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DIAGONOSIS OF REMAINING USEFUL LIFE ESTIMATION OF BALL BEARING USING ARTIFICIAL NEURAL NETWORK

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Abstract

Bearings are critical components in rotating machinery. Bearings which transfer loads via a rolling element are called as rolling element bearings. Rolling element bearings are critical components of many modern engines and machinery. A typical time-based maintenance schedule requires an often replacement of the bearings but most of the time, bearings still have long residual useful lives which are wasted. An estimation of this residual life based on their current condition could prolong the operating time between replacements and could lead to a maintenance cost reduction. Rolling contact fatigue failure is an unavoidable consequence of normal bearing operation and it results in the creation of spalling on the contact surfaces of the rolling elements and the raceways. Under alternative loading, small cracks initiate below the surface and propagate to the surface, finally causing spalling and reducing the performance of the bearing. ANN (Artificial Neural Network) has been used to make a mathematical model to diagnose the fault in rolling element bearing. Neural networks are composed of simple elements operating in parallel. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Vibration Monitoring is employed here as a method for monitoring the condition of the bearing. Vibration monitoring is carried out using any of the three methods, namely, Time domain analysis, Frequency domain analysis, and Time frequency analysis. Among the three techniques, time domain analysis is the simplest and easy to implement. It requires the calculation of statistical features, using which the faults can be classified. Various statistical time domain features such as mean, kurtosis, skewness, rms, crest factor, form factor etc. are provided as an input to ANN.

Keywords: ANN; Bearing; Statistical time domain features; Time domain analysis.

Introduction

Bearings is a important component in a machine. For classification, the bearings that transfer loads through a rolling element are regarded as rolling element bearings. In the present investigation a ball bearing is considered. There are four main parts in a bearing namely, inner ring or inner race, outer ring or outer race, rolling elements and a cage or separator. Generally, the faults occur in any one of these parts. The presence of these faults in bearings results in severe vibrations. Their timely detection and estimation of the time to failure are the key areas of concern for researchers as abrupt failure of bearings may cause malfunctioning of the entire system and this results in downtime for the system and economic loss to the customer. The failure has potential to damage machinery causing machinery repair and/or replacement costs.

To monitor the engine parameters regularly to ensure safer operation, Condition monitoring is done. It also includes prediction of faults before failure. The process consists of two stages: diagnosis and prognosis. Diagnosis is the process in which the data is collected and analyzed in order to find the faults of the machine (in this case, bearing). Prognosis is the process in which the remaining useful life (RUL) of the bearing is predicted using the data from diagnosis. The present investigation focuses only on part of the diagnosis stage for ball bearing health monitoring

For a long time, condition based maintenance (CBM) has been a key area of research. Fault detection, diagnosis and prognosis are the three mainstays of CBM. Detection comprises of determining that the damage has occurred to the bearing, while diagnosis is a determination of the location and type of fault, whereas prognosis involves estimation of the remaining life of the damaged bearing and investigation of failure modes. A important objective of CBM is to predict the remaining useful life (RUL) instead of its service time, which leads to anticipated usage of the machine, reduction in downtime and improved operational safety.[1]

CONDITION MONITORING TECHNIQUES:

The following conditional monitoring techniques are generally used:

a. Vibration

b. Oil / Debris analysis

c. Temperature.

d. Acoustic emission

Vibration monitoring technique is best as it is reliable and standardized method, responds immediately to changes and has ability to point out defective component

BEARING DEFECT DESCRIPTION

There are mainly three types of defects found on bearing. Defect may be present on ball of bearing commonly known as “BALL DEFECT (BD)”. Defect on inner race is termed as “INNER RACE DEFECT (IRD)”. Defect on outer race is termed as “OUTER RACE DEFECT (ORD)”. These defects are shown in figure. [11]

Fig. 1 Pitting on ball bearing elements

Fig. 2 Spalling on Inner race

Fig. 3 Spalling on Outer race

BEARING FAULT PROGRESSION:

The fault patterns exhibited by progressive stages of bearing damage are well established in industrial applications as described in and shown in Figure 4.

