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Performance and predict the ball bearing faults using wavelet packet decomposition and ANFIS

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Abstract

Element bearings are widespread significant parts of rotary machinery in industries and their condition monitoring through fault detection and isolation methods are of superior interests to engineers. Condition monitoring could assist in attaining effective system maintenance and the automation processes. Nonetheless, despite the availability of diverse bearing fault detection methods, there is paucity of literature concerning the theoretical modelling of the bearing faults using mathematical representations. The principal goal of this communication is to build up an approach to predict ball bearing fault, including ball fault, outer race fault and inner race fault. The proposed method uses the vibration data collected from the rotating ball bearing and predicts the type of fault. The proposed method is based on wavelet decomposition method, PCA, ANFIS and SVM. The vibration data is decomposed into 3rd level wavelet components using wavelet packet decomposition; each wavelet component has been divided into several energy segments, these 3rd level wavelet components are reduced to lower level components using Principal Component Analysis (PCA). ANFIS algorithm is trained using the reduced feature set as input and the type of fault as output. The trained ANFIS algorithm is validated using another set of data. Support Vector Machine (SVM) has been used instead of ANFIS algorithm, the SVM based method gives more accurate prediction compared to that of ANFIS. The proposed method has been validated using the real-time data collected from the ball bearing setup. The validation results show that the proposed method exactly predicts the type of ball bearing fault. The real-time data validation results confirm the accuracy of the fault prediction method.

Keywords: Principal component analysis, support vector machine; ANFIS; bearing

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1. Introduction

In the condition monitoring research and practice domain, judging the overall performance of rotary machinery may be regarded comprehensive if the dynamic performance of its rotary parts is incorporated in the evaluation scheme. However, determination in performance may be experienced due to the influence of over-usage and frictional forces, leading to component damage. For bearings, the occurrence of defects usually causes lessened efficiency, or worse, chronic damage to the machinery being considered. As a result, this places high premium on the effects to monitor progressive wear in bearings with the application of the diverse non-destructive know-how, with preference to vibration examination method and the application of modern signal processing schemes on the attained readings to aid supervisor diagnostic routes. Since bearing serves the purpose to lessen the friction the mating parts by disallowing physical interaction among them, the development of any fault or crack in the bearing will certainly limit the efficiency of the bearing, by implication, its influence on the output of the equipment. In the worse case, equipment breakdown may develop from it, and may even threaten the lives of workers associated with the machines. The idea is that there is necessity to change the faulty bearing by means of a superior one since the cost of bearing changes is extremely low when weighed against equipment shut down. Every bearing element has an outstanding feature of rotary defect frequency that is a function of the kinematic consideration. Knowledge of the bearing's rotational speed and geometry aid in the computation of this frequency, to give a value that is often less than 500 Hz. With the occurrence of a particular defect on a bearing element such as a rough defect, there is a noticeable growth of the vibration thresholds and this is the principal reason to analyse using the frequency-domain scheme of vibration recordings, often conducted to establish the situation of bearings. It should be noted that several methods exists, which could be engaged to predict the bearing condition, such as vibration monitoring, current signature analysis, thermography and tribology.

Table 1 shows the failure mechanisms and the associated reasons for damage while Table 2 reveals the damages and the corresponding effects.

Table 1. Failure Mechanisms and Reasons for damage (Bhende et al., 2011)

Failure Mechanisms	**Reason for damage**
Mechanical Damage	Permanent indentation created by rolling element overload
Crack Damage	Manufacturing defect or operating stress due to overload
Wear Damage	Gradual deterioration or abrasive particle entrained
Insufficient lubrication	When lubrication condition becomes inadequate increases friction
Corrosion	Humid ambient subjected to surface oxidation
Fatigue damage	Material fatigue after certain running time

Table 2. Damages and corresponding effects

Sl.No	**Method of analysis**	**Temperature**	**Pressure**	**Flow**	**Oil analysis**	**Vibration**
1	Out of balance					*x*
2	Misalignment	*x*				*x*
3	Bent shaft	*x*				*x*
4	Gear damage				*x*	*x*
5	Noise					*x*
6	Cracking					*x*
7	Ball bearing Damage	*x*			*x*	*x*
8	Mechanical rubbing		*x*	*x*	*x*	*x*

The proposed method is based on wavelet decomposition method, PCA, ANFIS and SVM. The performance of SVM and ANFIS algorithm is compared. It is found that SVM based prediction has higher accuracy compared to that of ANFIS.

2. Literature Review

The wavelet amplitude maps relating to the different gear health conditions are portioned into 6 sections and constant wavelet coefficients from ideal scales nourished specifically to the ANFIS as information tests. The outcomes exhibit that acoustic signs and ANFIS can viably be used to analyze the state of the gearbox (Anand and Singh, 2019). A wavelet packet denoising (WPD) procedure and an improved adaptive neuro-fuzzy inference system (ANFIS) based on Cauchy oscillation shuffled frog leaping algorithm (COSFLA).The wavelet packet denoising methodology is based on soft thresholding and Shannon entropy using a Db10 wavelet which is applied to remove the noise component from the measured apparent resistivity data (Jiang et al., 2018). A method for classification of fault and prediction of degradation of components and machines in manufacturing system, setup for the processing of the signals and collecting the data is explained in detail. The analysis is focused on the vibration signals collected from the sensors mounted on the machines for critical components monitoring (Zhang et al., 2013)

Condition-based maintenance (CBM) has attracted more attention and interest due to its advantages over the conventional breakdown-based or time-based maintenance. CBM of electrical machines such as motors is based on using data obtained by real-time condition monitoring, and fault detection and diagnosis to recommend an optimized maintenance. This paper presents an application of an Artificial Neural Network (ANN) for detecting a very small fault in a bearing shield of an induction motor. The experimental results show that the incipient fault can be efficiently detected. An alarm may be activated so that corrective actions are promptly taken before the detected fault manifests itself to be further serious failures (Liu et al., 2015). The use of c-SVC and nu-SVC models of support vector machine (SVM) with four kernel functions for classification of faults using statistical features extracted from vibration signals under good and faulty conditions of rotational mechanical system. Decision tree algorithm was used to select the prominent features. These features were given as inputs for training and testing the c-SVC and nu-SVC model of SVM and their fault classification accuracies were compared (Saimurugan et al., 2011). After several studies showed that the most important technique in predictive maintenance is vibration analysis as it gives clear indications regarding the condition of the machine in question, in addition the level of vibrations and the frequency at which these vibrations occur can serve in determining the exact location of the defect and possibly severity of such defect (Bhende et al., 2011).

Principal Component Analysis (PCA), advantages of PCA, feature reduction procedure using PCA, step by step procedure of obtaining Principal component matrix from the raw data sets is studied (Sun et al., 2007). A survey of machine condition was monitoring and fault diagnosis using support vector machine (SVM). It attempts to summarize and review the recent research and developments of SVM in machine condition monitoring and diagnosis. Numerous methods have been developed based on intelligent systems such as artificial neural network, fuzzy expert system, condition-based reasoning, random forest, etc. (Li et al., 2006). The three datasets, namely, DBALL, DINN, and DOUT, are used to test the classification performance of statistical features under the same fault type but with different fault degrees. The nonlinearity of the ball fault is more complicated than the inner race and outer race faults, which necessitates the addition of more features (Zhu et al., 2012). The approach is accurate up to local first order approximations of the nonlinearities. It is shown to provide successful weight initialization for many data sets in the reduced number of inputs leads to faster training requiring far less iterations making the procedure suitable for on-line condition monitoring and diagnostics of machines (Samanta and Al-Balushi, 2003)

3. Experimental Setup

In this research, two experimental setups are used (Figures 1 and 2). One is used to obtain vibration signals for running of classifiers and other setup is for real time condition monitoring of the bearing. Vibration data acquired from the sensor is converted instantly into displacement of sensor; frequency drive is used to change the speed of the motor. Motor in turn rotates the shaft and the bearing, thus it controls the speed of the bearing. Change in the speed of the motor, condition of the bearing changes the vibration of the bearing. This results in the changes in the vibration data.

