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USING ARTIFICIAL NEURAL NETWORK TO MONITOR AND PREDICT INDUCTION MOTOR BEARING (IMB) FAILURE.

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ABSTRACT

The purpose of this paper is to develop an appropriate artificial neural network (ANN) model of induction motor bearing (IMB) failure prediction. Acoustic emission (AE) represented the technique of collecting the data that was collected from the IMB and this data were measured in term of decibel (dB) and Distress level. The data was then used to develop the model using ANN for IMB failure prediction model. An experimental rig was setup to collect data on IMB by using Machine Health Checker (MHC) Memo assist with MHC Analysis software. In the development of ANN modeling, two networks were tested; Feedforward Neural Network (FFNN) and Elman Network for the performance of training, validation and testing with training algorithm, Levenberg-Marquardt Back-propagation and the suitable transfer function for hidden node and output node was logsig/purelin combination. The results show the performance of Elman network was good compared to FFNN to predict the IMB failure.

Keywords**:** *Neural Network, IMB, Feedforward Network, Elman Network.*

INTRODUCTION

The manufacturing and industrial sectors of the world are increasing rapidly demanding to production at higher output and better qualities while their operating process at maximum yields. The manufacturing of such products are textiles, aircraft, automobiles and appliances involving a large number of complex processes of nonlinear dynamic system. Therefore these processes are not well understood and its operation is usually understood by experience rather than through the application of scientific method.

The detection of IMB failure is conventionally performed by experts. For instance, by supervisors or engineers that have the knowledge on the operating characteristics of specific bearings that could be determined through the sense of touch, sight or noise as compared to the normal bearing performance. These approaches can susceptible to human errors and vary according to experience and individual skill which could contribute to the inaccuracies and time consumption. Today, advances in instrumentation and computing assisting manufacturing companies to improve substantially the production output. Moreover, condition monitoring is becoming popular in industry with considerable sums now being spent on condition monitoring hardware and software.

The root causes of IMB failures are normally attributed to improper installations, poor lubrication practices, excessive balance and alignment tolerances and handling techniques [1]. Monitoring the above causes of failure are very important for early detection before those bearings approach failure stage. This will avoid serious damage which might lead to potentially hazardous situation.

There are two methods for IMB maintenance: bearing life estimation based on statistical method and IMB condition monitoring [2]. The former method relies on the estimated life span based on statistical analysis performed on laboratory tests. However, this estimated life span normally may not match the actual life span due to possible real life operating conditions that may differ to laboratory test. Therefore the development of a new and efficient signal processing technique becomes a popular choice.

Today, various method are available to detect and monitor such failure which include vibration monitoring and acoustic emission but in this study the acoustic emission will be used to monitor sound defects from IMB. Vibration monitoring is typically insensitive to more subtle effects such as the early signs of bearing wear. To overcome this, vibration analysis has to be carried out in which the vibration signal is pre-processed by using

subjectively set filter and analysed in the frequency domain with Fast Fourier Transform (FFT) to provide a frequency spectrum[6]. To interpret the vibration frequencies spectrum, it is necessary to calculate possible defects within these frequencies range. This is quite tedious and time consuming.
On the contrary, acoustic emission (AE) technique has the ability to detect the high frequency of the elastic waves being generated by rotating machinery [7]. The AE signal captures noise emitted by faulty bearing and is not sensitive to noise on normal IMB. Due to this criterion, it is possible to analyze the overall AE signal in order to provide a clear indication of the presence of faults.

The selection of ANN for monitoring and prediction in this research is due to its wide application in many conditions. Its potential is not only on their capability to learn from experience, but also on their ability to recognize and learn the relationship of non-linearity process. Therefore, ANN has been chosen as the technique to model IMB failure prediction due to the non-linearity of data from IMB failure. This paper differs from others work because the technique for data collection was used acoustic emission which captures a faulty sound from IMB. In order to predict the IMB failure, ANN model have been developed to predict the remaining useful life of bearing. This system can be used in industries such as textile industry that operates 24 hours a day to monitor IMB and avoid sudden failure. All operations are monitored by using ANN and will be alerted when IMB approach failure stage.

