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Artificial Neural Network Model for Fault Diagnosis of Rotating Machine in ETRR-2 Research Reactor

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ABSTRACT

This article characterizes vibration signals using Artificial Neural Network (ANN) method to develop an effective and reliable feature sets for detecting and diagnosing faults in a centrifugal pump (ETRR-2 research reactor core coolant pumps). In this paper, a modular ANN are used for modeling the ETRR-2 research reactor core coolant pumps vibration monitoring. The input and the output signals of the vibration transducer are used as input source data for the ANN model. The amplitudes and frequency domain are inputted to the ANN separately from the vibration data. It is noted that the features statistical have good results based on frequency and amplitudes domains. The ANNs are used to detect the misalignment, unbalance severity, looseness bearing, and anti-fraction. The results are very useful for maintenance making decision. This methodology can be used for the research reactor coolant pumps. Hence, it may turn out to be a powerful tool for early detection of pump fault.

1. INTRODUCTION

Motors, gear boxes, turbines, pumps, conveyors, engines, fans, compressors, rollers, and machine tools that have rotational elements. These machines generate vibrations that get the rotating elements. The vibration amplitude indicates the performance of machine. In case of vibration increase meaning that failing rotational elements (bearings or gears). The frequencies determined from machine speed and compared to actual measurements to get failure mode [1], [2].

Vibration in to rotating equipment's caused by unbalance, misalignment, and bearing problems [3]. Vibration monitoring for coolant pump is very important in research reactor for reducing overall operating costs and prevent serious damage by predict problems [4], [5]. In case of detecting a large vibration, the reactor protection system shut-down the reactor [6], [7]. vibration measurement broad band (ISO 10816) is used to analysis machine condition. ISO 10816 Standards separates the working vibration into four zones: Red, Orange, Yellow and Green also detect four classes of machines as shown in Table 1. Machines examples are fans, turbo-compressors, gas turbines, generators, turbo-pumps, and motors [8], [9]. Predictive maintenance comprises advantages like increasing production-optimize machinery capabilities, improving machine reliability-reduced "unplanned failures", lubrication failures, reducing vibration and reducing maintenance costs [10].

In [11], presented technique based on neural network (NN) to diagnose faults in rotating machinery. This scheme is based on a convolutional NN. In [12], presented technique based on time frequency manifold (TFM) to diagnose faults in rotating machinery. But TFM need high computational cost and has challenge for reliable transient feature recovery. In [13], presented scheme based on combination between continuous wavelet transform and phase space reconstruction (PSR) to diagnose faults in rotating machinery. In this scheme the process is automatic. In [14], presented comprehensive review of artificial intelligent schemes (naive Bayes, deep learning, artificial neural network, k-nearest neighbor, support vector machine) in rotating machinery fault diagnosis. Also presented literature survey of these artificial intelligent schemes in industrial applications. In [15], presented technique based on motor current signals and deep extreme learning machine. In conclusion, this work is important in the field of nuclear reactor safety analysis. ANN is used for modeling the vibration monitoring in research reactors.

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2. Pump Supervision and Mathematical Models

2.1. Pump Supervision

Pumps are very important equipment in many industries including mining, mineral, air conditioning, power, heating, chemical and manufacturing as shown in Figure 2. Centrifugal pumps are used to transport fluids by the conversion of rotational kinetic energy to the hydrodynamic energy of the fluid flow. The rotational energy typically comes from a combustion engine or electric motor. The fluid enters the pump impeller along or near to the rotating axis and is accelerated by the impeller, flowing radially outward into a diffuser. The following signals are typically measured:

- Driving motor current
- Driving motor voltage
- Driving motor temperature
- Difference pressure between the outlet and inlet ΔP
- Fluid discharge rate *Q*
- Motor torque M_{mot}
- speed *ω*
- Fluid temperature, sediments (not considered here)

2.2. Mathematical Models of Pump and Pipe System

When torque M applied to rotor of a pump leads to a speed ω and a momentum increase of the pump fluid. Euler's turbine equations leads to the relationship between the speed ω, pressure differential ΔP and fluid discharge rate Q:

$$H_{th}=h_1\ \omega_2-h_2\ \omega Q \qquad \textbf{(1)}$$

where H_{th} =ΔPg is pump head measured in meters and h_1, h_2 are proportionality constants.