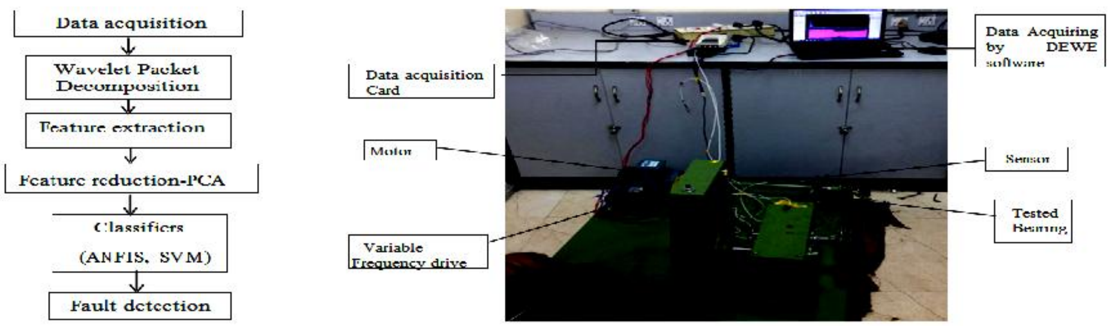

Figure 1. Flow chart of Fault detection system and Experimental setup

The Real time experiment setup differs from the training setup in such a way that the former has electronic components attached to the output of the sensor and the later has data acquisition card to convert from the vibration to displacement. Differences are listed below:

Proposed Setup	Conventional Setup
Electronic components are present	No electronic components
No data acquisition card	Data acquisition card is attached
Data is collected using Matlab	Data is collected using DEWE 7.0 software
ANFIS output is obtained from Matlab	Only storage of data

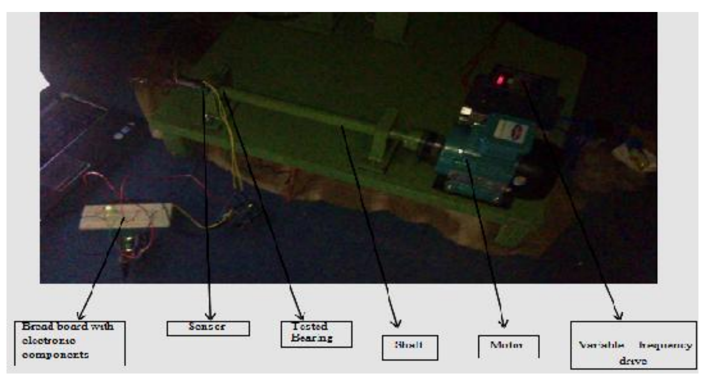

Figure 2. Proposed monitoring setup

Many signal processing techniques have been proposed in literature for machinery fault diagnosis. In time domain analysis, a bearing fault is diagnosed with the help of some statistical indexes (e.g., RMS value, crest factor, or kurtosis) however, most of these monitoring indexes are sensitive to noise and operating conditions (Bhende et al., 2011). Frequency analysis may be the most fundamental approach for bearing fault detection. Bearing health conditions are assessed by examining the fault-related characteristic frequency components in the spectra or some associated expressions such as bi spectrum and cepstrum maps (Bhende et al., 2011). Frequency based techniques however, are unsuitable for the analysis of non-stationary signatures that are usually related to machinery defects (Bhende et al., 2011). Non-stationary or transient signals can be analyzed using time–frequency domain techniques such as short-time Fourier transform (STFT), Wigner–Ville distribution, or wavelet transform (WT). In fault diagnosis, the WT is more suitable than either the Wigner–Ville transform that contains some cross terms or the short-time FT that has a limited multi resolution solution (Bhende et al., 2011). According to signal decomposition paradigms, the WT can be performed by the continuous WT, discrete WT, and wavelet packet analysis and extended WT with post processing. Although a wavelet packet map can provide more information, its processing results are usually difficult to explain especially when the bearing operates under different load/speed operating conditions. Displacement data of the sensor from its mean position is stored in an excel sheet using DEWE software (Bhende et al., 2011). One of the simpler detection and diagnostic approaches is to analyze the measured vibration signal in the time domain. Whilst this can be as simple as visually looking at the vibration signal, other more sophisticated approaches can be used such as trending time domain statistical parameters (Bhende et al., 2011). An arduino is being used for acquisition of the values thus monitoring the condition of the bearing (Figure 3). For the transfer of high dimensional fault data into low dimensional fault data Principal Component Analysis (PCA) is used.

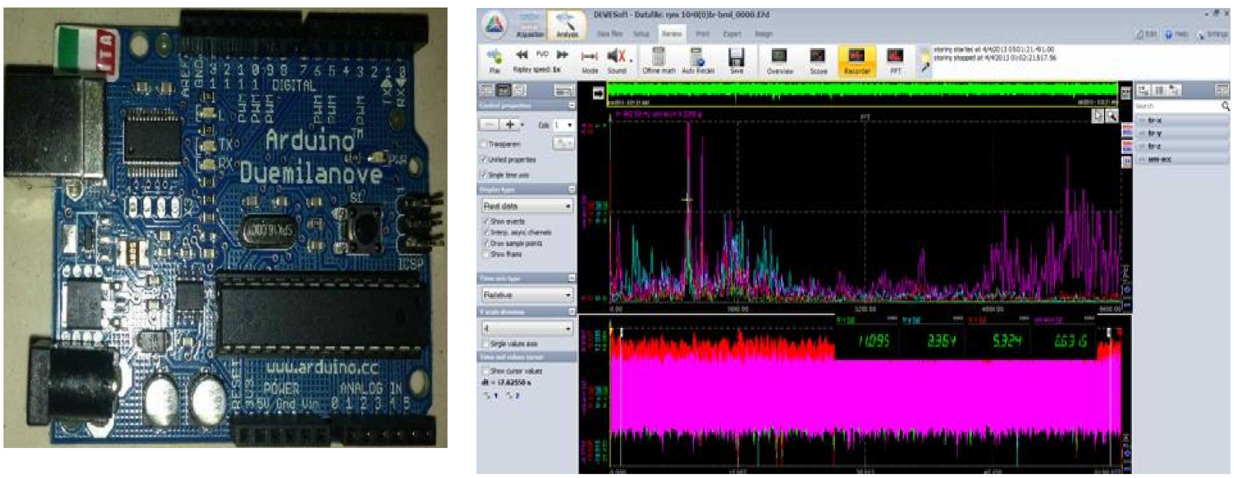

Figure 3. Arduino Board with Signal Processing Using DEWESoft

First step of vibrations measurement of the bearing is to collect the signals. The sensing element for collecting the signals will be accelerometer. The accelerometer gives a voltage reading that corresponds to the level of vibration. The analog signals given by the accelerometer are then collected by the Data Acquisition Card and transform them into digital signals so that it can read by an analyzing interface. The analyzing interface (computer software) is used to perform and use the analysis methods.

A number of transducer types exist for measuring machine vibration, including proximity probe, velocity transducers, accelerometers etc. The measurement of machine casing acceleration is the most common method used for bearing fault detection (Bhende et al., 2011) (Figure 4).

- Data Acquisition: This is normally achieved by mounting piezoelectric accelerometer externally on the machine casing, preferably near or on the bearing housing, or on the portion of the casing where relatively rigid connection exists between the bearing support and transducer. Piezoelectric sensors are less sensitive to temperature which is important since most machinery fault results in temperature increase. This will allow the bearing vibration to transmit readily through the structure to transducer. Accelerometers have the advantage of providing a wide dynamic range and a wide frequency range for vibration measurement. They have been found to be the most reliable, versatile and accurate vibration transducer available (Bhende et al., 2011).

- Sensor: used in this project for acquiring data is 3- axis accelerometer ADXL335 is a little, slim, depleted power, total 3-axis accelerometer with signal conditioned voltage outputs. The product measures acceleration with a minimum full-scale range of ±3 g. It can measure the static acceleration of gravity in tilt-sensing applications, as well as dynamic acceleration resulting from motion, shock, or vibration.

