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BEARING DEFECT SIZE ESTIMATION BASED ON SUPPORT VECTOR MACHINE AND ACOUSTIC EMISSION SIGNALS

N. Mary Jasmin[*1], Ch.Ratnam[1], V.Vital Rao[2]K.Venkata Rao[3]

[1*]*Department of Mechanical Engineering, A.U College of Engineering (A), Visakhapatnam, India*
[2]*DGM,Engg. Shops & Foundry Dept., Visakhapatnam Steel Plant, Visakhapatnam, India*
[3]*Department of Mechanical Engineering, Vignan's Foundation for Science, Technology and Research, A.P., India*

Abstract--*Rolling element bearings are widely used in rotating machinery with wide application in industry. A reliable condition monitoring method is required to avoid unplanned shutdowns in this category of machines. The major reason for machine breakdown is the failure of rolling element bearings. In this paper, a technique is proposed for identifying faults in the rolling element bearings, based on an intelligent classifier technique called support vector machine (SVM). The proposed technique is focused on outer race faults experienced by the rotating machinery. Experiments are conducted on the defective bearing at different levels of speed and load conditions and acoustic emission (AE) data is collected for analysis. The SVM is trained with the experimental data to identify outer race faults using Acoustic emission signals collected in real-time by a data acquisition system. Results showed that the proposed SVM-based method was effective in identifying different outer race faults in the Rolling element bearings.*

***Keywords**: Defect size, rolling element bearings, Acoustic emission, SVM*

I. INTRODUCTION

Rolling element bearings also known as anti-friction bearings [1]are widely used in rotating machinery across various industriess that include aerospace, construction, mining, steel, paper, textile, railways, and renewable energy [2]. During the operation, the bearings experiences different faults due to high loading and different speed conditions. The bearing defects can be either distributed or local type or combination of both[3].The Damage and the failure of bearings contribute to machinery break down, consequently causing significant economic losses and even loss of human lives in certain situations; for example, when an air craft engine fails or a train derails due to a bearing seizure. Undesirable vibrations in rolling element bearings can be caused by either faulty installation, poor maintenance and handling practices [4] or surface fatigue [5], which eventually leads to the formation of various types of defects [6], often referred to as spalls, with in rolling element bearings. When a defective component ofa rolling element such as an outer raceway or an inner race way interacts with its corresponding mating components. Soabrupt changes in the contact stresses occur [7]. These changes excite the bearing structure and encompassing structural components connected to the bearing, resulting in the generation of vibrations, and consequently acoustic signals, which can be monitored, to detect the presence of a defect using appropriate condition-based vibration or acoustic diagnostic techniques [4, 7–19].There are a various methods that can be employed for monitoring the machine condition. The methods used for detection and diagnosis of bearing defects rely on collecting data from vibration measurements [20–22], acoustic measurements [23-24], and wear debris analysis [25–27]. Among these, vibration measurements are the most widely used methods. Several techniques have been used for measuring the vibration and acoustic responses of bearings, i.e., vibration measurements in time and frequency domains [28–31], the shock pulse method [32], sound pressure and sound intensity techniques [24,33-34], and the acoustic emission method [23,35]. Although there has been a great interest in vibrational analysis [36, 37], acoustic signal diagnostics is still a new approach. Furthermore, due to the need for an accelerometer for each bearing, vibration analysis is a much more expensive approach than acoustic signal analysis where only a microphone is needed to record the sound signal. Furthermore, an acoustic signal of a bearing can also be monitored by recording sound pressure [38, 39] or sound intensity [40] signals. Because there is a direct relationship between sound amplitude and vibrational acceleration [38], acoustic signal poses sensitivity to incipient defects of the bearing. In contrast to vibration analysis, acoustic signal analysis is economical and practical in fault diagnosis due to its noncontact measurement features [41]. It is shown that acoustic signal analysis performs better than vibration signal analysis, especially in early detection of faults in rotating machine elements.However, there is still a need for automated intelligent fault diagnostic systems using acoustic signal analysis instead of conventional methods [33]. Therefore, many diagnostic approaches are devoted to the research of the high frequency Acoustic Emissions (AE) in the condition monitoring of many types of rotating machinery [35,42-45]. An experimental test-rig was designed to allow seeded defects on the inner and outer race of radial load bearing, concluded that irrespective of the radial load, rotational speed and high levels of background noise, simple AEs characteristic parameters such as r.m.s and AE counts provided an indication of bearing defect. To validate already established AE techniques, this investigation focuses on establishing an appropriate threshold level for AE counts.[46]. Use of two ultrasonic sensors such as air-coupled(noncontact sensor) and piezoelectric ultrasound transducers (contact sensor) to detect incipient and evolving defects in rotating components such as bearings and gears is more desirable due to their high resolution [47].

II. SUPPORT VECTOR MACHINE FOR REGRESSION

Support Vector Machine was introduced by Vapnik [48] for the classifying regression problems of good generalization. In ANN methodology, large number of samples or data is required to predict responses accurately. But in the SVM methodology, less number of samples or data is enough to predict the responses with less error [49].A support vector machine (SVM) is a part of supervised learning, a branch of statistical learning which learns through a series of examples and becomes trained, i.e., it creates a 'decision-maker' system which tries to predict new values. When SVM is applied to regression problems, then it is called support vector regression (SVR).The prediction of continuous variables is known as regression.