In Stage I, micro-defects and crack initiation causes ultra-high frequency activities. These activities are typically monitored using Acoustic Emission rather than accelerometers. In Stage II, the micro faults develops into pits which begin to excite bearing elements and causes signals associated with their natural frequencies to appear. Enveloping analysis is commonly used to demodulate a selected high frequency bandwidth of the FFT spectra and extract the bearing defect frequencies in this stage. As the pits become larger, fundamental bearing defect frequencies and their harmonics can be observed from the FFT spectra. Depending on the extent of the damage, these frequencies can be modulated by the shaft frequency and be observed as side bands that is the final condition before bearing failure. As the defect becomes widespread, the bearing elements vibrate more randomly with higher clearances. The localized defects may also have ‘smoothen’ out which reduces the signature of the periodic vibration. As such, the distinct bearing defect frequencies diminishes as an increase in noise floor or ‘haystack’ rises in the higher frequencies ranges.

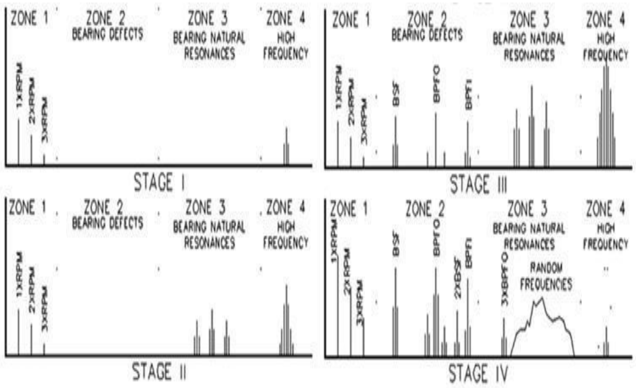

Fig. 4 Progression of defect in bearing

VIBRATION SIGNAL ANALYSIS ON ROLLING ELEMENT BEARINGS

Rolling contact fatigue is causing small subsurface cracks to propagate towards the surface until spalling occurs. These minor cracks and small scale spalling are the main source of vibration as rolling elements are passing by. This vibration can be measured close to its source, but often it can be detected on other elements which are in contact, but increased noise is affecting the signal. Displacement, velocity and acceleration transducers can be used to extract these vibration signals. The most common arrangement is the use of an accelerometer which is permanently attached on the bearing housing. The accelerometer can measure the excitation in one direction or even in three if it is a tri-axial one. The signal is processed in order to retrieve the desired characteristics and to reduce the noise. This can be achieved with the use of appropriate frequency filters (low - high pass filters, Wiener filter) and the compensation of the systemic noise . After this initial signal processing, data can be further processed in the time or in the frequency domain.

FAULT CLASSIFICATION TECHNIQUE:

Artificial neural network (ANN)

Artificial intelligence techniques such as fuzzy logic, artificial neural network (ANN) (Hassoun, 1995) have been continuously and successfully applied for bearing fault detection and diagnosis. ANNs are made up of interconnected processing units known as neurons and it is adaptively changes its structure during learning phase. ANN is a type of supervised learning methods which can be trained by supplying data.

ANNs can be grouped into two major categories: feed-forward and feedback (recurrent) networks. In the former network, no loops are formed by the network connections, while one or more loops may exist in the latter. The most commonly used family of feed-forward networks is a layered network in which neurons are organized into layers with connections strictly in one direction from one layer to another. Back propagation algorithm is used for training purpose during which weights are adjusted for error minimization between ANN predictions and outputs. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network