Feedforward Neural Networks

Three layer feedforward ANN are commonly encountered models found in the literature [3]. Computation nodes are arranged in layers and information feeds forward from layer to layer via weighted connections as illustrated in Figure 1. Circles represent computation nodes (transfer functions), and lines represent weighted connections. The bias thresholding nodes are represented by squares.

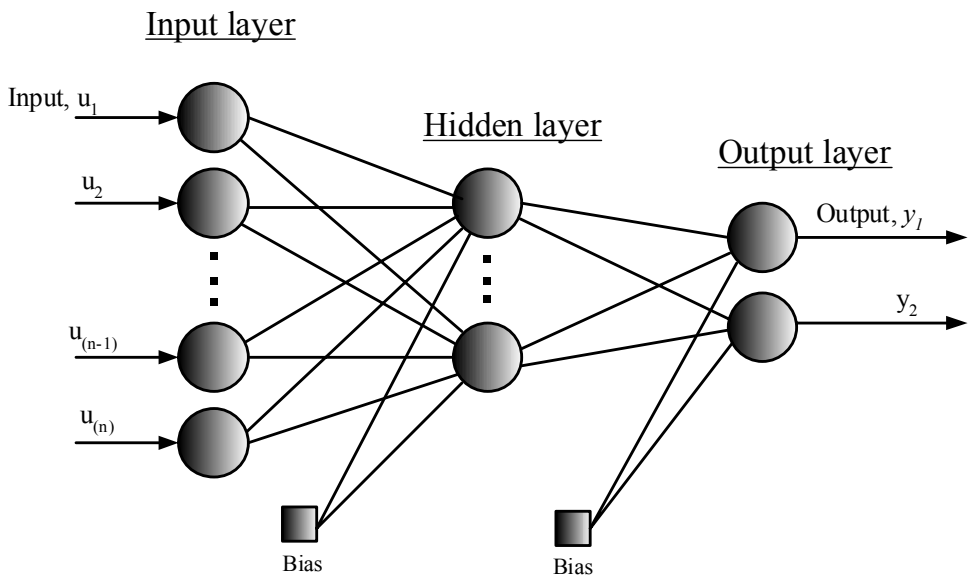

Figure 1: Graph of the information flow in a feedforward neural network [3].

Mathematically, the typical feedforward network can be expressed as

$$y_i = \varphi_o\left[C\varphi_h\left(Bu_i + b_h\right) + b_o\right] \tag{1}$$

where y_i is the output vector corresponding to input vector u_i, C is the *connection matrix* (matrix of weights) represented by arcs (the lines between two nodes) from the hidden layer to the output layer, B is the connection matrix from the input layer to the hidden layer, and b_h and b_o are the bias vector for the hidden and output layer, respectively. $\varphi_h(\cdot)$ and $\varphi_o(\cdot)$ are the vector valued functions corresponding to the *activation* (transfer) *functions* of the nodes in the hidden and output layers, respectively. Thus, feedforward neural network models have the general structure of

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$$y_i = f(u) \tag{2}$$

where $f(\cdot)$ is a nonlinear mapping. Hence feedforward neural networks are structurally similar to nonlinear regression models.

To use models for identification of dynamic systems or prediction of time series, a vector comprised of a moving window of past input values (*delayed coordinates*) must be introduced as inputs to the net. This procedure yields a model analogous to a nonlinear finite impulse response model where

$$y_i = y_t \text{ and } u_i = [u_t, u_{t-1}, \ldots, u_{t-m}] \text{ or } y_t = f([u_t, u_{t-1}, \ldots, u_{t-m}]) \tag{3}$$

The lengths of the moving window must be long enough to capture the system dynamics for each variable in practice. In practice, the duration of the data windows are determined by trial and error (cross validation) and each individual input and output variable might have a separate data window for optimal performance.

Backpropagation learning algorithm is one of the earliest and the most common method for training multilayer feedforward neural networks. Development of this learning algorithm was one of the main reasons for renewed interest in this area and this learning rule has become central to many current works on learning in ANN. It is used to train nonlinear, multilayered networks to successfully solve difficult and diverse problems.