The SVR model is given N training data$\{(x_i, y_i)\}_{i=1}^{N} \in R^m X\ R$,where xi is the inputvector to the SVR model and yiis the actual output value, from which it learns the input–output relationship. They have used the SVM methodology to predict defect size with less number of experimental data. Structure risk minimization principle is the main advantage of SVM and it is superior to conventional empirical risk minimization principle. The linear function is formulated in the high dimensional feature space, with the form of function given below [50].

$$y = f(x) = \sum_{i=1}^{N} w_i \emptyset_i(x) + b = w^T \emptyset(x) + b$$

where, ϕ *(x)* is the high dimensional feature space, which is nonlinearly mapped from the input space *x*. The weight vector *w=[w1,w2 ....wN],* $\emptyset = [\emptyset_1, \emptyset_2, \ldots\ldots]$and bias *b* are estimated by minimizing

$R(c) = C\frac{1}{n}\sum_{i=1}^{n} L(d_i, y_i) + \frac{1}{2}\|\omega^2\|$Where,

$$L_{\in(d,y)} = \begin{cases} |d-y| - \varepsilon, & |d - y(x)| \geq \varepsilon \\ 0, & otherwise \end{cases}$$

L (d, y) is called the ε-intensive loss function. This function indicates that errors below ε are not penalized. The term $C\frac{1}{n}\sum_{i-1}^{n} L(d_i, y_i)$ is the empirical error. $\frac{1}{2}\omega^2$measures the smoothness of the function. Both C and ε are prescribed parameters, ε is called the tube size of SVM, and C is the regularization constant determining the trade-off between the empirical error and the regularized term.

SVM regression model was executed using Rapidminer 5.0 software[49]. Scratch has been considered as a factor for fault analysis. The detection of the bearing fault is achieved by the Fast Fourier Transform. Finally, the diagnosis was performed with the help of Support Vector Machine [51]. To improve the diagnosis of normal bearing, inner race fault, and outer race fault conditions and itsaccuracy the parameter evaluation technique is used to select five features that are used as predictors in multi-class support vector machine (SVM) classification [52].Proposedfault detection method using support vector machine(SVM) and AE parameters. Experiments were conducted on a single stage reciprocating air compressor by combining healthy and faulty valve conditions to acquire the AE signals. SVM faults detection model was subsequently devised and validated based on training and testing samples [53]. The statistical time-domain features, extracted from a sample, were used as a single observation for training and testing SVM. The number of features varied from 5 to 10 to examine the effect on accuracy of SVM [54]. Good gears and face wear gears are used to collect vibration signals for good and faulty conditions of the gearbox. Each gear is tested with two different speeds and loading conditions. The statistical features are extracted from the acquired vibration signals. The extracted features are given as an input to the support vector machine (SVM) for fault identification[55]. Both time-domain and frequency-domain featureparameters are extracted from the vibration signals. Then,feature selection technique based on the class seperabilitycriterion is introduced. Finally, fault diagnosis is carried outusing Multi-class SVM classifier [56]. AE signal features and SVM network can be used for patternrecognition of the AE sources. The AE sources pattern recognition based on AE signal features andSVM network is more accurate than that based on BP neural network. [57].The SVM approach was also used in face milling process to predict tool breakage using cutting force data. For conducting experiments on the face milling of cast iron work piece Dynamometers were placed between work piece and table to measure cutting force. This cutting force data was used to train the SVM model in order to predict tool breakage[58]. The SVM methodology was also used in mining and civil engineering applications like prediction of ground vibration during blasting operation.

III. EXPERIMENTAL SETUP

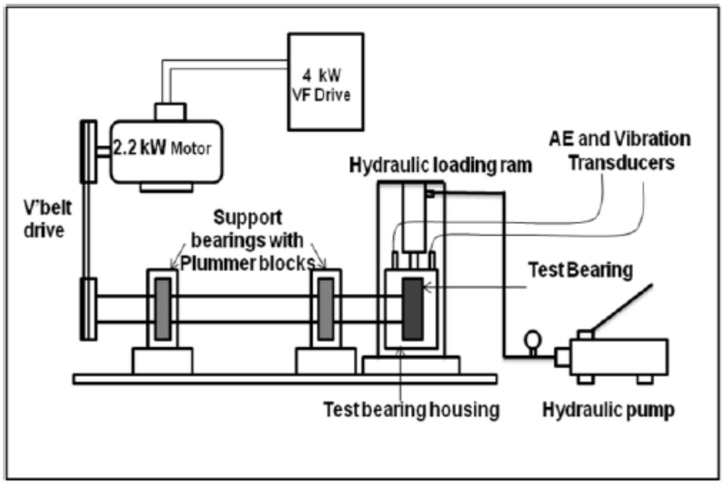

Figure 1. Schematic layout of test rig **Figure 2. Test Rig**

Tests were carried out in present work using experimental set up shown in figure 2. The testing involves mounting and running the defective bearing along with acquisition of AE data under various speed and load conditions. The experimental setup consists of a shaft driven by a variable speed range up to 2800 rpm with a maximum load capability of 16kN via a hydraulic ram. On left side the shaft is assembled by V-pulley and on the right side with the test bearings. And the shaft is supported on both sides by two concealed deep groove ball bearings with plumber blocks. The 2.2kW Motor placed on a separate base frame to free from vibrations to the test rig and the motor drives the shaft with the V-belt. The test bearing housing is square split housing which is made up of EN 24 steel material. On the top of split housing AE probe and hydraulic loading ram are placed while observing the test run. A schematic diagram of the rolling element bearings for experimental validation is shown in figure.1. In order to evaluate the proposed model, experiments are carried out for five different speeds. The Bearing parameters are tabulated in table-1.

