Design of poka-yoke system based on fuzzy neural network for rotary-machinery monitoring

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Abstract. Early detection of machine failure will improve the performance of the production process. The Poka-Yoke device was developed to monitor the machine. The vibration signal is captured by sensors and inputted in Poka-yoke device for processing. Poka-Yoke device has two components, Fuzzy-Neural Network identification and decision maker. The first component, the time-domain signal is transformed into the frequency domain, magnitude and frequency are treated as Fuzzy membership functions by using the statistical parameters as mechanical harmonic distortion and then are trained by Neural Network. The second component, the decision is in the form of machine condition statements such as normal, alarm, and shutdown. Simulation’s results show that the method can be applied to identify the machine condition in term of bearing faults. Moreover, the Poka-yoke system that developed can be used to monitor machine condition automatically.

1. Introduction
In the industrial processes such as cement, fertilizers or steel, the role of rotary machinery or electric motors greatly determines the performance of the production process. Failure or error on the rotary machine will degrade performance. Therefore, it needs to be done for an effort to prevent the appearance of failure. One technique to overcome this problem is to monitor the rotary machine such that the machine failure symptoms can be detected earlier. Some research has been done to detect early-failure by using vibration signal of rotating machinery. Hongyu et al. [1] use neural networks to perform diagnosis on rotating machinery condition whereas Phayung [2] and Yang [3] discussed the methods of fuzzy logic and combined with the neural network to undertake a diagnosis of rotating machinery. Furthermore, Zhenyu Yang [4] and Janjarasjitt [5] use other methods such as analysis of nonlinear dynamic for diagnosis or prognosis of the machine condition.

Implementation of early-failure-detection symptoms become a very important purpose. Therefore, it is necessary to get a novel method to give satisfactory results. Fuzzy logic is one of the common methods used to determine the pattern of a system in which this method can be implemented either in software or hardware. The functions that can be performed with the method of fuzzy are the identification of failure patterns and can then deliver the decision in the process of production of the good in the form of an alarm (warning) or shutdown (stop the process). The ability of fuzzy is examined by Stewart [6] to establish systems that can eliminate defects of the product. Meanwhile, Neural Network has capabilities to recognize patterns of machine faults [1], [10]. Moreover, the combination of Fuzzy and Neural Network contributes more precise of fault patterns than the existence of faults [2], [3], and [10].

Based on the Fuzzy and Neural Network abilities, this research is developed to make an automatic system that can eliminate or minimize the error which is caused primarily by human error such as
missetting by technicians. The device that has the ability like this in the industry is called the Poka-yoke device [7]. Robert [8] examines the Poka-yoke as the control of the process to help the operator to avoid errors in the measurement of the weight of the product, while Dudek [9] forms the concept of Poka-yoke based on three levels of the product which are alarming, controlling, and preventing. In contrast to research results [8, 9] or [6] which focus on observations of the product, the research focused on one element of the process, actuator, in this regard, that is the rotary machine as well as the results of [1-5]. Therefore, this work aims to design a Poka-yoke system based on Fuzzy Neural Network to form automatic monitoring for the rotary machine.

2. Research Method
This section supports materials on rotary machine condition monitoring, Fuzzy Neural Network as a hybrid method in pattern recognizing, and Poka-yoke system that develops an automatic monitoring system.

2.1. Condition Monitoring for Rotary Machinery
Some techniques applied to rotate machinery condition monitoring such as electrical measurements, vibration, or temperature [10]. However, vibration becomes a technique that is widely used because the technique is non-destructive and sensors for measuring vibration are relatively inexpensive. Therefore, the use of vibration for rotating machinery condition is to be the center of research focus [1-5, 10-11].

Error or failure of the machine will cause vibration in the higher levels. It is used for diagnosis or identification of rotating machine failure. Meanwhile, the occurrence of vibration is related to some causes such as the imbalance of the rotor, the old components, misalignment shafts or looseness (lax the bolt fastener machine with ‘house’ ) [10-11].

This research applies the characteristic of machine condition signal as stated in Ref? [10] where there are some stages of bearing to get failure or damage as seen in Figure 1 to get feature extraction of vibration signal. First, Stage I shows that bearing has a high-frequency spectrum and bearing’s defects cannot be identified by physical inspection. In Stage II, vibration signals are associated with the bearing parts’ natural resonance frequencies. Moreover, the bearing defects start to knock the bearing components, and physical inspection will show defects. Stage III is the condition that there are fundamental bearing defect frequencies. At last, before an extreme failure of bearing presents, the Stage IV condition shows that numerous modulated fundamental frequencies and harmonics exist indicating distributed defects around the bearing races.

