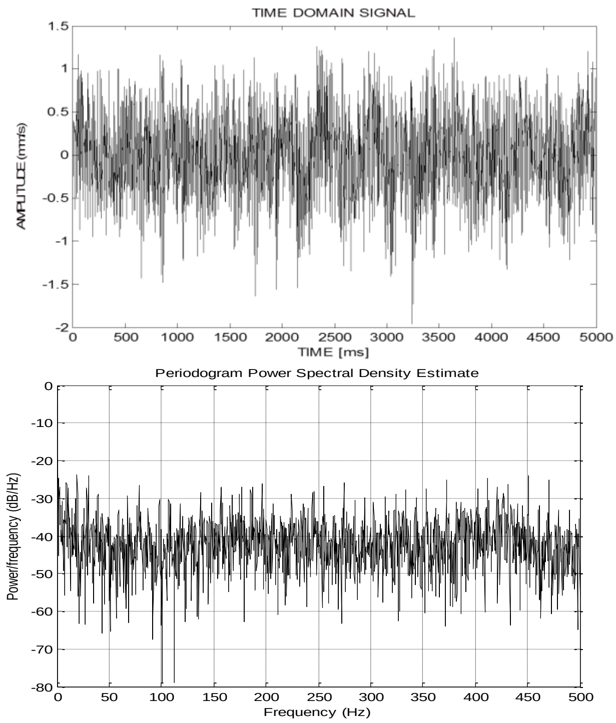
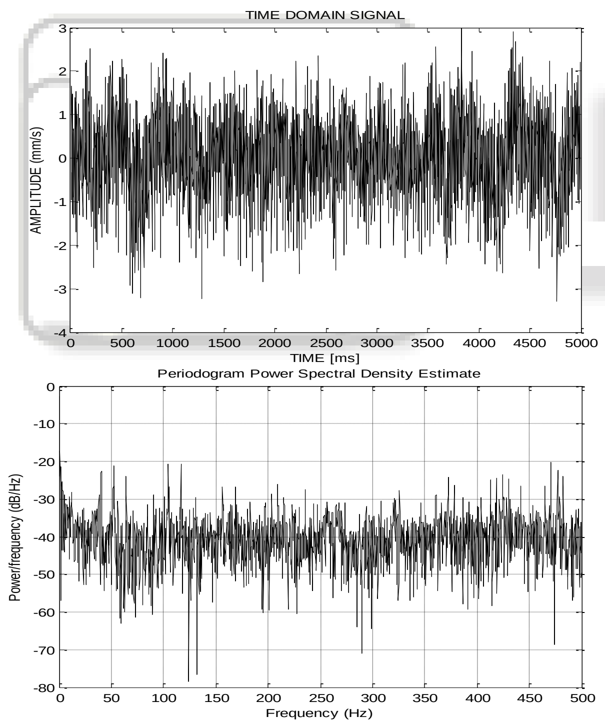
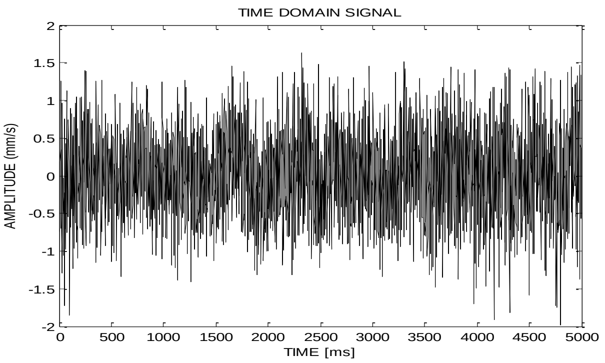


