Automated System for Condition Monitoring of Deep Groove Ball Bearing using Frequency Domain and Artificial Neural Network

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Abstract - *Frequency of bearing failure is high in any machinery as compared to its other components and hence they are often responsible for the machine breakdown. Defect in bearing may not be seen at an earlier stage by naked eyes. Increase in defect size may lead to catastrophic failure of bearing. This results in decrease in productivity and increases down time of a machine. This paper aims to do experimentation and analysis of healthy and faulty bearings. The methodology mainly consists of a time domain and frequency domain analysis. The time domain and frequency domain analysis is carried out using fast Fourier transform. The softwares used are labview and Matlab. The results from LabView were used to train the Artificial Neural Network in Matlab to form an automated system for condition monitoring.*

Key Words: Deep groove ball bearing, Fast Fourier Transform, Time and frequency domain analysis, Labview, Matlab, Automation, Artificial Neural Network

1. INTRODUCTION

The purpose of bearings is to reduce the friction and support loads. Most engineering applications such as electric motors, bicycles, roller skates from complex mechanisms of engineering such as power transmissions, gyroscopes, rolling mills and aircraft gas turbines use these bearings, which enable rotary motion of the shaft. In industry, breakdown of such crucial components causes heavy losses.

While rotors are responsible for only 10%, bearings are responsible for about 50% of all faults i.e. frequency of bearing failure is high in any machinery as compared to its other components and hence they are often responsible for the machine breakdown(fig.-1).

The presence of bearing faults such as spalling, peeling, galling, or failure of the bearings due to misalignment, shaft slope, surface roughness, high extent of waviness and inclusions etc. causes a sudden failure of the system. Bearing failures result in serious problems, mainly in places where machines rotate at constant and high speed. In order to prevent any catastrophic consequences caused by bearing failure, bearing condition monitoring techniques have been developed to identify the existence of flaws in running bearings. Vibration analysis is the most commonly accepted technique due to its ease of application.

Health of rolling element bearings can be easily identified using vibration monitoring because vibration signature reveals important information about the fault development within them. Numbers of vibration analysis techniques are being used to diagnose rolling element bearings faults such as wear debris analysis, motor current analysis, noise monitoring, temperature monitoring, vibration monitoring etc.

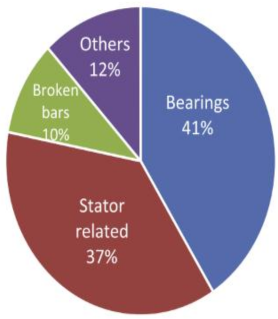

Fig. -1: Piechart depicting faults in components

2. Literature Review

S. V. Shelke A. G.Thakur Y.S.Pathare. Based on the studies carried out on vibration monitoring of bearings, it can be concluded that Fast Fourier Transformation spectrum indicates the location of the fault.[1] Additional findings- Additionally, RMS, Skewness, Variance, Mean, Standard Deviation, few of the statistical parameters are evaluated for above conditions of bearing. From the plots of extracted features against Load, it is clear that these features have potential to identify the defects in the bearing as the plots of healthy bearing and defective bearing are not overlapped.

Madhavendra Saxenaa, Olvin Oliver Bannettb, Vivek Sharmaa. The faulty bearing vibration data as compared with the healthy bearing. awt and power spectral density (psd) proved to be an effective tool for brief classification of fault.[2] Additional findings- The bearing fault detection

and its prognosis plays a vital role in saving money as well as production losses in very critical applications like wind turbine; oil refineries etc. From this paper we have seen three methods of bearing fault analysis and its prognostics.

Sukhjeet Singh, Amit Kumar, Navin Kumar. The bearing faults outside the induction motor can be detected by monitoring the magnitudes of the current harmonics at | fs +or- ff |. This fact is strengthened by comparing the analysis of these frequencies using acoustic and wavelet signatures.[3] Additional findings- A continuous increase of sidebands around the running speed also gives an indication of the faulty bearing, because it has been ensured in the system that no electrical fault exists in the system except the bearing fault outside the induction motor.