Elman Network Model.

Elman [4] has proposed a partially recurrent network, where the feedforward connections are modifiable as shown in Figure 2. The Elman network is a two-layer network with feedback from the first layer output to the first layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns.

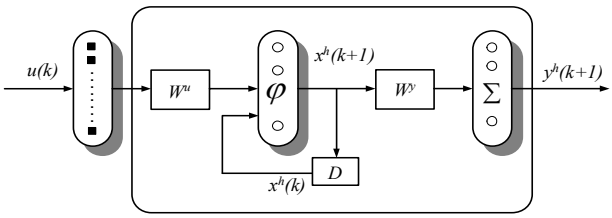

Figure 2 - Block diagram of Elman network

To understand the feature offered by Elman network, consider a multivariable plant with *m* inputs and *q* outputs, describe by a general nonlinear input-output discrete time state space model.

$$x(k+1) = f\{x(k), u(k)\} \tag{4}$$

$$y(k) g\{x(k)\} \tag{5}$$

where $f : \Re^{n+p} \to \Re^n$ and $g : \Re^n \to \Re^q$ are non-linear functions; $u(k) = \in \Re^m$, $y(k) \in \Re^q$ and $x(k) \in \Re^n$ are, respectively, the input vector, the output vector and the state vector, at a discrete time k. In addition to the input and the output units, the Elman network has a hidden unit, $x^h(k) \in \Re^n$. $W^u \in \Re^{nxp}$ and $W^y \in \Re^{qxn}$ are the interconnection matrices, respectively, for the context-hidden layer, input-hidden layer and hidden-output layer. Theoretically, an Elman network with *n* hidden units is able to represent an nth order dynamic system. The dynamics of the Elman network is described by the difference equations (6) – (8).

$$s(k+1) = x^h(k) + W^u u(k) \tag{6}$$

$$x^h(k+1) = \varphi\{s(k+1)\} \tag{7}$$

$$y^h(k+1) = W^y x^h(k+1) \tag{8}$$

where $s(k) \in \Re^n$ is an intermediate variable.

Note that the Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from previous time step, which can be used in the current time step. Because the network can store information for future reference, it is able to learn temporal patterns as

well as spatial patterns. The Elman network can be trained to respond to, and to generate, both kinds of patterns.

Elman network is preferred because it exhibits dynamic behaviour. In order to select an optimum network it can be chosen by trial and error, started with on two hidden nodes until twenty hidden nodes together with and Elman Network until the optimum network obtained. The selection corresponds based on the smallest cross-validation errors produced.

METHODOLOGY

The equipments involved for collecting data were experimental rig, IMB, sensor, electrical motor, hydraulic jack, personal computer (PC), load cell, data acquisition instrument (MHC Memo), and MHC Analysis software. The overall set-up to collect the data is shown in Figure 3. The main components in these experiments are;

1. Three phase motor, M
2. IMB, S2 (specimen)
3. Support bearings and housing, S1 and S3
4. Coupling, C
5. Applied load, P

There were 3 bearings that were used to support the one meter length of shaft. IMB (S2) at the center was tested bearing which applied to a load of 100 kgf. The purpose of bearing S1 and bearing S3 were to support the shaft. These distance can vary, depend on the setup chosen which enable the bearings to rotate freely in the housing