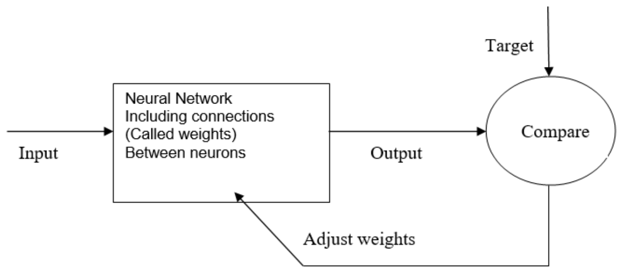

Fig. 5 Block Diagram of ANN

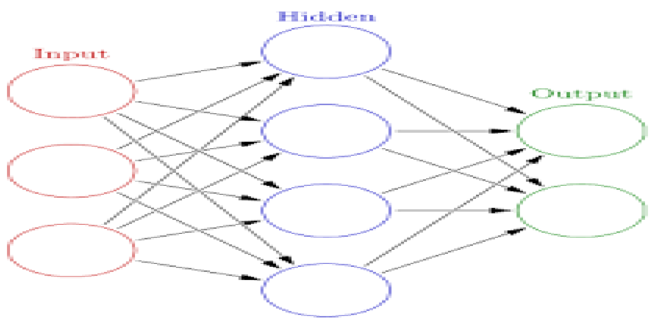

Fig. 6 ANN Diagram

Literature Review:

Following work has been done on the estimation of useful life of ball bearing:

Permutation entropy based feature extraction techniques can be used as a tool to select best wavelet for feature selection for the detection as well as fault classification of ball bearings. This provides higher classification accuracy even when there is a slight variation in operating condition which is useful for development of online fault diagnosis [Vakaharia et. Al] [1].

Condition Monitoring is one of the most important techniques for maintenance of a machine. This is done in order to increase the safety and reliability of the machine. [pratyusha et. Al][2]

Farzaneh Ahmadzadeh et. Al discussed the recent modelling developments in estimating the remaining useful life (RUL) of industrial systems. The RUL estimation models are categorized into experimental, data driven, physics based and hybrid approaches. Data driven methodologies are useful when a large quantity of noisy data needs to be transformed into a piece of logical information to diagnose the fault in bearing. [3]

Lei. Et al presented a new approach to intelligent fault diagnosis based on statistics analysis, an improved distance evaluation technique and adaptive neuro-fuzzy inference system (ANFIS). The approach was applied to fault diagnosis of rolling element bearings, and test results showed that the approach can reliably recognize different fault categories and severities. [4]

Sutrisno, et, al proposed the three methodologies for determining the remaining useful life. An experimental data set from seventeen ball bearings was provided by the FEMTO-ST Institute.[5]

Mahamad, et. Al [6] proposed artificial neural network (ANN) as a method to improve accurate RUL prediction of bearing failure. For this purpose, ANN model used time and fitted measurements. The results showed that better performance is achieved in order to predict bearing failure.

Benazzouz et. Al proposed a real-time fault diagnosis system by using Levenberg-Marquardt algorithm related to tuning parameters of Artificial Neural Network (ANN). The results showed that the real-time fault diagnosis system is of high accuracy and quick convergence. It is also found that this model is feasible in real-time fault diagnosis. [7]

Srivastava et. al discussed that Condition based maintenance is most widely used basic maintenance approach, during which inspection of machine is carried out at variable time interval instead of fixed time period. Condition monitoring is

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carried out to evaluate the lifetime or to find out the health condition of motor and to calculate the degree or grade of deterioration. [8]

Deepak Kumar Gaud et. al used some Neural Network (NN) geometry and parameters for describing the process of fault classification. There is no any predefined formula to select the optimal values for these network parameters. [9]
Al-Raheem et. al showed that bearing fault diagnosis can be done by using three types of artificial neural networks (ANNs), namely, Multilayer Perceptron with BP algorithm, Radial Basis Function network, and Probabilistic Neural Network. [10]

Stack et. al discussed that most condition monitoring techniques for rolling element bearings are designed to detect the four characteristic fault frequencies. This leads to the common practice of categorizing bearing faults according to fault location (i.e., inner race, outer race, ball, or cage fault). [11]

Li et. al concluded that many problems arising in motor operations are linked to bearing faults Vibration simulation is used to assist in the design of various motor rolling bearing fault diagnosis strategies. Both simulation and real-world testing results obtained indicate that neural networks can be effective agents in the diagnosis of various motor bearing faults. [12]
From the literature review it can be concluded that less work has been done on determining remaining useful life of ball bearing using artificial neural network.