Qiuhua Du, Shunian Yang. The time waveform indicated the severity of vibration in defective bearings.Frequency spectrum helps in identifying the exact nature of the defect in bearing.[4] Additional findings- In this study, the bearing with defects in outer race, inner race and rolling element defect has been studied and frequency spectrum and time domain graphs are obtained and drawn for various speeds. Bo Li, Gregory Goddu, Mo-Yuen Chow. A method of using neural networks to interpret vibration signals of electric motors in order to detect bearing faults were presented. Using the frequency spectrum of the vibration signal to train an artificial neural network, the authors were able to achieve excellent results with minimal data[5]. Additional findings - The neural networks are capable of high detection accuracy of bearing defects using frequency spectrum signals. By additionally incorporating the time domain signal, specifically the presence of peak amplitudes, the severity of the defect should be ascertainable. Eventually, this hybrid frequency and time-domain approach should give further insight into the presence and severity of motor bearing faults.

3. Methodology

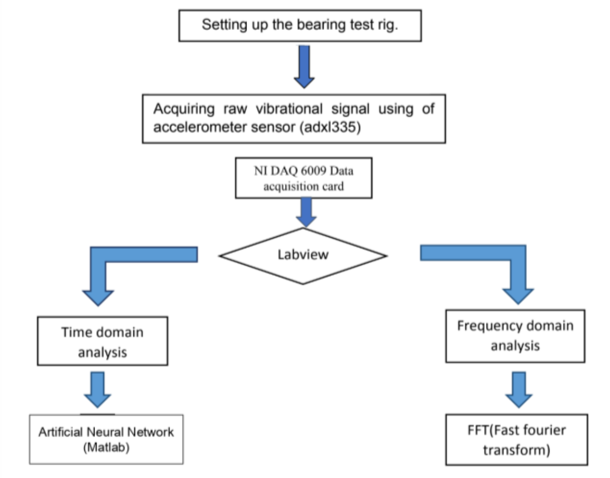

Fig -2: Methodology

4. Theoretical Background

Frequency domain, or spectral analysis, is the most popular approach for the diagnosis of bearing faults. Frequency-domain techniques convert time-domain vibration signals into discrete frequency components using a fast Fourier transform (Fast Fourier Transformation).

Simply stated, Fast Fourier Transformation mathematically converts time-domain vibration signals trace into a series of discrete frequency components. The main advantage of frequency-domain analysis over time-domain analysis is that it has the ability to easily detect the certain frequency components of interest. The detailed knowledge of bearing characteristics frequencies required to identify the location of defects in rolling element bearing. Power spectrum is used to identify the location of rolling element defects by relating the characteristic defect frequencies to the major frequency components which can be found in the spectrum.

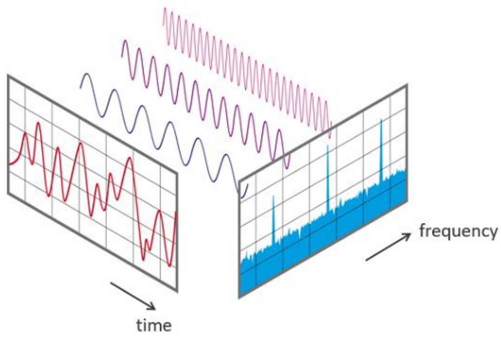

Fig -3: Fast Fourier Transform (FFT)

Each bearing element has a fundamental defect frequency that depends on the bearing geometrical parameter. The product of multipliers with the shaft rotational speed gives the defect frequency of bearing running at given shaft speed by identifying the type of the bearing characteristics frequency, the cause of the defect can be determined. The bearing frequency multipliers equations provide a theoretical value of the frequency whenever the bearing element fault takes place.

$$BPFI = \frac{\omega Z}{2}\left[1 + \left(\frac{D_e}{D_p}\right)\cos cos\, \beta\right]$$

$$BPFO = \frac{\omega Z}{2}\left[1 - \left(\frac{D_e}{D_p}\right)\cos cos\, \beta\right]$$

$$BSF = \frac{\omega D_p}{2D_e}\left[1 - \left(\frac{D_e}{D_p}\right)\cos cos\, \beta\right]^2$$

Where,

Dp = Pitch dia; De = Ball dia; ⍰ = contact angle;

z = No. of balls; ω = shaft speed.