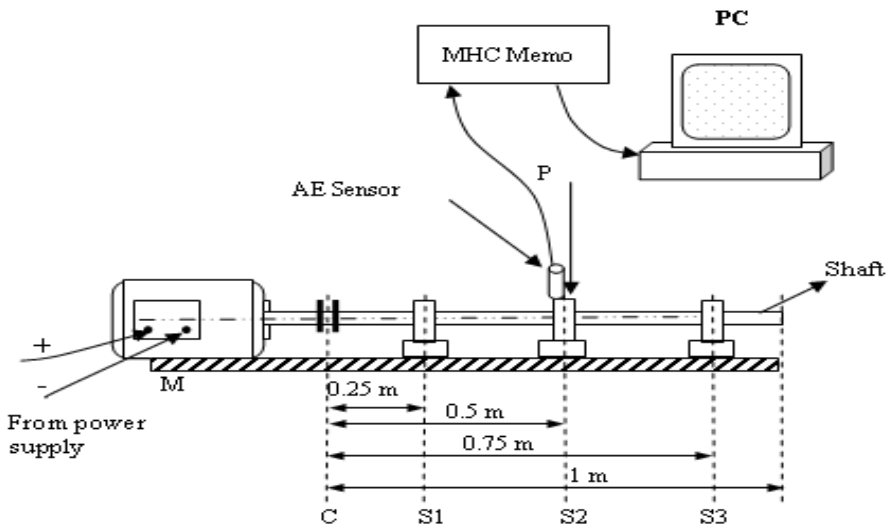

Figure 3 – The overall set-up to collect the data.

Figure 3 shows how the data was collected. Two parameters were given by MHC Memo equipment that is dB level and Distress level which were taken at fixed interval every day. The time of data collection is important in order to use it in IMB failure prediction.

The IMB (new bearing) was pre-conditioned for 3 hours to make sure that the bearing has no manufacturing defect. After three hours of free running, the test was stopped for one hour to cool it down before it was started again until it failed.

In this experiment, an important observation from collected data showed that the Distress and dB signal stay relatively flat in the early stage of the bearing life and will then increase rapidly after the Distress exceed a value of 10. Frequent data collection will be needed once the trend increases.

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RESULTS AND DISCUSSION

Result and Performance of ANN Model.

In order to choose the most appropriate network for the modeling process the network was tested depending on how efficient this network respond to any change in the modeling process. Thus, the performance of network was compared. The hidden layer and nodes were significant to the network. Therefore, the number of hidden layer used was one and the number of hidden nodes was chosen by trial and error because in most situations, there were no ways to define the number of hidden nodes without trying out several networks.

Typically, mean square error (MSE) was used to present the network performance in order to define the best network [3]. The equation is shown as below;

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{9}$$

where e_i = Error
t_i = Desired value
a_i = Actual value
N = Number of data.

The performance of an optimum network was done by trial and error, starting with two hidden nodes until twenty hidden nodes together with both networks (FFNN and Elman Network). Optimum network was selected among the networks based on the smallest cross-validation errors.

Table 1 shows the training performance for both networks that have been done. The result shows that the smallest cross-validation error between the two networks was Elman network with hidden nodes of 18. The validation error for this result was 0.0023 with testing error of 0.0033. Thus, this network was selected as an optimum network for FFNN. The performances of these selection networks are depicted in Figure 4 (a) and (b). Meanwhile, the minimum validation error for Feedforward Network was 0.0024 with hidden nodes of 10. Therefore this network was selected as the optimum network for Elman Network.

Table 1: Training results for selection network model.

No. of hidden nodes	Feedforward Network (newff)			Elman Network (newelm)		
	training	validation	testing	training	validation	testing
2	0.0019	0.0024	0.0058	0.002	0.0024	0.0081
3	0.002	0.0024	0.0106	0.002	0.0024	0.0078
4	0.002	0.0024	0.0168	0.002	0.0024	0.0082
5	0.0019	0.0024	0.3185	0.002	0.0024	0.0041
6	0.002	0.0024	0.2192	0.002	0.0024	0.0039
7	0.0019	0.0024	0.0222	0.002	0.0024	0.0041
8	0.0019	0.0024	0.1421	0.002	0.0024	0.0072
9	0.0019	0.0024	0.0092	0.002	0.0024	0.0051
10	0.0019	0.0024	0.004	0.0019	0.0024	0.0083
11	0.002	0.0024	0.0481	0.002	0.0024	0.023
12	0.0019	0.0024	0.0308	0.002	0.0024	0.0115
13	0.0019	0.0026	0.0232	0.0019	0.0024	0.0041
14	0.0019	0.0024	0.0231	0.002	0.0024	0.0144
15	0.002	0.0024	0.0119	0.002	0.0024	0.006
16	0.002	0.0024	0.0166	0.0019	0.0024	0.0084
17	0.0019	0.0024	0.0107	0.002	0.0024	0.0052
18	0.0019	0.0064	0.1076	0.0019	0.0023	0.0033
19	0.002	0.0027	0.1129	0.002	0.0024	0.0046
20	0.0019	0.0027	0.0199	0.0019	0.0024	0.0089