Table 1. Test bearing specifications

Bearing specification	mm
Model No.	NTN N312
Inner diameter	60
Outer diameter	130
Width	33
Number of rollers	12

Rolling element diameter (d)	18
Pitch circle diameter (Dp)	96
Contact angle (θ)	0^0
Mass	1.80 kg
Speed Range	10-3000 r/min
Max load	16 kN

N312 bearing is a test Roller bearing where outer race can be separated shown in figure 3. The main reason for selection of this bearing is easy assemblage and dissembling of outer race. Inside of the outer race surface, 0.3, 0.5, 0.7, 0.9 and 1.1mm width defects respectively are created with Wire cut EDM. AE probe with MHC-Pro Acoustic Emission instrument was used for acquisition of vibration data, No. of test runs conducted on test rig to check the consistency of the data acquisitioned. For the first instance, a healthy bearing assembled to conduct Test run-1. After that, outer race removed, defect seeded on same outer race and conducted Test run-2. In both the Test runs, 2KN and 4KN load were applied at different RPMs. Acoustic Emission data was collected.


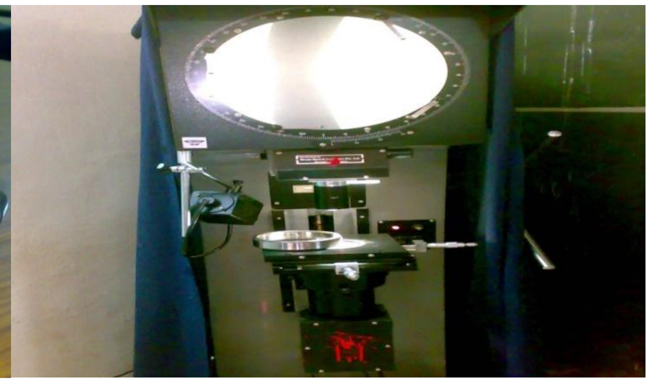

Figure 3. Test BearingFigure 4. Wire EDM m/c


Figure 5. Test rig with AE probes **Figure 6. Outer race seeded line defect**

IV. DATA ACQUISITION AND FEATURES EXTRACTION

First, the time versus Amplitude data of bearing in its running condition is collected. For acoustic emission (AE) data acquired from MHC-memo pro (Holroyd make) AE instrument with magnetic mount sensor of model 1030 Mag and 2048 samples (data points) are recorded per sec for each time wave. The AE sensor is resonant piezoelectric at 100 kHz frequency 24 dB gain. This instrument recorded the time wave of 2048 samples of data per second to enable a repetition frequency spectrum to be calculated. Each AE envelope spectrum covers the frequency range of 0 Hz to 1000 Hz and in representative of a one second period.A defect free bearing is assembled in the test bearing house and the test rig is run for minor adjustments. After that, the defect seeded bearing is assembled in the test bearing house and the defect is positioned at the top where the load is applied radially through hydraulic ram. Test runs are conducted at five speeds as N1=500, N2=700, N3=900, N4=1100, N5=1500 and at two loads as L1=4kN and L2=2kN in six steps. The rolling element bearing defect produces certain frequencies that depend on rolling element bearing geometry, number of rolling element, and shaft speed which is shown in Figure.7

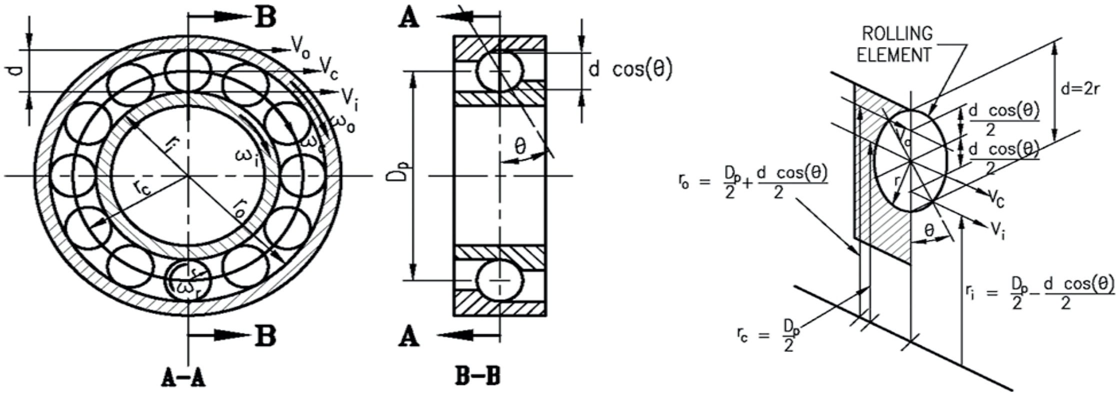

Figure 7. Schematic diagram of bearing geometry

These frequencies are expressed in Eqs.

