ERJ
Engineering Research Journal
Faculty of Engineering
Minoufiya University

FAULT DETECTION – CLASSIFICATION THROUGH VIBRATION MONITORING USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Vibration analysis can give an indication of the condition of rotating shaft highlighting potential fault such as unbalance and rubbing. Faults may however occur intermittently and consequently to detect these requires continuous monitoring with real time analysis. In this research, we describe how to use Artificial Neural Networks (ANN's) for classification of machine conditions by using two sensor techniques. In this technique, calculated moments from times series are used as input features as they can be quickly computed from measured data. Orthogonal vibrations are considered as two –dimension victor, the magnitude of which can be expressed as time series. Some signal processing operations are applied to the data to enhance the differences between signals. A fault signature data base is built which includes vibration signature of common failure modes of critical components in rotating equipment. The database is used to train the neural network to classify the different fault classes. Such expert system has some limitations because it is tailored to a specific machine and specific faults under certain operating conditions. Comparison is made with frequency domain analysis methods, which has some ambiguities when components may, more or less overlap and certain faults may exhibit themselves in different ways in spectrum. The results show that the success of the network is highly dependent on the deduced feature signal which contain the symptoms of faults and healthy operation.

إن تحليل الاهتزازات يعطي مؤشرا عن حالة الأعمدة الدوارة موضحا الأعطال الرئيسية مثل عدم الاتزان أو التاكل. ولكن غالبا ما تظهر الاعطال بصورة غير منتظمة وبالتالي تتطلب مراقبة مستمرة وتحليل للاشارات لاكتشاف هذه الأعطال. ويشرح هذا البحث كيفية استخدام الشبكات العصبية لتصنيف حالات الآلة باستخدام عنصري قياس. في هذه التقنية يتم استخدام العزوم المحسوبة من القياسات الزمنية بعد معالجة الاشارات المقاسة كإشارة ملامح الدخل ويتم دمج القياسات من عنصري القياس أحدهما محوري والآخر نصف قطري. تمثل القيمة كسلسلة زمنية ثم يتم معالجة الاشارات المقاسة ببعض تقنيات معالجة الاشارات لتحسين الاشارة. تم بناء قاعدة بيانات لبصمات الأعطال التي تشتمل على بصمات اهتزازات نماذج من الأعطال الشائعة للمكونات الرئيسية في الآلات الدوارة. تم استخدام قاعدة البيانات لتدريب الشبكة لتصنيف حالات الأعطال المختلفة. وقد أوضحت النتائج أهمية تحليل الإشارة للحصول على إشارة ملامح تحتوى على معلومات كافية لتشخيص حالة الآلة. ترتبط نتيجة التشخيص بإشارة الملامح للمعدة التى تعبر عن الحالة الفعلية للمعدة بعد تنقيتها من الضوضاء لا يمكن تعميم نتائج هذا النظام بجميع الآلات نظرا لتغيير ظروف التشغيل وتغير خصائص المكونات الاساسية للمعدة أو الالة ويكون هذا النظام محدودا لمعدة معينة ولاعطال معينة تحت ظروف تشغيل محددة. وقد تم مقارنة النتائج التي توصلنا اليها مع طرق التحليل الطيفي والتي تؤدي الى وجود تضارب عندما تتداخل الترددات الطبيعية لبعض المكونات وكذلك عندما تظهر العيوب بطرق مختلفة في الطيف الترددى.

