GW)
4. If (Kurtosis is not Kurt2) and (Variance is Var) and (Standard Deviation is not Stdev2) then (Output1 is BIFW)
5. If (Variance is not Var) and (Kurtosis is Kurt1) then (Output1 is B&GW)
6. If (Variance is not Var) and (Kurtosis is not Kurt1) and (Sum is Sum) and (Standard Deviation is Stdev1) then (Output1 is B&GW)
7. If (Variance is not Var) and (Kurtosis is not Kurt1) and (Sum is Sum) and (Standard Deviation is not Stdev1) then (Output1 is GOOD)
8. If (Variance is not Var) and (Kurtosis is not Kurt1) and (Sum is not Sum) then (Output1 is GOOD)

Fig. 13 illustrates the application of the rules designed. Here each row corresponds to each rule as discussed in this section. The first five blocks in rows represents the MF of kurtosis, average, variance, standard deviation, and sum, respectively. The sixth block corresponds to the MFs for output as shown in Fig. 10. With the help of sample inputs for kurtosis, average, variance, standard deviation, and sum the rules are tested as follows, for a sample input of kurtosis as 3000, average as 0.001, variance as 0.0001, standard deviation as 0.05, and sum as 0.5 which satisfies the third rule completely and the corresponding output condition is B&GW, which is shown in the output block of the third row in the rule viewer shown in Fig. 13.

2)Rules Designed for 1500 RPM Condition

1. If (Standard Deviation is Stdev) then (Output1 is GOOD)
2. If (Standard Deviation is not Stdev) and (Skewness is Skew) then (Output1 is BIFW)
3. If (Standard Deviation is not Stdev) and (Skewness is not Skew) and (Maximum is Max) then (Output1 is B&GW)
4. If (Standard Deviation is not Stdev) and (Skewness is not Skew) and (Maximum is not Max) then (Output1 is GTFW)

Fig. 14 is the rule viewer for the following test data. If standard deviation = 0.005, skewness = 50, and maximum = 0.5 then the output is 3.75, i.e., the condition is BIFW.

3)Rules Designed for 2000 RPM Condition

1. If (Standard Deviation is Stdev2) then (Output1 is B&GW)
2. If (Standard Deviation is not Stdev2) and (Maximum is Max) then (Output1 is GTFW)
3. If (Standard Deviation is not Stdev2) and (Maximum is not Max) and (Sum is Sum) and (Kurtosis is Kurt) then (Output1 is GOOD)
4. If (Standard Deviation is not Stdev2) and (Maximum is not Max) and (Sum is Sum) and (Kurtosis is not Kurt) then (Output1 is BIFW)
5. If (Maximum is not Max) and (Sum is not Sum) and (Standard Deviation is Stdev1) then (Output1 is BIFW)
6. If (Maximum is not Max) and (Sum is not Sum) and (Standard Deviation is not Stdev1) then (Output1 is GTFW)

Fig. 15 shows the rule viewer for the following test data. If standard deviation = 0.005, maximum = 0.5, sum = 0.5, and kurtosis = 2000 then the output is 8.8, i.e., the condition is B&GW. This satisfies the first rule completely.