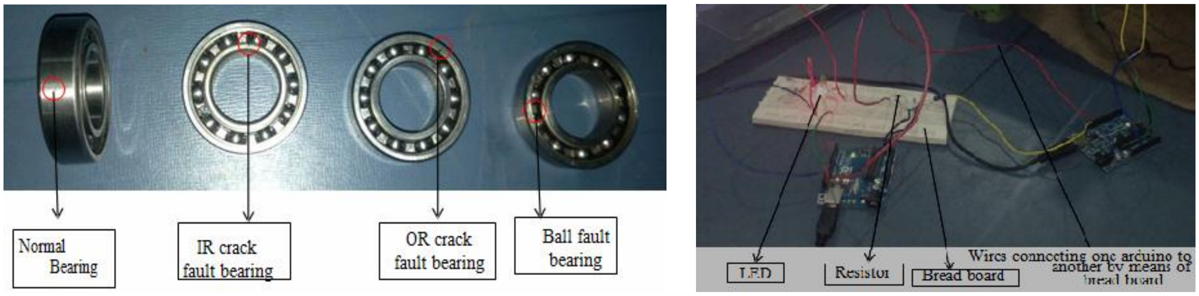

Figure 4. Types of bearing faults and Signal Acquisition

3. Methodology

In this research, two experimental setups are used. One is used to obtain vibration signals for running of classifiers. Additional details are provided in Table 3 and Figure 5.

Table 3. Damages and corresponding effects

DATA ACQUISITION ↓ Supervised learning ↓ Frequency Domain Features ↓ Fault by feature matrix ↓ Covariance Matrix ↓ Eigen values and Eigen vectors ↓ Significant values using PCA ↓ Feature reduction ↓ Principal Component Matix	Step-1: Displacement of the bearing from its rest position is determined by the sensor and is stored in time domain variable. Step-2: Frequency domain values for the data are calculated and are stored in adjacent columns of the time domain values. These are stored in another variable, say a. Step-3: Covariance matrix for the fault by feature matrix is calculated in Matlab using the keyword " cov(a) " and is stored in separate variable, say b Step-4: Eigen values and Eigen vectors for the covariant matrix are calculated. Since the output from the covariance matrix has the size of column size by column size (column size of covariant matrix), it is possible to determine Eigen values and Eigen vectors directly as they will be calculated only for square matrices. It is calculated in the Matlab by using syntax: [V, d]=eig (b) Step-5: Sum of the Eigen values is calculate and is multiplied by a number less than 1 to get precision parameter value. Step-6: Using the precision parameter value Eigen values having less significance are deleted. Step-7: Deleted Eigen value positions are noted and Eigen vectors at the same position are deleted. Step-8: Now the remaining Eigen values are multiplied with the initial values to get the Principal components. Thus the features are reduced into significant numbers so that calculation time taken will be less which will be useful for classifiers in real time monitoring.

Inputs: T=Training Matrix, C=Group, test=Testing matrix

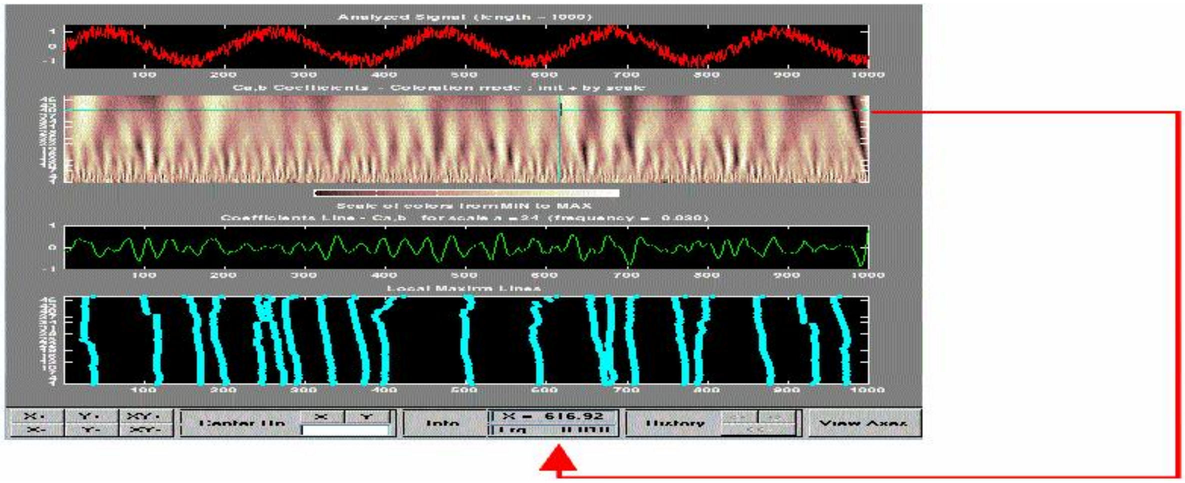

Figure 5. Wavelet analysis using Matlab

Outputs: itrfin=Resultant class (Group,USE ROW VECTOR MATRIX) to which tst set belongs:

Pseudo Code:

FOR tempind := 1 to number of training rows DO
u := unique elements in class vector (classes)
IF number of classes > 2 THEN
svmStruct := train SVM using rbf kernel classify the current row

4. Results and Discussion

The results obtained from the study are displayed in Figures 6 to 17 and Tables 4 to 14.