Keywords: Condition Monitoring-Signal Analysis-Vibration Measurements- Artificial Neural Networks

1. Introduction

In last thirty years predictive maintenance through vibration analysis has been used intensively in the process industries for machine health monitoring specially for rotating machine [1], [2], [3], [4], [5]. In this technique the oscillation forces are excited just in the place of defect appearance and the machine is "transparent" for vibration; where vibration contains maximum diagnostic information. This has two significant advantages in fault detection: first, short non stationary effects which periodic analysis could miss; will be detected; second a fault, which could have catastrophic effects in a short time could be detected and machine can be shut down before serious damage occur. The integrated use of neural network and vibration analysis technologies offers advantages not available by the use of either technology alone, [6],[7]. Machine condition monitoring requires the recognition of patterns in noisy data. Feed forward artificial neural networks have been used in a wide variety of pattern recognition applications including vibration monitoring [8], [9]. Their ability as a universal approximation allows the transformation of a set of input features for which the condition classes may be separated by a highly nonlinear boundary to a set of outputs which can be easily separated with very little computational cost. This transformation can be trained using input features for known conditions and by minimizing the mean squared error for the output. The two sensor technique in which the related responses of two sensors, as a system whose characteristics are unknown responding to an unknown driving source, is used to illustrate such integration [10].

Neural networks with their ability to learn characteristics associated with different types and sources of vibration can enhance the ability to interpret the measurements in this technique [11]. The purpose of health monitoring in rotating machine is to detect and diagnose faults in an early stage, which may be feasible since many faults will manifest themselves as pure tones or strange noises in the overall machine vibration. The conventional approach would be to use many heuristics about the structure properties of the machine and look in the vibration spectrum for specific fault – related components with increased amplitude compared to previous measurements. This could be done either manually (the skilled operator) or on the basic of a rule – based system. It becomes immediately clear that in this approach one has make large fault – databases for each new machine, since every machine vibrates in its own specific manner. Moreover, disturbances from nearby machines or irrelevant vibration sources along with ambiguities in the vibration spectrum may lead to situations that are not in the database, or wrongly assumed to be in the database. A frequency spectrum is often difficult to interpret because of the large amount of overlapping frequencies.

2. Machine Health Monitoring with Neural Network

A feed forward neural network is a network of interconnected neurons, arranged in at least three layers (an input, hidden and output layer), as shown in Fig. (1-d). A neuron consists of a summation of the incoming links to a neuron, followed by the application of a nonlinear function (usually a sigmoid activation function), see Fig. (1-b). An adjustable bias is included in each neuron as well. The outputs of neurons in the previous layer are weighted by adjustable weights before their value is used as input to a neuron in the next layer. A feed forward neural network is capable of approximating any function to arbitrary accuracy, provided the number of hidden units is chosen adequately. For example, the network can be taught to learn indicator functions, in which case a classifier is obtained, see Fig (1-c) Neural network training is a supervised learning procedure see Fig(1-a) in that the outputs corresponding to a training sample are known and used to adjust the network weights to decrease the error on the output. This is done for multilayer neural networks with the error back propagation algorithm [12]. The neural network training procedure is a form of empirical risk minimization (ERM) and bares the risk of overtraining. Recall that the performance of a learning machine is determined by its capacity to learn a function (bias) and by the spread in its predictions over several instances of the learning set (the variance). Because of its universal approximation property [13], a neural network with zero bias can always be constructed if the architecture is chosen properly.

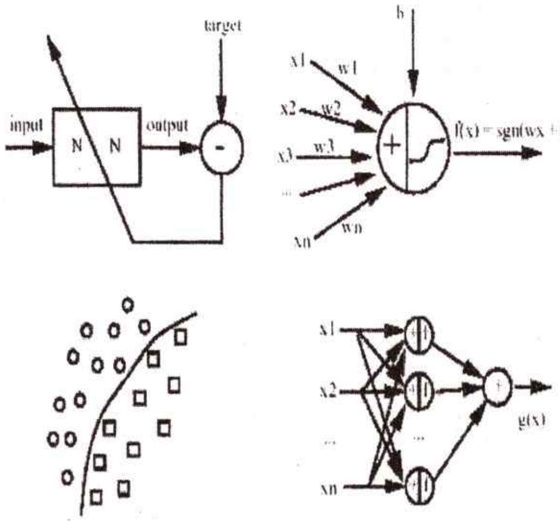


Fig. (1) Feed-forward Neural Networks:
a. Supervised Learning b. Artificial Neuron.
c. Neural Classifier. d. Layer of Neurons.