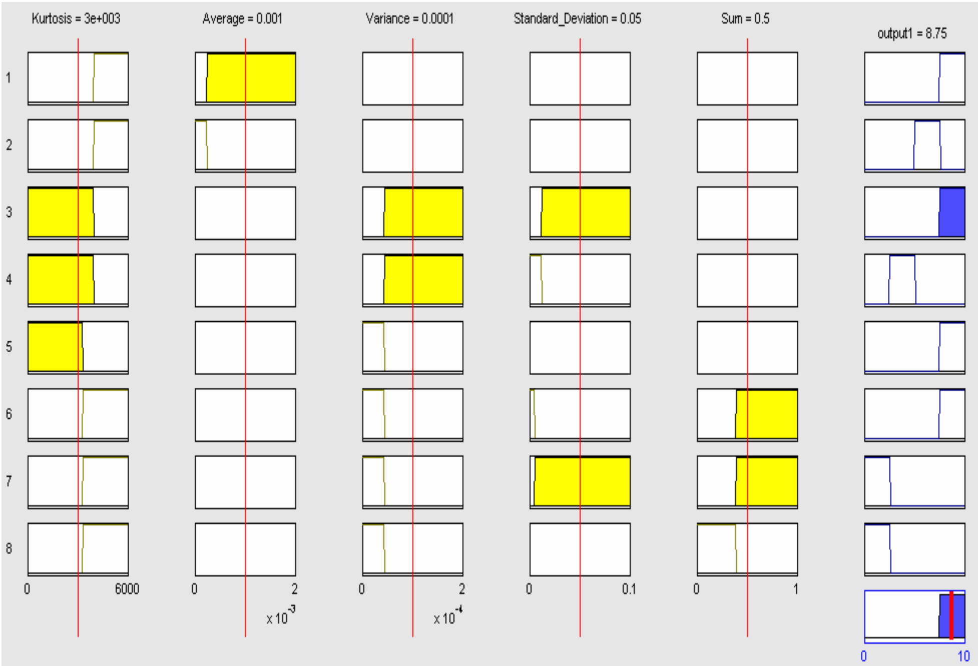


Fig. 13 Rule viewer for one of the test data of 1000 rpm condition

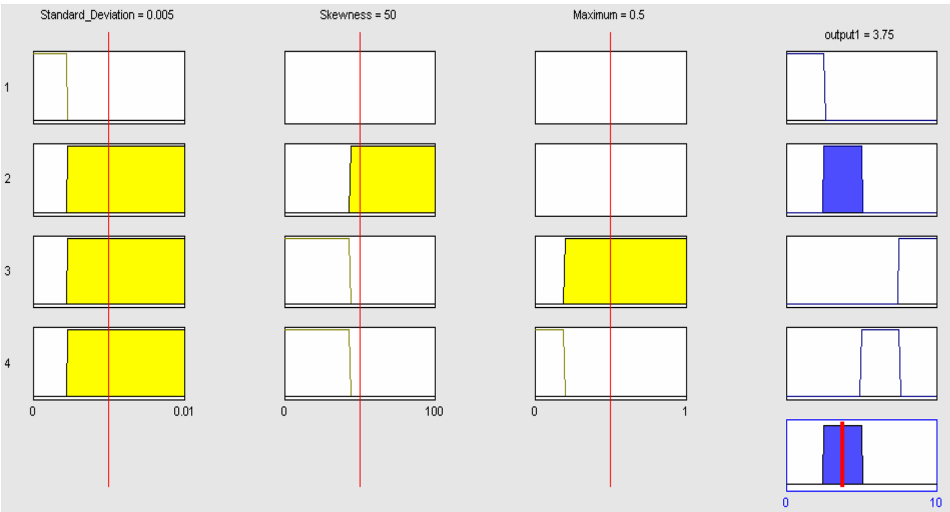


Fig. 14 Rule viewer for one of the test data of 1500 rpm condition

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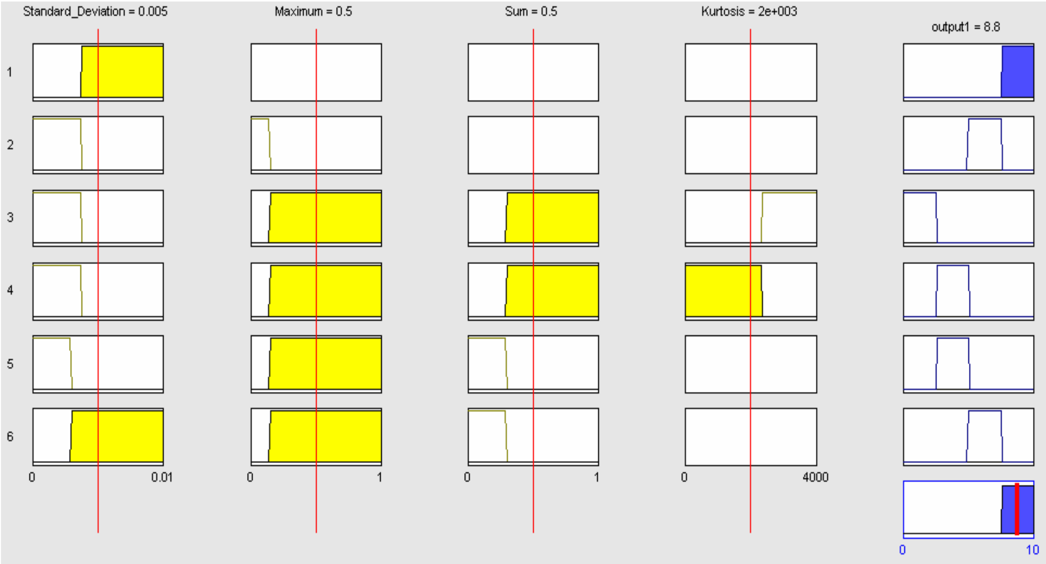