Table -1: Characteristics frequency factor

Bearing characteristics frequency	Factor
Ball pass frequency of inner race (BPFI)	5.43
Ball pass frequency of outer race (BPFO)	3.57
Rolling element defect frequency (2 x BSF)	3.02

5. Experimental Setup

The bearing test rig is designed and used to identify the defects on a deep groove ball bearing by vibration analysis technique is shown in Figure 1. The test rig consists of a circular shaft, having two deep groove ball bearings of 6206-z2 series. An induction motor with variable speed drive is coupled to drive the shaft. The shaft is coupled with a coupling to minimize the effect of the high vibration frequency generated by the 1/4HP motor. The motor is connected to a variable speed control unit for achieving variable speeds. The bearing test rig was operated at 900 rpm. For analyzing vibration signals from the test rig a provision is made to mount the accelerometer on top of the test bearing housing. The connection from accelerometer is connected to NI Daq card, which is further connected to Labview software in the device.

Fig -4: Experimental Setup

5.1 Labview Circuit

The circuit was designed in the software Labview which is used for the diagnosis of signals from the sensor.

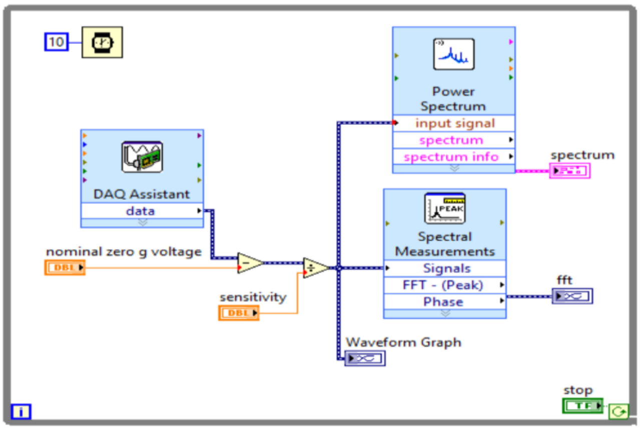

Fig -5: Labview Circuit

5.2 Elements calculated

The data has been analysed for a For deep groove ball bearing (6206-z2) at 900 rpm.

i. Ball diameter = 9.53mm

ii. Pitch diameter = 46mm

iii. Contact angle = 0

iv. Number of balls = 9

Table -2: Statistical elements calculated

Sr. No	Statistical Indicator	Formula	Remark
1	Root Mean Square (RMS)	$\sqrt{\frac{\sum_{n=1}^{N}(x(n)-\mu)^2}{N}}$	It is the normalized second statistical moment of the signal.
2	Kurtosis	$\frac{\sum_{n=1}^{N}(x(n)-\mu)^4}{N\ \sigma^4}$	It is the normalized fourth statistical moment of the signal. Provides measure of the impulsive nature of the signal.
3	Skewness	$\frac{\sum_{n=1}^{N}(x(n)-\mu)^3}{N\ \sigma^3}$	It is a measure of symmetry, or more precisely, the lack of symmetry.
4	Maximum	$\max[x]$	Finds the highest point in a set of values.
5	Minimum	$\min[x]$	Finds the lowest point in a set of values.
6	Range	$\max[x]-\min[x]$	It is the difference in maximum & minimum point values.
7	Crest Factor	$\frac{peak\ vlue}{RMS\ Value}$	Its ratio of peak level to RMS level. It indicates the presence of high amplitude peaks caused by local damages.
8	Form Factor	$\frac{RMS\ Value}{Mean\ Value}$	Ratio of RMS value to mean value. Indicates the overall status of signal.
9	Mean	$\frac{\sum_{n=1}^{N}(x(n))}{N}$	Average of all the amplitude of digitised points sampled.
11	Variance	$\frac{\sum_{n=1}^{N}(x(n)-\mu)^2}{N}$	Indicates the spread of the amplitude of the values from its mean.
Where x(n) = amplitude of the n^{th} digitized point in the time domain, N = number of points in time domain and μ = mean of the N points, σ = standard deviation,			

6. Results and Discussions

The results are carried out on a healthy bearing 6206-z2, The results were carried out using the Labview software. The frequency values are carried out using NI daq 6009.