The real pump head is given by:

$$H=h_{nn}\ \omega 2-h_{nv}\ \omega Q-h_{vv}\ Q_2 \qquad \textbf{(2)}$$

where h_{nn}, h_{nv} and h_{vv} are proportionality constants to be treated as model parameters.

The corresponding pump torque is:

$$MP=Pg\ (h_{nn}\ \omega Q-h_{nv}\ Q_2-h_{vv}\ Q_3\ \omega) \qquad \textbf{(3)}$$

The mechanical parts of the motor and the pump when torque is applied according to:

$$JPd\omega(t)dt=Mmot(t)-MP(t)-Mf(t) \qquad \textbf{(4)}$$

where JP is the ratio of inertia of the pump and the motor, and Mf is the frictional torque consisting.

The pump is connected to a piping system. The momentum balance equation yields:

$$H(t)=aFdQ(t)dt+h_{rr}\ Q_t(t)+Hstatic \qquad \textbf{(5)}$$

where h_{rr} is a resistance coefficient, aF=lgA with pipe length l and cross-sectional area A, and Hstatic is the height of the storage over the pump. The type of the model used may depend upon the operating conditions under which the pump is run.

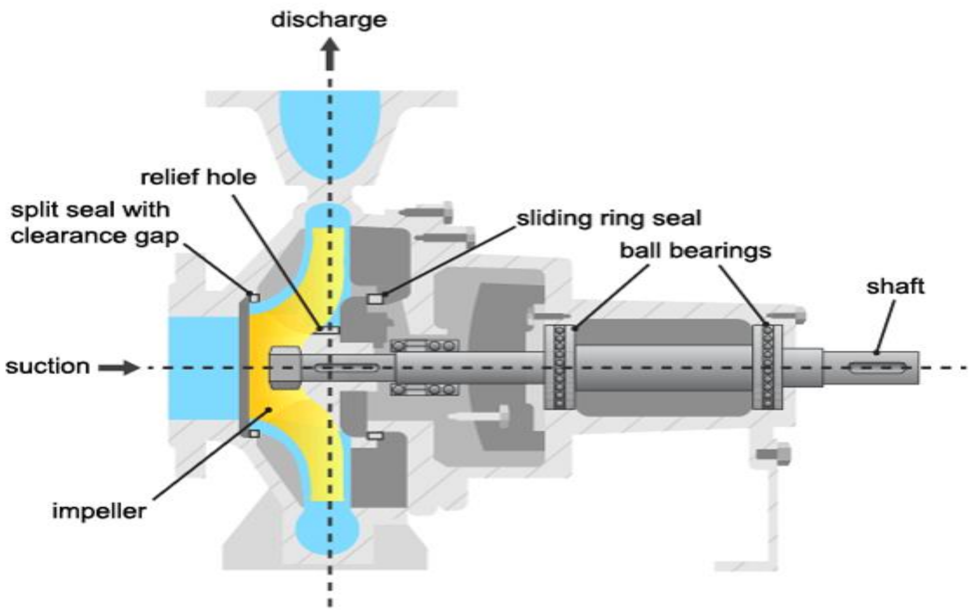


Fig. (1): Pump design

3. Modeling of ANN for Classification of Vibration Problems in Rotary Machines

3.1. Modeling of ANN for Classification

Vibrations cause faults in rotating machinery such as unbalance, looseness, etc. In this paper a technique is proposed to determine looseness and unbalance in rotor bearing system using ANN by determine the frequency amplitude domain as shown in Figure 2. In this situation, frequency and amplitude domain are used to test and train the ANN. Training Data of Artificial Neural Networks for Classification of Vibration Problems in Rotary Machines is shown in Table 2.

