Fault Diagnosis of Water Pump Based on Acoustic Emission Signal Using Fast Fourier Transform Technique and Fuzzy Logic Inference

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Abstract— **Acoustic emission technique was used to examine four different water pumps in order to monitor the condition. The audio signal from a microphone was captured for the following conditions: normal pump, unbalance, misalignment, and bearing fault. The data were recorded 20 times for each pump. The sampling frequency used was 48 kHz and a measured time duration was 5 s. To execute damaged pattern classification, Fuzzy Inference System was applied and processed data extraction in time and frequency domain. The features in time domain were extracted from audio signal into several parameters, for example Root Mean Square (RMS), Kurtosis, Crest-Factor, Shape-Factor, and Skewness. Meanwhile, frequency domain data was extracted into instantaneous frequency parameter using the Fast Fourier Transform (FFT) approach. The experimental results showed that the classification accuracy yielded 90%. Therefore, the usage of FIS in acoustic emission analysis could potentially detect different fault categories.**

Keywords: Acoustic Emission, Fuzzy Inference System, Pump Faults

I. Introduction

Condition-based maintenance has an essential activity concept comprising machinery process evaluations and mechanical condition assessment [1]. Several parameters such as vibration, temperature, lubricant quality, and acoustic emission could be contributed to monitor machinery conditions [2] [3] [4]. Acoustic emission (AE) has been extensively used to monitor rotating machines condition. Unlike vibration inspection which needs three axes to gather the information, AE requires only one sensor [5]. Due to high sensitivity, AE is also able to provides earlier fault detection compared to vibration analysis. Based on a comparative study between AE and vibrations conducted by Singh et al [6], it is concluded that AE identified damage in gearbox earlier than those of vibration monitoring.

Artificial intelligent is a recent method to analyze the acoustic emission signal for machine health monitoring and fault diagnosis. V. Muralidharan and V. Sugumaran observed A. Moosavian et al. [7] applied adaptive neuro-fuzzy inference system (ANFIS) combined with fast fourier transform (FFT) to distinguish different fault categories occurred in water pump based on vibration signal. It is found that the technique could produce maximum classification accuracy. A. Widodo et al. [8] conducted the classification of low speed bearing fault diagnosis based on AE using relevance vector machine (RVM) and support vector machine (SVM). The comparison result shows that both RVM and SVM could generate 4.08 % testing error at rotating speed 80 rpm. M Khazaee et al [9] proposed wavelet transform and artificial neural network to identify defect occurred in planetary gearbox using acoustic signals. The accuracy of fault diagnosis using fused features was 98.6%.

According to literature review process, the research related to the application of AI in AE especially in term of monitoring the type of pump damage based on acoustic emission is still limited. The method of processing the acquired data which involves interpreting and classifying also need to be explored. N R Sakhtivel et al [10] simulated six types of faulty condition on centrifugal pump which are normal, bearing fault impeller fault, seal fault, combination of impeller and bearing fault, and cavitation to test the accuracy of some pattern classification approaches. K Mollazade [11] utilized power spectral density, decision trees and fuzzy logic to identify hydraulic pumps with defect conditions as follows: journal-bearing with inner face wear (BIFW), gear with tooth face wear, the mixture of two aforementioned fault.

The novelty of the present study is the application of Fuzzy Inference System (FIS) to investigate four type of pump condition. The pumps were modified to encounter the following conditions: normal, unbalance, misalignment, and bearing fault. Furthermore, in this work, instead of time domain approach, FFT were applied to perform time frequency domain approach based on the collected acoustic signals. By using keyword index machine condition monitoring and fault diagnosis, it is found that none of the research detected those three fault types using the combination

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of FIS and FFT based on AE. All analysis was carried out using MATLAB software.