In this work machine health monitoring is seen as a learning problem. We use learning methods for automatic processing and interpretation tasks in machine health monitoring. A practical system for on –line machine health monitoring comprises the subtasks shown in Fig. (2),[9]. After measuring machine vibration (usually with a set of vibration transducers), the instantaneous measurement time series have to be characterized in order to use them for health indication (feature extraction). Prior to this processing of measurement signals in the time domain (temporal processing), we can improve signal –to-noise ratios or focus on fault –related vibration sources by using the spatial diversity and redundancy in a multi-channel vibration measurement taking several measurements of a machine that operates normally in varying operating conditions and finding a suitable characterization of the measurements (using monitoring heuristics and prior knowledge about the machine) leads to a description of the normal behavior of the machine (signature or generalized fingerprint). This description can be used to detect deviating vibration patterns, which may be used as the basis for detection of faults in a machine. Knowledge about the parts of the space occupied by failures can then be used for diagnosis of faults. This knowledge can either be present beforehand, e.g. in the form of heuristics and knowledge from previous case studies, or be acquired during machine operation. Ultimately, one would like to use the transition of the machine to a wear – or 'incipient failure' state as an indicator of the time – to- failure, in other words to analyze the trend in the health index.

The two sensor technique, in which one accelerometer is used, as the input to the neural network and the Power Spectral Density PSD often sampled time series from the other accelerometer, taken at the same time, is taken as the desired output of the neural network is used. The network is trained using pairs of spectra when the component or system is known to be operating properly. The trained neural network is then put into a monitoring mode to predict the output (second) sensor from the input (first) sensor and a comparison is made between the predicated and actual output signal. In almost every situation, both sensors measure output vibration induced by a driving function (e.g., unbalance in a rotating system or rub in a shaft, or wear in moving parts).

3. Experimental Setup

To design an effective machine condition monitoring system, data must be acquired for all the conditions, which need to be classified. It is necessary to have data for use in the design stage of the condition monitoring system (this is the training data for the artificial neural network) as well as independent test data, which has not been used in the design stage to validate the system.

Test data has been taken from the maintenance record at Abu Sultan Power Station Unit shown schematically in Fig.(3). Axial and radial transducers were attached to one of the bearing blocks. The data taken from bearing # x1 is used as input to the network training, and the data taken from bearing #x2 is used as desired output to the network testing.

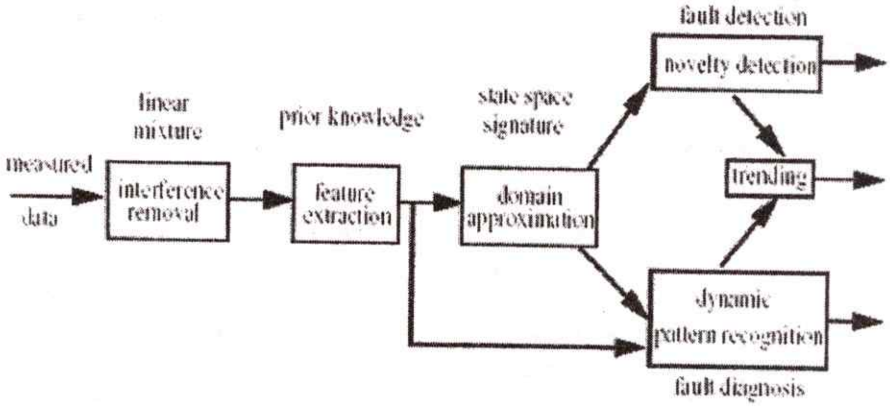


Fig.(2) Machine Health Monitoring with Learning Methods.