Fig (7): Defective Bearing 1200 RPM



Fig(8): Defective Bearing 1800 RPM



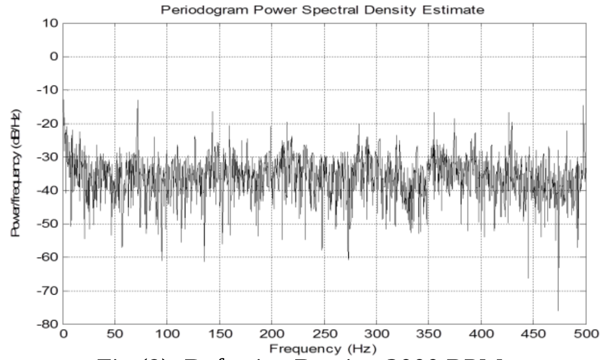


Fig (9): Defective Bearing 2000 RPM

V. FEATURE SELECTION

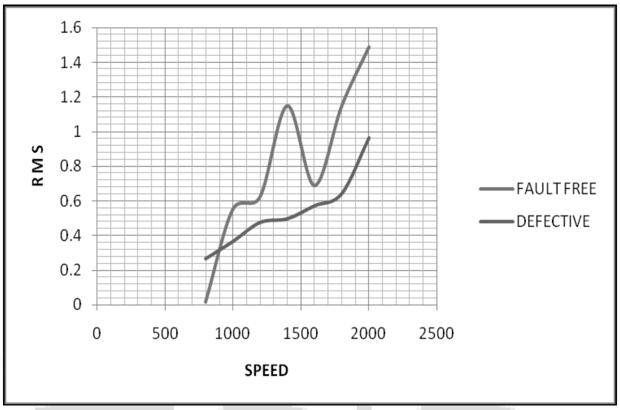


Fig (10): Comparison of RMS

Here we compare different 17 features of the fault free bearing with defective bearing and the feature which have distinct value from two bearing are selected for further analysis.