The following graphs shows the raw signal and their Fast Fourier Transformation for 900 rpm:

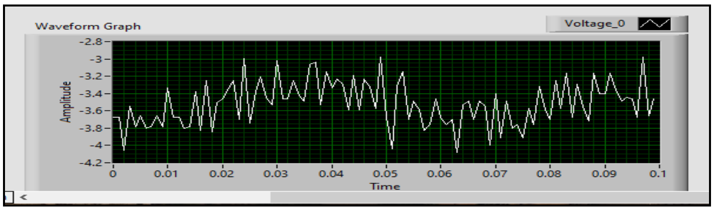

Fig -6: Waveform graph

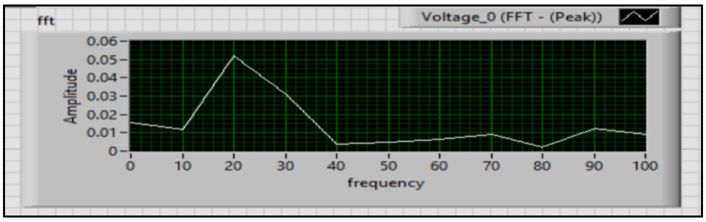

Fig -7: FFT graph

Figure 6 and 7 represents the raw signal and frequency signal at 900rpm respectively.

In figure 7 we can see the highest or peak frequency.

Table -3: Fault frequencies at 900 rpm

	Frequency (Hz)	Fault frequencies calculated theoretically at 900 rpm (15 Hz)	Fault frequencies calculated experimentally at 900 rpm (15 Hz)
BPFI	15	81.45	20
BPFO	15	53.55	20
2 x BSF	15	45.3	20

The following table shows the theoretical and experimental frequency at 900 rpm

Experimental test results clearly show the bearing is not faulty as the peak frequency in the frequency spectrum is below the characteristic fault frequencies.

7. Automation of System using Artificial Neural Network

Drawbacks of Fast Fourier Transformation

- It is hard to analyse data in time domain as the data has very less observational differentiations.
- Observational classifications need a lot of expertise.
- The data obtained is not very ideal. It contains a lot of noise. Also to pick up exact detail from the spectrum which points towards the fault has a lot of scope of human errors.

To overcome the drawbacks of Fast Fourier Transformation, an algorithm can be developed using an Artificial neural network which predicts the outcome instantaneously based upon the given training data and thus eliminates the need to perform the above process repetitively. And thus providing an accurate automated system.

7.1 Artificial Neural Network

Artificial neural networks are computational models which work similar to the functioning of a human nervous system. Artificial Neural Network, work on the principle of training the software. Artificial Neural Network was applied using the MATLAB Artificial Neural Network toolbox.

Learning Rule:

The Neural Network information is stored in the form of weights and bias.

i. Weights- Amount of effect that a certain input has in the output.

ii. Bias : A constant to shift the value obtained by activation function

iii. Activation functions: mathematical equations that determine the output of a neural network

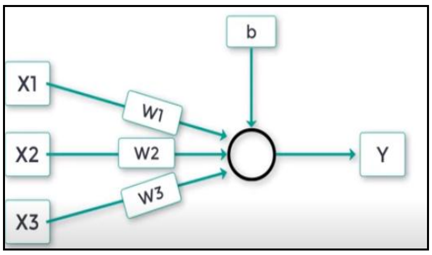

Fig -8: Learning rule

7.2 Typical Workflow for Designing Neural Networks

Each neural network application is unique, but developing the network typically follows these steps:

i. Access and prepare your data

ii. Create the neural network

iii. Configure the network's inputs and outputs

iv. Tune the network parameters (the weights and biases) to optimize performance

v. Train the network

vi. Validate the network's results

vii. Integrate the network into a production system

7.3 Artificial Neural Network Data Analysis

We gave input data in the form of 11 different statistical parameters (Rms (g), Standard deviation, variance, kurtosis, skewness, maximum, minium, range ,arithmetic mean 1, arithmetic mean 2, cf=max/rms)