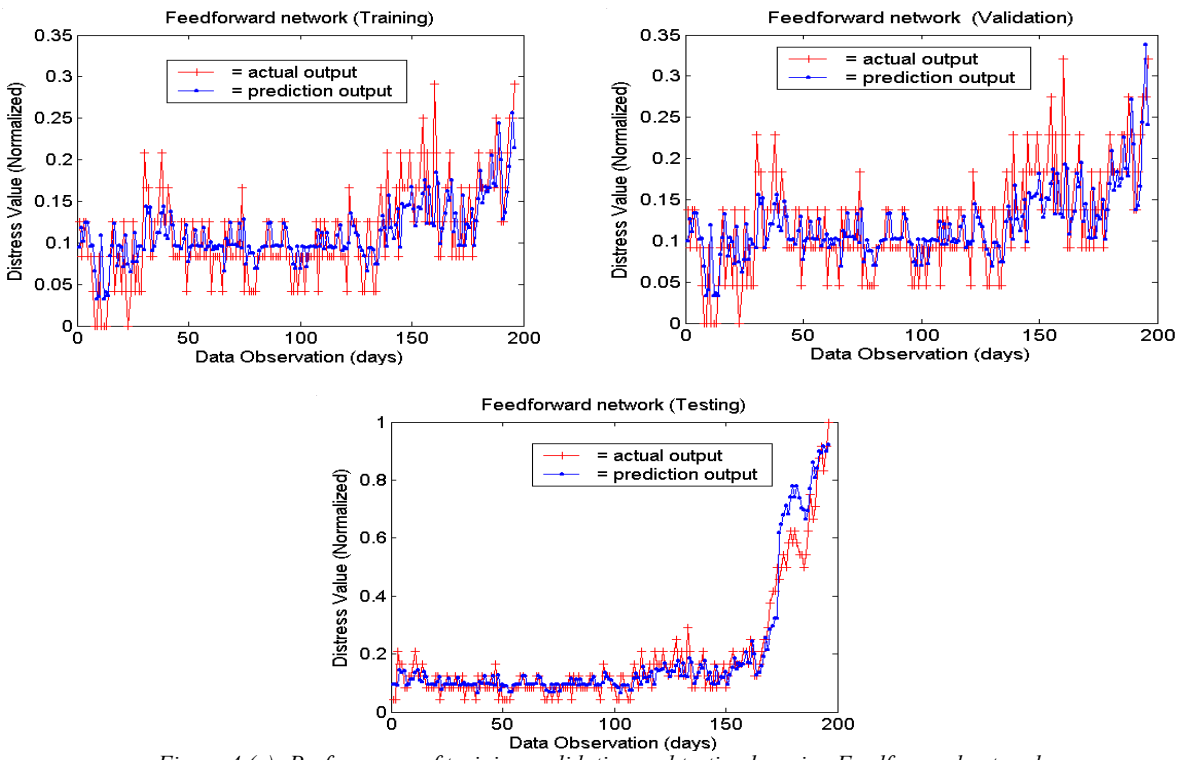

Figure 4 (a): Performance of training, validation and testing by using Feedforward network.