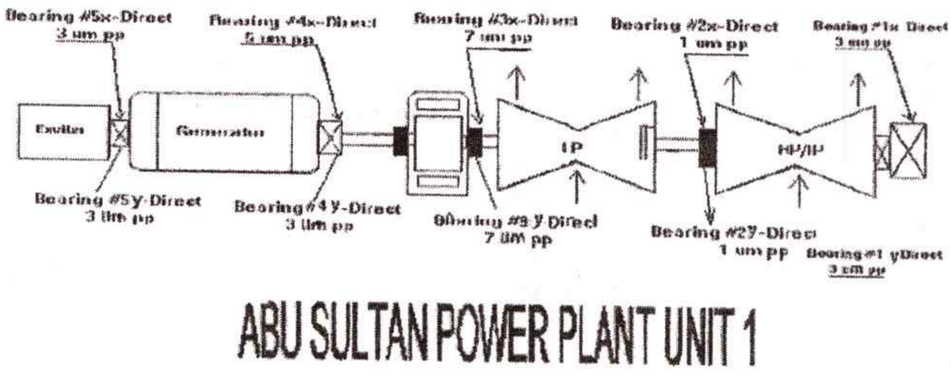


Fig.(3) Experimental Setup

Axial and radial vibration signals taken by piezoelectric amplifiers were conditioned and then recorded using a Data Collector. Using this equipment, it was possible to create four different machine conditions.

a. (N-N) No faults applied the shaft displacement is small.
b. (R-N) Only rub is applied: The shaft orbit follows a highly irregular path.
c. (U-N) Only unbalance fault is considered: the shaft orbit is an approximate circle.
d. (U-R) Both rub and Unbalance are applied.

The shaft follows an irregular path, but the average displacement from the center is larger than without the unbalance. These conditions were created for a range of different machine speeds from 735RPM to 955RPM. Changing the motor speed changes the exact path the shaft follows. For example with the U-N condition, as the motor speed increases, the radius of the circle increases. The automatic classification system has to be insensitive to these changes.

The feed forward neural networks were trained and implemented using the back propagation with adaptive learning [14], [15]. For training we used bearing #x1as input and bearing #x2 as desired output (without input scaling) Fig.(4) shows the variation of the measured amplitude at bearing at no fault case. Fig.(5) shows the amplitude for the rub fault case. Fig.(6) shows the amplitude for the unbalance fault. Fig. (7) shows the amplitude for both rub and unbalance fault case. Each figure has two graphs, one represent measurement at bearing #x1 used for training and the second at bearing #x2 used for testing. The network architecture is taken as (16-5-4) which means 16 input feature being used for classification, as shown in Fig.(8). Each input was scaled by a constant factor, which is taken equal to the largest estimate of that feature in the training data set. The network has a hidden layer with five neurons. The output layer has four neurons to represent the different fault classes, these are:

a. (0,0,0,0) For no Fault.
b. (0,1,0,0) For Rub Fault.
c. (0,0,1,0) For Unbalance Fault
d. (0,1,0,1) For Rub and Unbalance fault condition.

The error tolerance is taken equal to 0.01 and the learning parameter is taken equal to 0.1 and the number of cycle is taken equal to 1000 cycle. The network shows a training success equal to 99.67% for training and 99.66 for testing the No fault case. The network shows a success equal to 74.75 % for training and 74.67% for testing for the case of Rub Fault.

For the case of unbalance, the network shows a success result of 74.62% for training and 74.27% for testing. For both fault scenario, and increasing the input feature to 20 readings instead of 16, so we have (20-5-4) architecture, keeping the other parameter values, the network shows a success of 50.3% for training and 48.20% for testing. The result shows that the model is good for single fault but is week for mixed faults, and we have to increase the sample data for combined faults.

4. Comparison with Frequency Domain Analysis

Of the frequency domain methods, only direct application of the FFT is suitable for real-time implementation. This method however requires the signal to be statistically stable. Since an FFT produces many frequencies bins, related to the number of samples used to compute it, there still requires a decision over which frequency components to use as features.