Based on the zone I to IV at the Stages, in this research, we use the terminology of mechanical harmonic distortion as well as total harmonic distortion in the electrical field. The partial mechanical harmonic distortion of the zone is to be one of the three input of the artificial intelligence architecture that is developed. Equations (1)-(2) denote as the partial mechanical harmonic distortion for the zone and the total mechanical distortion respectively.

\[
MHD_{z_i} = \frac{\sqrt{\sum X_i^2}}{MHD} \quad (1)
\]

\[
MHD = \sqrt{X_{1RPM}^2 + X_{2RPM}^2 + X_{3RPM}^2} \quad (2)
\]

where \( X_i \) for spectral under \( z_i \) (\( z_1, z_2, z_3, z_4 \) are zone 1, zone 2, zone 3, and zone 4 respectively), and \( MHD_{z_1} = 1 \)
Figure 1. Four Stages Spectral Characteristic of Bearing Faults [10]

The next sub-section discusses how to extract the feature of the spectral characteristic in Figure 1 by using artificial intelligence. In this work, the method is the hybrid of Fuzzy Logic and Neural Network.

2.2. Fuzzy Neural Network for Feature Extraction

Improvement of computer technology and computing has contributed to the development of artificial intelligence that can be used to identify patterns of signals generated by the machine. Artificial intelligence is not only capable of performing storage knowledge but also can apply knowledge to
solve problems and to take new knowledge from experience. The techniques that widely used in the intelligent system are an expert system, fuzzy, neural network, and a combination of these techniques [1-4, 10, 12]. The hybrid between Fuzzy Logic and Neural Network that called as Fuzzy Neural Network or FNN is proposed to extract the feature of faults' pattern. The structure of FNN and algorithm to train and to test the FNN are based on [12].

Figure 2. Structure of FNN

Figure 2 describes the architecture of FNN based on first-order Sugeno fuzzy model [12]. It is seen from Figure 2(a) that the reasoning mechanism of the fuzzy model has two rules as denoted in Eqs. (3)-(4). Meanwhile, Figure 2(b) shows the implementation of FNN. This FNN has five layers in which each layer has a different function. The box nodes are adaptive nodes such as a node in layer 1 and layer 4. It means that the parameter can be changed as a result of the training process. The others, circle nodes, are non-adaptive nodes, for example, nodes in layer 2, 3, and 5, which have the constant parameter. The output of each layer is modeled in Eqs. (5)-(11), except Eq. (7) which is an equation for the input membership function that has a Generalized-Bell function.

Rule 1: If $x$ is $A_i$ and $y$ is $B_i$ then $f_i = p_i x + q_i y + r_i$  \hspace{1cm} (3)

Rule 2: If $x$ is $A_j$ and $y$ is $B_j$ then $f_j = p_j x + q_j y + r_j$  \hspace{1cm} (4)

$O_{1,i} = \mu_{A_i} (x), \hspace{1cm} \text{for } i = 1, 2$ or

$O_{3,i} = \mu_{B_i} (y), \hspace{1cm} \text{for } i = 3, 4$  \hspace{1cm} (5)
\[
\mu_A(x) = \frac{1}{1 + \left(\frac{x-c_1}{a_1}\right)^{2h}}
\]

(7)

\[
O_{2,i} = w_i = \mu_A(x) \mu_B(y), \quad \text{for } i = 1, 2
\]

(8)

\[
O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad \text{for } i = 1, 2
\]

(9)

\[
O_{4,i} = \bar{w}_i f_i = \bar{w}_i \left( p_i x + q_i y + r_i \right), \quad \text{for } i = 1, 2
\]

(10)

\[
O_{5,i} = \sum_i \bar{w}_i f_i = \sum_i \bar{w}_i f_i
\]

(11)

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2.3. Poka-yoke System for Automatic Fault Detection

Poka-yoke is the term of Japanese that means is an error or failure resistant. Poka-yoke is firstly applied by Shigeo Shingo from Toyota to increase product quality by keeping human error [7]. Poka-yoke can be applied in each step of the process. Poka-yoke was originally applied to the review of the quality of the resulting product, for example, the jig is used to pay attention to the orientation of the product. Poka-yoke, in its evolution, is applied in a complex form as the integration of poka-yoke devices with all production machines[8]. Robert [8] uses a microcontroller as a center for processing all the data acquired from a production machine to avoid human errors.

Based on Figure 3, data obtained from the experimental results, that is vibration signal, is extracted using FFT for obtaining magnitude and frequency. Data are differentiated into normal conditions and abnormal conditions (presence of an error in rotating machinery). Data is trained and tested using FNN. FNN result from training and testing process is implemented on Poka-yoke system by online monitoring. The results or output are fed to three LCDs. The first Display is the result of identification showing the normal condition of the rotary machine. The second Display shows the alarm sign that an increase in the level of vibrations of rotating machinery. Lastly, the display will provide information it needs action to shut down because of the heavy fault.

