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# ARTIFICIAL NEURAL NETWORK BASED INTELLIGENT FAULT IDENTIFICATION OF ROTATING MACHINERY

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## ABSTRACT

In general intelligent diagnosis is carried out when known inputs are fed into black boxes which subsequently produce outputs in accordance with machine faults. Neural networks (NN) are suitable for these tasks and have been widely researched as an artificial intelligence tool for machinery fault diagnosis. By employing such a tool, maintenance personnel need not understand or operate the internal mechanisms of a neural network. They will only be responsible for inputting the appropriate data to a neural network. The neural network will then be trained on this data so that it can diagnose faults. Artificial neural networks demonstrated to provide an effective method for fault diagnosis in rotating machinery in terms of reliability. In this paper, vibration frequency features of mechanical unbalance, angular misalignment, and mechanical looseness are discussed for rotating machinery fault diagnosis. This paper then presents an approach for rotating machinery fault diagnosis using pattern classification tool of neural networks and frequency domain vibration analysis. Finally this pattern recognition approach applied on a real world case with effective results.

**KEYWORDS:** Neural networks NN, pattern recognition, fault diagnosis, vibration analysis.

## INTRODUCTION

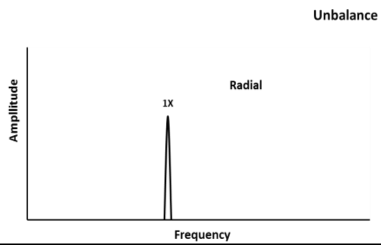
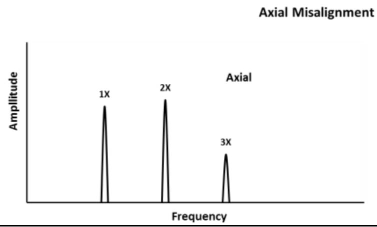
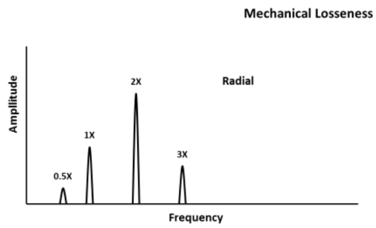
The neural network is usually viewed as a fault classifier. Neural networks find application in fault detection due to their main ability of pattern recognition. The network is trained to learn, from the presentation of the examples, to form an internal representation of the problem. Research work on neural networks in on-line fault detection processes has been developed during the few last years. Kalkat, Yildirim, and Uzmay, 2005 proposed backpropagation neural network for vibration parameters prediction of a rotating mechanical system at the bearing points in vertical direction. Han et al., 2006 proposes an online fault diagnosis system for induction motors through the combination of discrete wavelet transform (DWT), feature extraction, genetic algorithm (GA), and neural network (ANN) techniques using stator motor current. Sreejith, Verma, and Srividya, 2008 introduced a feed forward neural network approach for automated fault diagnosis of rolling element bearing from vibration data by the time domain parameters. Xia, and Ghasempoor, 2009 introduced an effective, adaptable, and real-time online active vibration control AVC system to suppress noisy sinusoidal vibrations of a cantilever beam. Srinivas, Srinivasan and Umesh, 2010 using multiplayer feed forward back propagation algorithm to quantify unbalance and shaft bow faults, and investigated the feasibility of applying discrete wavelet transform to identify the combined faults of unbalance mass and shaft bow of vibration signals. Asgari, Chen, Sainudiin, 2011 presented a brief overview of important applications of ANNs to rotating equipment using temperature and pressure as an input parameters. Reddy, and Sekhar, 2013 studied a procedure for unbalance and looseness diagnosis using artificial neural networks. Singh, and Kumar, 2014 studied artificial neural networks (ANN) and support vector machine (SVM) techniques to determine the effectiveness of statistical features for fault diagnosis in rotating mechanical system using healthy and faulty rotors. Nath, and Saha, 2015 proposed ANN approach of rotating machinery fault detection using genetic algorithm for feature extraction.

## ROTATING MACHINERY FAULTS

Due to the progress made in engineering and materials science, rotating machinery is becoming faster and lightweight. They are also required to run for longer periods of time. All of these factors mean that the detection, location and analysis of faults play a vital role in the quest for highly reliable operations [Scheffer and Girdhar 2004].