Harmonics of the rotation frequency dominate the signal and therefore the features chosen were those bins, which correspond to the first ten harmonics of the signal. This creates a network with the same number of inputs as the network, which classified using amplitude. However, using these would require a larger network. It is also possible that spectral energy lies at frequencies, which are not harmonics of the rotation speed, and therefore a better choice of FFT bins, not arbitrarily chosen, could possibly give improved results. However it may be that problem such as the random nature of the signal, spectral leakage and the low spectral condition than might have been expected. In many other machines, it may be that FFT analysis could provide a useful set of features, which could be used as an alternative or in addition to time averages.

Conclusion

In this research, the use of artificial neural networks, as part of a system for continuously classifying the loading conditions of a shaft has been described. Simple signal processing operations were applied to estimate time –invariant features, which were used as network inputs.

Amplitude of the vibration time series was evaluated as they can be computed quickly and can therefore be estimated in real time. It was found that by combining the orthogonal measured vibrations into a complex time series, the magnitude of this could be used as a time series.

From this research we demonstrate two faults only. But it can be used to demonstrate any other type of signal faults by making the same modeling. From the obtained results, we can conclude that the network give very good results for classify no fault case. Also it gives good results classifying rub or unbalance faults for different simulated network architecture.

But using network for classifying two faults at the same time gives result artificial neural networks for one fault classification would be preferred. However there is some fundamental limitation of such system in real implementation.

- It is often no feasible to specify all possible fault scenarios beforehand.
- Explicit heuristics will rely too much on the operating conditions of the machine.
- Individual machine vibration behavior can deviate largely from the expected behavior.

Hence, such an expert system may be tailored to a specific machine in a specific environment at specific time, but generalizing the knowledge that is present in the system to somewhat different machines may be impossible.