$$FTF = \frac{1}{2}(f_i)\left(1 - \frac{dcos\theta}{D_p}\right)$$

$$BPFO = \frac{N}{2}(f_i)\left(1 - \frac{dcos\theta}{D_p}\right)$$

$$BPFI = \frac{N}{2}(f_i)\left(1 + \frac{dcos\theta}{D_p}\right)$$

$$\mathrm{BSF} = \frac{\mathrm{D_p}}{2\mathrm{d}}(f_i)\left(1 - \left(\frac{\mathrm{dcos}\,\theta}{\mathrm{D_p}}\right)^2\right)$$

Where,

FTF = Fundamental Train Frequency
BPFO = Ball Pass Frequency of the Outer race
BPFI = Ball Pass Frequency of the Inner race
BSF = Ball Spin Frequency

Dp = Pitch diameter
fi = Rotation frequency of inner race
N = Number of rolling elements
d = diameter of rolling element

The defect frequencies of rolling element bearings used in this study were given in Table 1

Table-2: Defect frequencies

rpm	Characteristic defect frequency in Hertz			
	FTF	BSF	BPFI	BPFO
500	3.38	21.43	59.35	40.61
700	4.74	30.03	83.15	56.89
900	6.09	38.59	106.88	73.13
1100	7.45	47.16	130.60	89.36
1300	8.80	55.76	154.40	105.64
1500	10.16	64.32	178.13	121.98

The AE data is processed through FFT with respect to AE lab software. Time waves and frequency spectrums at all test runs are analyzed. The time waves and frequency spectrums of acoustic emission without defect and with defect are presented in Figures 2 and 3.Similarly.remaining test runs were conducted with different defect sizes with various speeds and load conditions. The peak raised for all frequency spectra is at only one frequency i.e., BPFO=121.98 Hz and in subsequent super-harmonics no other peaks were observed. There are 12 impulses recorded for every 0.1 sec in the expanded time waves which matches with its BPFO. As the peak width increases defect size also increases and gives clear idea about the defect size increment. Consisted AE amplitudes (dB level) at defect frequencies for a good bearing and a defective bearing with different defects width 0.3, 0.5, 0.7, 0.9 and 1.1mm at outer race under 2 kN and 4kN loads are recorded.

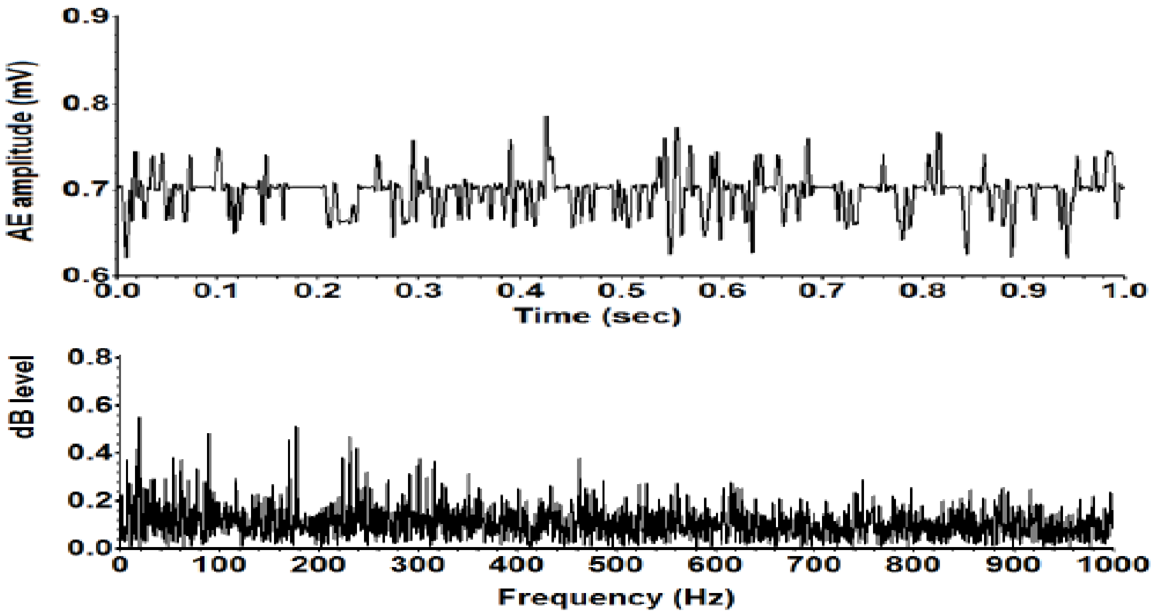

Figure 8. AE: (a) time wave and (b) frequency spectrum of test conditions L2 - S6.