All mechanical equipment in motion generates a vibration profile, or signature, that reflects its operation condition. This is regardless of speed or whether the mode of operation is rotation, reciprocation, or liner motion. Vibration analysis is applicable to all mechanical equipment and common way for condition evaluation. Vibration profile analysis is a useful tool for predictive maintenance, and diagnostics [Wowk 1991]. Many types of mechanical problems are affected on machine condition. This paper concentrated on the most common machinery faults which listed in Table 1. Frequency features and vibration direction used for fault type evaluation [Scheffer and Girdhar 2004, Wowk 1991, Berry 1997, Bently and Hatch 2002].

**Table 1: Vibration diagnostic chart.**

| Problem Source | Typical Spectrum | Remarks |
|---|---|---|
| Static Unbalance |  | Predominant of 1X RPM with radial vibration. |
| Angular Misalignment |  | Primarily generates high axial vibration, particularly at 1X and 2X RPM. |
| Mechanical Looseness |  | Shows up in the frequency domain as a large number of harmonics of running speed (1X RPM) when lightly loaded in radial direction. |

## ARTIFICIAL NEURAL NETWORKS

The main idea for creating artificial neural network ANN which is a subset of artificial intelligence is to provide a simple model of human brain in order to solve complex scientific and industrial problems. ANNs are high-value and low-cost tools in modeling, simulation, control, condition monitoring, sensor validation and fault diagnosis of different systems including different kinds of rotating equipment. They learn from the data obtained from a system instead of learning from a specific program. ANNs can solve a variety of problems in optimization, pattern recognition, clustering, function approximation, time series analysis, prediction and validation [Asgari, Chen, and Sainudiin 2011]. The basic architecture of ANN consists of three types of neuron layers: input, hidden, and output layers shown in Fig. 1. In feed-forward networks, the signal flow is from input to output units, strictly in a feed-forward direction. The data processing can extend over multiple (layers of) units, but no feedback connections are present [Sydenham and Thorn 2005].

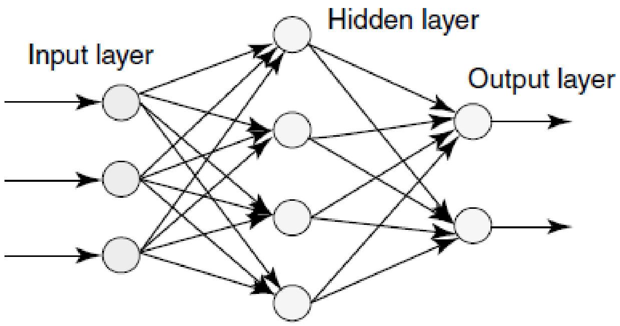



**Fig. 1 Neural network architecture [Baillie and Mathew 1994]**

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes (Fig. 2). In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

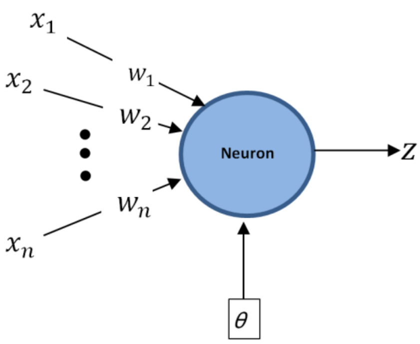



**Fig. 2 Artificial neuron**

The signal flow from inputs $x_1, \ldots, x_n$ is considered to be unidirectional, which are indicated by arrows, as is a neuron's output signal flow (*O*). The neuron output signal *O* is given by the following relationship [Sydenham and Thorn 2005]:

$$O = f\,(net) = f\left(\sum_{j=1}^{n} w_j x_j\right) \qquad (1)$$

Where $w_j$ is the weight vector, and the function *f(net)* is referred to as an activation (transfer) function.

A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to train the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. The learning situations in neural networks may be classified into three distinct sorts. These are supervised learning, unsupervised learning, and reinforcement learning.

## EXPERIMENTAL SETUP

The vibration analysis demonstrator in Fig. 3 is a versatile training device designed for demonstrating the causes of vibration in rotating machinery. The device is compatible with all common vibration diagnostic equipment and allows the user to isolate individual, vibration causing variables to distinguish the vibration signature of those variables.