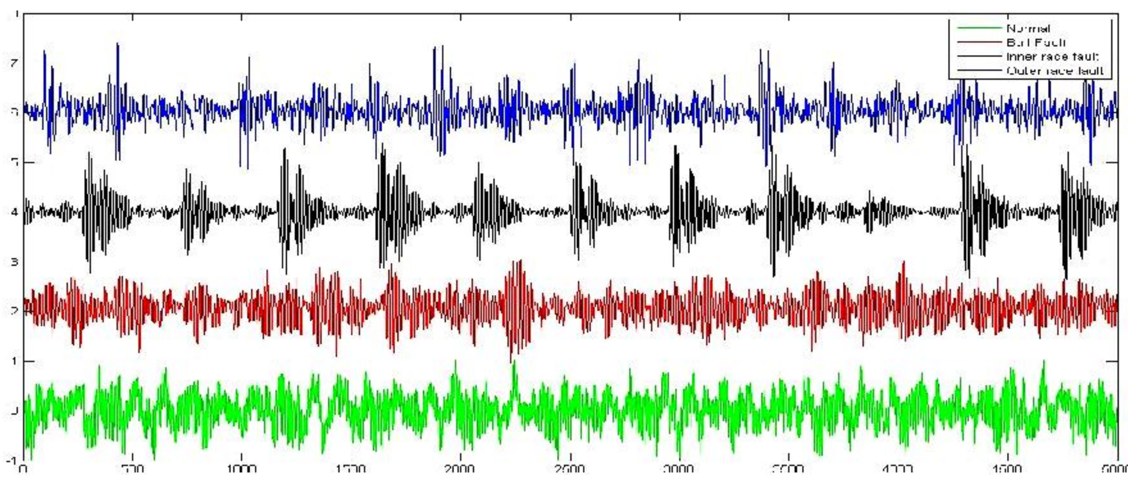

Figure 6. Raw signals

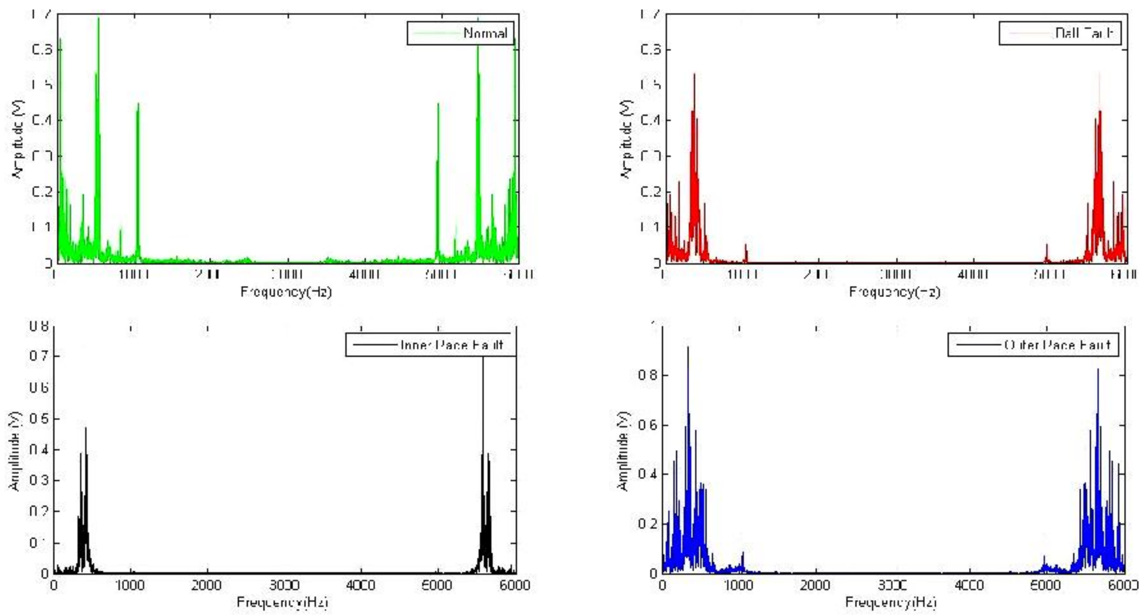

Figure 7. FFT of Raw signals

Table 4. Frequency domain features

	Mean	Variance	SMR	RMS	Pk-Pk	skewness	Kurtosis	sFactor
I.R.wearMin	35.0608502	36744.2648	194.867588	194.867588	23823.6246	296228171	3.9299E+12	5.55798239
I.R.wearMax	12.8978048	5556.41461	75.6486786	75.6486786	7934.16441	11110135.8	4.8013E+10	5.86523672
O.R.wearMin	77.0373881	541843.635	740.119023	740.119023	87394.2265	1.7484E+10	8.8716E+14	9.60727046
O.R.wearMax	76.0969066	487730.05	702.508925	702.508925	66609.6611	1.2016E+10	4.4564E+14	9.23176719
BallWearMin	17.4435478	9617.2334	99.6065826	99.6065826	9275.24444	21348030.9	9.3872E+10	5.71022501
BallWearMax	19.2077958	9.76E+003	100.631742	100.631742	7.16E+003	1.92E+007	7.34E+010	5.23910933
I.R.crackMin	59.1835625	176150.308	423.854074	423.854074	40746.18	2326260920	5.174E+13	7.16168571
I.R.crackMax	35.9934824	82586.4468	289.623272	289.623272	33394.2045	959423351	2.0064E+13	8.04654768
O.R.crackMir	77.0373881	541843.635	740.119023	740.119023	87394.2265	1.7484E+10	8.8716E+14	9.60727046
O.R.crackMa	86.2680054	163344.469	413.262592	413.262592	30747.0418	1159940390	1.6015E+13	4.7904503
BallCrackMin	27.8810615	2.15E+004	149.140038	149.140038	8.53E+003	5.19E+007	2.17E+011	5.34915209
BallCrackMax	42.9041085	4.89E+004	225.245111	225.245111	1.65E+004	1.48E+008	9.30E+011	5.249966

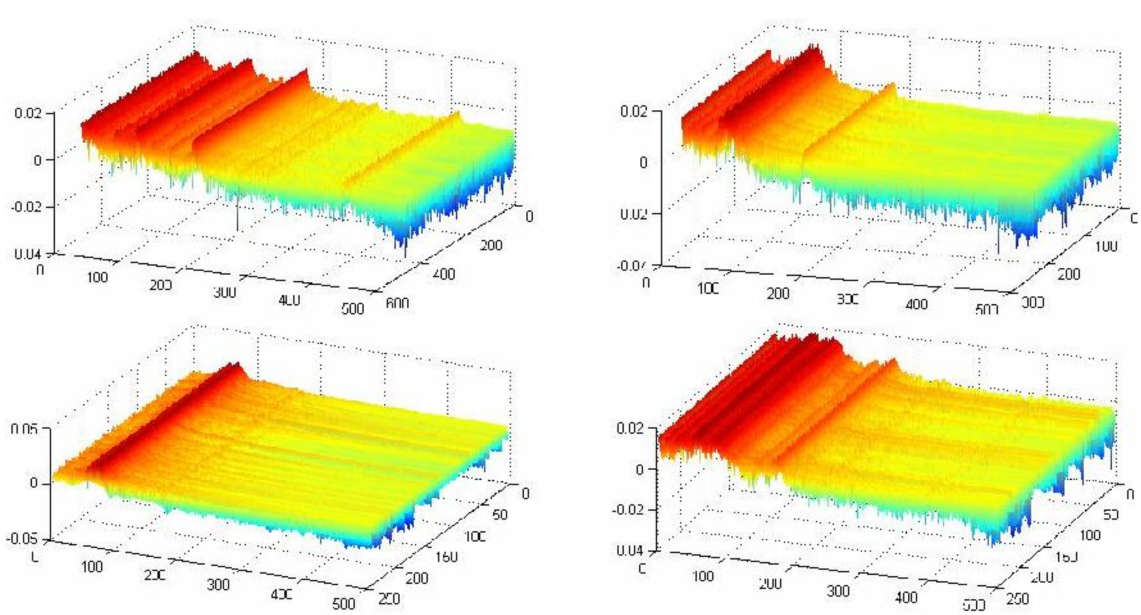

Figure 8. STFT of Raw signals

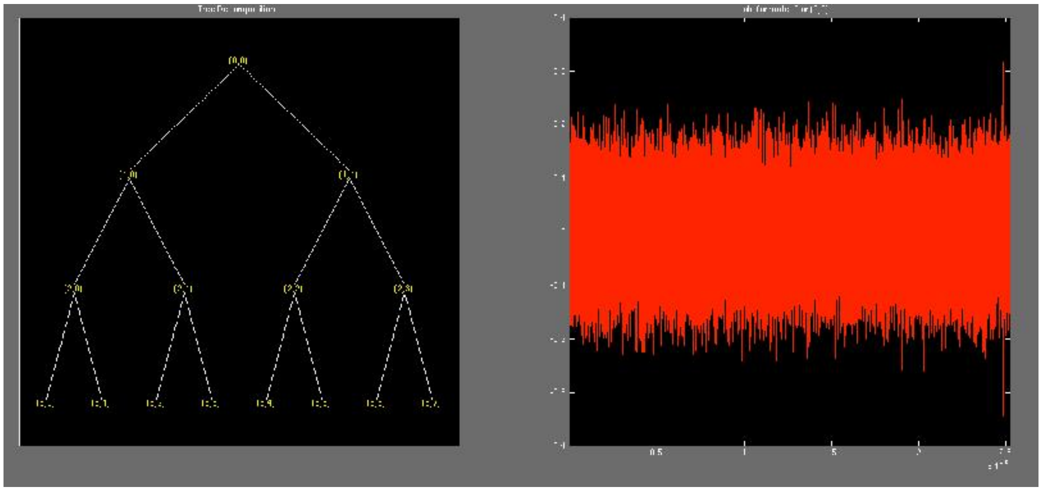

Figure 9. Wavelet Packet Decomposition Tree in Matlab

Table 5. Output for frequency domain features

5.393516479	-3.075082489	-0.046836224	0.382966626	-0.82188709	2.932806798	-1.673590966	-2.286455902	-0.046836224
-9.578348898	-0.471171635	0.396999713	-2.512513555	0.991952588	7.986779056	8.239316157	2.993133163	0.396999713
4.968046457	40.04846746	0.414294625	-1.788527578	16.546493	-3.730031348	-2.454370976	-4.717912367	0.414294625
8137.982076	-2510.096179	446.7337769	-2742.143509	-1999.891375	-4114.781394	5547.897631	11123.07811	446.7337769
8428.680131	25212.54777	-5587.478209	27782.09485	21649.30376	21828.76464	-26354.29012	-4522.53734	-5587.478209
270938030.8	478669989.8	690376688.4	-2642907701	469346296.9	471086212.8	-806003523.7	-70630248.43	690376688.4
-1.88826E+14	-1.92708E+14	6.94404E+14	2.52886E+14	-1.92662E+14	-1.92683E+14	-1.41016E+14	-1.72692E+14	6.94404E+14

Table 6. Output for frequency domain features

0.122527158	0.131692234	0.119904465	0.127974726	0.128974824	0.125920067	0.127032959	0.12799026	0.127112444	0.124870256	0.137909355	0.141652817	0.135884095	0.138508543	0.141359424	0.136338278	0.14166224	0.13707571	0.135847158	0.140922089
0.032969818	0.031558319	0.033076664	0.031733074	0.033070649	0.032612849	0.032798178	0.032757977	0.032538179	0.032322668	0.007217701	0.008156101	0.007837504	0.007680501	0.007152094	0.007944705	0.007797001	0.007570359	0.007574765	0.00757003