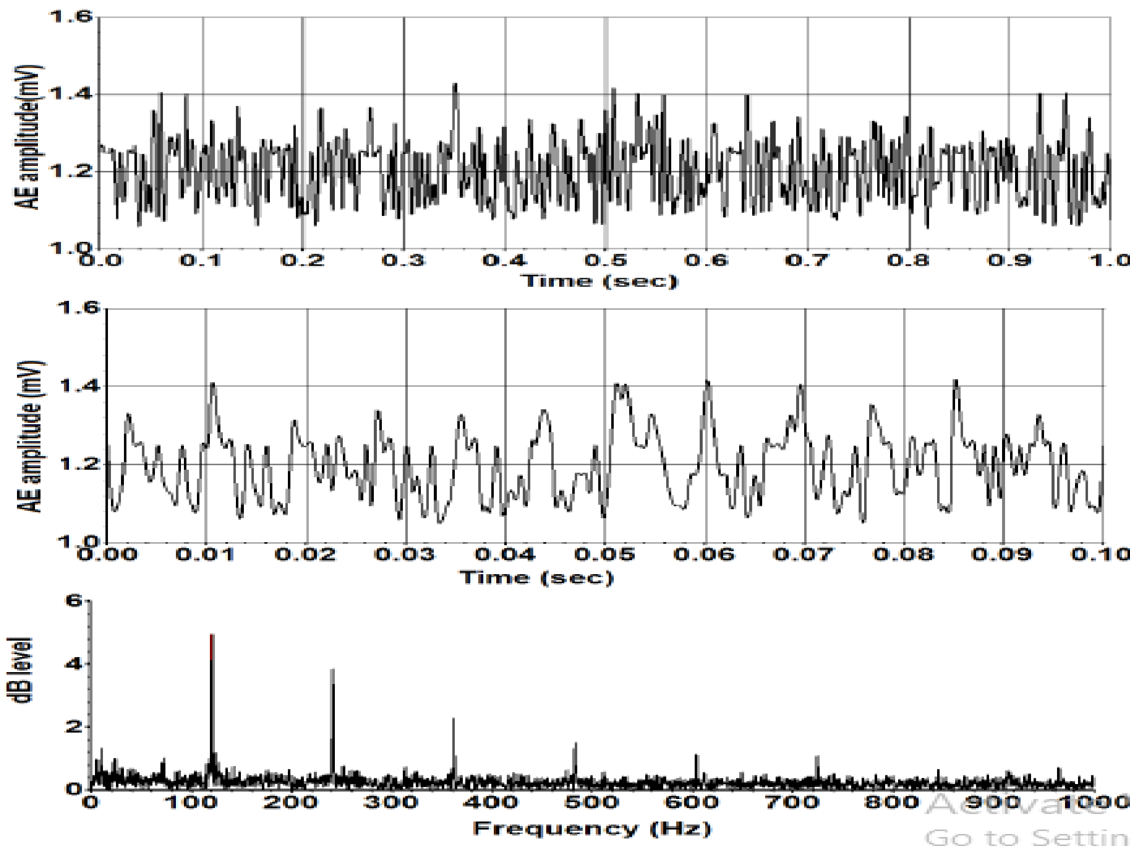

Figure 9. AE: (a) time wave; (b) enlarged time wave; and (c) frequency spectrum of test conditions L2-D4-S6.

In the field of fault diagnosis, statistical feature parameters calculated from the AE signals are used to identify the machinery condition they promote information indicated by a signal measured for diagnostics purpose. The statistical time-domain features[59], extracted from a sample, and were used as a single observation for training and testing SVM.

Table3. Features used for training and testing the SVM obtained from each sample of N data points f_n.

$\text{RMS} = \sqrt{\frac{1}{\text{N}}\sum_{n-1}^{N} f_n^2}$	$Mean = \frac{1}{N}\sum_{i=1}^{N} f_n$	$P_v = \frac{1}{2}[max(f_n) - min(f_n)]$
$Crest\ Factor = \frac{P_v}{RMS}$	$Skewness = \frac{\frac{1}{N}\sum_{n-1}^{N}(f_n - \bar{f})^3}{RMS^3}$	$Kurtosis = \frac{\frac{1}{N}\sum_{n-1}^{N}(f_n - \bar{f})^4}{RMS^4}$
$variance = \sigma^2 = \frac{\sum_{n=1}^{N}(f_n - \mu)^2}{N}$	Clearance Factore, $Cl_f = \frac{P_v}{\left(\frac{1}{N}\sum_{n=1}^{N}\lvert f_n \rvert\right)^2}$	
$Impulse\ Factor\ , I_f = \frac{P_v}{\frac{1}{N}\sum_{n=1}^{N}\lvert f_n \rvert}$	$shape\ Factor = S_f = \frac{RMS}{\frac{1}{N}\sum_{n=1}^{N}\lvert f_n \rvert}$	

Table 3 shows the definitions of the time-domainstatistical feature set used. The six time-domain statisticalfeatures are RMS, Peak value(Pv), Crest factor(CrF), skewness(SKEW), Kurtosis(KUR), Clearance Factor(ClF) along with AE amplitude(dB level), speeds and loads are used for training and testing of SVM. Flow chart as shown in figure.10.