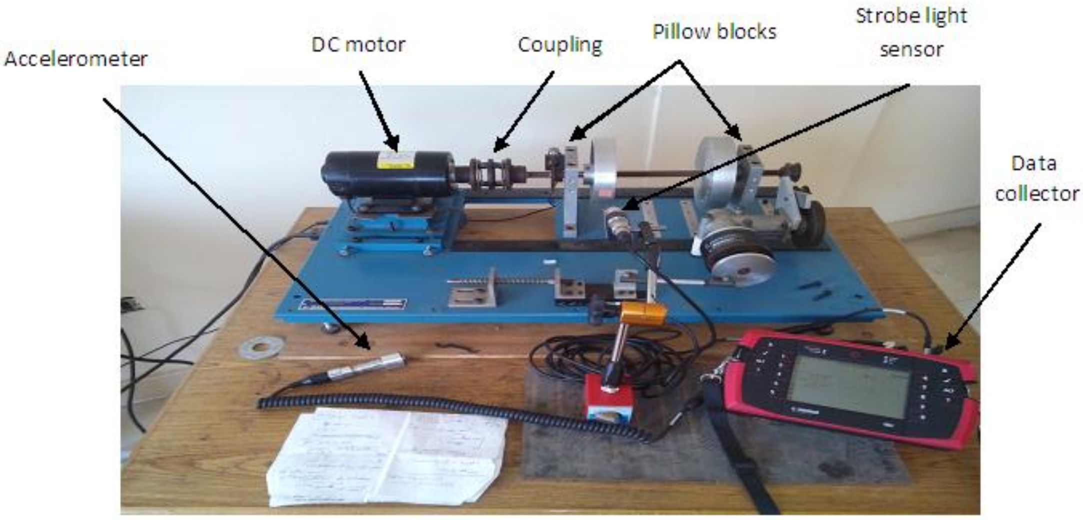



**Fig. 3 Vibration analysis demonstrator**

The basic device includes a high-accuracy, variable-speed control and digital tachometer. The demonstrator is designed for convenient reconfiguration, via a system of indexing pins and precision-machined pillow blocks, to allow for a multitude of alignment, balancing, and mechanical fault scenarios.

