IGWO ALGORITHM BASED WSVM CLASSIFICATION OF DIFFERENT FAULTS IN INDUCTION MOTOR ROLLER BEARING USING VIBRATION SIGNALS

Agnes Prema MARY K[1], Dr. Subburaj P[2], Dr. Maheswari R V[3]

[1]Anna University, Jayaraj Annapackiam CSI College of Engineering, Tuticorin, Tamil Nadu, India

agnesmarythesis@gmail.com

[2] Anna University, Sri Lakshmi Ammal Engineering College, Chennai, Tamil Nadu, India

subbuneceee@yahoo.com

[3] Anna University, National Engineering College, Tuticorin, Tamil Nadu, India

rvmaheswari@gmail.com

ABSTRACT:- *The changes in electrical and mechanical components creates many problems and complications in roller bearing element which results in production of vibration signals and cause the whole system damaged. So diagnosis of fault in roller element bearing has to be made more sophisticated to reduce the roller breakdown. In this paper, the vibration signals are obtained from the roller bearings in four different conditions namely normal condition, inner race fault, outer race fault and roller rub fault. Then the signals are decomposed using improved Empirical mode decomposition (EMD) denoising technique. By applying shifting, the Intrinsic Mode Functions (IMF) components are extracted from the measured signal after performing three iterations. To classify different faults, the statistical features like mean, standard deviation, kurtosis, skewness, energy and entropy are extracted. These statistical features are used in wavelet support vector machine (WSVM) based classifier to classify the different faults. The improved grey wolf optimization (IGWO) is used to improve the performance of WSVM. The results reveal that, IGWO implemented WSVM classifier shows better performance in terms of fitness strength and confusion matrix due to flexibility in fitness strength and good out-of-sample generalization.*

Keywords –Induction Motor, Roller bearing, EMD denoising, IMF, IGWO, WSVM

1. INTRODUCTION

In machineries, the mechanical elements and electrical components are maintained properly for efficient function of the system. The roller bearing can withstand higher load compared to ball bearings makes it suitable for heavy load industrial applications with moderate speed *[1]*. The faults if any occurs in roller bearing will produces heavy damage both in rotating and stationary parts which necessitates the faults must be detected and diagnosed initially. The fault in roller element occurs due to the machinery operated in high speed or with heavy load or in low operating temperature and interruption of lubricant supply. The roller bearing faults can be predicted both in time domain and in frequency domain of the system. Even though it has ease of use, it cannot classify the fault in high accuracy *[2]*. For determining the different type of faults, the vibrating signals can be used as an effective tool *[3]*. The demanding factor in this rotating machinery is to determine the fault affected area with the vibration signal chosen in high level *[4]*.

The traditional decomposition techniques like Proper Orthogonal Decomposition (POD) and Singular Value Decomposition (SVD) have drawback of high dimensional values which requires rescaling *[5, 6]*. The signals are preprocessed by EMD denoising and the noise signals were discarded and then signal is decomposed using several Intrinsic Mode Functions (IMF) *[7]*. The advantage of EMD is to adapt non-linear and non-stationary signals. The statistical features in time and frequency domains were considered for extracting the features of normal and fault signal and it can be done by artificial intelligent methods such as expert systems, fuzzy logic and artificial neural networks (ANN) *[8, 9]*. The SVM classifier was used in fault classification in roller bearing, ball bearing, motor variation and in gear changes *[10]*. The wavelet based approaches compares the varying vibration signals in the system. For extracting the suitable parameters and to select the optimal feature set, the WSVM classifier was used.

The genetic algorithm, the Ant colony Optimization (ACO) and Particle Swarm Optimization (PSO) was also used for optimization. The ACO algorithm is based on the food searching of ant where its goal is to find the shortest path for obtaining food. The PSO algorithm is based on the swarm search of birds and fishes was used for fault classification. The convergence rate is lower in these techniques. The Harmony Search (HS) algorithm, Harmony Search Differential Evolution (DE), Evolutionary Programming made Faster (FEP), Gravitational Search Algorithm (GSA), where the drawback is low value for the fitness strength, slow convergence rate, local optimal solution and poor generalization problems. So in this work, SVM classifier is considered as it has good generalization with few samples. To optimize the WSVM classifier, Grey Wolf Optimization technique is implemented, as it provides best optimal solution and fitness strength.