Table 7. Energy ratio-Normal

0.122527158	0.085073828	0.006396437	0.032969818	4.64289520509262	0.000382887	0.00087141	0.002453876
0.131692234	0.077582523	0.005892048	0.031558319	3.97341309611524	0.000388523	0.000773082	0.002452956
0.119904465	0.087569727	0.006098771	0.033076664	3.85502507964842	0.000376517	0.000823712	0.002421776
0.127974726	0.080759883	0.006040159	0.031733074	4.19803642170569	0.000372462	0.000766034	0.002405773
0.128974824	0.078343392	0.005942993	0.033070649	3.75368194790226	0.000341562	0.000835148	0.00249705
0.125920067	0.081857445	0.006199972	0.032612849	4.18124465744954	0.000386093	0.000826552	0.002473283
0.127032959	0.08100016	0.005690814	0.032798178	3.65316547857871	0.000369982	0.000781807	0.002353203
0.12799026	0.079392699	0.006374685	0.032757977	4.29914675852748	0.000406515	0.000857567	0.002500443
0.127112444	0.081124059	0.006055545	0.032538179	3.69359749626754	0.000370439	0.000802989	0.002436924
0.124870256	0.083222085	0.006223319	0.032322668	4.05072056072017	0.000375729	0.000878884	0.002403483
0.128112953	0.080506262	0.006013139	0.031815692	3.72347088938784	0.000376282	0.000797724	0.002418588
0.128297322	0.078861908	0.00630215	0.033227962	4.10244522883351	0.000411222	0.000873412	0.002524756
0.125325719	0.083874496	0.006006114	0.031664096	4.05983992325716	0.000372733	0.000827813	0.002326891
0.123923021	0.085587421	0.005806481	0.031584502	4.22314044699101	0.000392526	0.000769972	0.002316759
0.123915505	0.085733332	0.005825487	0.031641829	3.77788618778836	0.000379702	0.000787006	0.002288128
0.12990445	0.0785098	0.006090417	0.031991406	4.55298713121565	0.000428188	0.000825367	0.002481529
0.129924259	0.080184339	0.005538605	0.031140152	3.97040573545211	0.000391358	0.000751381	0.002279664
0.118582301	0.090196461	0.005885391	0.032230744	3.75044344959924	0.00038755	0.00081654	0.002357159
0.132407995	0.078522455	0.005826094	0.029975125	3.34526977403635	0.000323964	0.000757712	0.002265323
0.127112192	0.081324872	0.005982874	0.031996563	3.71111187759764	0.000378467	0.000802777	0.002404962

Table 8. Ball fault

0.137909355	0.10352466	0.001099761	0.007217701	7.22560060764479	6.98363709787668	5.09556866219134	0.000137255
0.141652817	0.098785764	0.001133742	0.008156101	6.70040107946022	6.89125820109429	5.52221516329903	0.000152541
0.135884095	0.10500081	0.001090706	0.007837504	6.86839338560677	7.05021959853611	5.10656677740831	0.000144314
0.138508543	0.102421987	0.001137074	0.007680501	6.65594622530962	6.73778720069972	5.94886578685309	0.000142381
0.141359424	0.100333816	0.001061247	0.007152094	8.37057927038982	7.16865047993998	4.53727236813076	0.000154237
0.136338278	0.106313294	0.001095648	0.007944705	9.43844721657841	7.12500116280796	5.62105739025975	0.000155142
0.14166224	0.099922532	0.001154889	0.007797001	8.85450668122178	7.19992742672873	6.08776373987953	0.000154009
0.13707571	0.104556467	0.001090045	0.007570359	7.94178345223239	7.27101443292945	5.56345591706923	0.000141637
0.135847158	0.105795737	0.001062543	0.007574765	8.51705448954850	7.14521442684629	5.42382225316695	0.000142681
0.140922089	0.100378271	0.001141415	0.00757003	7.20761826745023	7.33076344975837	5.35234199485244	0.00014746
0.1390979	0.101792629	0.001137191	0.007972541	6.79E-06	6.94020486521416	4.61492869152757	0.000147995
0.137330344	0.103460916	0.001047212	0.007975671	7.48566927518148	6.52601047269533	4.52689789825708	0.000145661
0.140914213	0.099627845	0.001101029	0.008221531	7.40377658388247	6.77228568776042	4.52417709968597	0.000136295
0.131666935	0.109303885	0.001043992	0.007893238	7.47313504197948	7.27826541000501	5.10317349533309	0.00014944
0.139721648	0.101875943	0.001047382	0.007128643	7.32948589287757	6.90483246463835	4.52945298959637	0.000138325
0.1354692	0.106480895	0.001003171	0.006959289	7.36195695257322	6.82525586100596	5.03291163404162	0.000149027

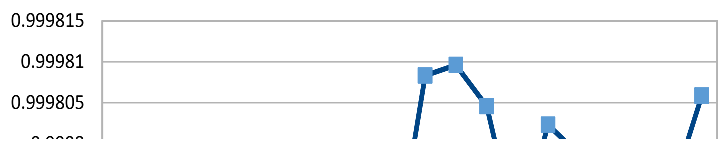

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Table 9. Inner race fault

0.136359588	0.109931542	0.001316664	0.002488037	7.96290905663794	2.13776367537029	1.64165528228629	3.41249930376856
0.127676034	0.119457153	0.001218883	0.002487345	9.32602237392842	2.20281446992638	1.89441011398836	3.93034401243899
0.142205462	0.104939519	0.001351828	0.002368397	7.82290181703301	2.24785950107614	1.79609213366565	3.69572984603224
0.129250018	0.118031069	0.001217609	0.002564201	8.95292451657496	2.25491527257360	1.78366722438522	3.40483173616672
0.136119051	0.11070007	0.001281083	0.0024861	7.96211262162183	2.29972915324107	1.80681990678811	3.87223140248543
0.126477033	0.120531955	0.00129041	0.002475187	8.95828158109864	2.38428846284281	2.46908091187886	3.90370145483479
0.137315292	0.11005855	0.001235278	0.002461735	8.25998513008871	2.20024910713028	1.77823544375094	3.97328141283838
0.140646479	0.106198686	0.001306706	0.002370722	7.92188860776892	2.19410788310657	1.62776991473039	3.42283120090289
0.140483132	0.106063723	0.001233856	0.002402088	7.75621834018270	2.18502401048131	1.76429314391108	3.78137274052676
0.141648829	0.104773344	0.001311949	0.002435254	7.87076373931425	2.34439605762138	1.65400090677692	3.67611672765952
0.146269212	0.100405858	0.001247935	0.002444421	7.97E-06	2.35458762357152	1.79977350724832	3.75158426476863
0.128086273	0.118178621	0.001396964	0.002571332	8.99716301926945	2.53848396020348	1.84665058049196	3.97795931275413
0.138079352	0.108482875	0.001380209	0.002427728	7.63839996016290	2.33586180672249	1.60633056082220	3.63802979160129
0.139998322	0.106184792	0.001275073	0.002531351	8.63315179697805	2.32006424748736	1.73005058327221	3.64480736623165
0.124778813	0.121540072	0.001235434	0.002574763	8.91842463423631	2.35112526398864	1.89268405167601	4.24119315008329
0.137205885	0.109745023	0.001316681	0.002413584	8.12187752057269	2.36545452064621	1.83479290130603	3.85600062207490
0.148165606	0.099947978	0.001351799	0.002296961	7.05547471985839	2.45451715979788	2.14222827683232	3.97460747088004
0.134694588	0.111980107	0.001201827	0.002696871	8.86378169963285	2.42176[illegible]	[illegible]	[illegible]

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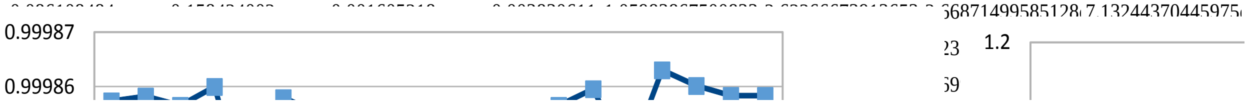
Table 10. Outer race fault