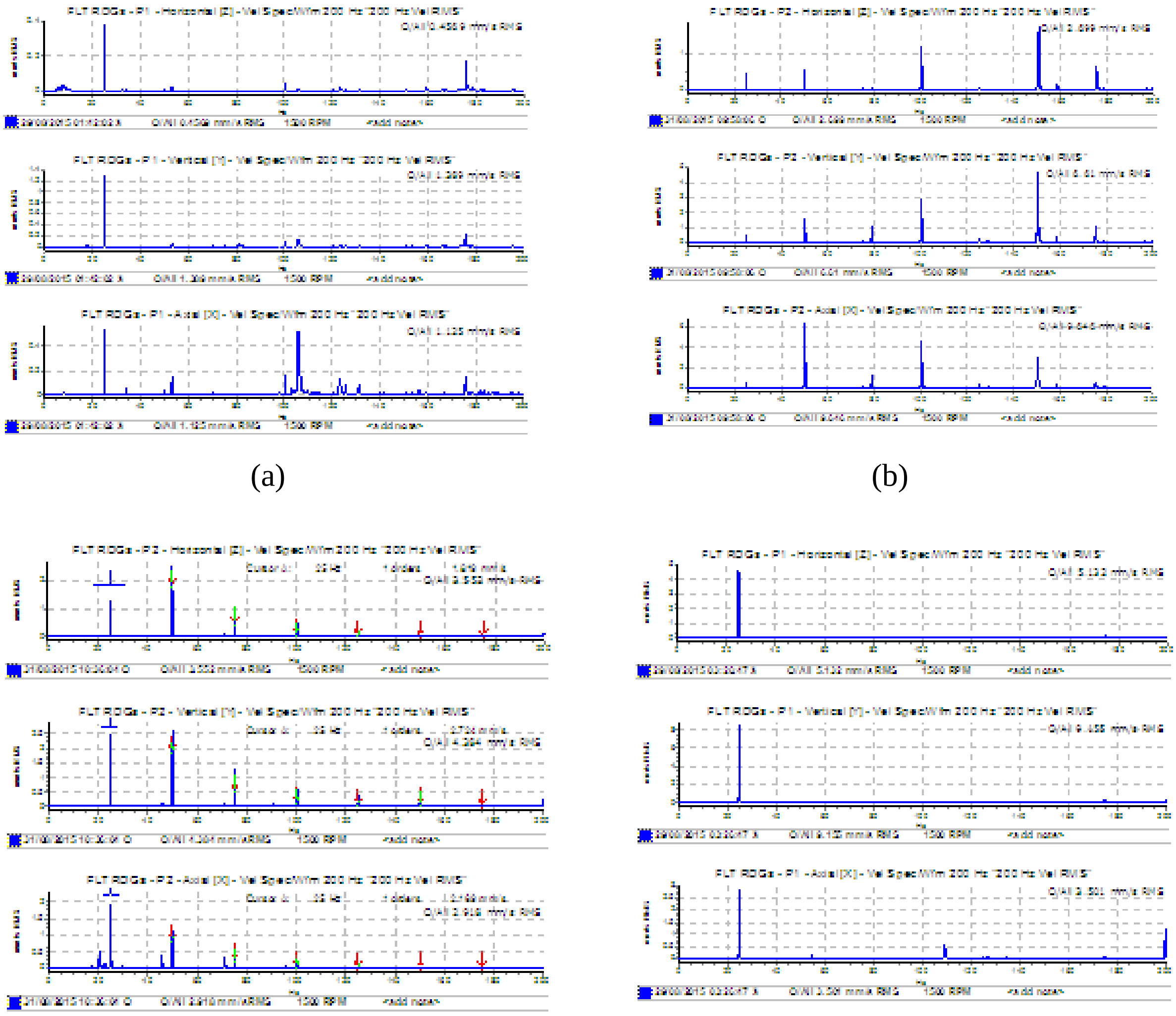
### Faults creation

Measurement Specification:

- Speed: 1500 RPM
- Frequency Range: F-min = 0 & F-max = 200 Hz
- Amplitude: mm/sec

- Frequency: Hz
- Waveform: Peak to Peak
- Power level: RMS
- Direction: Horizontal [H], Vertical [V], and Axial [X]
- Pillow block 1 (pb1)
- Number of lines: 1600

The Neural Network Pattern Recognition MATLAB Toolbox used to diagnosing rotating machinery faults. Frequency domain in axial, vertical, and horizontal directions employed for four cases. As shown in Fig. 4, these four cases represented by taken a frequency domain sample from each case.



(a) (b)

(c) (d)

**Fig. 4 Frequency domain sample in horizontal, vertical, and axial directions, (a) acceptable condition, (b) mechanical looseness, (c) angular misalignment, and (d) unbalance.**

Frequency domain converted into digits for all vibration sample sets as frequencies with corresponded amplitudes using ".csv" extension, then using MATLAB code for every set (rotating condition vibration samples cases) for recalling data as a matrices to represent neural network input variables as follows:

Acceptable data matrix dimension = [130×1600]

Unbalance data matrix dimension = [158×1600]

Axial misalignment data matrix dimension = [123×1600]

Looseness data matrix dimension = [20×1600]

Where the number of samples represented by columns and vibration amplitudes represented by rows. Every condition set taken in axial, vertical, and horizontal directions. Other code collecting all input data in one matrix with corresponding output matrix as:

Input matrix dimension = [4800×431]

$$\begin{bmatrix} Acc.In. & \dots & Loose\ In. & \dots & Misalign.In. & \dots & Unb.In. & \dots \\ A\_data & \cdots & A\_data & \dots & A\_data & \dots & A\_data & \dots \\ \vdots & & \vdots & & \vdots & & \vdots & \\ H\_data & \dots & H\_data & \dots & H\_data & \dots & H\_data & \dots \\ \vdots & & \vdots & & \vdots & & \vdots & \\ V\_data & \dots & V\_data & \cdots & V\_data & \dots & V\_data & \dots \\ \vdots & & \vdots & & \vdots & & \vdots & \end{bmatrix}$$

Pattern recognition networks are feed-forward networks that can be trained to classify inputs according to target classes. The target data for pattern recognition networks should consist of vectors of all zero values except for a 1 in element i, where i is the class they are to represent, hence output matrix dimension = [4×431].