II. METHODOLOGY

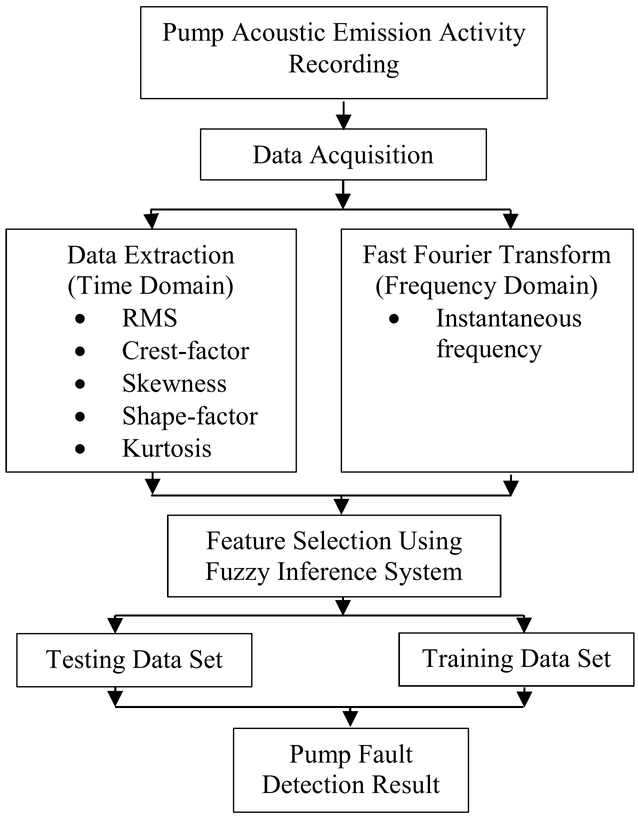


Figure 1. Research Flowchart

A. Experimental Setup and Data Acquisition

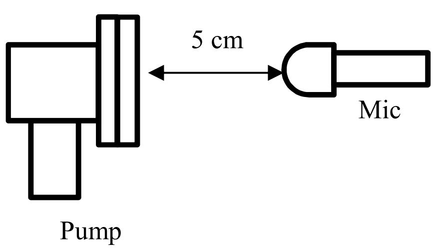


Figure 2. Data Collection Configuration

Figure 1 presents the flowchart of the research work. The acoustic emission signals were recorded from four different conditions of water pumps using a sensor in a semi-anechoic room. The pumps were simulated into following case: unbalance, misalignment, and bearing fault. The pumps have similar characteristics and rotational speed was adjusted at 3000 rpm. The experiment setup is shown in Figure 2. The distance between the sound source and sensor was 5 cm as shown in Figure. The data were acquired 20 times for each pump. The sampling frequency used was 48 kHz and a measured time duration was 5 s. The output of acoustic emission activity was saved with the .wav extension.

B. Signal Processing using Fast Fourier Transform

Each data sample in time domain was transferred into frequency-domain by Fast Fourier Transform (FFT) using MATLAB. The acquired data in .wav format was imported to workspace and entered in FFT process.

C. Feature Extraction

The time domain data was calculated by feature extraction using statistical parameters, that were root mean square, kurtosis, crest-factor, shape-factor and skewness. Meanwhile, data in frequency domain was extracted into instantaneous frequency.

D. Pump Fault Analysis using Fuzzy Inference System

AE signal extracted data would be processed using FIS Mamdani as inputs. Fuzzy Inference System (FIS) could be designed using four following steps:

1. Fuzzification
   The extraction value from statistical parameters (root mean square, kurtosis, crest-factor, shape-factor and skewness, Instantaneous Frequency) were mapped into certain range based on trained data. 10 top data were chosen as trained data for each parameter.
2. Fuzzy Reasoning (Inference Machine)
   The purpose of these stage is to determine the output as a form of decision making which is automatically processed in fuzzy logic toolbox available in MATLAB.
3. Creating Rule Base
   It contains of mapping the designed input value in fuzzification step with expected output value. Linguistic terms were used by defining rules such as IF (condition) THEN (result). The rule base is given as follows:

> "*If (RMS is high) and (kurtosis is high) and (skewness is medium) and (Crest-Factor is high) and (Shape-Factor is high) and (Instantaneous_Frequency is high) then (output is BearingFault)*"
> *"If (RMS is medium) and (kurtosis is low) and (skewness is high) and (Crest-Factor is medium) and (Shape-Factor is low) and (Instantaneous_Frequency is low) then (output is Missalignment)"*
> *"If (RMS is low) and (kurtosis is high) and (skewness is medium) and (Crest-Factor is medium) and (Shape-Factor is low) and (Instantaneous_Frequency is high) then (output is Normal)"*
> *"If (RMS is medium) and (kurtosis is low) and (skewness is low) and (Crest-Factor is low) and (Shape-Factor is low) and (Instantaneous_Frequency is low) then (output is Unbalance)"*

4. Defuzzification
   The type of defuzzification used in the present study is COA (Center of Area). Crisp solution is gained by taking center point of fuzzy area.

E. Performance Testing

The test is executed to find out whether the output results of machinery damage detection using fuzzy logic are in accordance with the actual conditions or not. It could be done by comparing the output results when the training data and testing data include in the design. The training and testing data sets, each consisting of 40 samples and would be entered into the input column emerged in rule viewer display. The parameter values for each pump will be inputted one by one and then recorded the output.

III. Analysis and Discussion

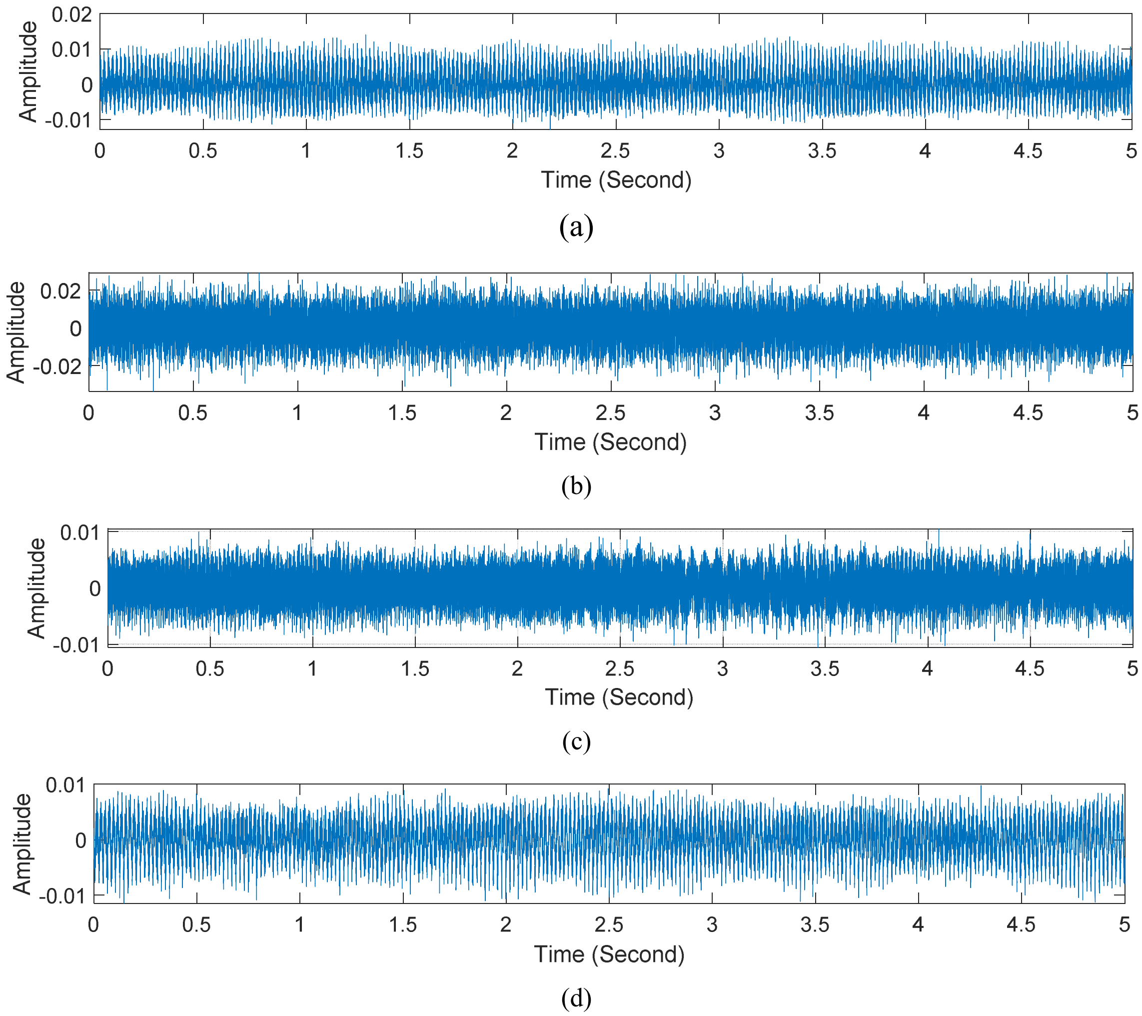
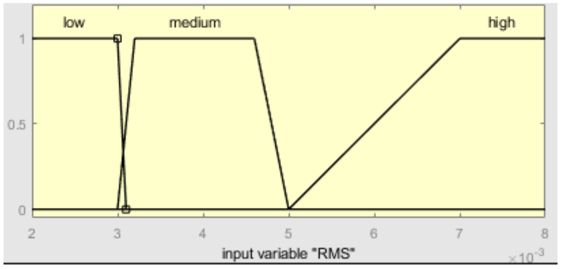
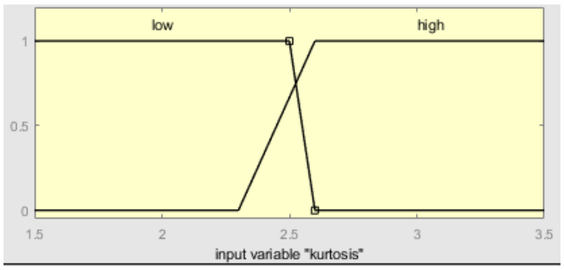