The organization of the paper is as follows. Section.2 gives the details about the fault produced in roller bearings and in rotating machinery. Section.3 denoising of vibration signals using Empirical Mode Decomposition algorithm with shifting done by Intrinsic Mode Functions. The feature extraction and fault classification using WSVM optimization with IGWO technique is explained in Section.4. Section.5 describes the performance measures taken for the IGWO based WSVM classification. Section6 gives the experimental details and their analysis of the classification and optimization algorithm. Finally Section.7 gives the conclusion and further work.

2. FAULTS IN ROLLER BEARING

Due to the manufacturing defect, poor lubrication techniques, overstress, overload and misalignment, the faults such as inner race fault, outer race fault and roller rub can occur in roller bearing. The different types of frequency involved are Basic Train Frequency (BTF), Roller Rub (RR), Inner Race (IR) and Outer Race (OR). The formula used are

$$\mathrm{BTF} = \frac{\mathrm{rps}}{2}\left[1 - \frac{\mathrm{Bd}}{\mathrm{Pd}}\cos\emptyset\right]; \tag{1}$$

$$\mathrm{RR} = \frac{\mathrm{Pd}}{2\mathrm{Bd}}(\mathrm{rps})\left[1 - \left(\frac{\mathrm{Bd}}{\mathrm{pd}}\right)^2 \cos^2\emptyset\right]; \tag{1a}$$

$$\mathrm{IR} = \mathrm{N}(\mathrm{rps} - \mathrm{BTF}); \tag{1b}$$

$$\mathrm{OR} = \mathrm{N}(\mathrm{BTF}). \tag{1c}$$

where, rps-revolution per second of inner race, Bd-Ball Diameter, Pd-Pitch Diameter, N-Number of ball, $\emptyset$-Contact angle. To find the signal distortion and the analysis of damage in the system, the amplitude of the bearing signals is taken.

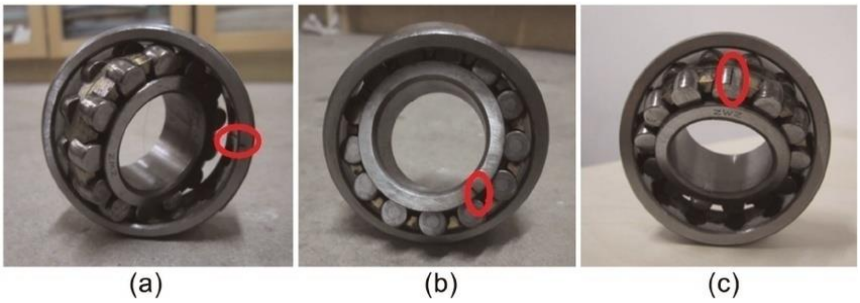

Figure 1 Roller Bearing

Figure 2 a) Outer race fault b) Inner race fault c) Roller rub fault

Figure 1 shows the roller bearing and Figure 2 shows the bearing with outer race fault, inner race fault and roller rub fault occurs due to the manual misleading and natural changes in the roller bearings.

3. EMD DENOISING

The data from the rotating machinery should be analyzed from non-linear and non-stationary basis and for improved denoising the decomposition should be adaptive. For the prediction of the fault signal to be accurate, several samples are needed for comparison, hence the oscillation of the signals split into IMF components.

3.1 Intrinsic Mode Functions

The initial step of EMD is to determine the lower and upper envelopes from the extrema. The cubic splines, boundary conditions and the interpolation method are mainly considered for the decomposition. The IMF must satisfy the conditions such as convergence, completeness, orthogonality and uniqueness.

3.1.1 *Conditions for IMF*

The conditions to be satisfied for extracting the IMF signal are, 1) The number of zero crossing elements and the number of extrema differs only by one. 2) The average of upper envelope and lower envelope is maintained as zero.

3.2 Shifting process in EMD Denoising

The vibration signal in the roller bearing is transformed into IMF components using shifting process. The effects involved in shifting process are eliminating the riding waves for equaling the number of extrema to the zero crossing levels and the envelope of the signal is symmetrically composed even though the amplitude of oscillation of the vibrated signal differs.