0.099042638	0.145502099	0.001408388	0.004042849	1.06006588081974	2.69294688111643	3.13348325666125	6.99089843181154
0.078970137	0.167044826	0.001590577	0.003886175	1.09886353760810	2.69564657046670	2.95755555586056	6.74097405213235
0.10108304	0.143730974	0.00181964	0.003693036	9.48323538884373	2.80691953288068	2.88642038201682	7.59505219124349
0.097056283	0.147567499	0.001440932	0.00400308	1.06684900580037	2.70188983334259	2.55682241588316	6.45856039501392
0.077129681	0.167721082	0.001510177	0.004016248	1.17171266472531	2.80544764341548	8.75714565674446	8.21793788898269
0.099740731	0.145910301	0.001810613	0.003698203	9.63461145741840	2.81286834124851	3.59632832712731	6.29875865781657
0.105705874	0.138785362	0.001616359	0.003869873	9.62261388796554	2.82486070628119	3.72987085033520	6.63710767804452
0.071920517	0.172837914	0.00165981	0.003839886	1.09585402796761	2.66723914961541	5.43510008698121	8.77844733675693
0.094996424	0.149561006	0.001721767	0.003874868	9.94985892505244	2.79210839029442	3.23724054679831	8.67259974974561
0.074893011	0.16961275	0.001609437	0.003876239	1.09290956948210	2.63030019877577	3.19759386947489	9.55430700525330
0.096735202	0.147677981	0.001671255	0.003927368	9.92574105698957	2.74436114714962	3.70392242419794	9.50004557133015
0.078549053	0.165880997	0.001620016	0.003977217	1.08519146949689	2.69332641163090	2.90150595012630	9.24417603850937
0.097236581	0.148215854	0.001734875	0.003952622	1.07916754155880	3.37138512248984	1.22792527817699	1.10256816472904
0.090098675	0.15850427	0.001651202	0.003880241	1.05086347349774	2.64419646348692	3.22316967304925	7.83986228132879
0.095818274	0.1486947	0.001689082	0.003820118	9.89758658192955	2.65402073992566	2.58589837492600	7.80055464982141
0.092798462	0.151898413	0.001560302	0.003901911	1.08718748314933	2.80665077656808	5.67902907812535	8.10256281386038
0.087186273	0.15819036	0.001621389	0.003823434	1.06007295730726	2.63953269206887	2.46786957868394	6.28571059597236
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]



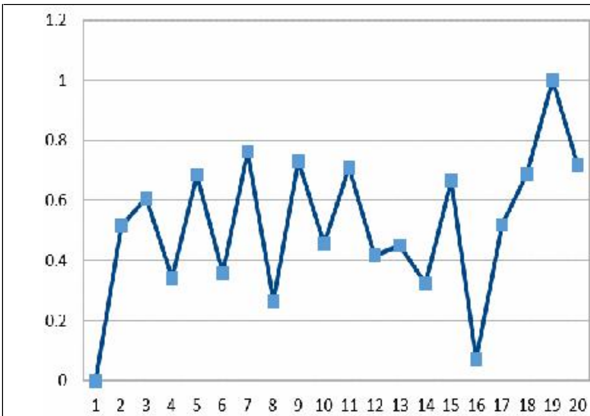


Figure.10 Normal Energy ratio

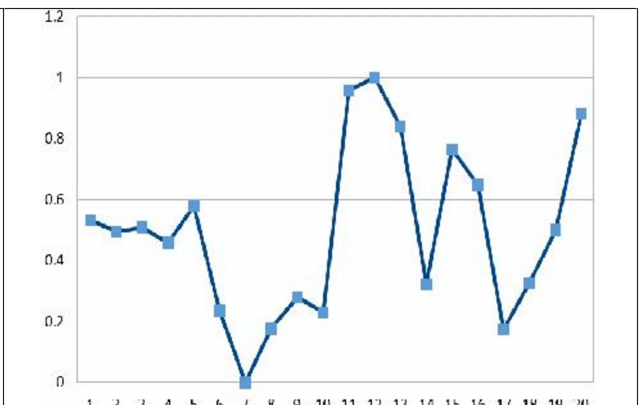


Figure.11 Ball fault

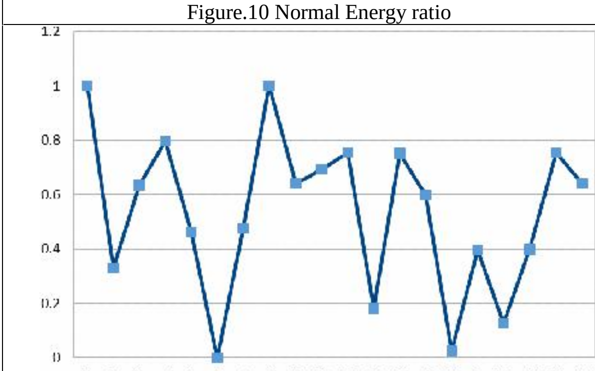


Figure.12 Inner race fault

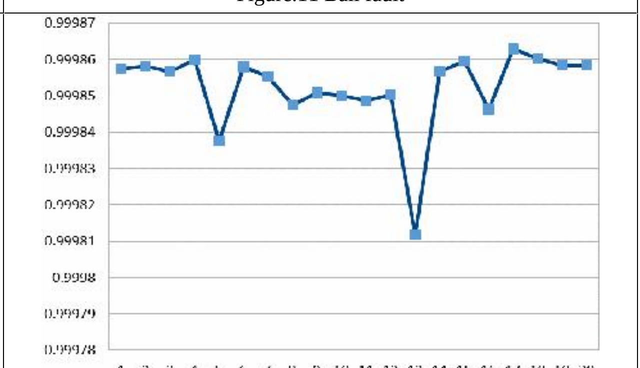


Figure.13 Outer race fault

Table 11. Training input for SVM

SVM Training(Normalized)								Classes
0.72002107	0.07864442	1	0.99652061	1	0.93865046	0.99147122	0.98132947	1
0.85041992	0	0.90545997	0.95055582	0.83167425	0.9532842	0.87926655	0.9809606	1
0.68270592	0.1048466	0.94420705	1	0.80190833	0.92211091	0.93704178	0.96845932	1
0.79752796	0.03335622	0.93322112	0.95624664	0.88815057	0.9115822	0.8712239	0.96204309	1
0.81175716	0.00798767	0.91500884	0.99980412	0.77642795	0.83135108	0.9500917	0.99863961	1
0.76829469	0.04487853	0.96317563	0.98489609	0.88392868	0.94697476	0.94028258	0.98911049	1
0.78412869	0.03587867	0.86774173	0.99093124	0.75115541	0.90514293	0.88922288	0.94096572	1
0.79774898	0.0190034	0.99592292	0.98962211	0.91357242	1	0.97567461	1	1
0.78525959	0.03717938	0.93610499	0.98246449	0.7613211	0.90632952	0.91339422	0.97453275	1
0.75335819	0.05920465	0.96755167	0.97544648	0.85111142	0.92006488	1	0.96112494	1
0.93887586	0.27234298	0.00721886	0.15791526	0.01432264	0.12582195	0.05522922	0.05250548	2
0.99213708	0.22259361	0.01358808	0.18847381	0.00111771	0.12342335	0.06009779	0.05863424	2
0.91006087	0.28783974	0.00552164	0.17809885	0.00534149	0.12755075	0.05535472	0.05533571	2
0.94740098	0.26076702	0.01421261	0.17298612	0	0.11943852	0.06496642	0.05456069	2
0.98796274	0.2388452	0	0.1557788	0.04311047	0.13062578	0.04885835	0.05931423	2
0.91652289	0.30161832	0.00644794	0.1815898	0.06995953	0.12949243	0.06122571	0.05967708	2
0.99227115	0.2345275	0.01755176	0.17677989	0.0552777	0.13143788	0.06655142	0.05922281	2
0.92701492	0.28317499	0.00539775	0.1693994	0.0323294	0.13328363	0.0605684	0.0542624	2
0.90953534	0.29618496	0.00024292	0.16954288	0.04679325	0.13001727	0.05897501	0.05468098	2
0.98174043	0.23931189	0.01502627	0.16938869	0.01387051	0.134835	0.05815933	0.05659706	2
0.91682609	0.33960303	0.04787402	0.00389602	0.03286055	0	0.0158157	0.01115663	3
0.79327823	0.43960378	0.02954646	0.00387348	0.06713287	0.00168903	0.01869995	0.01323287	3
1	0.2871963	0.05446498	0	0.02934039	0.00285861	0.01757802	0.01229221	3
0.81567256	0.42463262	0.02930767	0.00637626	0.05775219	0.00304181	0.01743624	0.01112588	3
0.91340377	0.3476711	0.04120491	0.00383294	0.03284053	0.0042054	0.01770044	0.01299987	3
0.77621909	0.45088715	0.04295311	0.00347757	0.05788688	0.00640096	0.02525767	0.01312605	3
0.93042365	0.34093637	0.03261946	0.00303951	0.04032984	0.00162242	0.01737426	0.01340502	3
0.9778191	0.30041515	0.04600755	7.57E-05	0.03182919	0.00146296	0.01565725	0.01119805	3
0.97549504	0.2989983	0.03235292	0.00109713	0.02766379	0.0012271	0.01721516	0.01263558	3
0.99208034	0.28545178	0.04699027	0.00217717	0.03054377	0.00536516	0.01595658	0.01221357	3
0.38588806	0.71302606	0.06506629	0.05452773	0.09918065	0.0144152	0.00065804	0.00027751	4
0.10030057	0.93918362	0.09921484	0.04942571	0.10893542	0.0144853	0.00045729	0.0001773	4
0.41491849	0.69443262	0.1421492	0.04313623	0.07108563	0.01737447	0.00037611	0.00051973	4
0.3576266	0.73470882	0.07116616	0.05323267	0.10088611	0.0146474	0	6.41E-05	4
0.07411493	0.94628302	0.08414508	0.05366148	0.12725165	0.01733626	0.00707535	0.00076947	4
0.39582039	0.7173114	0.14045723	0.0433045	0.07489163	0.01752893	0.00118621	0	4
0.48069123	0.64251313	0.10404728	0.04889485	0.07458998	0.01784031	0.0013386	0.00013566	4
0	1	0.11219151	0.04791833	0.10817875	0.0137477	0.00328448	0.0009942	4
0.32831934	0.75563684	0.1238044	0.04905751	0.0828178	0.0169899	0.00077644	0.00095177	4
0.04229204	0.96614193	0.10274986	0.04910215	0.10743843	0.01278859	0.0007312	0.00130528	4