$$\begin{bmatrix} Acc.out. & \dots & Loose\ out. & \dots & Misalign.out. & \dots & Unb.out. & \dots \\ 1 & \dots & 0 & \dots & 0 & \dots & 0 & \dots \\ 0 & \dots & 1 & \dots & 0 & \dots & 0 & \dots \\ 0 & \dots & 0 & \dots & 1 & \dots & 0 & \dots \\ 0 & \dots & 0 & \cdots & 0 & \dots & 1 & \dots \end{bmatrix}$$

As shown in Fig. 5, the architecture of the three-layer feed-forward back-propagation (FFBP) ANN used in this research. On the top is the layer of inputs, or branching nodes, which are not artificial neurons. Neurons in the input layer act as buffers for distributing the input feature data $\boldsymbol{x} = (x_1,..., x_n)$ to neurons in the hidden layer. The middle or hidden layer contains artificial neural nodes, as does the output layer on the bottom.

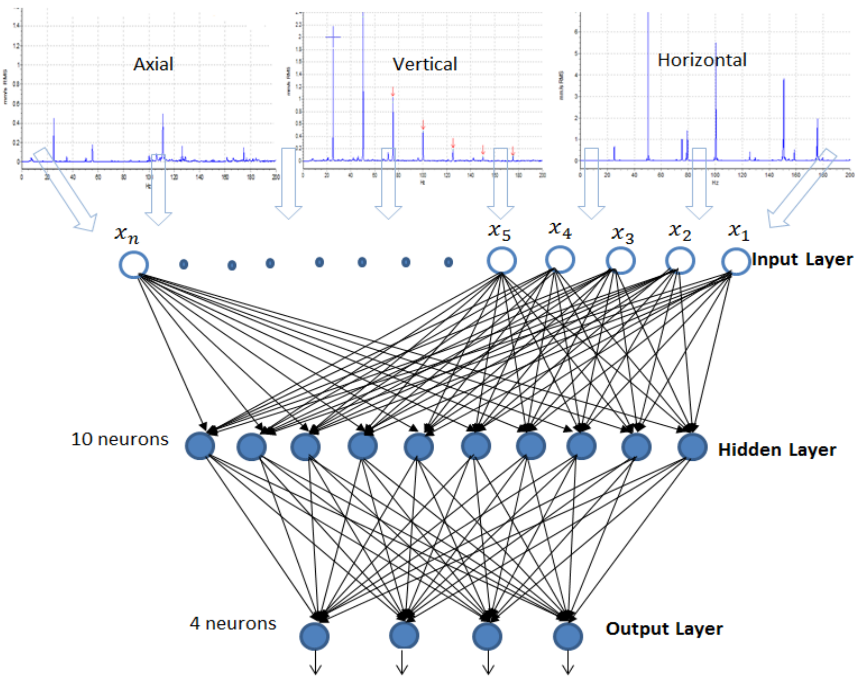



**Fig. 5 Pattern recognition NN architecture**

The hidden layer is used to process and connect the information from the input layer to the output layer only in a forward direction. The hidden layer performs feature extraction on the input data. Only one hidden layer was used in the present study. Each neuron in the hidden layer as shown in Fig. 6 sums up its input signals after weighting them with the strengths of the respective connections $w_n$ and computes its output $v_n$ as a function of the sum;

$$v = \sum_{i=1}^{n} x_i w_i \qquad (2)$$

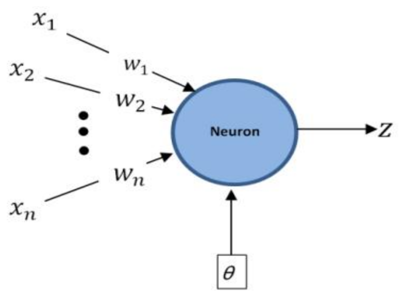



**Fig. 6 Artificial neuron**

Where the input represented by vibration signal amplitudes at each line frequency in axial, vertical, and horizontal directions ($i$ = 1, 2,.…., 4800), and $f$ ($v$) can be a simple threshold function or a sigmoidal, hyperbolic tangent or radial basis function. The numerical data generated often differs only by very small magnitude, these relatively small differences in vibration values makes it very difficult for the ANNs fault analyzer to detect a fault state. The solution is to preprocess the input data for the ANNs unit. The results from this experiment demonstrated that the preprocess (normalization) method is essential to obtain a solution and it also helps to reduce the training process time. This ANN used a sigmoid (S shape) activation function which bounds its output range between zero and one [Kriesel 2005]:

$$f(v) = \frac{1}{1 + e^{-v}} \qquad (3)$$

$$z = f(v) \qquad (4)$$

The outputs of the neuron in the output layer *y* are computed similarly,

$$u = \sum_{j=1}^{m} z_j k_j + q \qquad (5)$$

For multinomial classification problems (1-of-n, where n > 2) we use a network with n outputs, one corresponding to each class, and target values of 1 for the correct class, and 0 otherwise. Since these targets are not independent of each other, however, it is no longer appropriate to use logistic output units. The correct generalization of the logistic sigmoid to the multinomial case is the softmax activation function [Hajek 2005]:

$$f(u)_j = \frac{e^{u_j}}{\sum_{h=1}^{H} e^{u_h}} \qquad (6)$$

Applying the softmax function, or normalized exponential, is a generalization of the logistic function that "squashes" a real values in the range (0, 1) that add up to 1. Hence the output given by:

$$y = f(u) \qquad (7)$$

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion so as to attain a desired design objective.

The learning procedure consists of both forward-propagation and backpropagation in Fig. 7. During forward-propagation, all information is entered at the input layer and processed at the hidden layers, and finally transferred to the output layer.

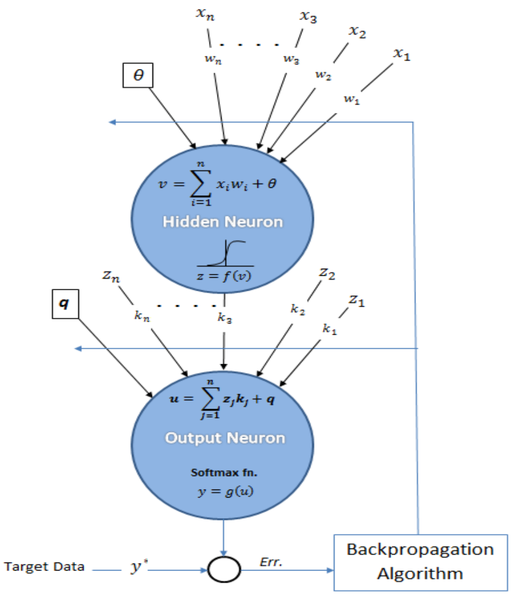



**Fig. 7 Forward-propagation and backpropagation.**

In the present work 431 samples divided into:

- Training set with 301 samples (70%) which presented to the network during training, and the network is adjusted according to its error.
- Validation set with 65 samples (15%) used to measure network generalization, and to pause training when generalization stops improving.
- Testing set with 65 samples (15%) provide an independent measure of network performance during and after training.

Fig. 8 shows a typical error development of a training set (green curve) and a validation set (blue curve). The learning stopped in the minimum of the validation set error which corresponding 6.0172e-05 on the error axis and at iteration number 91. At this point the net generalizes best. After finishing the learning phase, the net should be finally checked with the third data set, the test set.

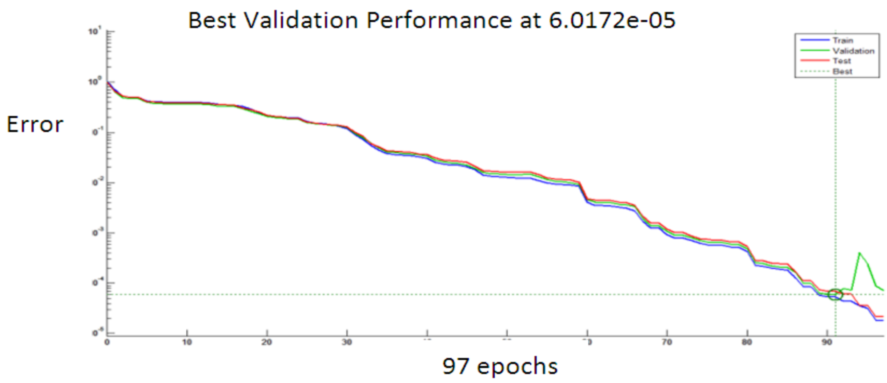



**Fig. 8 Neural network training performance**

As shown in Fig. 9 the confusion matrices for training, testing, and validation, and the three kinds of data combined. The network outputs are very accurate, by the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares.