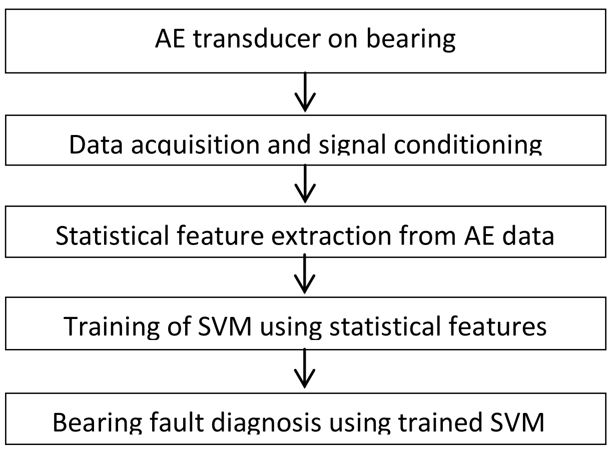

Figure.10 Methodology of flow chart

V. PREDICTION OF RESPONSES WITH SVM

Sixty experiments were planned and for each experiment at least two test runs were conducted. The same AE amplitude (dB level) is observed in the two successive test runs. For some experiments, test runs were conducted three to four times to achieve a consistency. A total of 146 test runs were conducted. In the acoustic emission analysis of the damaged bearing, the damage can be detected in its incipient stage but the defect size cannot be predicted. Hence, SVM model is used to predict theseeded faultsize and compare with the experimental data.In this study, SVM regression model was executed using Rapid miner 5.0 software. For better performance of SVM model, a nonlinear kernel was chosen than using linear kernel [49]. Then dot function kernel was selected as kernel function for the SVM model. SVM factors or coefficients such as C and ε are optimized using optimization of SVM parameters in the Rapidminer 5.0 software. The optimized values of C and ε are 1000 and 0.001 for defect size shown in figure 11. Basic pairs of (C and ε) are tried and the one with the best cross-validation performance is picked. Exponentially growing sequences of C and ε is a practical method to identify good parameters. For example, $C = e^{-4}, e^{-2}, \dots., e^{6}$ $\quad \varepsilon = e^{-6}, e^{-4}, \dots, e^{-2}$. After repeated tests, coefficient C and ε are chosen as 1,000 and 0.001 for Defect size-SVM model. Then the SVM model is trained using training data.