EXPERIMENTAL SETUP:
Experiments were conducted using a 2 hp Reliance Electric motor, and acceleration data was measured at locations near to and remote from the motor bearings. The test stand consists of a 2 hp motor (left), a torque transducer/encoder (center), a dynamometer (right), and control electronics (not shown). The test bearings support the motor shaft. Single point faults were introduced to the test bearings using electro-discharge machining with fault diameters of 7 mils, 14 mils, 21 mils, 28 mils, and 40 mils (1 mil=0.001 inches).
The vibration data using accelerometers which were attached to the housing with magnetic bases. Accelerometers were placed at the 12 o'clock position at both the drive end and fan end of the motor housing. During some experiments, an accelerometer was attached to the motor supporting base plate as well. Vibration signals were collected using a 16 channel DAT recorder, and were post processed in a Matlab environment. All data files are in Matlab (*.mat) format. Digital data was collected at 12,000 samples per second, and data was also collected at 48,000 samples per second for drive end bearing faults. Speed and horsepower data were collected using the torque transducer/encoder and were recorded by hand.

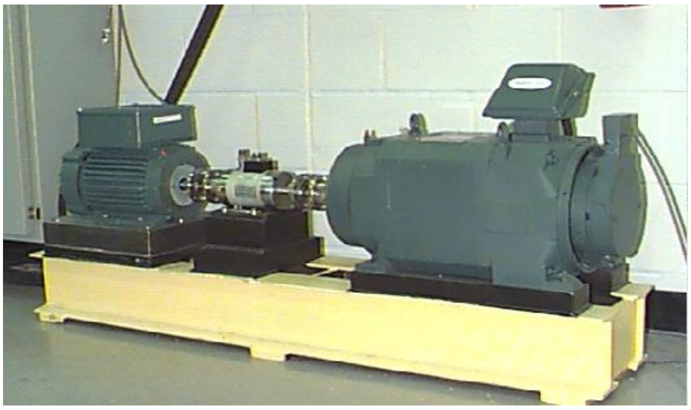


Fig. 7 Experimental Setup

Bearing Specifications:
Drive end Bearing 6205-2RS JEM SKF, deep groove ball bearing
Size- inches
Table 1 Specification of bearing

Inside Diameter	Outside Diameter	Thickness	Ball Diameter	Pitch Diameter
0.9843	2.0472	0.5906	0.3126	1.537

Result And Discussion:
Input data is trained for each corresponding output. Through hit and trail method of repetitive training we get a MATHEMATICAL MODEL having best co-relation between input and output.

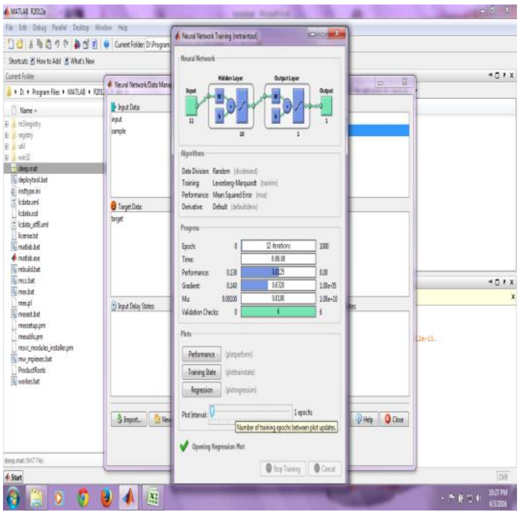


Fig. 8 Data Training

Performance Plot:
Performance plot shows variation of MSE (Mean Square Error) for training validating and testing data. From graph we can see error is continuously decreasing and best validation performance is at epoch 6. Hence we can say a very good simulation result will be obtained.