3. Result and Analysis

In this section, it is explained how to get data for the research, how to get the best structure of FNN and as well as how to discuss the results comprehensively.
3.1 Data
The data that observed was secondary data of Bearing I and II CE FAN 5W1P31.

![Figure 4](image_url). A sample of Bearing Vibration Signal: (a) Light Fault Signal (b) Heavy fault Signal

It is seen from Figure 4 that the data is in time-domain form. Before data is treated for FNN training, the data was processed for several procedures. First, data were categorized into normal and abnormal data. Then, data were converted to frequency-domain form by using FFT (Fast Fourier Transform). Finally, the normalization of data is treated for getting ease in membership function.

3.2 FNN Training
Training of FNN is optimized using hybrid learning, and FNN is trained until the RMSE approach to $10^{-5}$. Meanwhile, three input was chosen for the training process. The first input is the frequency of all the Zone as stated in the explanation of Figure 1. The second input is the magnitude of spectrum under the Zone. Last input that is chosen is the partial mechanical harmonic distortion as denoted in Eqs. (1) and (2). Moreover, the function of the membership function used is generalized-bell (the best result), and the number of the membership function for each input is four.

To get the optimal results, The FNN is validated by using the same data as training data. If validation RMSE is larger than training RSME, the structure of FNN must be evaluated again until the validation RMSE is approaching training RMSE.

Table 1 shows the results of training and validation of FNN for several types of the membership function. Although the training epochs of Generalized-bell membership function undertake 300 epochs which is the largest epoch number of the four types of the membership function, the RMSE validation has the minimum difference among the others. Therefore, the type of Generalized-bell is used as a type of membership function form.

| No. | Membership Function Type | Training Epochs | Training RMSE | Validation RMSE |
|-----|--------------------------|-----------------|---------------|----------------|
| 1   | Triangular               | 52              | 0.004578      | 15.657500      |
| 2   | Trapezoidal              | 156             | 0.000375      | 115.897600     |
| 3   | Gaussian                 | 250             | 0.000045      | 0.008570       |
| 4   | Generalized-bell         | 300             | 0.000025      | 0.000032       |

3.3 Poka-yoke System Simulation
Based on the results of the validation procedure, Poka-yoke system that developed was tested by using different data from training or validation data. The simulation result is shown in Table 2. Even though there is the wrong detection on Testing No.2 - that is normal data was detected as the light fault,
almost the data can be recognized as the original types of data. The classification of the signal condition such as normal, light fault, or heavy fault can be drawn from the Stages of Bearing failure as stated in the explanation of Figure 1.

Different from the results of the other researchers that used statistical parameter such as kurtosis, skewness, or mean for diagnosing bearing [13], this research has introduced a new statistical parameter that defined as mechanical harmonic distortion as seen in Eqs. (1) And (2). The result not only can recognize normal or abnormal condition but also can detect the level of the failure.

Table 2. Simulation Results Based on The RMSE Testing

| No | Type of Data | RMSE Testing | Type of Fault | Poka-yoke Decision |
|----|--------------|--------------|---------------|--------------------|
| 1  | Normal       | 0.142512     | Normal        | Normal             |
| 2  | Normal       | 0.762733     | Light Fault   | Alarming           |
| 3  | Normal       | 0.266834     | Normal        | Normal             |
| 4  | Abnormal     | 1.796323     | Light Fault   | Alarming           |
| 5  | Abnormal     | 1.281130     | Light Fault   | Alarming           |
| 6  | Abnormal     | 1.985265     | Light Fault   | Alarming           |
| 7  | Abnormal     | 2.002860     | Light Fault   | Alarming           |
| 8  | Abnormal     | 3.250744     | Light Fault   | Alarming           |
| 9  | Abnormal     | 1.705055     | Light Fault   | Alarming           |
| 10 | Abnormal     | 3.522663     | Light Fault   | Alarming           |
| 11 | Abnormal     | 10.143100    | Heavy Fault   | Shutdown           |
| 12 | Abnormal     | 1.927063     | Light Fault   | Alarming           |

4. Conclusion
The Poka-yoke system that provides automatic fault detection or monitoring has been proposed. The mechanical harmonic distortion has been introduced as a statistical parameter of a vibration signal for additional input in fuzzy membership function. The simulation results show that Poka-yoke system is not only can detect the failure of rotary machine-in this research the point of view is the bearing failure but also can monitor the machine condition automatically.

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