Fig. (4-a) Measurement for No Fault used for Training

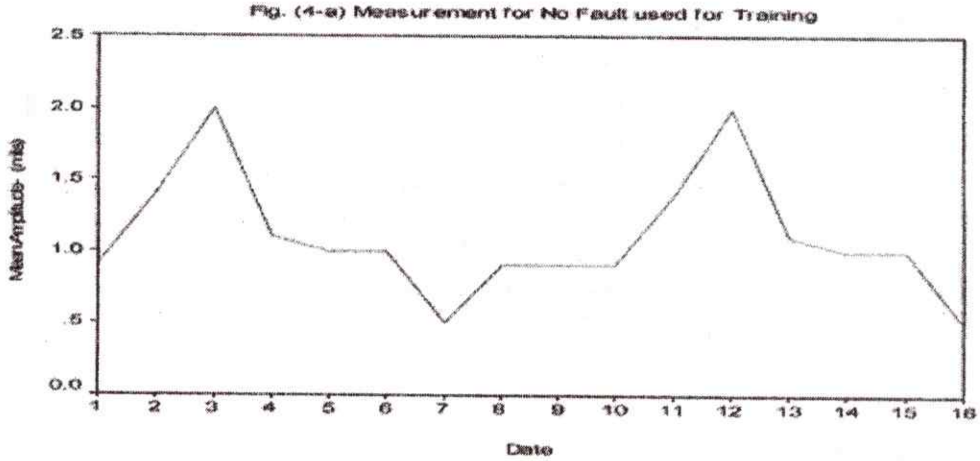


Fig. (4-b) Measurement for No Fault used for Testing

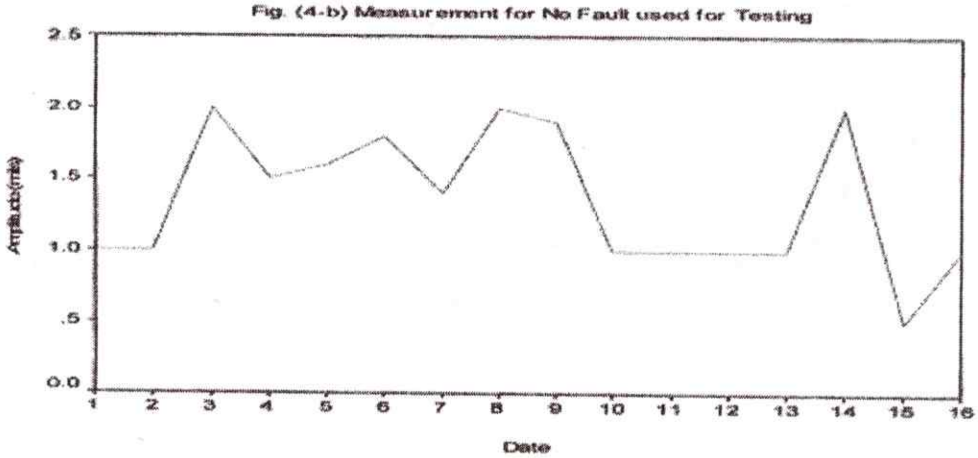


Fig. (5-a) Measurement for Rub Fault Condition used for Training

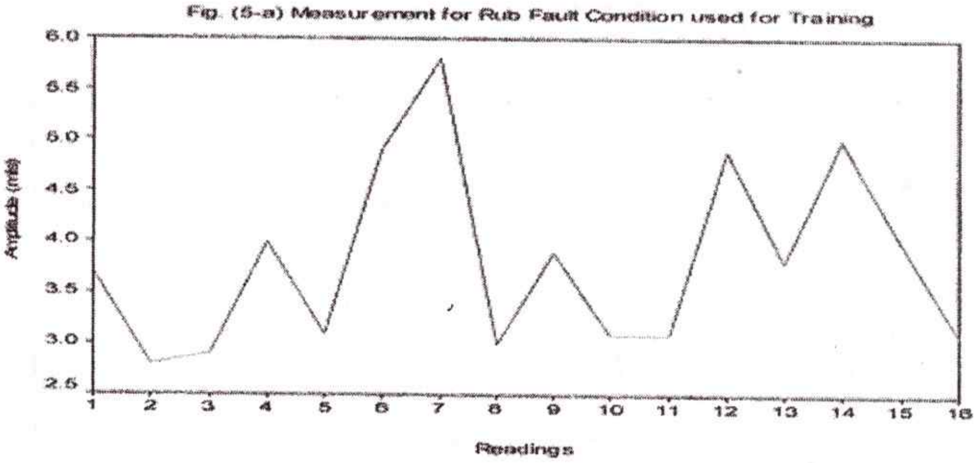