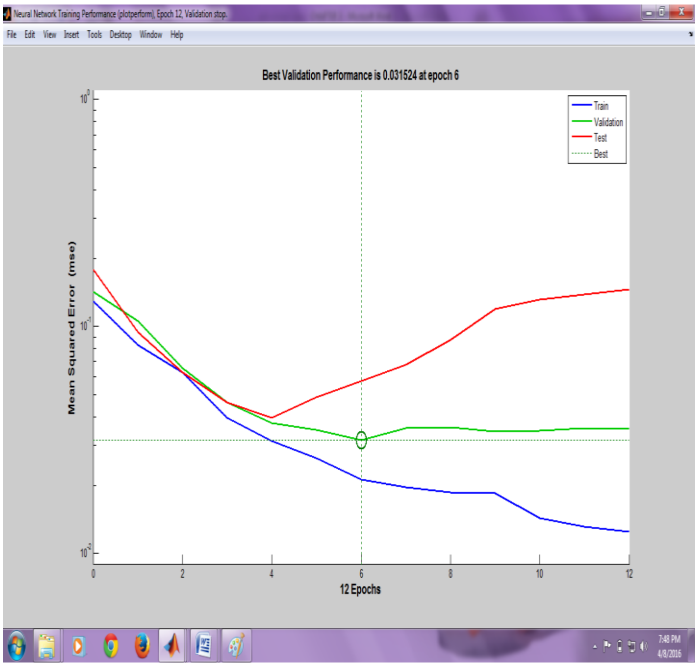


Fig. 9 Performance Plot

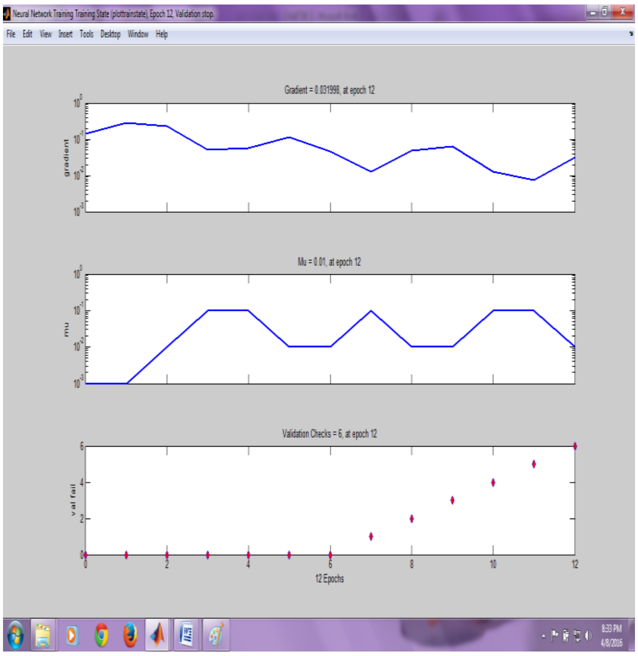


Fig.11 Training State plot

Regression Plot:

While training data, network creates its own output corresponding every target value. Regression plot shows the difference between them. For least difference and more accuracy, the curves for training, validating and testing must come closer to the dotted line.

