Artificial Neural Network Based Identification System for Abnormal Vibration of Motor Rotating Disc System

Hardianto Dwi PA,
Mechanical and Energy Department
Electronic Engineering Polytechnic Institute of Surabaya
Surabaya, Indonesia
hadepea@me.student.pens.ac.id

Faza Alfaradin, Zaqiatud Darojah, Raden Sanggar D.
Mechanical and Energy Department
Electronic Engineering Polytechnic Institute of Surabaya
Surabaya, Indonesia
fazaalfaradin@me.student.pens.ac.id, zaqiah@pens.ac.id, sanggar@pens.ac.id

***Abstract*—This paper reports an early work of machinery fault detection system module development. The system is developed and employed on a mechanical platform having a series of 3 aluminum rotating discs with unbalanced rotating mass to simulate an abnormal condition of a real machinery. This detection system is intended to have a capability of either to give an early warning due to an abnormality of the machine vibration or to localize the position of such abnormality among the discs. Artificial Neural Network (ANN) method is used to determine and to localize the abnormality by utilizing the vibration data. The method utilizes 3 features of time domain and 2 feature frequency domain signal characteristics. After the ANN was trained, this detection system was able to identify the plant condition of 90% accuracy.**

Keywords—vibration; fault detection; artificial neural network; Fourier transform

I. Introduction

Motion parts of an industrial machinery are mostly consisted of rotating mechanisms. These rotating mechanism give rise of a unique vibration pattern of a machine due to the presence of unbalance rotating mass that can be used to characterise such a machine. Thus, a dissimilar vibration pattern being compared to such a pattern can be regarded as an indication to a machine abnormality condition [1].

During their operations, industrial machineries are considered to function continuously. Therefore, a fault diagnosis monitoring is necessary to allow an early notification of vibration abnormality prior to the machine faulty. By providing such an early warning system, an anticipation can be carried on to prevent a catastrophic machine failure.

Practically, the condition of abnormality or damage of a machine with a rotating mechanism can be identified by comparing its normal conditions vibration with the one taken after a considered time of use [2]. There are wide variety of physical condition of the moving parts of the machine that can give rise to a vibration pattern changing. A long duration of a continuous dynamic or cyclic load can leads the parts to a fatigue condition, change in dimension/wear due to frictions, or change in its shape due to deformations.

In this work, we develop a system capable of detecting an early indication of such abnormalities to reduce the risk of a fatal damage of a machine by utilizing Artificial Neural Network (ANN) method.

II. Fault Diagnosis

One of the common way to specify a fault condition of a machine is to determine whether the magnitudes of measurable parameters of such a system are either normal or still tolerable [1]. If such measured values exceed their tolerable ranges, the system will alarms immediately or takes an appropriate action to prevent a further damage. Yet, our system utilizes an ANN intelligent identification method in either detecting or localizing the abnormality of the machine. Hence, expert analysis is not necessary. In this research the vibration data is obtained from a rotating mechanism when it is running. This system has three procedures, as shown in Figure 1.

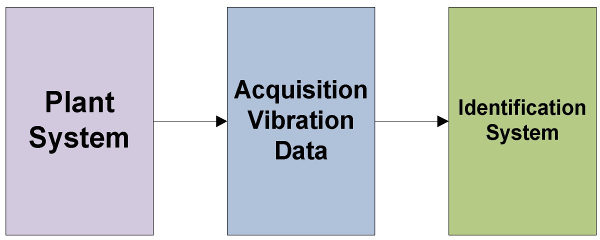

FIGURE I. RESEARCH PROCEDURE

Plant system, the mechanical platform, in this research is consist of a series three discs, a shaft, and a coupling. The design is shown in Figure 2 and plant of rotating mechanism shown in Figure 3.