Table 12. Checking input for SVM

SVM Checking (Normalized)								Output
0.72632806	0.02191435	0.94545912	0.95434128	0.78587532	0.87248946	0.91309661	0.95784425	1
0.72884427	0.00386495	1	1	0.88370072	0.95832189	1	1	1
0.68828882	0.05888608	0.94413339	0.94944017	0.87270293	0.8637711	0.94764417	0.92143445	1
0.66914527	0.07768816	0.90645953	0.9468669	0.91485602	0.91239392	0.88123234	0.91741137	1
0.66904269	0.07928977	0.91004626	0.94872028	0.79992165	0.88089091	0.90079042	0.90604297	1
0.75077782	0	0.96004268	0.96002212	1	1	0.94483573	0.98283601	1
0.75104816	0.01838073	0.85590715	0.93250105	0.84961711	0.90952465	0.85988653	0.9026822	1
0.5962569	0.12827972	0.92135108	0.96775992	0.7928378	0.90017005	0.93470075	0.93345286	1
0.78494537	0.00013891	0.91016081	0.8948357	0.68824952	0.74396681	0.86715566	0.89698787	1
0.71267001	0.0308999	0.93974764	0.96018884	0.78268507	0.87785705	0.91889836	0.95243382	1
0.87624697	0.25556614	0.02529166	0.18349164	0.00E+00	0.11861843	0.0501541	0.056268	2
0.85212395	0.27387824	0.00831122	0.18359283	0.01795745	0.10844346	0.04914335	0.05534125	2
0.9010354	0.23180418	0.01846733	0.19154149	0.01584354	0.11449338	0.04911211	0.05162232	2
0.77483163	0.33801414	0.00770356	0.18092777	0.0176339	0.12692311	0.05576002	0.05684176	2
0.88475967	0.25648064	0.00834331	0.15620839	0.01392586	0.11774948	0.04917268	0.05242837	2
0.82672367	0.30702732	0	0.15073318	0.01476404	0.11579463	0.05495329	0.05667777	2
0.90536369	0.24052693	0.00382432	0.1605005	0.02192979	0.12865738	0.05945597	0.05255861	2
0.81006091	0.32965398	0.01007553	0.16463247	0.05803845	0.12385548	0.05576322	0.0544415	2
0.86437441	0.27141997	0.00982604	0.16034253	0.02259756	0.13223146	0.04538201	0.05534165	2
0.90415751	0.24690576	0.00196113	0.15889622	0.01011891	0.11361013	0.04902006	0.06004371	2
0.97411865	0.24034412	0.04619079	0.00476739	3.05E-02	0.00596969	0.01783107	0.01240044	3
0.72596394	0.4354285	0.07431488	0.00887042	0.05697394	0.01048722	0.0183693	0.0132993	3
0.86234616	0.32900224	0.07115295	0.0042277	0.02189992	0.00550967	0.01561	0.01194955	3
0.88853563	0.30377712	0.05131215	0.00757783	0.04757764	0.0051216	0.01703053	0.01197646	3
0.68082483	0.47232578	0.04383165	0.00898135	0.05494145	0.00588463	0.01889785	0.01434451	3
0.85042537	0.34285633	0.05916423	0.00377042	0.03438002	0.00623664	0.01823316	0.01281504	3
1	0.23531815	0.06579154	0	0.00685275	0.00842452	0.02176306	0.01328599	3
0.81615203	0.36738994	0.03748949	0.0129291	0.05353094	0.00762001	0.01694446	0.01271766	3
0.74646496	0.42019637	0.05453428	0.00228441	0.03849979	0	0.01571368	0.01252173	3
0.74058102	0.42451711	0.06511613	0.00124118	0.02976521	0.00408461	0.014584	0.01302473	3
0	1	0.11441185	0.0510581	0.1068433	0.01274275	0.00083785	0.00129785	4
0.29809496	0.75923097	0.12607787	0.0527111	0.08094351	0.01554473	0.00141921	0.0012763	4
0.04989644	0.95903807	0.11640827	0.05432272	0.10485101	0.01429103	0.00049789	0.00117471	4
0.30493761	0.76513498	0.13808396	0.05352756	0.10329604	0.03094799	0.01126523	0.00188208	4
0.20752184	0.87806674	0.12229356	0.05118748	0.09598986	0.01308412	0.00086722	0.0006171	4
0.28558103	0.77039108	0.12944211	0.0492437	0.08021675	0.01332546	0.00013552	0.00060149	4
0.24436764	0.80555693	0.10513931	0.05188807	0.10536625	0.01707492	0.00368699	0.00072141	4
0.16777435	0.87462107	0.11666738	0.04935091	0.09836712	0.01296955	0	0	4
0.15306504	0.87718567	0.11361566	0.04958294	0.09830664	0.01255523	0.00023061	0.00033621	4
0.25551257	0.80472706	0.10964773	0.05048986	0.09366604	0.01387219	0.00087828	0.00026721	4
0.2427171	0.80696899	0.12803146	0.04942756	0.08684275	0.01304779	0.00026636	0.00070877	4

Table 13. Checking input for ANFIS

ER-4	ER-5	ACTUAL O/P	PREDICTED O/P	ERROR
0.12811295	0.03181569	0	-0.0003	0.0003
0.12829732	0.03322796	0	0.0002	0.0002
0.12532572	0.0316641	0	-0.0001	0.0001
0.12392302	0.0315845	0	-0.0002	0.0002
0.12391551	0.03164183	0	-0.0003	0.0003
0.12990445	0.03199141	0	-0.0005	0.0005
0.12992426	0.03114015	0	-0.0005	0.0005
0.1185823	0.03223074	0	-0.0001	0.0001
0.132408	0.02997512	0	-0.0043	0.0043
0.12711219	0.03199656	0	-0.0002	0.0002
0.1390979	0.00797254	0.333333	0.3527	0.019367
0.13733034	0.00797567	0.333333	0.3531	0.019767
0.14091421	0.00822153	0.333333	0.3741	0.040767
0.13166693	0.00789324	0.333333	0.3465	0.013167
0.13972165	0.00712864	0.333333	0.3122	0.021133
0.1354692	0.00695929	0.333333	0.3149	0.018433
0.14123136	0.0072614	0.333333	0.3134	0.019933