Fig. (5-b) Measurement for rub Fault Condition used for Testing

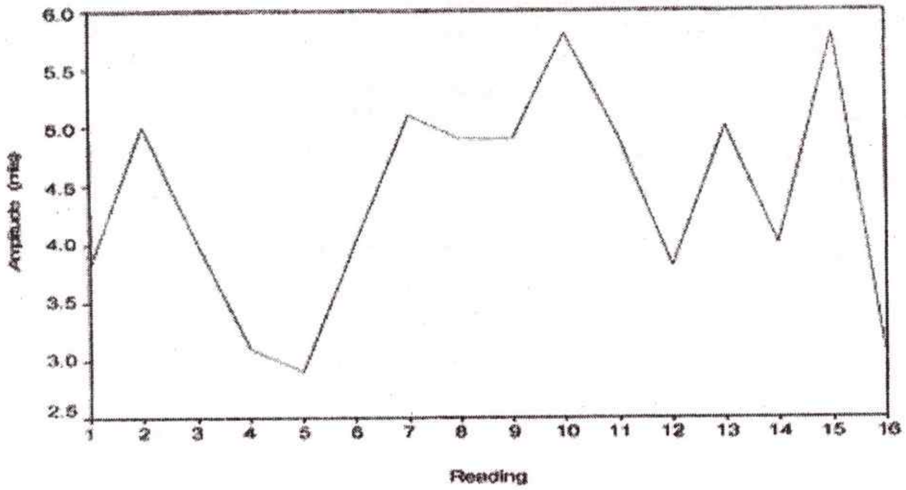


Fig. (6-a) Measurement for Unbalance Fault used for Training

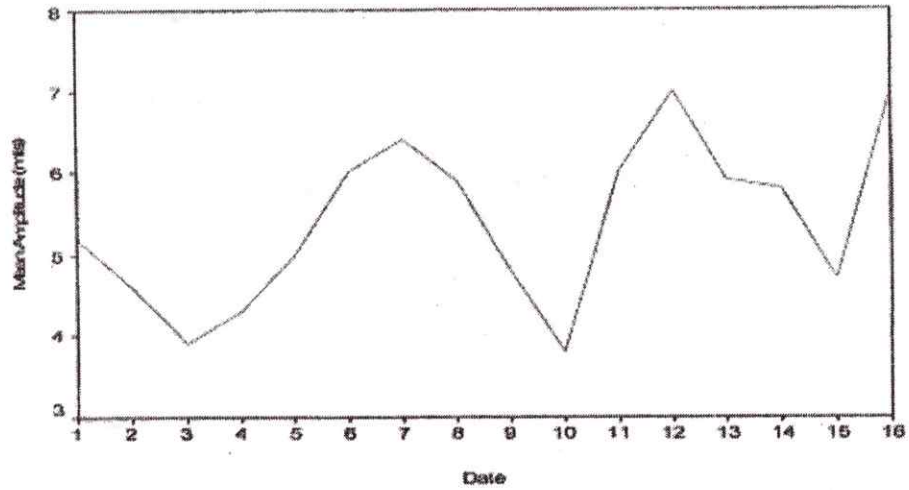


Fig. (6-b) Measurement for Unbalance Fault used for Testing

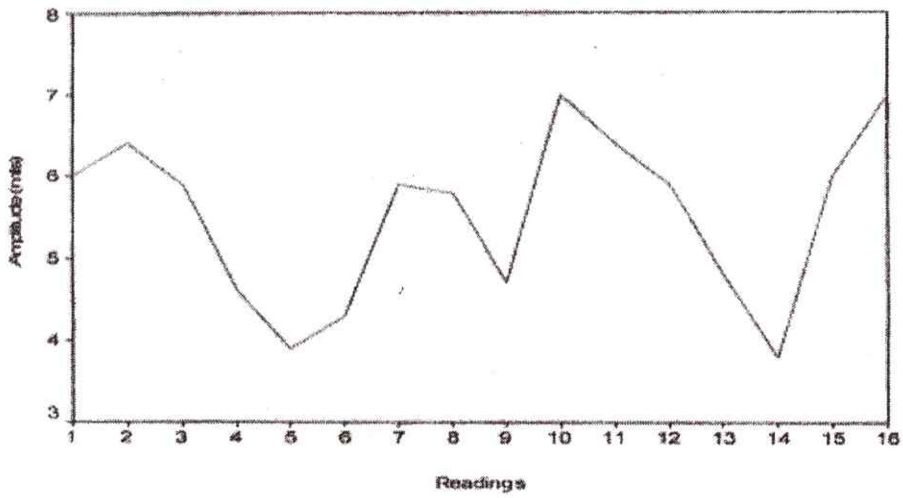


Fig. (7-a) Measurement for Unbalance and Rub Fault used for Training