3.3 EMD denoising Algorithm

The decomposed signal are in the time domain and having the same amplitude as the original signal permits for diverging frequency and should be saved. Decomposing the signal into IMFs is necessary because the real world signals have many causes and occurs in particular time intervals. The decomposing cannot be performed many epoch which leads to over decomposition. The EMD Denoising Algorithm is given below:

1) Determine the local extrema or maxima.
2) By using cubic spline, link the points to extend a higher envelope.
3) The lower envelope is also found by means of local minima.
4) Find the average envelope where the original signal frequency higher than mean value.
5) Subtract the average value of upper and lower envelope from the original signal.
6) IMF signal get extracted from the residue signal. This iterative algorithm is called sifting.
7) EMD decomposes the original vibrated and fault signal into finite frequency signals
8) Finally, the decomposed signal is achieved by adding all the IMFs.

4. FAULT DIAGONSIS PROCEDURE

Figure 3 shows the overall block diagram of fault classification technique. The vibrated signals are obtained from the accelerometer and it is

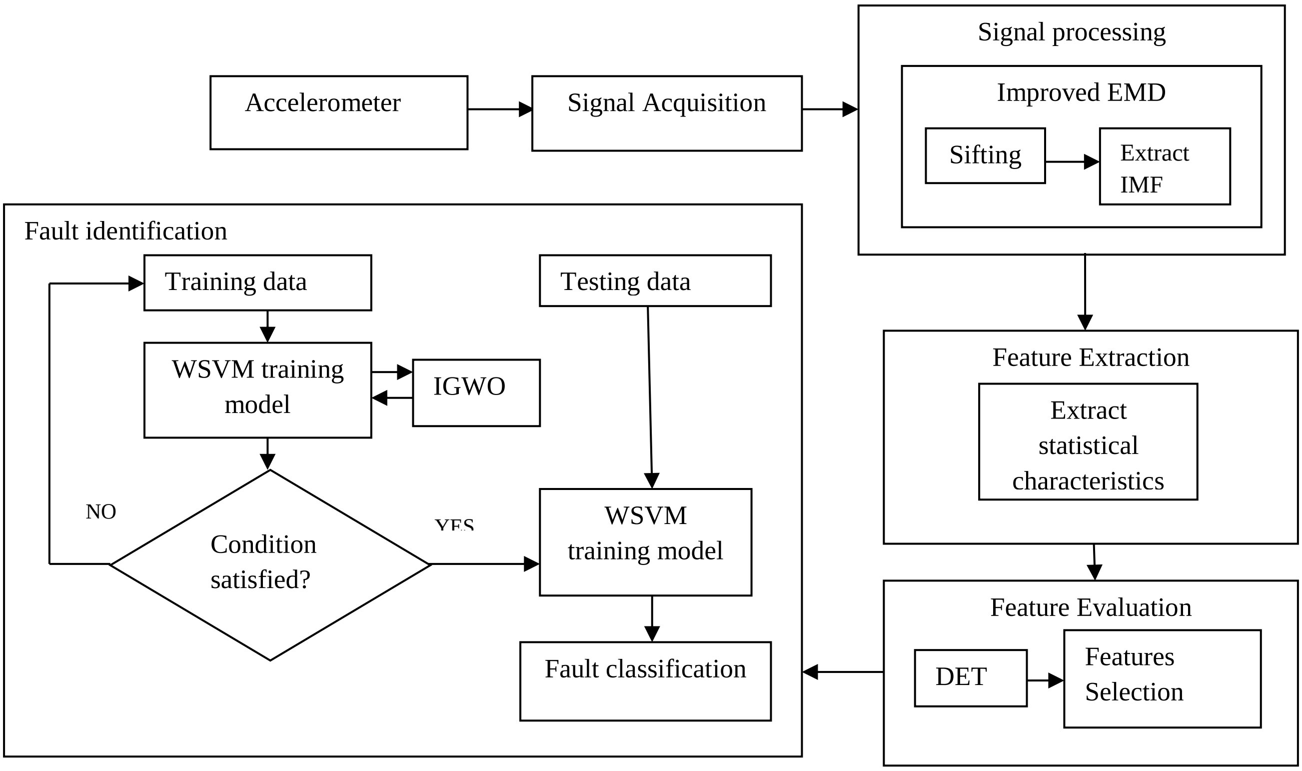

Figure 3 Block diagram of fault classification technique

preprocessed and the noise in the signals is removed using EMD denoising technique. The statistical features are extracted and evaluated using distance evaluation technique. The features are given to the WSVM classifier and the parameters are optimized using IGWO algorithm.