Table -4: Target output

Type	Target Output
Healthy	1
Faulty	0

	A	B	C	F	G	H	I	J	K	L	M	N	O
1	Time	Amplitude	Kurtosis	rms	Standard Deviatio	Variance	Skewness	Maximum	Minimum	Range	Arithematic Mean	cf=max/rms	Output
2	3.577058	0.460072	-1.26703	0.784539	0.730405482	0.533492	-0.10638	0.460072	-1.37845	1.838523	-0.434404494	0.58642391	0
3	0.022932	-3.54374	-1.594	3.461695	0.228567973	0.052243	0.721827	-3.13642	-3.66943	0.533012	-3.455653036	-0.906035	1
4	0.013528	-3.7765	-1.65369	3.615312	0.130041098	0.016911	-0.0936	-3.45607	-3.7765	0.320422	-3.613440298	-0.9559544	1
5	3.956932	-1.37845	-2.70374	1.16796	1.284451894	1.649817	-0.39694	1.126039	-1.75627	2.882313	-0.210420436	0.96410739	0
6	10.89518	-0.68596	-1.26548	0.678	0.721275073	0.520238	0.12096	1.132375	-0.68596	1.818333	0.208552706	1.67016918	0
7	5.628253	0.405042	-0.86039	0.712847	0.795386528	0.63264	0.283373	1.031979	-1.00188	2.033861	-0.045163228	1.44768577	0
8	5.30863	-0.40985	2.188371	1.30214	1.313515425	1.725323	1.404881	1.594283	-1.77954	3.373826	-0.561525385	1.22435624	0
9	0.006864	-3.77612	-0.99963	3.639604	0.161066438	0.025942	0.875114	-3.40209	-3.77612	0.374035	-3.636751425	-0.9347412	1
10	0.03139	-3.36256	-1.08669	3.371349	0.077370744	0.005986	0.376819	-3.26349	-3.45182	0.188334	-3.370638908	-0.9680062	1
11	4.637687	-1.96568	-2.86901	1.530386	1.630390728	2.658174	-0.55864	1.063744	-2.47176	3.535503	-0.464266819	0.69508205	0
12	0.033386	-3.33654	0.733064	3.308147	0.087848544	0.007717	-0.69344	-3.20435	-3.43879	0.234437	-3.307214044	-0.9686249	1
13	6.252529	2.312041	2.229548	2.284592	1.296430819	1.680733	-1.46834	3.110566	-0.17019	3.280755	1.968444385	1.36154129	0
14	4.954668	0.686841	-2.04491	1.991716	1.156692361	1.337937	-0.06674	3.1222	0.365524	2.756676	1.701935608	1.56759254	0
15	4.047498	-0.42436	0.522722	1.136327	0.95826849	0.918278	0.878552	0.713382	-1.75627	2.469657	-0.746066489	0.62779685	0
16	4.163028	-0.88463	-2.27888	1.125634	1.055834224	1.114786	0.351277	0.713382	-1.75627	2.469657	-0.612553843	0.63376061	0
17	0.018771	-3.64916	-1.30018	3.476594	0.13609797	0.018523	-0.06342	-3.30709	-3.64916	0.342071	-3.474462105	-0.9512435	1
18	7.564479	0.199941	-1.79734	0.923386	0.681356696	0.464247	-0.01286	1.525773	-0.13787	1.663645	0.693717543	1.65236736	0
19	4.352714	0.713382	-1.85202	0.888345	0.611456831	0.373879	0.019984	1.452092	-0.03452	1.486614	0.700038326	1.63460275	0
20	6.250328	3.110566	-3.06284	1.896011	1.767677425	3.124683	0.517316	3.110566	-0.6361	3.746664	1.046475311	1.64058446	0

Fig -9: Sample Training Data (900 rpm)

Similarly around 150 datasets were used to train the network.

7.4 Artificial Neural Network Data Analysis

Time	Amplitude	Kurtosis	rms	Standard Deviatio	Variance	Skewness	Maximum	Minimum	Range	Arithematic Mean	cf=max/rms	Output
0.054234	-3.6825	1.285122	3.678637	0.070737829	0.005004	-0.5375	-3.58972	-3.78363	0.193912	-3.678092758	-0.975829	1
0.05605	-3.58972	-0.12593	3.649054	0.095846596	0.009187	-0.38026	-3.53227	-3.78363	0.251362	-3.648047119	-0.9679962	1
0.056499	-3.68749	0.46485	3.679573	0.096908456	0.009391	0.797465	-3.53227	-3.78363	0.251362	-3.678552371	-0.9599675	1
11.51354	0.981566	0.964436	0.536564	0.589391772	0.347383	0.648642	0.981566	-0.6125	1.594063	0.099972414	1.82935525	0
11.79844	-0.6125	-1.69883	0.417408	0.395158159	0.15615	0.116419	0.295167	-0.62858	0.923748	-0.222056964	0.70714203	0
12.10457	-0.0711	0.356764	0.361049	0.403006292	0.162414	-0.77727	0.394701	-0.62858	1.023282	-0.020617221	1.0932062	0