Table (1): Vibration measurement band ISO 10816

Vibration Severity PER ISO 10816					
Machine		Class I small machines	Class II medium machines	Class III Large rigid foundation	Class IV Large soft foundation
Vibration velocity Vrms in/s	mm/s				
0.01	0.28	Good	Good	Good	Good
0.02	0.45	Good	Good	Good	Good
0.03	0.71	Good	Good	Good	Good
0.04	1.12	Satisfactory	Good	Good	Good
0.07	1.8	Satisfactory	Satisfactory	Good	Good
0.11	2.8	Unsatisfactory	Satisfactory	Satisfactory	Good
0.18	4.5	Unsatisfactory	Unsatisfactory	Satisfactory	Satisfactory
0.28	7.1	Unacceptable	Unsatisfactory	Unsatisfactory	Satisfactory
0.44	11.2	Unacceptable	Unacceptable	Unsatisfactory	Unsatisfactory
0.7	18.0	Unacceptable	Unacceptable	Unacceptable	Unsatisfactory
0.71	28.0	Unacceptable	Unacceptable	Unacceptable	Unacceptable
1.1	45.0	Unacceptable	Unacceptable	Unacceptable	Unacceptable

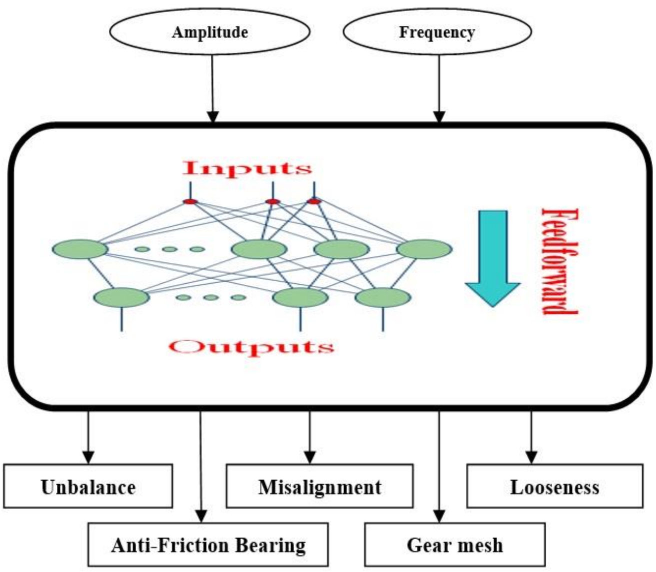


Fig. (2): Modeling of ANN for identification and prediction of vibration problems by using amplitude in frequency domain

Table (2): Training Data for Classification of Vibration Problems in Rotary Machines

Inputs		Outputs	Classification Type
Frequency (F Hz)	Amplitude (A mm)		
F≤ 2000	A> 45	0 0 0 0 1	Unbalance
2000 <F≤ 3000	30 <A ≤ 45	0 0 0 1 0	Misalignment
3000 <F≤ 7000	15 <A ≤ 30	0 0 1 0 0	Looseness
7000 <F≤ 13000	7.5< A≤ 15	0 1 0 0 0	Anti-Friction Bearing
13000<F≤ 21000	0 < A≤ 7.5	1 0 0 0 0	Gearmesh

3.2. Significant Frequencies for classification

To get various information about a machine, it should know which frequencies would likely occur in such a spectrum (bearings, blade pass, gear-mesh, rotational, etc.). The spectrum frequency contains number of discrete lines. It should divide the spectrum frequency to areas, in which various symptoms occur:

1. From identification of the frequency pertinent to the rotational speed, the spectra evaluation process starts for which the notation 1X is used.
2. rotational frequency integral multiplies (2X, 3X, 4X, 5X, ...) are identified (harmonics).
3. Figures 3 and 4 show the spectrum (divided into three main areas)
4. Area below (1X) rotational frequency called sub synchronous, and it is dangerous when peaks occur.
5. Area from rotational frequency up to ten times of it (1X to 10X), when peaks occur in this area, meaning that misalignment, unbalance, looseness, etc.
6. Area above (10X), the area of high-frequency events it is dangerous when peaks occur in this area, meaning that gear faults, roller bearing defects, etc.