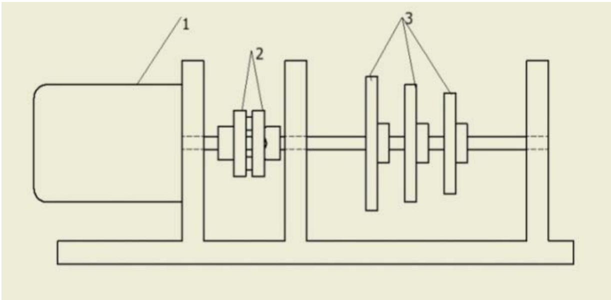

FIGURE II. DESIGN OF THE PLANT

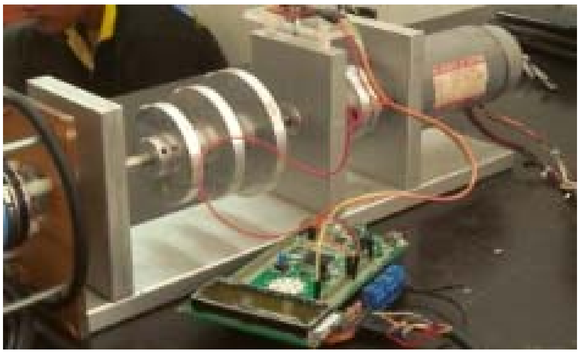

FIGURE III. PLANT OF ROTATING MECHANISM

Description of Figure III:

1. DC motor 3300 rpm; 33VDC
2. Coupling mechanic
3. Aluminum discs

The developed system is capable to localize the unbalance condition among the first, the second, or the third disc. The unbalance condition are identified with notations as shown in Table 1.

TABLE I. NOTATTION OF PLANT CONDITION

Plant Condition	Notation
Healthy on All	HoA
Unbalance on 1^{st} disc	UoSt
Unbalance on 2^{nd} disc	Uond
Unbalance on 3^{rd} disc	Uord

The unbalance conditions in this research generated by using an additional mass that was fixed on one of the discs. This solid mass is a tin weighing of 50 grams. This additional solid mass changes the pattern of the vibration signal taken from the plant. The changes that occur on this vibration data can be of the shift value of the natural frequency, or changes in the magnitude of the amplitude. Designs of the unbalance condition on the disc is shown in Figure 4.

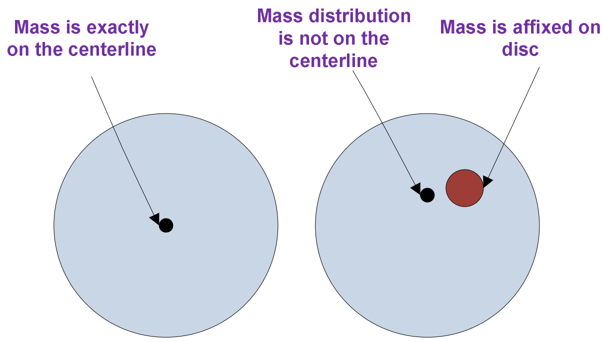

FIGURE IV. DESIGN OF THE UNBALANCE CONDITION

III. ACQUISITION OF VIBRATION DATA

The Acquisition data in this research is intended to process vibration data which taken from the plant until the data sent to he personal computer (PC). We use *accelerometer* MPU6050 sensor that accessed using the 12C serial communication lines. We also use UART peripheral to communicate between personal computer and microcontroller and timer peripheral that used as a trigger sampling frequency of vibration of sensor data retrieval.

Fig. 5 shows the flowchart of sending vibration data from the microcontroller to the PC. After we go got the data, the next process is identification of data using artificial neural network algorithm. Before doing this step, we test the validity of data that we got and then we extract the vibration data in all of condition.