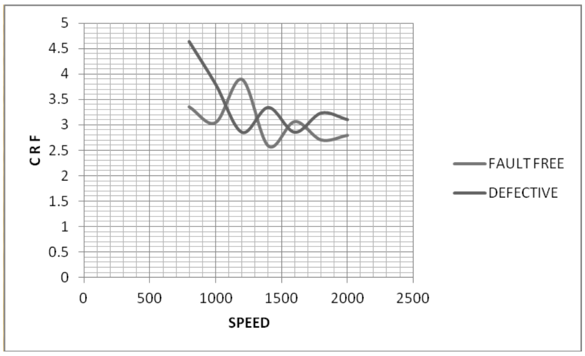


Fig (11): Comparison of CRF

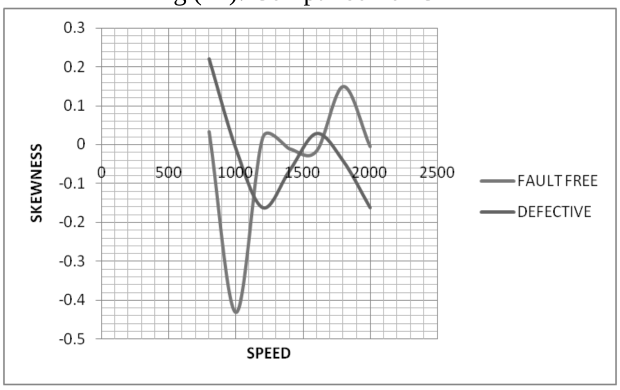


Fig.(12): Comparison of SKEWNESS

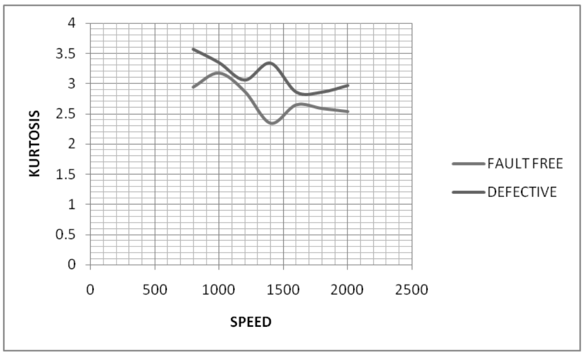


Fig (13): Comparison of KURTOSIS

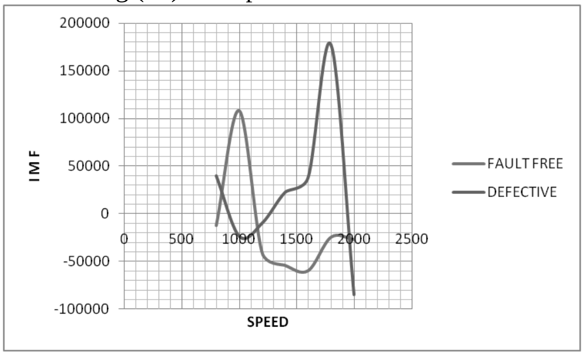


Fig (14): Comparison of IMF

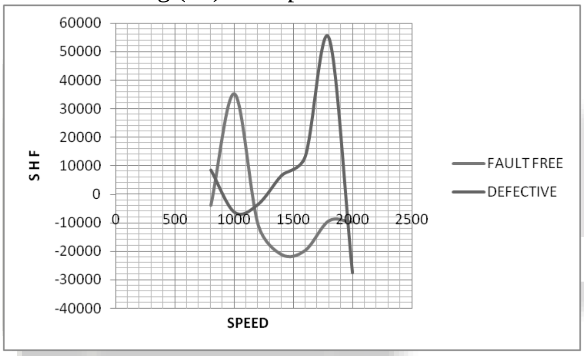


Fig (15):.Comparison of SHF

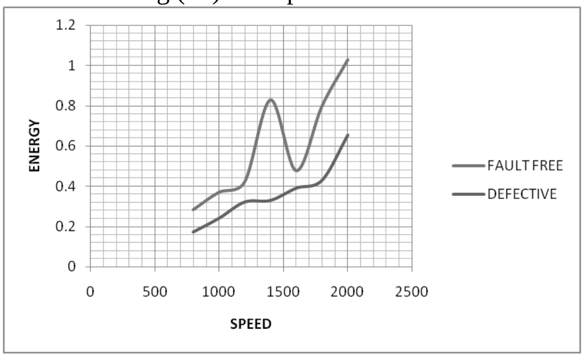


Fig (16): Comparison of Energy

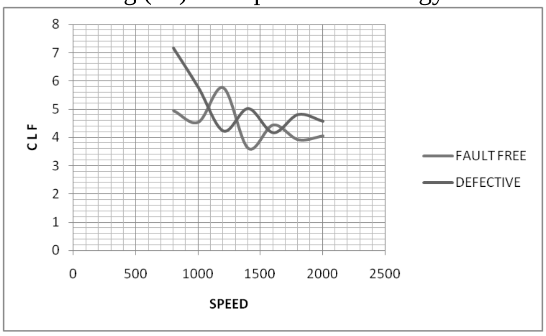


Fig (17): Comparison of CLF

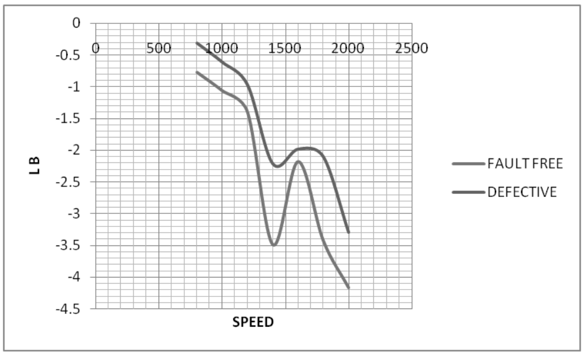


Fig (18): Comparison of LB

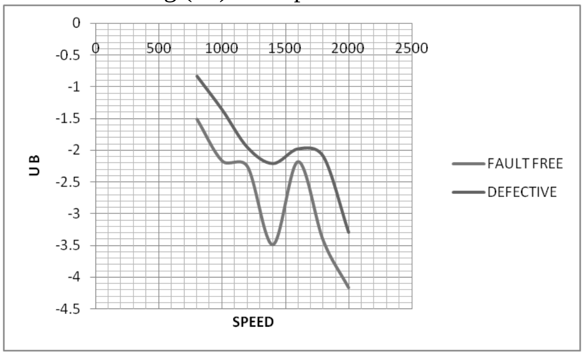


Fig (19).Comparison of UB

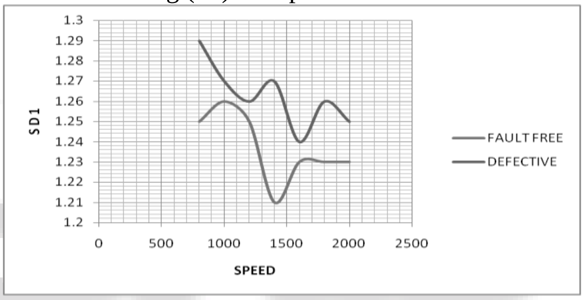


Fig (22): Comparison of SD 1

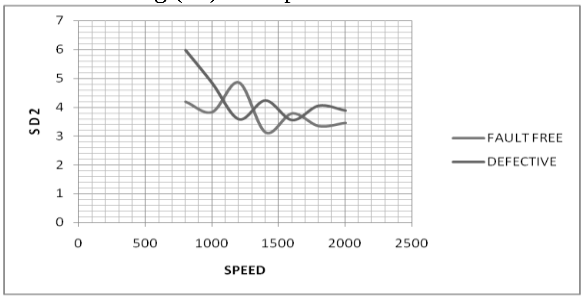


Fig (23): Comparison of SD 2

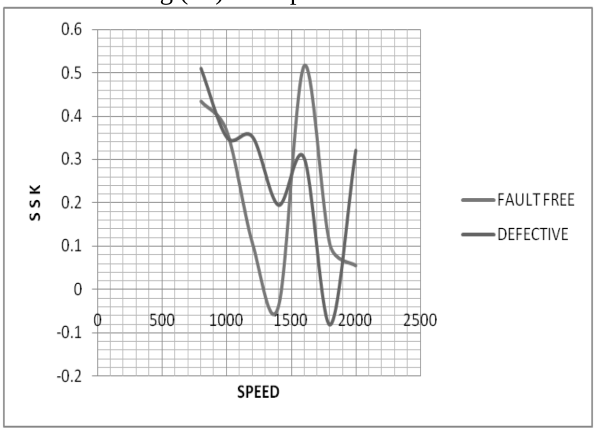


Fig (24).Comparison of SSK

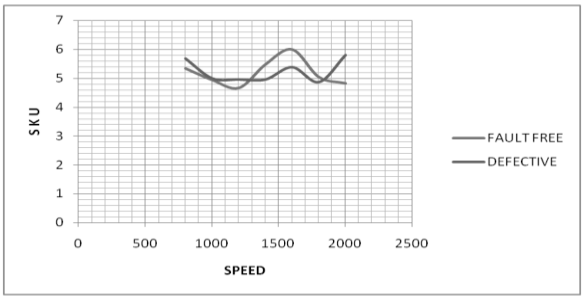


Fig (25): Comparison of SKU

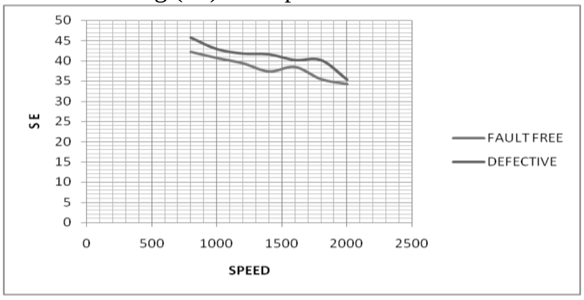


Fig (26): Comparison of SE

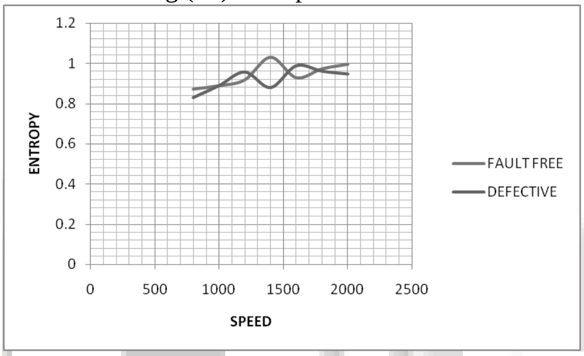