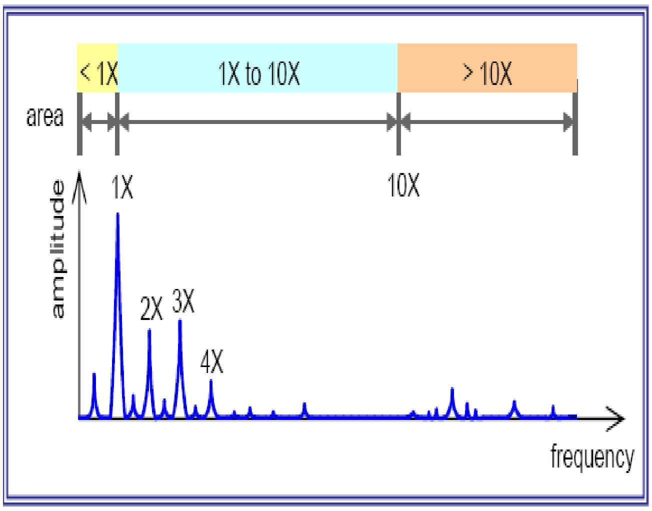


Fig. (3): Dividing the Spectrum into Significant Areas

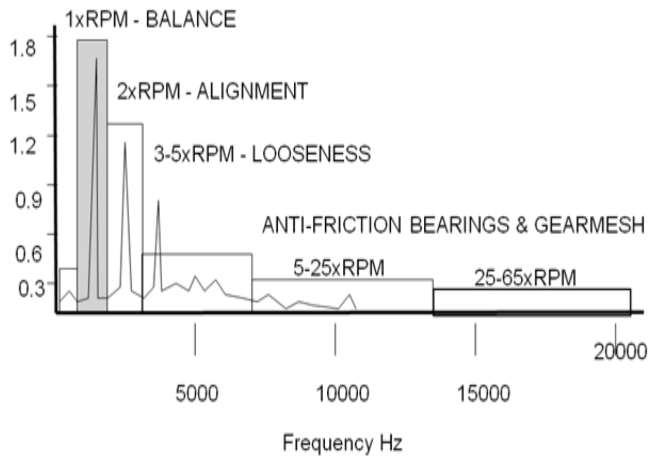


Fig. (4): Predefined Spectrum Analysis Bands

4. RESULTS AND DISCUSSION

Function fitting consists of a two layer feedforward network, with a linear transfer function in the output layer and a sigmoid transfer function in the hidden layer. Hidden neurons number is set to 10. Continuous training until the validation error failed to decrease for number iterations. The best validation performance is $3.8883e^{-08}$ at epochs 214 the network performance is shown in Figure 5. the training gradient state as shown in Figure 6 is $3.0101e^{-06}$. The plot training Regression R=1 for validation and testing is shown in Figure 7. Figure 8 show regression plots display for network outputs to targets for training, test sets, and validation.