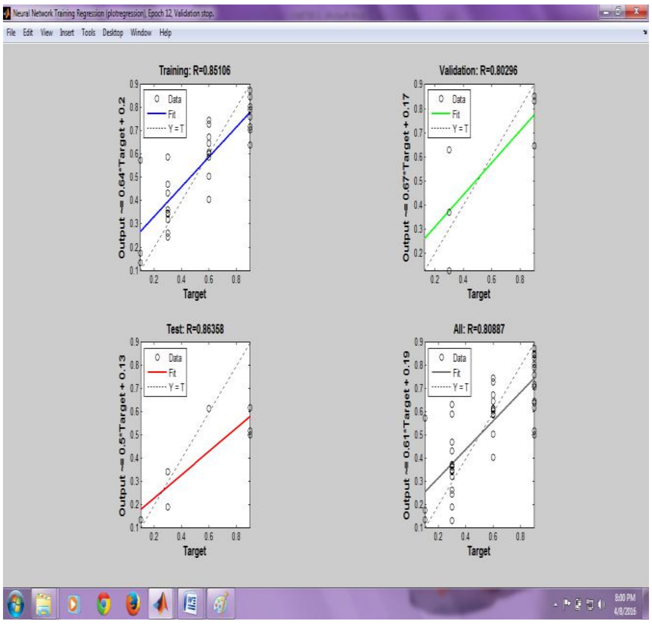


Fig. 10 Regression Plot

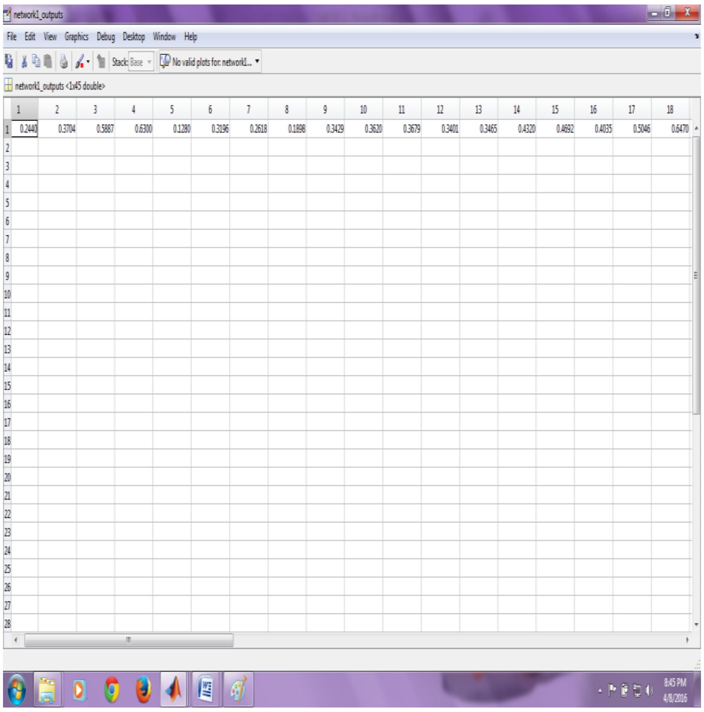
Training State Plot:

Training state plot shows gradient, mu and validation fail of input data during training.

Generation of network output

Output data is generated in neural network window as "network1_outputs".

Network output is the output generated by model network corresponding each target value


network1_outputs <1x45 double>

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	0.2440	0.3704	0.5887	0.6300	0.1280	0.3196	0.2618	0.1898	0.3429	0.3620	0.3679	0.3401	0.3465	0.4320	0.4692	0.4035	0.5046	0.6470

Fig. 12 Generated set of output data for inner race defect in bearing

International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 6 (2018) pp. 53-59