4.1 Feature extraction and evaluation

The statistical features extracted are

- *Mean*

  Mean: $\mu_i = \frac{1}{N}\sum_{j-1}^{N} f_{ij}$ (2)

- *Standard deviation*

  SD: $\sigma_i = \left(\frac{1}{N}\sum_{j-1}^{N}\left(f_{ij} - \mu_i\right)^2\right)^{\frac{1}{2}}$ (3)

- *Root Mean square(RMS)*

  To diagnose the signal the RMS will take the difference between two data sets and the value is compared with the average which could be denoted as zero.

- *Crest factor*

  The crest factor can be determined by the peak value of the signal divided by the RMS factor.

- *Skewness*

$$skew(X) = \frac{E[(X - \mu)^3]}{\sigma^3} \quad (4)$$

Where µ - mean of X and σ - Standard deviation of X.

- *Kurtosis*

$$Kurt(X) = \frac{E[(X - \mu)^2]}{\sigma^4} \quad (5)$$

Where µ - mean of X and σ - Standard deviation of X.

- *Wenergy*

  The wavelet energy can be found as the ratio of total energy level of the signal to the energy of each level.

- *Wentropy*

  Entropy: $\varepsilon_i = -\sum_{j-1}^{N}(f_{ij} * \log f_{ij})$ (6)

- *iqr(interquartile range)*

  The iqr determines the midspread value. It is the measure of variability. The value is obtained by finding the difference between the first quartile and third quartile.

- *logenergy*

  $$H_{LogEn}(\mathrm{x})=-\sum_{i=0}^{N-1}\left(log_2\left(pi(x)\right)\right)^2 \quad (7)$$

- *Shanon entropy*

  $$H_{Shanon}(\mathrm{x})=-\sum_{i=0}^{N-1}(pi(x))^2\, log_2((pi(x)))^2 \quad (8)$$

4.2 Wavelet Support Vector Machine (WSVM) classifier

The Wavelet Support Vector Machine is a supervised learning models used for classification and regression There are four types of signals are considered for classification. The signals are, normal vibrating signal, outer race fault signal, inner race fault signal, roller rub signal. Two types of classifiers are used in this work. They are two classes WSVM and four classes WSVM. Fifty signals of each category are taken for process and 11 features are using for two classes WSVM classification.

4.2.1 *Improved Grey Wolf Optimization (IGWO)*

GWO algorithm provides information of every search space of all iterations where the Evolutionary algorithms discard the previous value information.
This algorithm have two steps: 1) Exploration 2) Exploitation

Exploration is the process of enquiring the potential area of the search space where the exploitation is the local search ability around the regions receiving from the exploration process. Grey wolves are the top line predators in the food pyramid. The order of the wolves can be classified as four types, they are alpha, beta, omega and delta. Here the female wolves are the decision makers known as alpha and reinforces the command of alpha is said to be beta. The lowest rank orders in the grey wolf level which obey all orders of the upper level wolves are called as omega. Delta wolves are dominant to omega and inferior to both alphas and betas. The classical algorithm takes only one pack for creation, but in this proposed method it takes more than one pack for replication. To reduce the local optima and to distribute the values for developing the search space, the migration strategy of wolves are taken. In first phase, a group of individuals forms a new habitat, then it divides into sublevels. The third stage is the one which has the competition between new formed levels with the native level. The process is based on its size and its number. The pack which has the best fitness value is selected for the migration operation. Except the best pack the number of wolves is unequal and it is migrated towards the best pack, this will lead to the minimization of wolves in best pack.