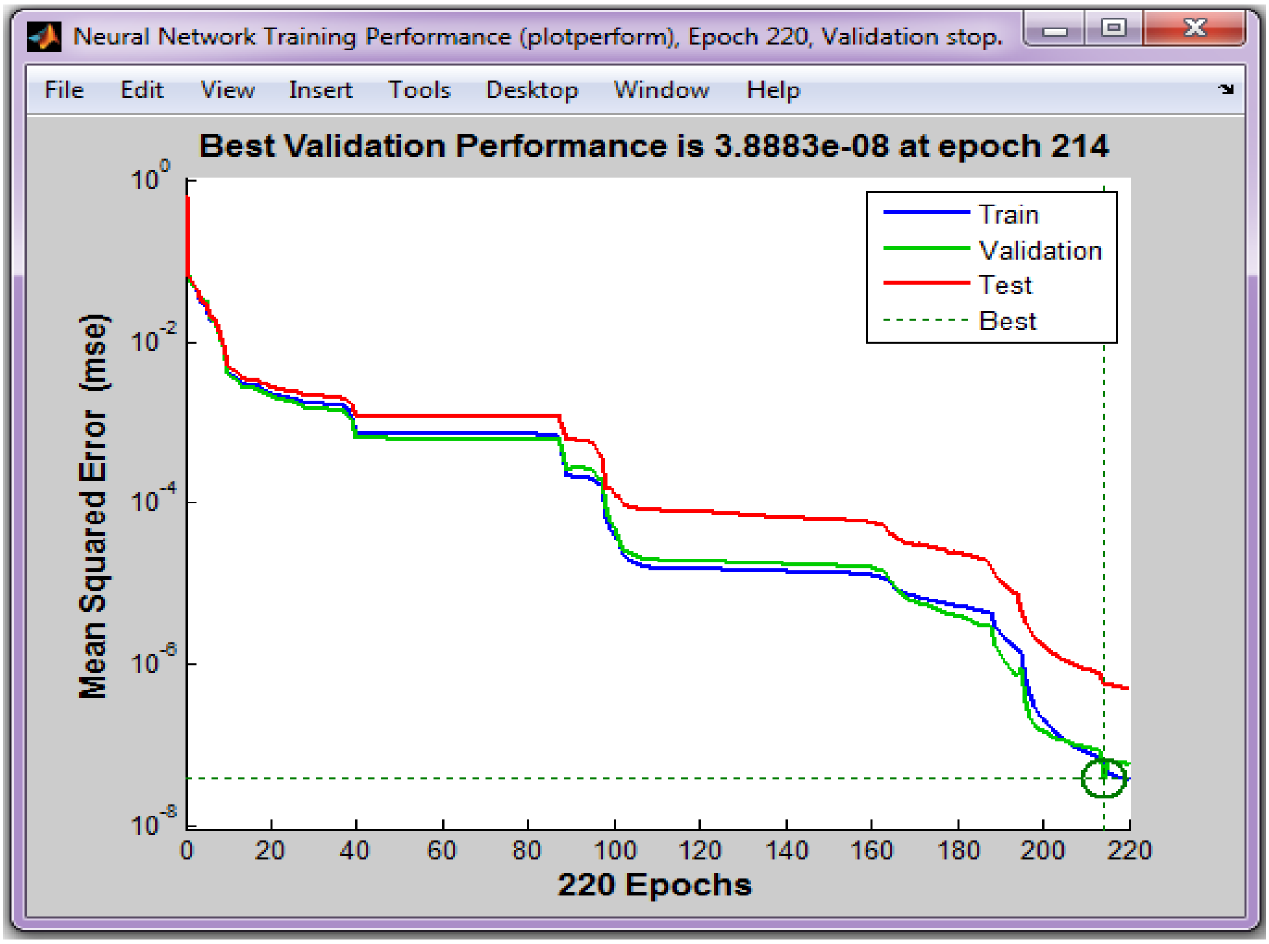


Fig. (5): Best Validation Performance Learning Curve in Second Module