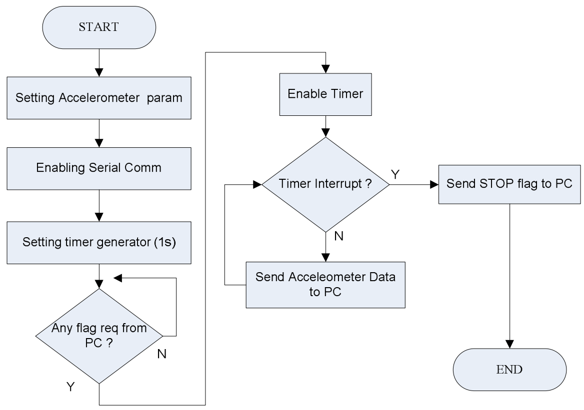

FIGURE V. FLOWCHART OF SENDING VIBRATION DATA TO THE PC

A. *Validity of Vibration Signal Data*

We test the validity of vibration signal that we get by comparing the value of frequency obtained from the plant with Discreet Fourier Transform (DFT) algorithm and measure the frequency physically using tachometer. We test the simulator in normal condition (HoA).

The vibration signal data resulted from the plant in time domain and frequency domain using the Discreet Fourier Transform (DFT) each shown in Figure 6 and Figure 7.

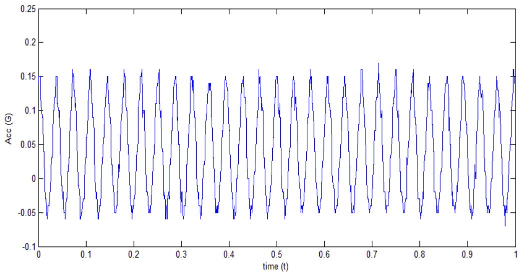

FIGURE VI. VIBRATION SIGNAL IN TIME DOMAIN IN HOA CONDITION

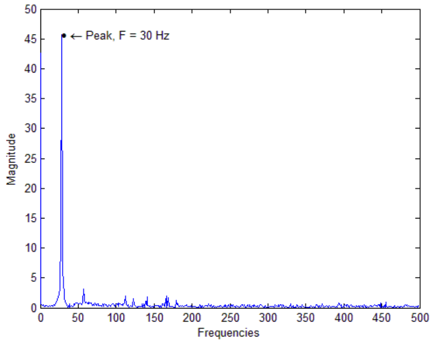

FIGURE VII. VIBRATION SIGNAL IN FREQUENCY DOMAIN IN HOA CONDITION

We can see from the Figure 7 that the vibration signal in HoA has 30 Hz. Next, we compare this result by taking the actuation frequency data using tachometer physically which described in Figure 8.

FIGURE VIII. MEASUREMENT OF MOTOR SPEED USING *TACHOMETER*

The data resulted using tachometer is the speed in rev/min. So, we convert it to the Hz by the Equation of 1-2.

$$f = \frac{rev/min}{60}\ Hz \qquad (1)$$

$$f = \frac{2028}{60} = 33{,}8\ Hz \qquad (2)$$

There is a difference of about 3 Hz, the measurement made using the microcontroller and measurement made physically. However, DFT algorithms used in this study, can be considered valid, because the difference between the real measurements in physical form and a numerical measurement (DFT) is not much different.

B. Vibration Signal Data in All Condition

After we test the validity of the data generated by plant, we take the vibration signal data in another condition, that is UoST, UoND, UoRD as described before. These data will be used as input in ANN algorithm. Figure 9-12 show the vibration signal in various conditions in both the time domain and frequency domain.