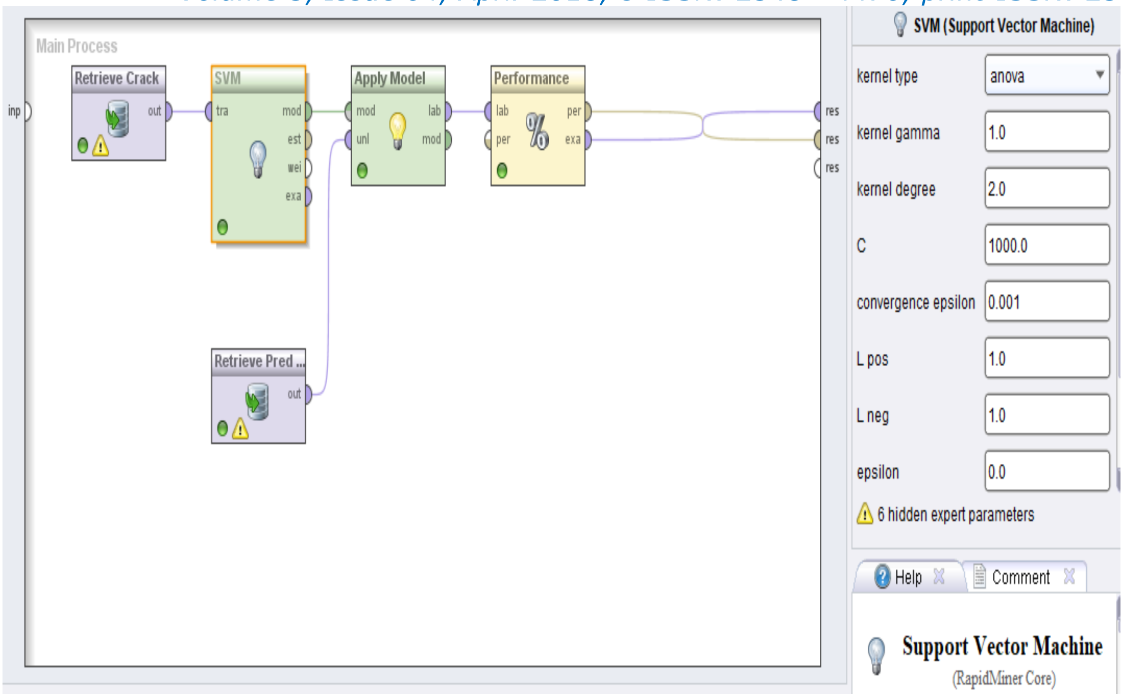

Figure 11. RapidMiner 5.3S/w for SVM model

Table 4 Parameter values from the experimental data

S. No.	LOAD (kN)	RPM	AE AMP (dB level)	RMS	PEAK VALUE	CREST FACTOR	SKEWNESS	KURTOSIS	CLEARANCE FACTOR	DEFECT SIZE(mm)
1	2	500	1.14	0.82	0.27	0.33	0.0004	0.0001	0.05	0.3
2	2	700	1.30	0.67	0.23	0.34	0.0008	0.0003	0.05	0.3
3	2	900	1.08	0.75	0.22	0.30	0.0004	0.0002	0.05	0.3
4	2	1100	1.74	0.81	0.27	0.34	0.0008	0.0003	0.05	0.3
5	2	1300	2.06	0.85	0.23	0.28	0.0007	0.0003	0.06	0.3
6	2	1500	1.84	0.46	0.23	0.26	0.0005	0.0002	0.06	0.3
7	**2**	**500**	**1.80**	**0.89**	**0.27**	**0.33**	**0.0004**	**0.0001**	**0.05**	**0.5**
8	2	700	1.46	0.94	0.23	0.25	0.0002	0.0001	0.06	0.5
9	2	900	2.16	1.01	0.26	0.25	0.0004	0.0001	0.07	0.5
10	2	1100	2.89	1.09	0.20	0.18	0.0003	0.0001	0.08	0.5
11	2	1300	3.21	1.14	0.24	0.21	0.0002	0.0001	0.08	0.5
12	2	1500	3.52	1.18	0.27	0.23	0.0001	0.0001	0.08	0.5
13	2	500	2.53	0.80	0.27	0.34	0.0014	0.0006	0.07	0.7
14	2	700	2.71	0.91	0.24	0.27	0.0006	0.0003	0.07	0.7
15	**2**	**900**	**3.75**	**0.99**	**0.27**	**0.28**	**0.0007**	**0.0002**	**0.08**	**0.7**
16	2	1100	4.58	1.07	0.26	0.24	0.0005	0.0002	0.08	0.7
17	2	1300	5.47	1.13	0.24	0.21	0.0006	0.0002	0.09	0.7
18	2	1500	4.62	1.27	0.24	0.18	0.0002	0.0001	0.06	0.7
19	2	500	3.01	0.82	0.27	0.34	0.0013	0.0005	0.06	0.9
20	2	700	4.22	0.79	0.22	0.28	0.0009	0.0003	0.07	0.9
21	2	900	4.99	0.88	0.27	0.31	0.0007	0.0003	0.08	0.9
22	2	1100	5.27	0.94	0.23	0.25	0.0006	0.0002	0.08	0.9
23	2	1300	5.76	1.21	0.20	0.16	0.0006	0.0002	0.08	0.9
24	2	1500	6.76	1.18	0.23	0.19	0.0004	0.0001	0.10	0.9
25	2	500	3.16	0.85	0.18	0.22	0.0003	0.0001	0.06	1.1
26	2	700	4.27	0.96	0.25	0.27	0.0008	0.0003	0.07	1.1
27	2	900	5.81	1.06	0.20	0.18	0.0005	0.0001	0.08	1.1
28	2	1100	6.49	1.14	0.23	0.20	0.0004	0.0001	0.08	1.1
29	2	1300	5.98	1.00	0.23	0.24	0.0007	0.0002	0.08	1.1
30	2	1500	6.87	1.06	0.22	0.20	0.0004	0.0001	0.09	1.1
31	4	500	1.13	0.60	0.23	0.39	0.0004	0.0004	0.05	0.3
32	4	700	1.25	0.69	0.20	0.29	0.0007	0.0003	0.05	0.3
33	4	900	1.39	0.78	0.22	0.29	0.0005	0.0002	0.05	0.3
34	4	1100	2.18	0.83	0.23	0.26	0.0004	0.0002	0.06	0.3
35	4	1300	2.21	0.87	0.25	0.29	0.0005	0.0002	0.06	0.3
36	4	1500	2.34	0.91	0.23	0.26	0.0004	0.0002	0.06	0.3
37	4	500	2.04	0.82	0.19	0.23	0.0005	0.0001	0.06	0.5
38	4	700	3.43	0.92	0.25	0.28	0.0002	0.0001	0.07	0.5
39	**4**	**900**	**4.32**	**0.95**	**0.23**	**0.25**	**0.0005**	**0.0002**	**0.07**	**0.5**
40	4	1100	5.84	1.12	0.20	0.18	0.0003	0.0001	0.08	0.5
41	4	1300	4.21	1.26	0.20	0.16	0.0003	0.0001	0.07	0.5
42	4	1500	5.07	1.20	0.20	0.16	0.0003	0.0001	0.08	0.5
43	4	500	2.96	0.84	0.23	0.33	0.0007	0.0002	0.06	0.7
44	4	700	3.52	0.94	0.22	0.22	0.0006	0.0002	0.07	0.7
45	4	900	5.78	1.04	0.22	0.21	0.0005	0.0002	0.08	0.7
46	4	1100	5.83	1.20	0.22	0.22	0.0008	0.0002	0.08	0.7
47	4	1300	5.31	1.08	0.23	0.21	0.0002	0.0002	0.08	0.7
48	4	1500	6.02	1.32	0.24	0.21	0.0003	0.0002	0.09	0.7
49	**4**	**500**	**3.04**	**0.84**	**0.30**	**0.36**	**0.0004**	**0.0002**	**0.07**	**0.9**
50	4	700	4.55	0.94	0.27	0.29	0.0016	0.0006	0.09	0.9
51	4	900	6.94	1.04	0.30	0.28	0.0014	0.0005	0.10	0.9
52	4	1100	6.95	1.20	0.20	0.16	0.0005	0.0005	0.08	0.9