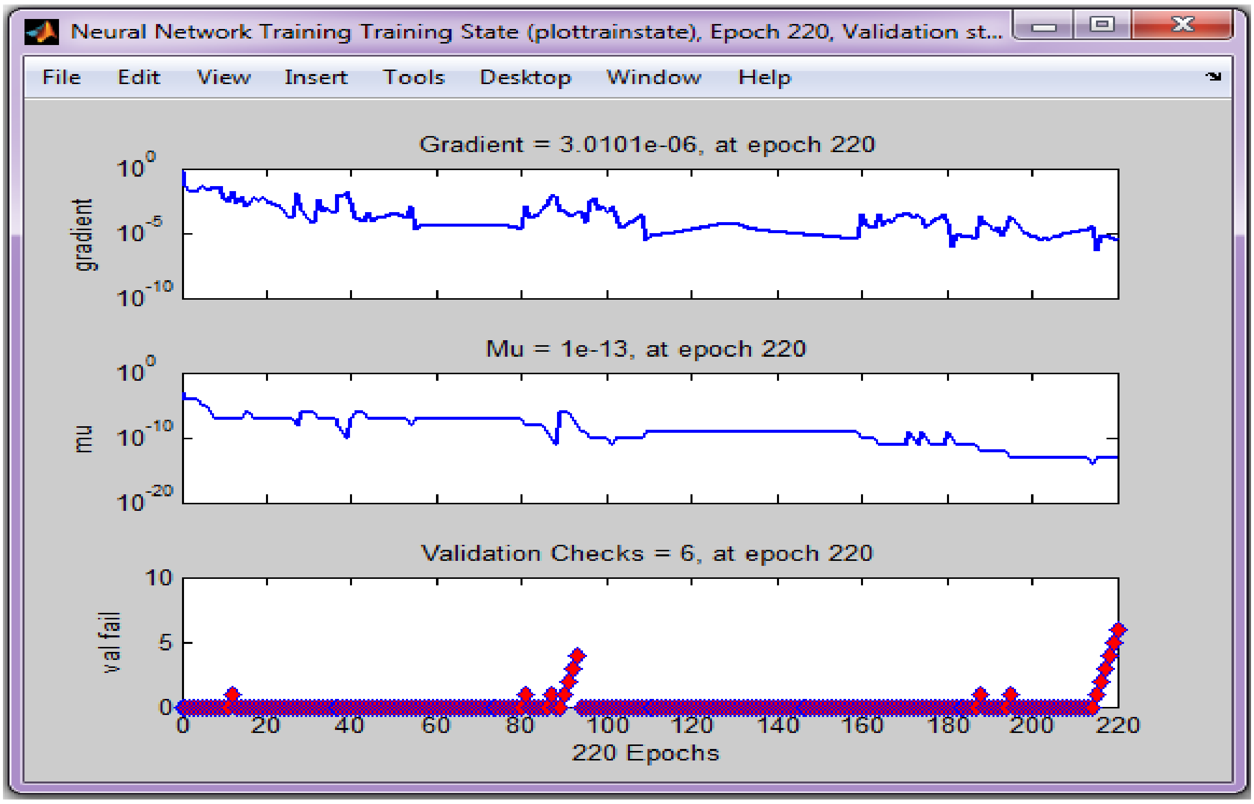


Fig. (6): Neural Network for Training State in the Module

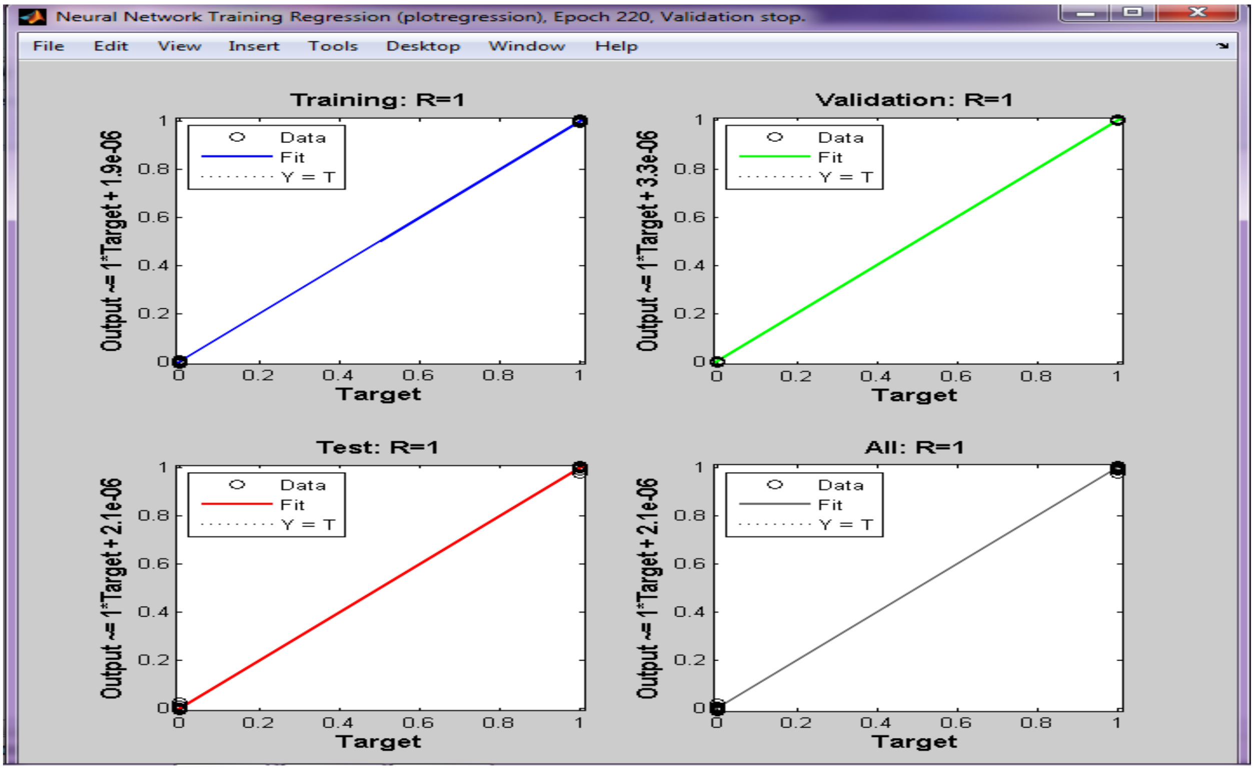