Figure 3. Baseline Signal in Time Domain for Pump Condition: (a) Misalignment (b) Bearing Fault (c) Normal (d) Unbalance

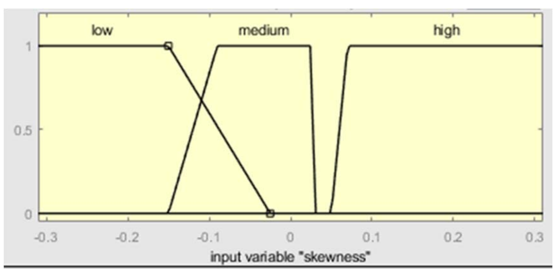
Figure 3 illustrates the baseline signal recording result in time domain. As shown in Figure, it will be difficult to determine the characteristic of faulty pump if the acquired data is still in time domain. Thus, time domain data need to be extracted into several parameters, for example RMS, Kurtosis, Skewness, Crest-Factor, and Shape-Factor. In addition, frequency domain data was also extracted to obtain instantaneous frequency parameter. Prior to this process, the baseline data in time domain were converted into frequency domain data using FFT. The extraction process was performed by observing the highest frequency peak for each frequency domain graph as shown in. Those six parameters would be used as input in FIS to identify the pump fault.



(a)



(b)



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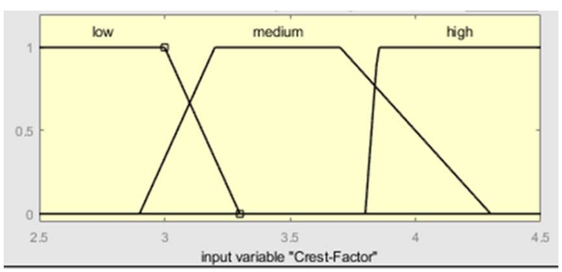

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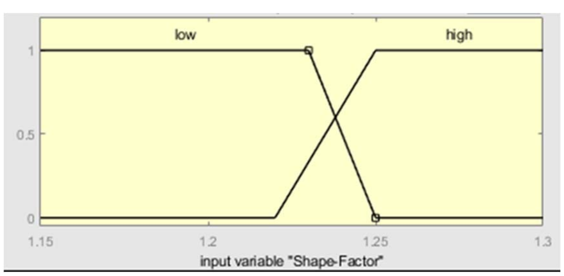