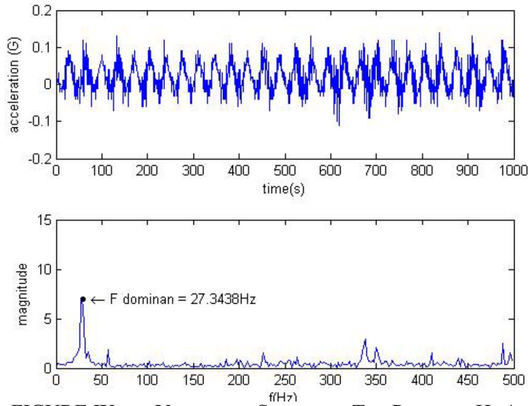

FIGURE IX. VIBRATION SIGNAL OF THE PLANT IN HOA

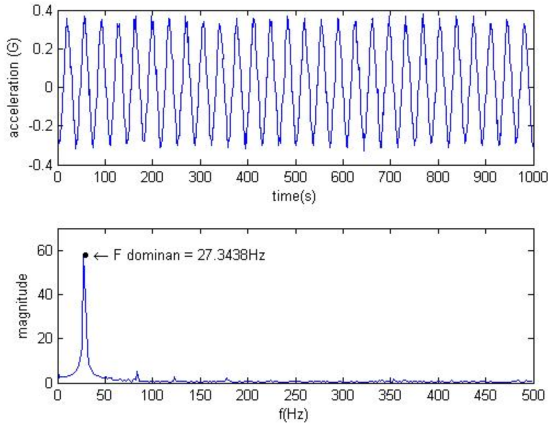

FIGURE X. VIBRATION SIGNAL OF THE PLANT IN UOST

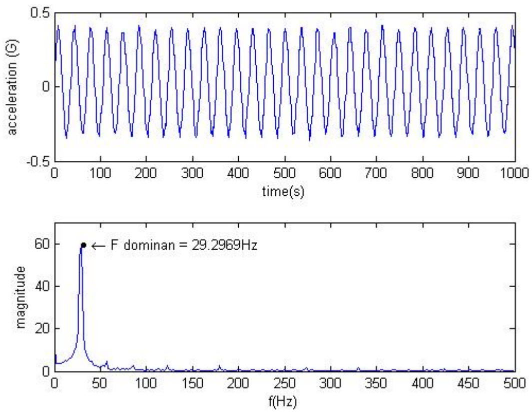

FIGURE XI. VIBRATION SIGNAL OF THE PLANT IN UOND

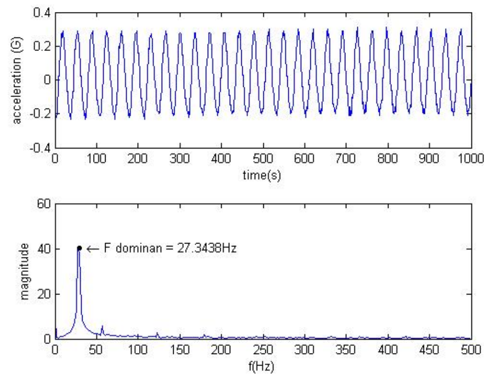

FIGURE XII. VIBRATION SIGNAL OF THE PLANT IN UORD

From the figures, we can see that each plant has a different amplitude obviously. Physically, the amplitude of the vibration signal is a resultant of the entire amount of each component in the response of each plant system when working. The difference of amplitude in each different plant conditions is due to the moment of force occurs at the point where the accelerometer sensor is placed.

IV. IDENTIFICSTION SYSTEM

During recent decades, artificial neural network (ANN) method has been employed as a powerful tool for identification of complex industrial systems with nonlinear dynamics. In this research, we also use backpropagation ANN to perform the vibration identification system. This processes were done on personal computer (PC).

The input is obtained from the vibration data and the target is defined corresponding with the plant condition. It is impossible to use the vibration signal data directly, so we must first extract the feature of the signal data, in this study we use statistical based feature extraction. From the previous study, statistical based feature extraction has a good performance [3].

The parameters of statistical based feature extraction used in this study are shown in Table 2. There are 3 parameters in time domain and 2 parameters in frequency domain using Discrete Fourier Transform (DFT) algorithm.

TABLE II. STATISTICAL VALUE

Statistical Value	Formula
Mean Value (Time Domain)	$T_1 = \frac{\sum_{n=1}^{N} x(n)}{N}$
Peak Value (Time Domain)	$T_4 = max[x(n)]$
Kurtosis (Time Domain)	$T_{10} = \frac{\sum_{n=1}^{N}(x(n) - T_1)^4}{N * \left(\frac{n\sum_{n=1}^{N} x^2(n) - (\sum_{n=1}^{N} x(n))^2}{n(n-1)}\right)^2}$
Crest Factor (Frequency Domain)	$A_7 = \frac{\max(x(k))}{\sqrt{\frac{\sum_{k=1}^{K}(x(k))^2}{K}}}$
Shape Factor (Frequency Domain)	$A_5 = \frac{\sqrt{\frac{\sum_{k=1}^{K}(x(k))^2}{K}}}{\frac{1}{K}\sum_{k=1}^{K}[x(k)]}$

where:
x(n) = data-n in time domain
x(k) = data-k in frequency domain

The target in this study is defined corresponding with the plant condition using biner code described in Table 3.