Fig. (7): Neural Network Training Regression in the module

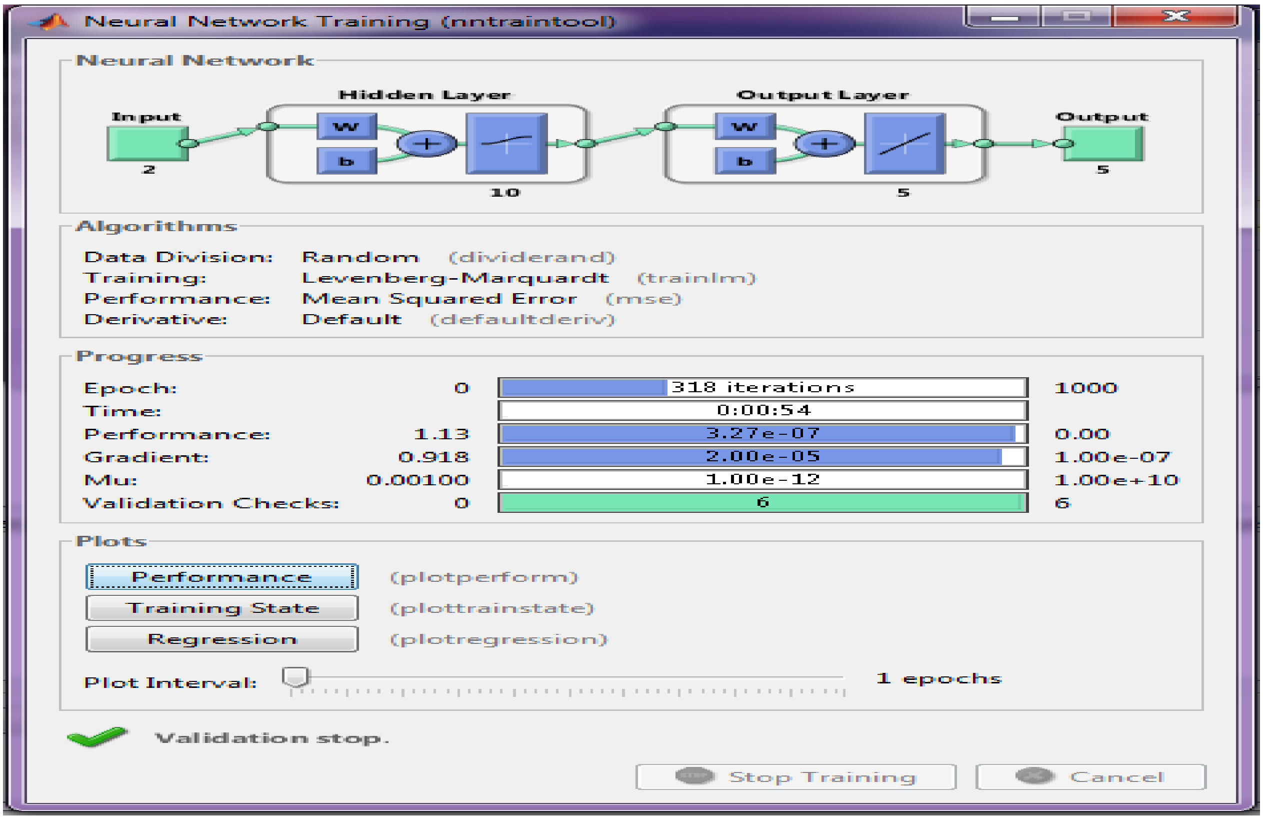
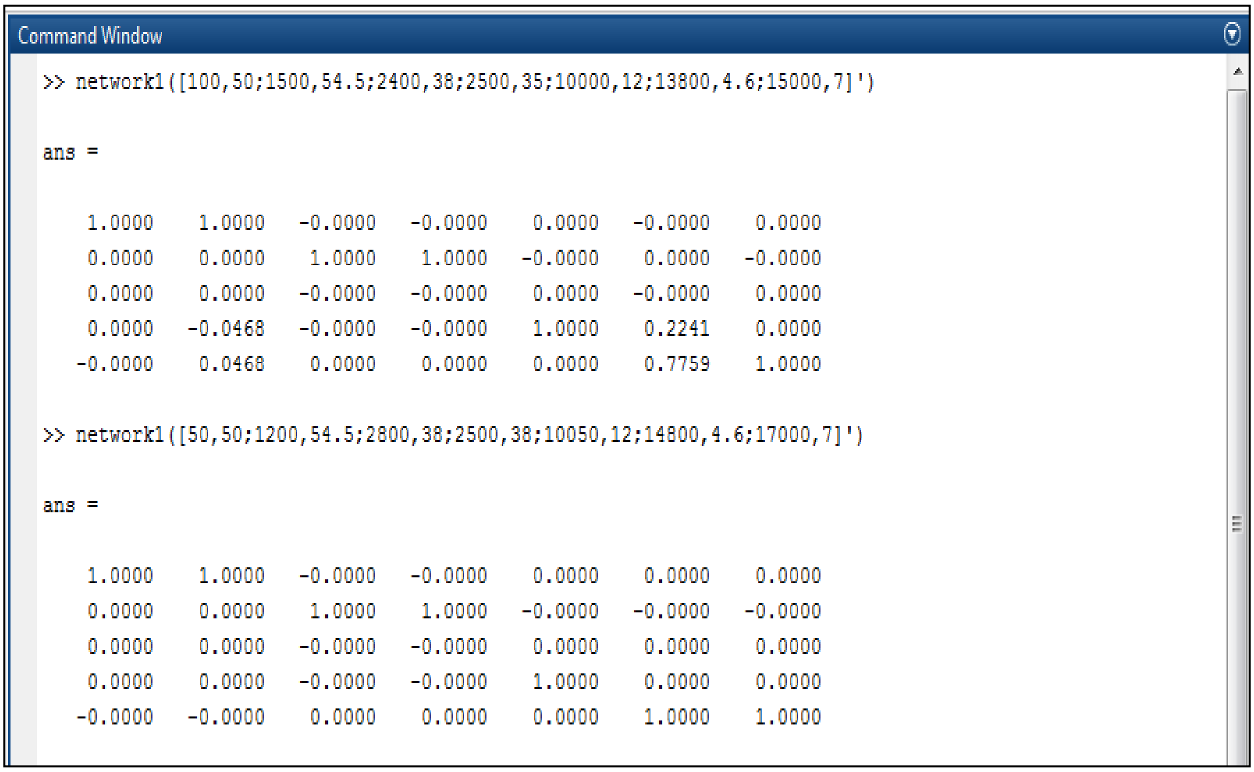