Fig (27):Comparison of Entropy

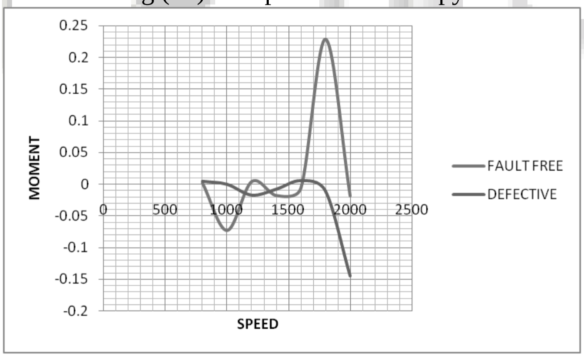


Fig (28): Comparison of Moment

VI. SYSTEM MODELING WITH NEURAL TECHNIQUE

The feed forward neural network, used in this work, consists of input layer, hidden layer and output layer. The input layer has nodes representing the features extracted from the measured vibration signals. The ANN was created, trained and implemented using Matlab neural network function with back propagation. First we start the work by assuming a fixed structure for the ANN for our convenience. The structure is given by: This ANN has 3 layers in total they include the input layer having 7 nodes, the output layer having 2 nodes, and one hidden layers. In the ANN, the activation functions of sigmoid were used in the hidden layers and in the output layer. The results of convergence plots for various structures of ANN i.e. for various no. of neurons in each layer, various training algorithm are obtained and the conclusion for the optimum no. of neurons in each layer and the optimum training algorithm are deduced.