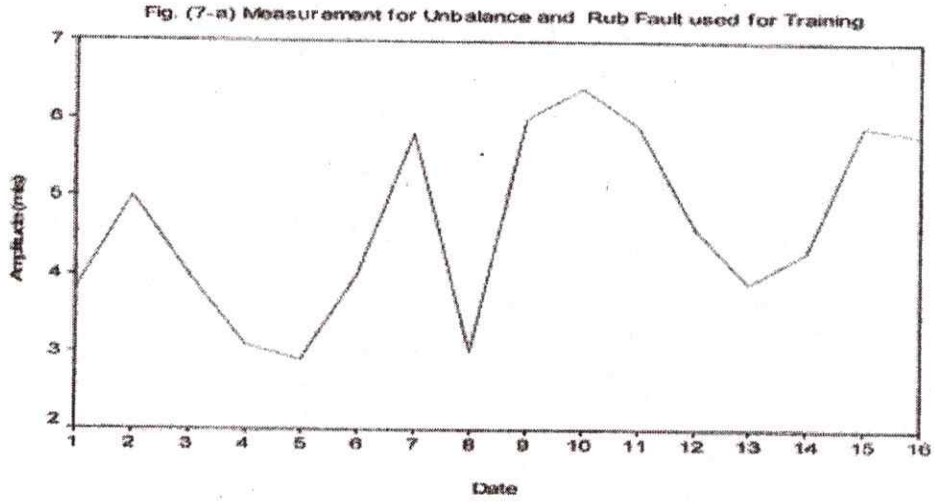
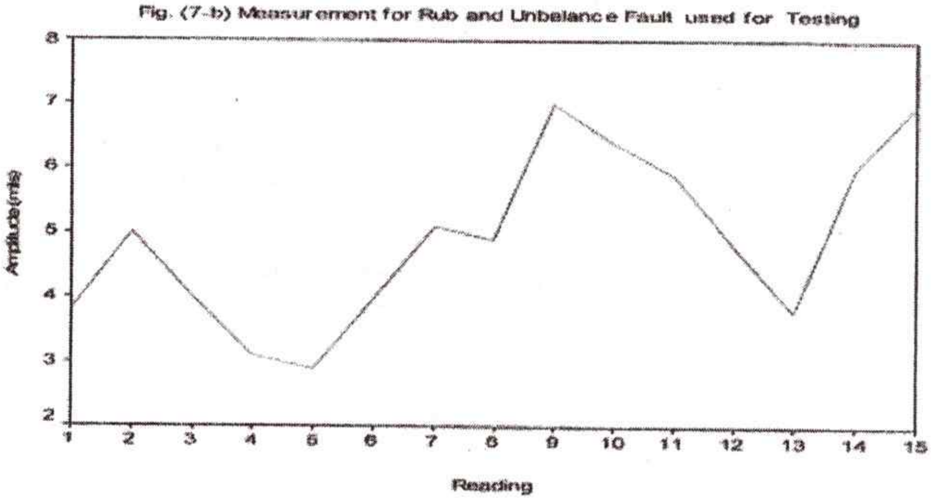


Fig. (7-b) Measurement for Rub and Unbalance Fault used for Testing



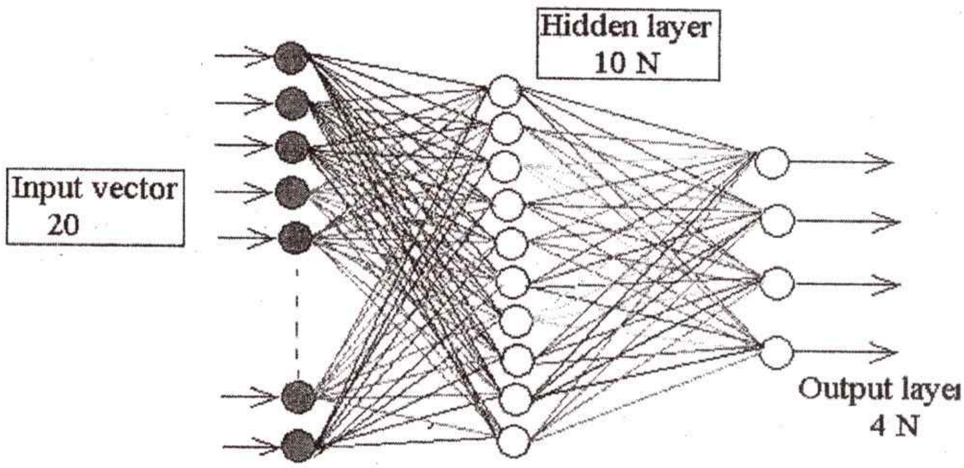


Fig. (8) Neural Network Architecture (20-10-4).

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