Fig (8): Neural Network Training in the Module

The network outputs are equal to the targets in case of data fall along a 45 degree line. The test data is shown in Figure 9.



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Command Window
>> network1([100,50;1500,54.5;2400,38;2500,35;10000,12;13800,4.6;15000,7]')

ans =

    1.0000    1.0000   -0.0000   -0.0000    0.0000   -0.0000    0.0000
    0.0000    0.0000    1.0000    1.0000   -0.0000    0.0000   -0.0000
    0.0000    0.0000   -0.0000   -0.0000    0.0000   -0.0000    0.0000
    0.0000   -0.0468   -0.0000   -0.0000    1.0000    0.2241    0.0000
   -0.0000    0.0468    0.0000    0.0000    0.0000    0.7759    1.0000

>> network1([50,50;1200,54.5;2800,38;2500,38;10050,12;14800,4.6;17000,7]')

ans =

    1.0000    1.0000   -0.0000   -0.0000    0.0000    0.0000    0.0000
    0.0000    0.0000    1.0000    1.0000   -0.0000   -0.0000   -0.0000
    0.0000    0.0000   -0.0000   -0.0000    0.0000    0.0000    0.0000
    0.0000    0.0000   -0.0000   -0.0000    1.0000    0.0000    0.0000
   -0.0000   -0.0000    0.0000    0.0000    0.0000    1.0000    1.0000
```

Fig. (9): Examples of Output Data for testing in the module

4. CONCLUSIONS

In this paper, the developed technique presents a procedure for detection and classification of Misalignment, unbalance severity, looseness, Anti-fraction bearing and Gearmech using ANNs. Various statistical features are extracted from vibration signals and fed to the neural network by frequency domain amplitude to train and test the ANN. The neural network is modeled as a classification problem by dividing the core coolant pumps signals into five different ranges in term of frequency and amplitudes. It is noted that features statistical output has a very good result over amplitude frequency domain. The obtained results are useful for making a maintenance decision based on result of classification.

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