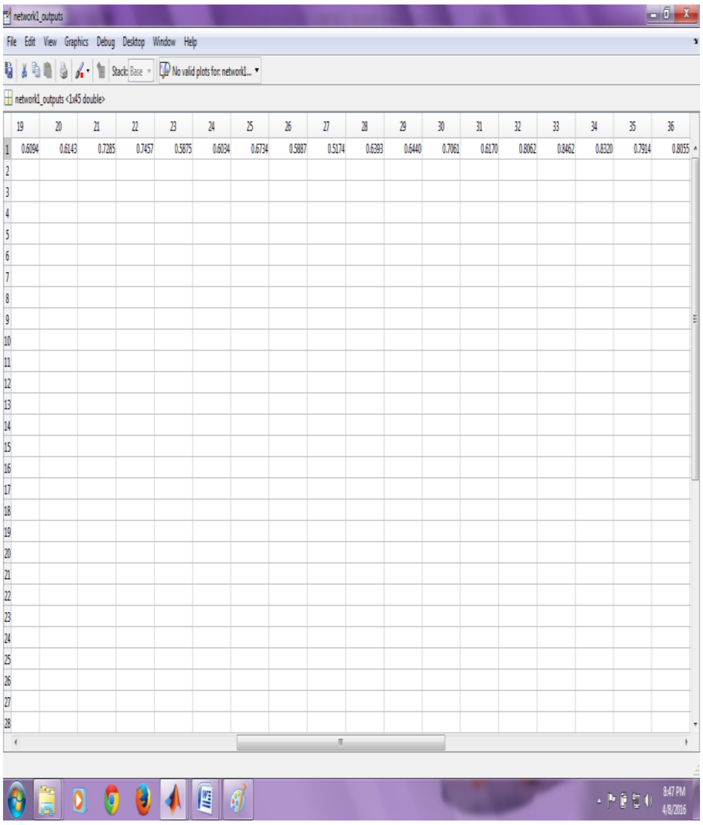


Fig. 13 Generated set of output data for outer race defect in bearing

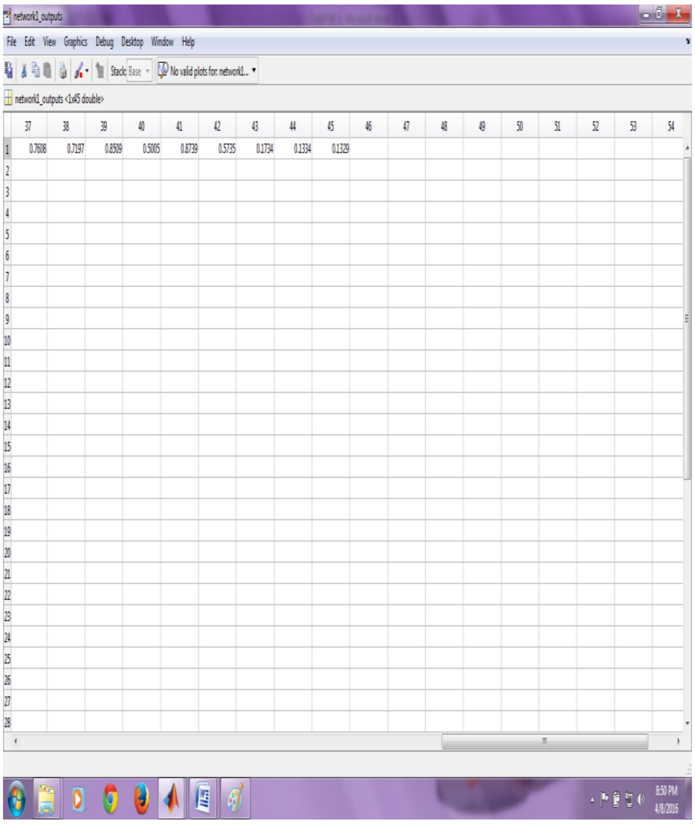


Fig. 14 Generated set of output data for ball defect in bearing

Predicted output corresponding each input sample is " 0.2429 , 0.5989 and 0.8029" (as shown in fig.15)

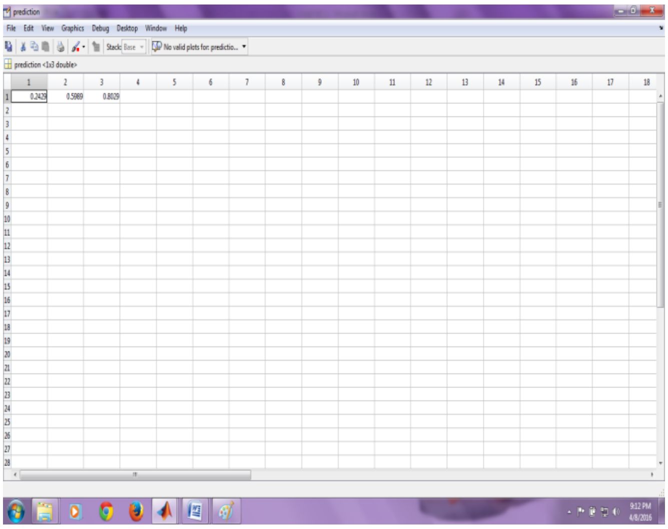


Fig.15 Predicted data for sample

Exact output corresponding each input sample is " 0.3 , 0.6 and 0.9". Where,

0.3 shows INNER RACE DEFECT IN BEARING

0.6 shows OUTER RACE DEFECT IN BEARING

0.9 shows BALL DEFECT IN BEARING

The closeness of the predicted output data corresponding to given sample with values 0.3, 0.6 and 0.9 shows the respective fault in the bearing. This shows that the Mathematical model created in Matllab gives best possible result and can be used to predict the defect in any bearing provided that sample input data is to be in normalized form.

Conclusion:

From the above mentioned results it can be concluded that proposed methodology along with machine learning techniques shows potential application for development of real time fault diagnosis system.

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