Table 13 (Cont'd). Checking input for ANFIS

ER-4	ER-5	ACTUAL O/P	PREDICTED O/P	ERROR
0.13424828	0.00738921	0.333333	0.3171	0.016233
0.13822797	0.00725652	0.333333	0.3134	0.019933
0.14114298	0.00721178	0.333333	0.3126	0.020733
0.14626921	0.00244442	0.666667	0.6664	0.000267
0.12808627	0.00257133	0.666667	0.7298	0.063133
0.13807935	0.00242773	0.666667	0.6575	0.009167
0.13999832	0.00253135	0.666667	0.7105	0.043833
0.12477881	0.00257476	0.666667	0.7314	0.064733
0.13720589	0.00241358	0.666667	0.6501	0.016567
0.14816561	0.00229696	0.666667	0.585	0.081667
0.13469459	0.00269687	0.666667	0.786	0.119333
0.12958844	0.00236762	0.666667	0.6251	0.041567
0.1291573	0.00233535	0.666667	0.6071	0.059567
0.0967352	0.00392737	1	0.9953	0.0047
0.07854905	0.00397722	1	0.9915	0.0085
0.09723658	0.00395262	1	0.9935	0.0065
0.09009868	0.00388024	1	0.9983	0.0017
0.09581827	0.00382012	1	1.0008	0.0008
0.09279846	0.00390191	1	0.9971	0.0029
0.08718627	0.00382343	1	1.0008	0.0008
0.08610848	0.00383061	1	1.0006	0.0006
0.09361508	0.00385866	1	0.9994	0.0006
0.09267752	0.0038258	1	1.0007	0.0007

Mean Absolute Error for selected Combinations:

combo45 7.71E-04 **combo16** 0.0015 **combo27** 0.019 **combo83** 0.0025

Table 14. Error table for different combination

S.NO	1	2	3	4	5	6	7	8
1	0	0.007436	0.008213	-0.00393	-0.00129	-0.00152	-0.01703	-0.00211
2	0	0	0.002467	-0.00162	-0.00841	-0.00702	-0.01896	-0.0075
3	0	0	0	-0.01195	0.014379	0.008492	-0.01058	0.002451
4	0	0	0	0	-0.00077	0.004262	-0.00749	-0.00578
5	0	0	0	0	0	0.00707	-0.01329	0.003778
6	0	0	0	0	0	0	-0.0283	-0.00199
7	0	0	0	0	0	0	0	-0.01463
8	0	0	0	0	0	0	0	0

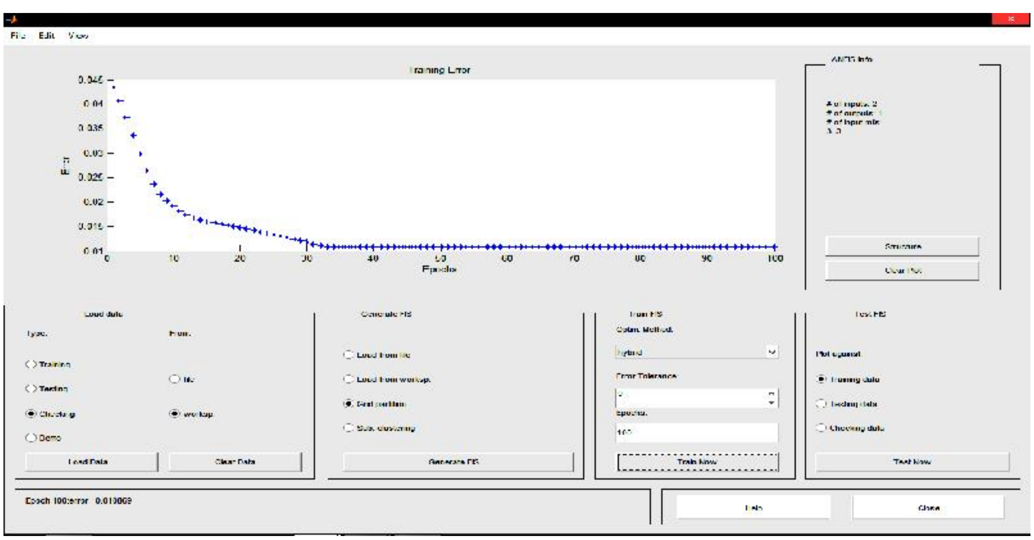


Figure 14. ANFIS Mean square error

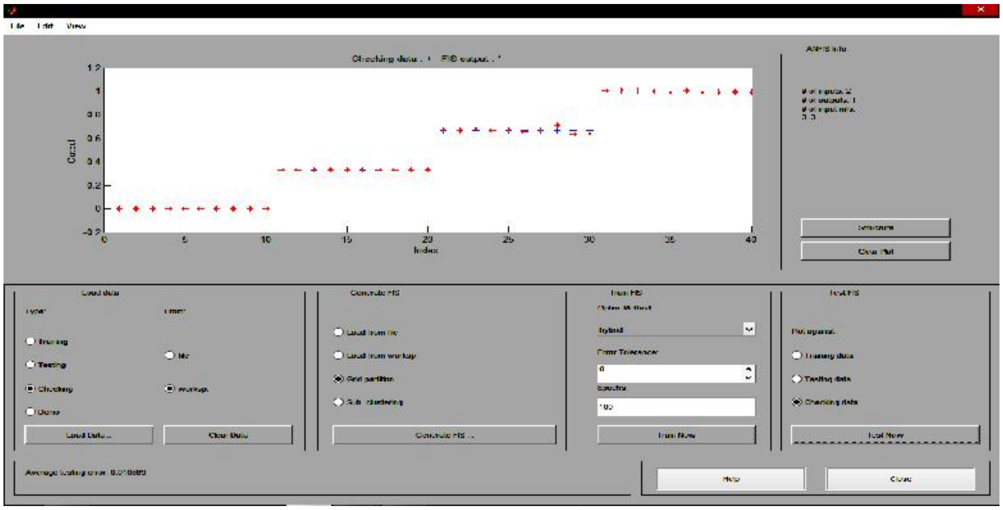


Figure 15. ANFIS classification

Figure 16. ANFIS rules

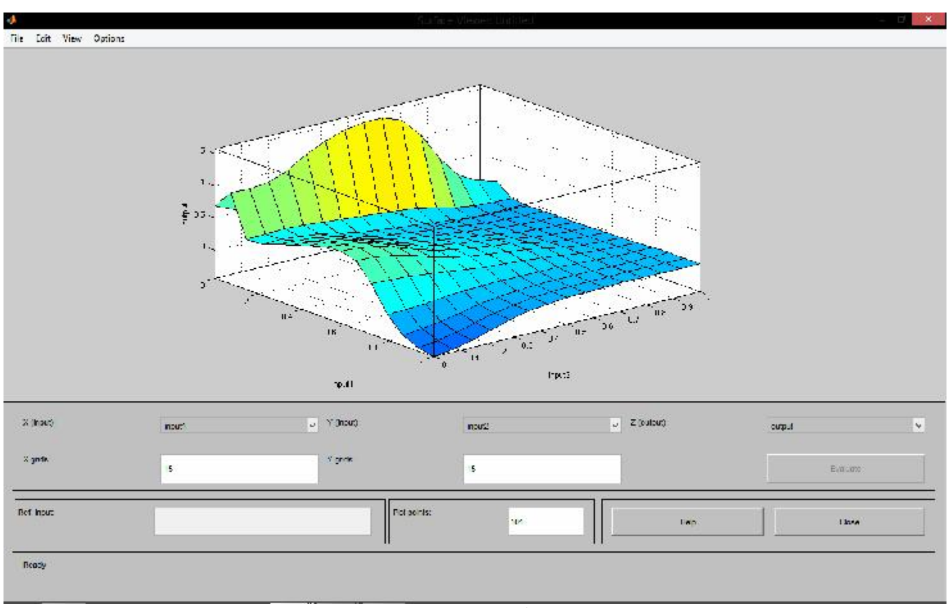


Figure 17. Surface

5. Conclusions

In this paper, a fault identification method has been proposed to identify the type of ball bearing fault. The proposed method is the combination of wavelet decomposition method, Principal component analysis and ANFIS or SVM. ANN and fuzzy based algorithm has been popularly used in the fault identification process. However, the use of SVM for machine condition monitoring and fault diagnosis is still rare. In this work, both conventional ANFIS and SVM techniques are implemented. It is found that SVM technique has higher accuracy compared to ANFIS. The proposed method has been simulated and validated using the vibration data collected from the ball bearing setup. The simulation result shows that the proposed method exactly predicts the type of fault and it has very good accuracy. Some improved version of SVM and ANFIS algorithm can be used to further improve accuracy of prediction is the future work. The proposed method may be extend to fault detection in other mechanical rotating elements

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