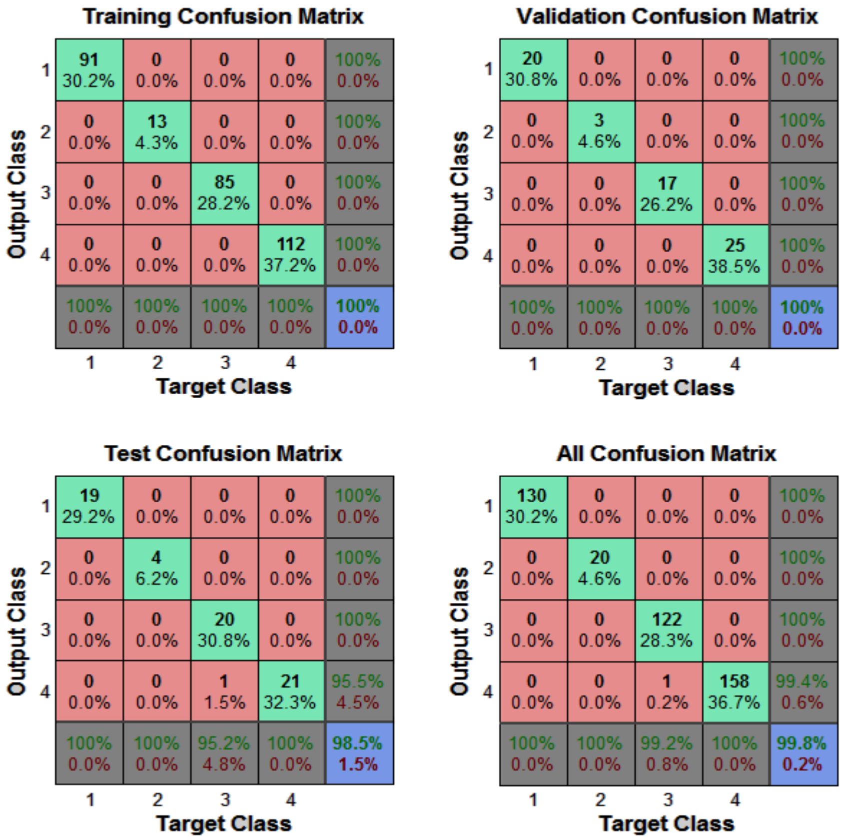



**Fig. 9 Confusion matrix.**

## RESULTS AND DESCUSION

Two cases tested by feeding amplitudes of vibration frequencies in axial, vertical, and horizontal directions to the network as the inputs to recognize machine condition. The neural network pattern recognition technique simulates by MATLAB/SIMULINK tool shown in Fig. 10 for easier usage.

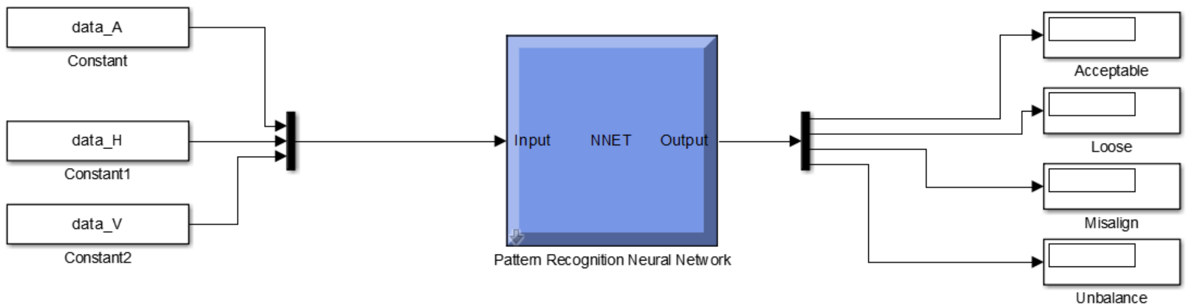



**Fig. 10 Neural network simulation**

**Case study**

This case for a synchronous motor (2960 RPM) used to drive centrifugal pump to cooling generator stator windings. Vibration measurement was taken at motor non drive end (MNDE) in axial, vertical, and horizontal directions as shown in Fig. 11.