Fig -10: Testing Data Set

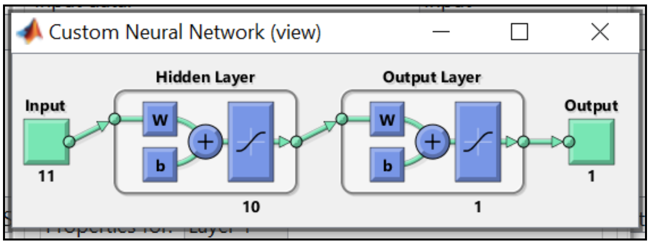

Fig -11: Neural Network

7.5 Artificial Neural Network Training

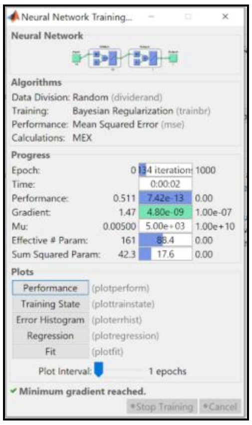

Fig -12: Network Training in Matlab

Number of inputs : 11

Number of layers: 10

Number of output: 1 (healthy or faulty)

The training algorithm used here is Bayesian Regularization.

For a given set of amplitudes, the known output was given to the system for training.

7.6 Analysis

(i) Performance Graph -

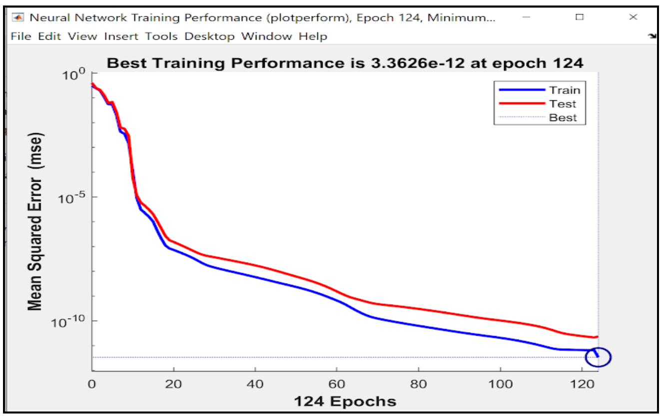

Fig -13: Performance Graph

Performance is measured in terms of mean squared error, and shown in log scale. It rapidly decreased as the network was trained.

(ii) Error Histogram -

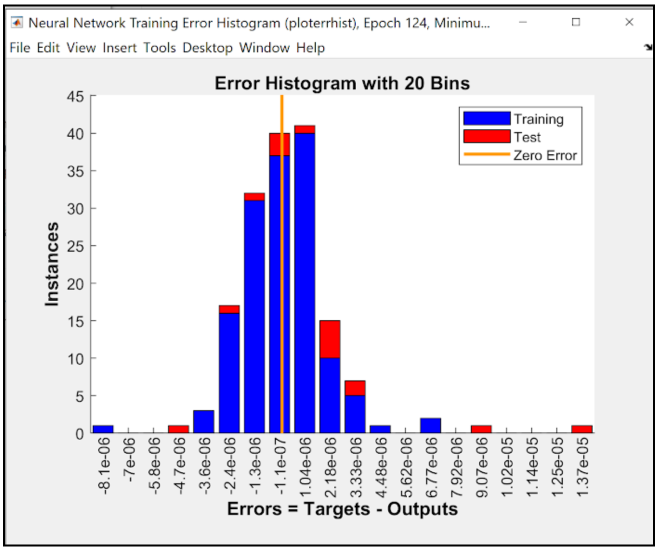

Fig -14: Error Histogram

The error histogram shows how the error sizes are distributed. Typically most errors are near zero, with very few errors far from that.