TABLE III. BINER CODE AS A TARGET

Plant Condition	Kode biner
HoA	0 0
UoST	0 1
UoN	1 0
UoRD	1 1

Generally, the architecture of ANN built in this study can be seen in Figure 13.

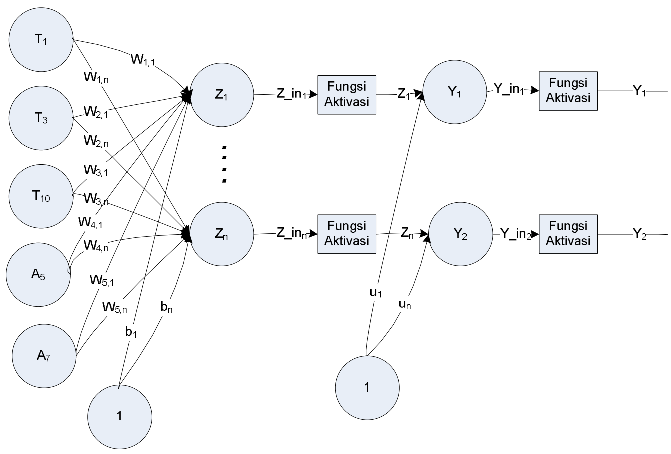

FIGURE XIII. ANN ARCHITECTURE

The process of the ANN backpropagation training has three steps i.e. feed forward input, back propagation to get error value, and the justification of weights value [4]. In the first step, which is the feed forward, every input neuron (x_i) receives input signals and then forwards those signals to the hidden layer Z1,…,Zp. Then, every hidden layer calculates the activation function. The results of activation function are then forwarded to the output neuron. The next step, the output neuron calculates the data using an activation function. Then the result of this activation function from the output neuron becomes the output of the ANN. The feed forward mathematically described in Equation 3-6.

$$z\_in_j = v_{0j} + \sum_{i=1}^{n} x_i v_{ij} \quad (3)$$

$$z_j = f\left(Z_{in_j}\right) \quad (4)$$

$$y\_in_k = w_{0k} + \sum_{j=1}^{p} z_i w_{ij} \quad (5)$$

$$y_k = f(y_{in_k}) \quad (6)$$

Common activation function used on back propagation method is a sigmoid function described in Equation 7.

$$f(x) = \frac{1}{1 + \exp(-x)} \quad (7)$$

where$x$ is input vector; $x = x1, ...xi, ...xn.$

Z_j = unit in hidden layer

Z_in_j = line of input to neuron on hidden layer.

v_{oj} = bias value in hidden layer

w_{ok} = bias value in output neuron

y_k = output unit

During the training process, the ANN output is compared with the target (t_k). This process is called back propagation of error. The goal is intended to determine the error value that is used to get the calculation of factor error value (d_k). d_k is used to distribute an amount of error in the output neurons (Y_k) to all of previous layer, that is hidden layer which directly connected with $Y_{k.}$. An error factor is also utilized to improve the value of the weights factor between output layer and hidden layer. Using the same method, the value of factor error in every hidden layer is calculated, and be used to improve the weights value between the hidden layer and the input neurons layer. The back propagation of error mathematically described in Equation 8-12.