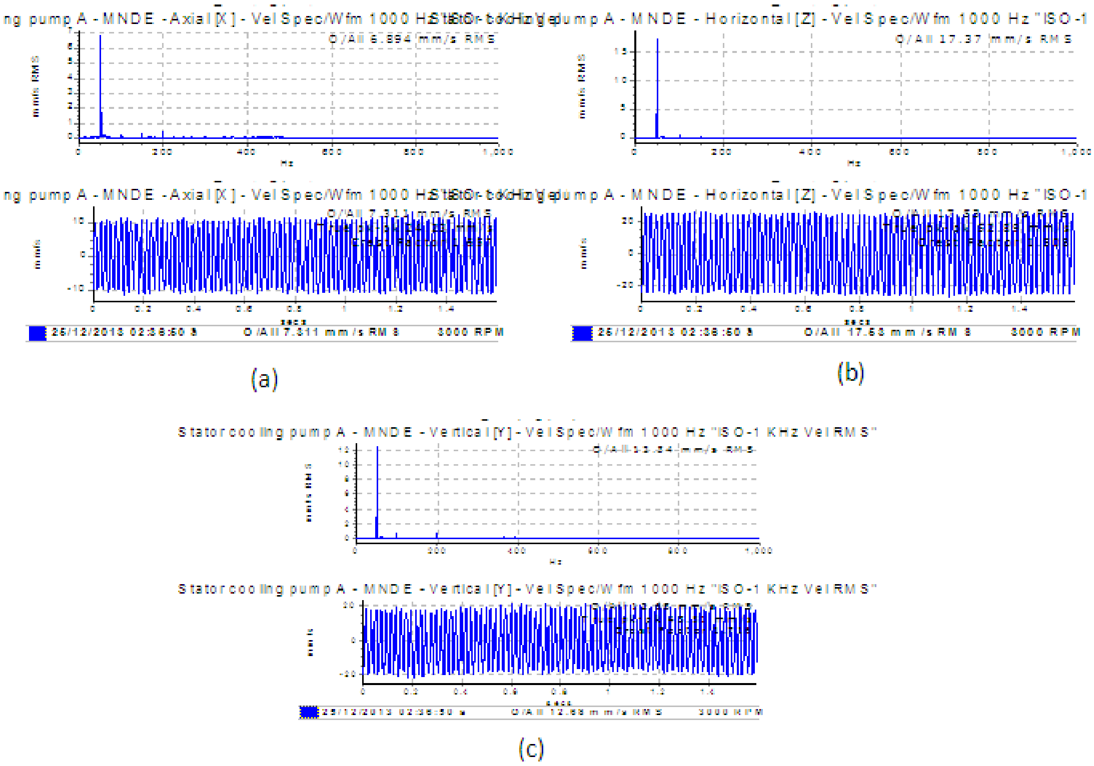



**Fig. 11 Time waveform and FFT spectrum for motor non-drive end in (a) axial, (b) horizontal, and (c) vertical.**

After feeding frequency domain of the previous case, Table 2 illustrates the results of machinery condition which represented by activation levels of four cases that machine trained on it. The nearer the activation levels to number 1, the higher the possibility of failure. Higher activation level shows unbalance fault.

**Table 2: Rotating machinery condition**

| | Acceptable | Looseness | Angular Misalignment | Unbalance |
|---|---|---|---|---|
| Activation level | 0.0006505 | 2.246e-06 | 0.0001788 | 0.9992 |

## CONCLUSION

This paper indicated the presences of faults by using the amplitudes of vibration harmonics of a rotor system in horizontal, vertical and axial directions for unbalance, mechanical looseness, and misalignment. To recognize these faults the approach of using artificial neural network of multiplayer feed forward back propagation algorithm presented. It has been seen by training of the network by simulated data obtained experimentally and testing it the effective way using ANN approach illustrated by network performance and confusion matrix. The features obtained by proposed method for vibration signal yields nearly 99.9% correct when used as input to a neural network.

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