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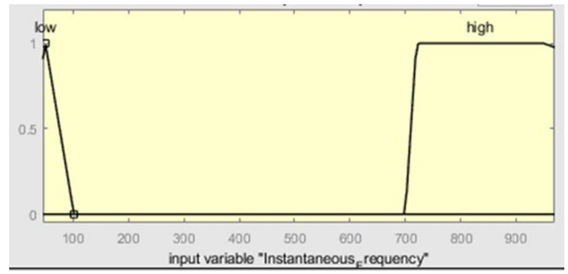


(f)

Figure 4. Membership Function (**a:** RMS; **b:** Kurtosis, **c:** skewness, **d:** crest-factor, **e:** shape-factor, **f:** Instantaneous Frequency)

Membership function for each parameter could be seen in Figure 4. Next, the range would be divided again into three categories, i.e. low, medium, and high based on trendline of trained data as described in Table 1. As the input is entered, the output value would be immediately appeared as shown in Figure 5 where output value "1","2", "3", "4" represents bearing fault, misalignment, normal, and unbalance, respectively.

TABLE I. RANGE CLASSIFICATION

Parameter	**Category Characteristics**
RMS	*low* = [0 0 0.003 0.0031] *medium* = [0.003 0.0032 0.0046 0.005] *high* = [0.005 0.007 0.008 0.009].
Kurtosis	*low* = [0 0 2.5 2.6] *high* = [2.3 2.6 3.5 4].
skewness	*low* = [-0.4 -0.4 -0.15 -0.025] *medium* = [-0.15 -0.09 0.025 0.03] *high* = [0.05 0.07 0.35 0.4]
crest-factor	*low* = [0 0 3 3.3] *medium* = [2.9 3.2 3.7 4.25] *high* = [3.8 3.85 4.5 5].
shape-factor	*low* = [0 0 1.23 1.25] *high* = [1.22 1.25 1.3 1.5]
Instantaneous Frequency	*low* = [0 49.6 100] *high* = [700 720 950 950]

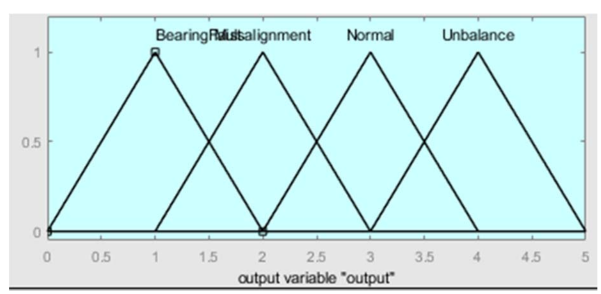


Figure 5. Pump Fault Detection Result

Table 2 and 3 show the FIS output for training and testing data respectively. As shown in Table 2, the output fits to the representation number of each pump condition. Thus, the accuracy of training data is 100%. Meanwhile, in Table 3, some errors could be found, specifically 1 error in misalignment data, 1 error in normal data, and 6 errors in unbalance data. Based on both results, the final accuracy reaches 90% which could be calculated as follows:

$$Total\ data = 80$$

$$Error\ Ratio = \frac{80 - 8}{80} \times 100\% = 90\%$$

TABLE II. FIS OUTPUT FOR TRAINING DATA

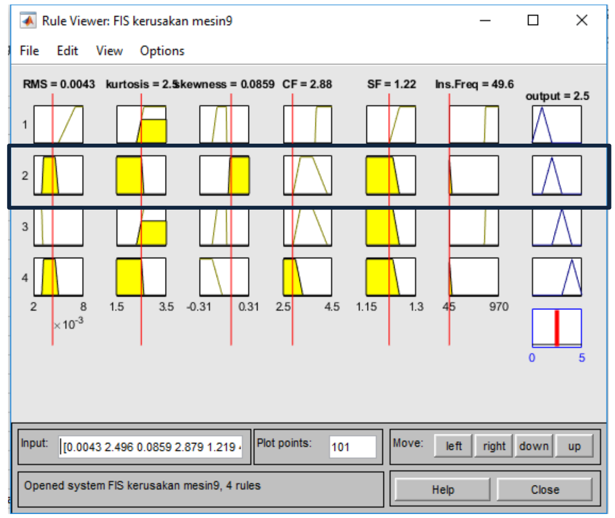
No	Pump Condition			
	Bearing Fault	Misalignment	Normal	Unbalance
1	1	2	3	4
2	1	2	3	4
3	1	2	3	4
4	1	2	3	4
5	1	2	3	4
6	1	2	3	4
7	1	2	3	4
8	1	2	3	4
9	1	2	3	4
10	1	2	3	4

TABLE III. FIS OUTPUT FOR TESTING DATA

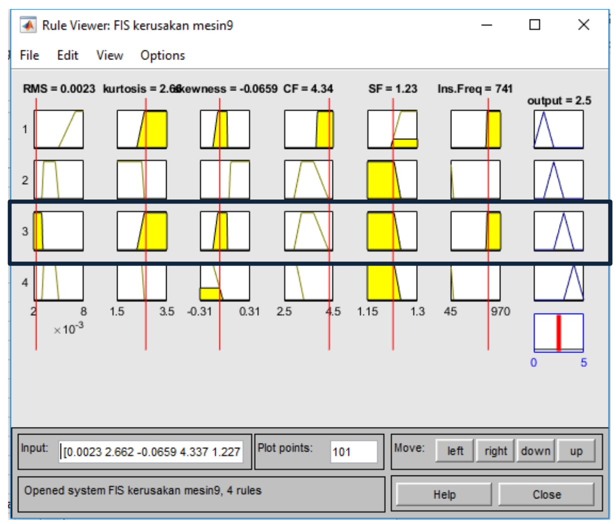
No	Pump Condition			
	Bearing Fault	Misalignment	Normal	Unbalance
1	1	2	2.5	4
2	1	2	3	4
3	1	2	3	4
4	1	2	3	2.5
5	1	2	3	2.5
6	1	2	3	2.5
7	1	2	3	4
8	1	2.5	3	2.5
9	1	2	3	2.5
10	1	2	3	2.5

The errors occurred since some statistics parameters value did not include in particular range. For example, in Figure 6a, crest-factor value 2.8793 in 8th misalignment data does not include in membership function, where this value does not represent any pump condition. Figure 6b also presents that crest factor value 4.3371 does not fit in any membership function. According to the analysis of the error occurred in pump fault detection, leading causes of the error take place in skewness and crest-factor parameters. Therefore, to observe the heterogeneity of data, standard deviations of those parameter were calculated.

As presented in Table 4, standard deviation of skewness parameters on unbalance pump have the highest value among other machines. It means that unbalance pump has a more varied number of data and is less homogeneous. Moreover, the standard deviation of the crest-factor on the misalignment and normal machines also reach the highest value. As consequence, value of some data is not included in the membership function.



(a)



(b)

Figure 6. Rule Viewer of Error on (a) 8th misalignment pump data and (b) 1st normal pump data

TABLE IV. STANDARD DEVIATION RESULTS

Skewness			
Bearing Fault	**Misalignment**	**Normal**	**Unbalance**
0.016	0.02714	0.03692	0.118
Crest-Factor			
Bearing Fault	**Misalignment**	**Normal**	**Unbalance**

0.1383	0.2278	0.307	0.1898

IV. CONCLUSION

Four types of pump condition, normal, unbalance, misalignment, and bearing fault were simulated on water pump. The proposed method comprising FFT, feature extraction, and FIS were utilized to diagnose the pump status. Five statistical features (Root Mean Square (RMS), Kurtosis, Crest-Factor, Shape-Factor, and Skewness) were extracted from baseline data in time domain. In addition, instantaneous frequency was extracted using FFT. These features were performed to FIS for pump fault classification and recognition. The result showed that the combination of these techniques produced 90% accuracy.

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