Output neuron → hidden layer

$$\delta_k = (t_k - y_k) f'(y_{in_k}) \quad (8)$$

$$\Delta w_{jk} = \alpha \delta_k z_j \quad (9)$$

$$\Delta w_{0k} = \alpha \delta_k \quad (10)$$

Hidden layer→ input neuron

$$\delta\_in_j = \sum_{k=1}^{m} \delta_k w_{jk} \quad (11)$$

$$\delta_j = \delta_{in_j} f'\left(z_{in_j}\right) \quad (12)$$

$$\Delta v_{ij} = \alpha \delta_j x_i \quad (13)$$

$$\Delta v_{ij} = \alpha \delta_j \quad (12)$$

Where δ_k is the error factor to improve w_{jk}value based on error of the output unit y_k

δ_j = error factor to improve v_{jk}value based on information error from output unit tohidden layer.

α = learning rate.

The last process is adjustment of the weight values. These process mathematically described in Equation 14-15.

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \quad (14)$$

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \quad (15)$$

V. RESULT

We train first the data by offline. We took 60 data in each condition to be trained and also we took 60 data to be tested. Hence, there are 240 data training and 240 data testing. The result of our detection system in this study when the training is offline could be shown in Table 4.

TABLE IV. CONFUSION MATRIX OF TESTING DATA OFFLINE

		Output Class				
		HoA	**UoST**	**UoND**	**UoRD**	**Accuracy**
Target Class	**HoA**	60	0	0	0	100%
	UoST	0	46	1	13	77 %
	UoND	0	0	51	9	85%
	UoRD	0	3	0	57	95%

From the Table 4, we can see that the identification system built has a good performance. In HoA condition, 100% the target was recognized. Overall, the accuracy of the identification system by offline is 89.2%.

Further, the result of the test using the online training could be seen in Table 5. It can be seen that the performance of the online trial is also has a good performance. Overall, the accuracy of the identification system by offline is 91%.

TABLE V. CONFUSION MATRIX OF TESTING DATA ONLINE

		Output Class				
		HoA	**UoST**	**UoND**	**UoRD**	**Accuracy**
Target Class	**HoA**	60	0	0	0	100%
	UoST	0	54	0	6	90%
	UoND	0	0	53	7	88%
	UoRD	0	8	0	52	86%

The results show inTable 6 are of the accuracy and the test performance of the classifiers. Overall, the accuracy of the identification system is 90.12%.

TABLE VI. THE ACCURACY OF THE DETECTION SYSTEM

Fault Condition	**Percent Accuracy Data Result of Trial**		
	Offline (%)	***Online (%)***	***Total classification accuracy (%)***
HoA	100	100	90.12
UoSt	76.6	90	
Uond	85	88.3	
Uord	95	86.6	

VI. CONCLUSION

Detection system using ANN can identify four conditions of the plant properly. It can be seen on the result of the online and the offline trial.The accuracy of the online trial is of 89.2% whilst the offline trial is of 91.2% and having a total classification of accuracy is of 90.12%.

ACKNOWLEDGMENT

This work was supported by Electronic Engineering Polytechnic Institute of Surabaya (EEPIS) Center for Research and Community Service (*Pusat Penelitian dan Pengabdian kepada Masysrakat, Politeknik Elektronika Negeri Surabaya*) and Ditlitabmas Dikti.

REFERENCES

[1] Ebrahimi, Mollazade, "Intellegent Fault Classification of a Tractor Starter Motor Using Vibration Monitoring and Adaptive Neuro-fuzzy Inference System", *The British Institute of Non-Destructive Testing on Behalf of its Condition Monitoring Group,* pp. 561-566, 2010.

[2] Miftahuddin, "Identifikasi Kerusakan Mesin Berputar Berdasarkan Sinyal Suara dengan Metode Adaptive Neuro Fuzzy Inference System", *InstituteTeknologi Sepuluh Nopember, Surabaya*, Final Project, 2010.

[3] Reddy, M.Chandra., A.S. Sekhar, "Application of Artificial Neural Networks for Identification ofUnbalance and Looseness in Rotor Bearing Systems" International Journal of Applied Science and Engineering, 11(1) 69-84, 2013.

[4] Fausset, L. Fundamental of Neural Network : Architectures, Algorithms, and Applications, PrenticeHall, New Jersey, 1996.