4.2.2 *Improved Grey Wolf Optimization (IGWO) algorithm*

The Improved Grey Wolf Optimization (IGWO) algorithm filters the redundant and irrelevant information by searching the optimal feature. The selection operation is performed by considering the fitness value, and it is calculated and sorted from the minimize function. Then the followed packs are created arbitrarily to replace the emigration wolf. The optimal solution is improved by applying the IGWO algorithm for optimization.

The distance of the wolf and the victim can be calculated by using the equation

$$\overrightarrow{D_\propto} = \left|\overrightarrow{C_1}.\overrightarrow{X_\propto} - \vec{X}\right| \quad (9)$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right| \quad (9a)$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \quad (9b)$$

Where $D_{\propto}, D_{\beta}, D_\delta$ are the distances of α, β, δ of the wolves. The remaining wolves values are given as $\overrightarrow{X_1}, \overrightarrow{X_2}, \overrightarrow{X_3}$

$$\overrightarrow{X_1} = \overrightarrow{X_\propto} - \overrightarrow{A_1}.\overrightarrow{D_\propto} \quad (10)$$
$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta} \quad (10a)$$
$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta} \quad (10b)$$

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a}, \vec{c} = 2.\overrightarrow{r_2},$$

$$\vec{X}(t+1) = {\left(\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}\right)}\Big/{3} \quad (11)$$

where a, c, A are the controlling parameters in the algorithm. r1 and r2 are the random variables. These random vectors will help the wolf to predict the victim at any point. The component vectors decrease as the iterations go longer. Fig 5 shows the flowchart of IGWO algorithm which performs the optimization of the roller bearing design by considering some benchmarks. The Improved Grey Wolf Optimization algorithm is given below

1) Initialize the population of wolf in the counter.
2) Initialize the suitable values for the population.
3) Initialize the search agent values.
4) The fitness strength values are calculated for each wolf.
5) Characterize the wolves based on the quality and rank among them as the best wolf.
6) The grey wolves are arranged based on the fitness strength.
7) Update the values based on the IGWO algorithm map.
8) Update the positions of grey wolf based on the number of iterations and the quality of the wolf.
9) Update the best fit values for each search and replace the worst fit values for each iteration.

5. PERFORMANCE MEASURES

The performance parameters are listed as Accuracy, Sensitivity, Specificity and Classification Error

Accuracy: It takes into account both normal vibration signal and fault signal that have been truly detected by the automated method. The accuracy of the SVM classifier is calculated by using the formula which is given by,

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \times 100\% \quad (12)$$

Sensitivity: It shows the percentage of the normal vibrating signal that has been truly detected by the automated method.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \times 100\% \quad (13)$$

Specificity: It shows the percentage of the fault vibrating signal that has been truly detected by the automated method.

$$\text{Specificity} = \frac{TN}{TN + FP} \times 100\% \quad (14)$$

Classification Error: It measures the discrepancy between these two signals,

$$\text{Border Error} = \frac{FP+FN}{TP+FN} \times 100\% \quad (15)$$

6. EXPERIMENTAL RESULTS AND ANALYSIS

For analysis, the data set is collected from Case Western Reserve University. The experimental setup consists of a transducer, dynamometer and a 2 hp induction motor. The normal and fault vibrated signals are collected from The Improved Grey Wolf Optimization algorithm is compared with several algorithms for its optimal solution, fitness strength, accuracy and performance.

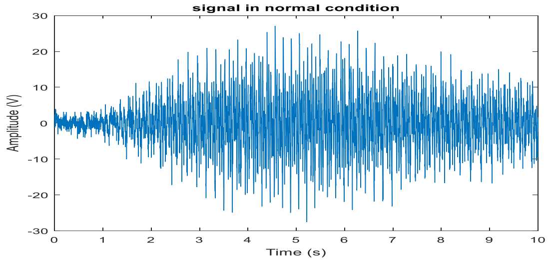

Figure 4 Normal vibrating signal

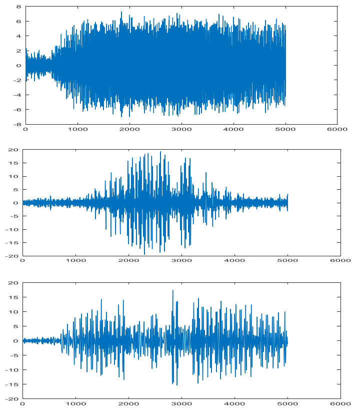

Figure 5 IMFs of normal vibrating signal

Figure 4 shows the signal in normal vibration mode obtaining from the accelerometer which runs in 1750rpm and samples at 12 KHz and Fig 5 shows their extracted IMFs of normal vibrating signal by sifting process in several iterations by satisfying the required conditions.