NO. OF HIDDEN LAYER	TRAINBFG		
	Error	Iteration	Accuracy (%)
20	0.0605	6	66.66
25	0.1494	9	66.66
30	0.4286	9	100
35	0.3965	8	100

Table (3): Performance of TRAINBFG

NO. OF HIDDEN LAYER	TRAINGDM		
	Error	Iteration	Accuracy (%)
20	0.47145	36	33.33
25	0.17883	10	66.66
30	0.47145	36	33.33
35	0.48421	41	100

Table (4): Performance of TRAINGDM

NO. OF HIDDEN LAYER	TRAINLM		
	Error	Iteration	Accuracy (%)
20	0.0605	6	66.66
25	0.49714	6	33.33
30	1.265	5	100
35	0.40586	7	33.33

Table (5): Performance of TRAINLM

From Table we can conclude that TRAINGDM is 100% accurate at 35 hidden layers but its run for highest no. of iteration compare to other. While TRAINLM give 100% accuracy but at a highest cost of error compare to other, So we get best performance in terms of error, No. of iteration and Accuracy in TRAINBFG training algorithm with no. of hidden neurons 35. So we train our feed forward neuron network with TRAINBFG training algorithm and with 35 no. of hidden neurons which give 100% classification accuracy. Then this train network is used for test new fresh data which taken from interpolation of the original data.

VII. CLASSIFICATION RESULT

It has been noticed that the network clearly distinguished a defective bearing from a normal bearing with cent per cent accuracy, as seen from the Table bellow.

Test Pattern	Speed	Actual Class	Network Classification	
			NB	DB
1	900	NB	NB	

2	1100	NB	DB	
3	1300	NB	NB	
4	1500	NB	NB	
5	1700	NB	NB	
6	1900	NB	NB	
7	900	DB		DB
8	1100	DB		DB
9	1300	DB		DB
10	1500	DB		DB
11	1700	DB		NB
12	1900	DB		DB

Table (6): Classification Result

Architecture	No. of test patterns	No. of correct classifications	Accuracy
7-35-1 TRAINBFG	12	10	83.33 %

Table (7): Classification Conclusion

VIII. CONCLUSION

It is not advisable to use all the features for online condition monitoring of the system. The reason is that some of the features have correlation with each other. And give ambiguous behaviour.

The performance of the back propagation neural network in recognizing bearing states has been found to be exceptionally good. Using the proposed neural network, any defective bearing can be distinguished from a normal one with cent per cent reliability.

IX. REFERENCES

[1] Liu, T. I. and Mengel, J. M. 1992. Intelligent monitoring of ball bearing conditions, Mechanical Systems and Signal Processing, Vol. 6, No. 5, pp.419-431.

[2] B. Liu, S. Ling, Machinery diagnostic based on wavelet packets, Journal of Vibration and Control 3 (1997) 5–17

[3] Subrahmanyam, M. and Sujatha, C. 1997. Using neural networks for the diagnosis of localized defects in ball bearings, Tribology International, Vol. 30, No. 10, pp. 739 – 752.

[4] Zeki Kiral, Hira Karagulle "Simulation and analysis of vibration signals generated by rolling element bearing with defects", Journal of Tribology International (2003) Vol.36, pp.667–678.

[5] K.L.X. Lou, Bearing fault diagnosis based on wavelet transform and fuzzy inference, Mechanical Systems and Signal Processing 18 (2004) 1077–1095.

[6] Yang Yu, YuDejie, Cheng Junsheng, A roller bearing fault diagnosis method based on EMD energy entropy and ANN, Journal of Sound and Vibration 294 (2006) 269–277

[7] Q.Hu,Z.He,Z.Zhang,Y.Zi, Fault diagnosis of rotating machinery based on improved wavelet pakage transform and SVMs ensemble, Mechanical System and Signal Processing21(2007)688–705.

[8] García-Prada.J.C, Castejón.C and Lara.O.J "Incipient bearing fault diagnosis using DWT for feature extraction", (2007) 12th IFToMM World Congress, Besançon (France), June18-21.

[9] C. Castejon , O.Lara,J.C.Garcıa-Prada, "Automated diagnosis of rolling bearings Using MRA and neural networks" (2010) Mechanical Systems and Signal Processing 24 (2010) 289–299

[10] Khalid F. Al-Raheem, Waleed Abdul-Karem, "Rolling bearing fault diagnostics using artificial neural networks based on Laplace wavelet analysis'' International Journal of Engineering, Science and Technology Vol. 2, No. 6, 2010, pp. 278-290

[11] Jafar Zarei, "Induction motors bearing fault detection using pattern recognition techniques'' Expert Systems with Applications 39 (2012) 68–73