Fig. 15 Rule viewer for one of the test data of 2000 rpm condition

C. System Accuracy

The classification results are calculated using a 10-fold cross-validation evaluation where the data set to be evaluated is randomly partitioned so that in each condition 52 samples are used for training and 28 samples are used for testing. The process is iterated with different random partitions and the results are averaged. The confusion matrix for each condition is given in table III to V. In confusion matrix, each cell contains the number of samples that was classified corresponding to actual algorithm outputs. The diagonal elements in the confusion matrix show the number of correctly classified instances.

TABLE III
CONFUSION MATRIX FOR 1000 RPM CONDITION

Condition	Good	BIFW	GTFW	B&GW
Good	7	0	0	0
BIFW	0	6	0	1
GTFW	0	0	7	0
B&GW	0	0	0	7

TABLE IV
CONFUSION MATRIX FOR 1500 RPM CONDITION

Condition	Good	BIFW	GTFW	B&GW
Good	7	0	0	0
BIFW	0	7	0	0
GTFW	0	0	7	0
B& GW	0	0	0	7

TABLE V
CONFUSION MATRIX FOR 2000 RPM CONDITION

Condition	Good	BIFW	GTFW	B&GW
Good	7	0	0	0
BIFW	0	7	0	0
GTFW	0	1	6	0
B& GW	0	0	0	7

The performance of the classifier can be checked by computing the statistical parameters such as sensitivity, specificity and total classification accuracy defined by

- **Sensitivity:** number of true positive decisions/number of actually positive cases.
- **Specificity:** number of true negative decisions/number of actually negative cases.
- **Total classification accuracy:** number of correct decisions/total number of cases.

The values of statistical parameters are given in Table VI to VII. Results show that the total classification accuracy for 1000, 1500, and 2000 rpm conditions are 96.42%, 100%, and 96.42% respectively. It is to be stressed here that because rules and MFs for fuzzy logic inference system were extracted from J48 algorithm directly, accuracy of fuzzy system is closely equal with that of decision tree built by J48 algorithm. Therefore, it is true that to say these amounts show the accuracy of fuzzy inference system and PSD-J48-FIS model too.

TABLE VI
THE VALUE OF STATISTICAL PARAMETERS FOR 1000 RPM CONDITION

Data Sets Label	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
GOOD	100	100	96.42
BIFW	85.71	95.23	
GTFW	100	100	
B&GW	100	100	

TABLE VII
THE VALUE OF STATISTICAL PARAMETERS FOR 1500 RPM CONDITION

Data Sets Label	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
GOOD	100	100	100
BIFW	100	100	
GTFW	100	100	
B&GW	100	100	

TABLE VIII
THE VALUE OF STATISTICAL PARAMETERS FOR 2000 RPM CONDITION

Data Sets Label	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
GOOD	100	100	96.42
BIFW	85.71	95.23	
GTFW	100	100	
B&GW	100	100	

IV. CONCLUSION

A combined power spectral density (PSD), classification tree (J48 algorithm) and fuzzy inference system (FIS) have been presented to perform fault diagnosis of an external gear hydraulic pump. The implementation of PSD-J48-FIS based classifier requires three consecutive steps. Firstly, PSD values of vibration signal of pump were calculated from obtained spectrums. Secondly J48 algorithm is utilized to select the relevant features in data set obtained from feature extraction part. The output of J48 algorithm is decision tree that is employed to produce the crisp if-then rule and MF sets. Thirdly, the structure of FIS classifier is defined based on the obtained rules, which were fuzzified in order to avoid classification surface discontinuity. The classification results and statistical measures are then used for evaluating the PSD-J48-FIS model. The total classification accuracy for 1000, 1500, and 2000 rpm conditions were 96.42%, 100%, and 96.42% respectively. The results indicate that the proposed PSD-J48-FIS model can be used in diagnosing external gear hydraulic pump faults and developing an online condition monitoring tests. Works in this direction is in progress.

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