53	4	1300	5.99	1.08	0.26	0.24	0.0005	0.0001	0.08	0.9
54	4	1500	6.95	1.32	0.22	0.16	0.0005	0.0001	0.07	0.9
55	4	500	3.98	0.83	0.27	0.33	0.0013	0.0004	0.07	1.1
56	4	700	5.96	0.99	0.26	0.26	0.0011	0.0003	0.09	1.1
57	4	900	7.41	1.13	0.20	0.17	0.0002	0.0003	0.09	1.1
58	4	1100	8.55	1.12	0.27	0.24	0.0013	0.0004	0.11	1.1
59	4	1300	9.76	1.20	0.27	0.23	0.0013	0.0003	0.12	1.1
60	**4**	**1500**	**11.8**	**1.26**	**0.31**	**0.25**	**0.0009**	**0.0003**	**0.13**	**1.1**

This Rapid miner 5.0 software has been used here for the application of SVR in predicting the defect size of the test bearings. The input parameters have been normalized between 0 and 1. The training set X is the combined vector of all the nine input parameters such as speed, load, amplitude level, RMS, Peak value, Crest factor, skewness, Kurtosis, Clearance Factor and the training set Y is one output parameter i.e., defect size. Sixty sets of input-output pairs from Table 2 have been used for training of the SVR model. After training the models, the final prediction models for output objectives are obtained. The five groups of testing data are used to test the models. The comparison results between the actual and predicted values are shown in Table 5.

Table 5. Test results of SVM using the five groups of parameter combinations

S.No	Load (KN)	rpm	Amplitude (dB level)	RMS	Peak Value	Crest Factor	Skewness	Kurtosis	Cl Factor	Seeded Defect size (mm)	Predicted defect size (mm)	% error
1	2	500	1.8	0.89	0.27	0.33	0.0004	0.0001	0.05	**0.5**	**0.506**	1.19
2	2	900	3.75	0.99	0.27	0.28	0.0007	0.0002	0.08	**0.7**	**0.73**	4.11
3	4	900	4.32	0.95	0.23	0.25	0.0005	0.0002	0.07	**0.5**	**0.57**	12.28
4	4	500	3.04	0.84	0.3	0.36	0.0004	0.0002	0.07	**0.9**	**0.911**	1.21
5	4	1500	11.8	1.26	0.31	0.25	0.0009	0.0003	0.13	**1.1**	**1.15**	14.09
Average of % error												6.57

The calculation of percentage error between the actual defect size and its predicted size shows an average defect size error of 6.57% as shown in table 5.Figure 12 shows a graph of comparison between the actual and the predicted defect sizes of testing data.

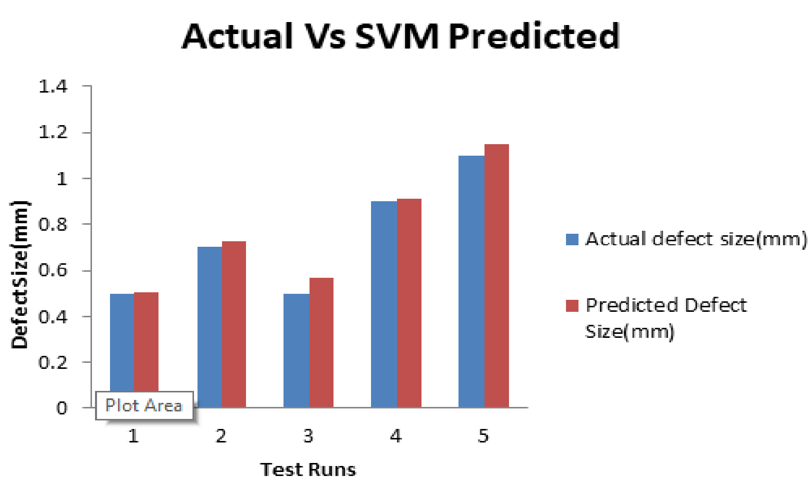

Figure12. Defect size comparison with actual versus SVM predicted values

VI. CONCLUSIONS

The experiments were carried out on Rolling Element Bearings, to estimate defect size with six levels of speed, five levels of defect size and two levels of load. AE time wave signals acquired with an AE probe are analyzed through FFT with AE lab software. This Rapid miner 5.0 software has been used here for the application of SVR in predicting the defect size of the test bearings. Statistical model SVM was effective in identifying different outer race faults in the Rolling element bearings. The following conclusions can be drawn from this study.

1. As the peak width increases defect size also increases and gives clear idea about the defect size increment. Consisted AE amplitudes (dB level) at defect frequencies for a good bearing and a defective bearing with different defects width 0.3, 0.5, 0.7, 0.9 and 1.1mm at outer race under two loads as 2kN,4kN and five different speeds such as 500,700,900,1100,1500 (rpms) were recorded.
2. In the acoustic emission analysis, the damage in the outer race can be detected in its incipient stage and the defect size can be predicted by SVM model bearing with different defects width 0.3, 0.5, 0.7, 0.9 and 1.1mm at outer race under loads 2kN&4kN and speeds 500, 700, 900, 1100& 1500 (rpms) respectively.
3. The six time-domain statistical features such as RMS, Peak value, Crest factor, skewness, Kurtosis, Clearance Factor along with AE amplitude (dB level), speeds and loads were used for training and testing of SVM.
4. It was observed that there was near relation between experimental data and predicted values for AE level (6.57% of error).

VII. DECLARATION OF CONFLICTING INTERESTS

The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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