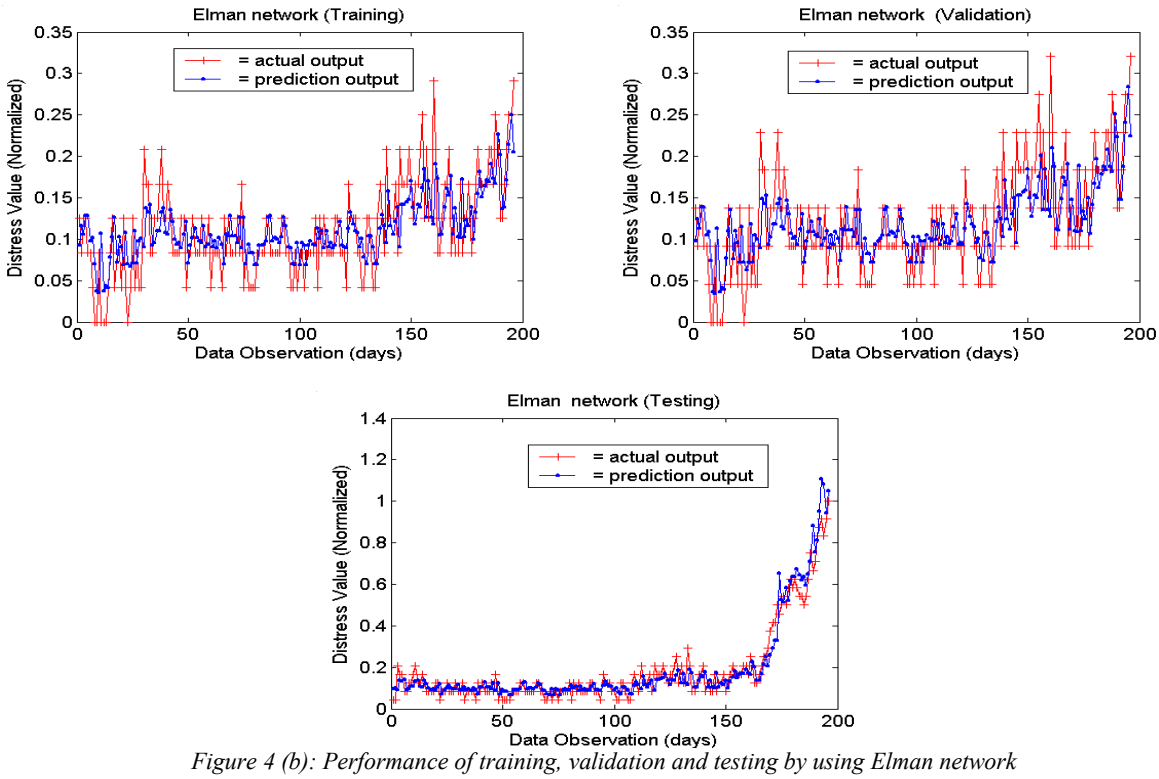

Figure 4 (b): Performance of training, validation and testing by using Elman network

Discussion on Performance of Network Model.

Figure 4 (a) and (b) show the performance of training, validation and testing for Feedforward Network and Elman Network respectively. The '+' sign in red colour indicates the actual output and the '•' sign indicates the prediction output. The performances of training and validation were difficult to differentiate because they look

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very similar. Meanwhile, the performance of testing obviously shows the Elman Network was better than Feedforward Network because the prediction output was quiet similar to the actual output and this shows that it is the optimum network in this analysis.

The optimum network was selected among the networks based on the smallest cross-validation errors produced. Table1 shows that the Elman Network with validation error of 0.0023 and 18 hidden nodes was the optimum network compared to Feedforward Network with validation error of 0.0024. Although the differences error between these two network was only 0.0001, the testing error for Elman Network was less than Feedforward Network. The Elman Network produced testing error of 0.0033 compared to Feedforward Network of 0.004. The difference between them was 0.0007. Therefore, the performance of Feedforward Network testing in Figure 4 (a) get worst compared to the performance of Elman Network.

Other issues were the selection of hidden nodes to determine the optimum network. Table 1 shows the Elman Network with 18 hidden nodes was the optimum network compared to Feedforward Network of 10 hidden nodes since the more hidden nodes will make the network more complicated. These issues were only reliable on the multiple hidden layers which needed more time to process the input data [5].

CONCLUSION

The main objectives of this paper to monitor and predict the IMB failure have been done. From the results on development of IMB failure prediction, it was found that the Elman networks have successfully predicted the process accurately with a combination of 'logsig / purelin' transfer function and Levenberg-Marquardt Backpropagation (trainlm) compared to FFNN.

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