(iii) Regression curve-

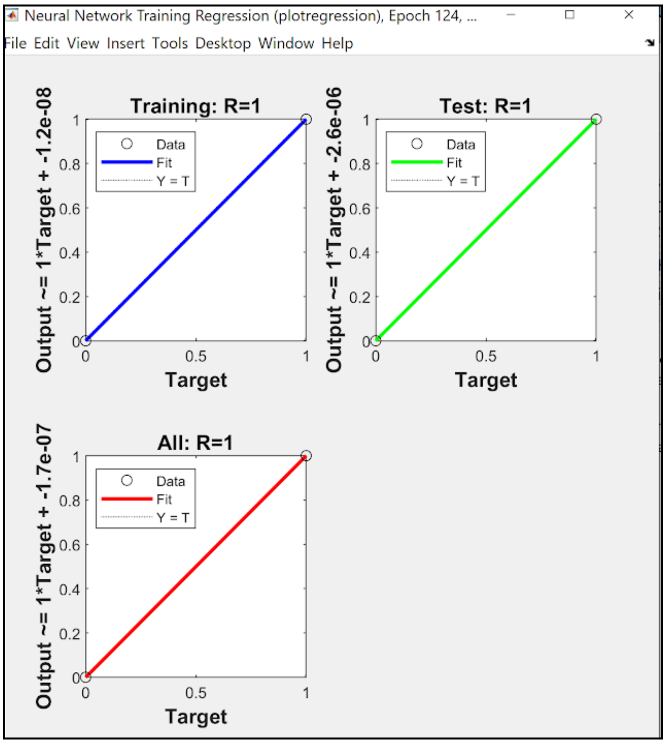

Fig -15: Regression Curve

The regression plot shows the actual network outputs plotted in terms of the associated target values. If the network has learned to fit the data well, the linear fit to this output-target relationship should closely intersect the bottom-left and top-right corners of the plot.

7.7 Artificial Neural Network Results

Table -5: Predicted Results by network network

Expected Result	Predicted Result
1	1
1	1
1	1
0	2.6367e-05
0	4.8102e-05
0	1.7605e-05

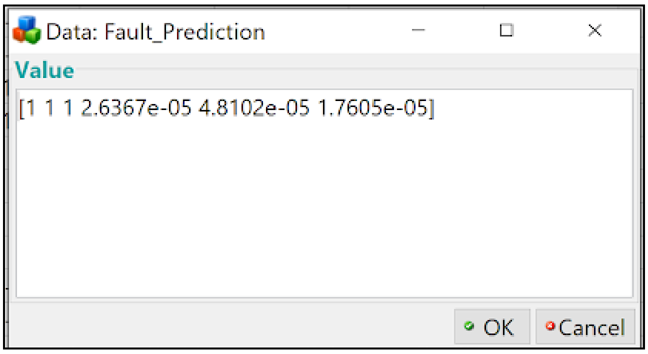

Fig -16: Fault Prediction

8. Results

Experimental setup was developed for condition monitoring of healthy bearing. Data was collected using NI LabView and NI DAQ cards. Data was processed to obtain statistical features. Artificial Neural Network was trained with statistical features of Time domain vibration signals. For given sample data, the output was correctly predicted using Artificial Neural Network.

The software was trained using the artificial neural network of Matlab. 80% of data was used in training, 10% for validation and 10% for testing. Regression plot shows high accuracy, which provides the data is valid. The error histogram also gives minor errors. The algorithm developed can be further improved and used to correctly predict if the bearing is faulty or healthy.

Thus due to drawbacks of Fast Fourier Transformation, an algorithm can be developed using an Artificial neural network which predicts the outcome instantaneously based upon the given training data and thus eliminates the need to perform the above process repetitively. And thus providing an accurate automated system.

9. Conclusion

The data has been analysed for a bearing (6206-z2) at no load condition and 900 rpm. Different methods of data analysis were used, including time domain analysis (in Matlab), frequency domain analysis (in Matlab), Artificial Neural Network (deep learning toolbox Matlab). Comparison of fault frequencies for theoretical and experimental data was done for healthy bearing. 11 elements of data are used for the analysis. The elements are obtained directly through labview. Analysis using a deep learning toolbox of matlab have generated expected results validating the data. Both Fast Fourier Transformation and Artificial Neural Network can be used for analysing vibrational faults. But the Artificial Neural Network being more statistically accurate, yielded better results than Fast Fourier Transformation.

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Thank You.

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