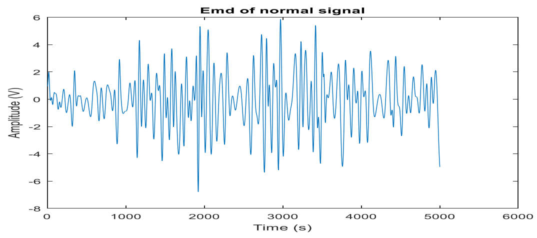

Figure 6 EMD of normal vibrating signal

Figure 6 shows the EMD of normal vibrating signal which is obtained by removing all noises in the signal using empirical mode decomposition with denoising technique.

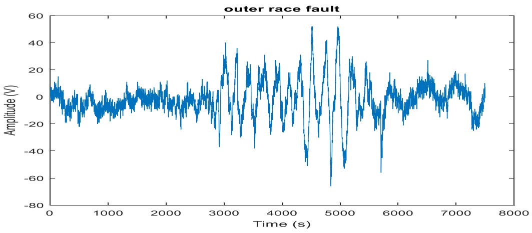

Figure 7 outer race fault signal

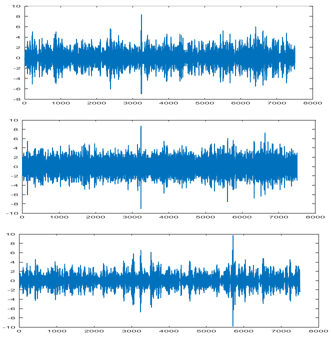

Figure 8 IMFs of outer race fault signal

Figure 7, shows the signal obtained from the accelerometer having the outer race fault with diameter 0.067 and the fault depth 0.014which runs in 1750rpm and samples at 12 KHz and Fig 8 shows their extracted IMFs of outer race fault vibrating signal by sifting process in several iterations on satisfying the required conditions.

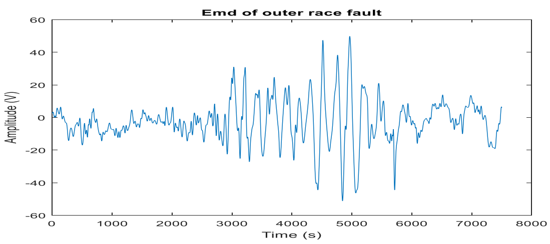

Figure 9 EMD of outer race fault signal

Figure 9 shows the EMD of outer race fault signal which is obtained by removing all noises in the signal using empirical mode decomposition with denoising technique.

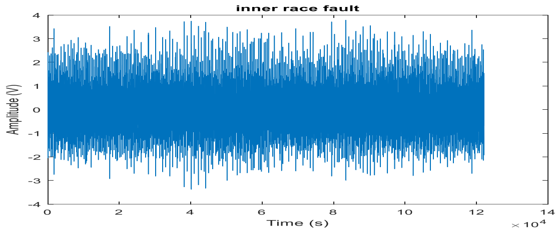

Figure 10 Inner race Fault signal

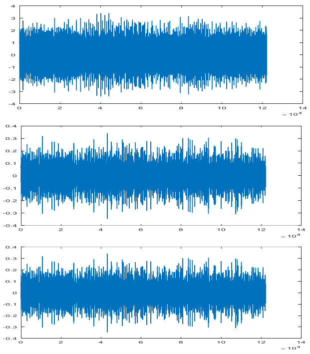

Figure 11 IMFs of Inner race Fault signal

Figure 10, shows the signal obtained from the accelerometer having the inner race fault with diameter 0.07 and the fault depth 0.014 which runs in 1750rpm and samples at 12 KHz and Figure 11 shows their extracted IMFs of inner race fault vibrating signal by sifting process in several iterations on satisfying the required conditions.

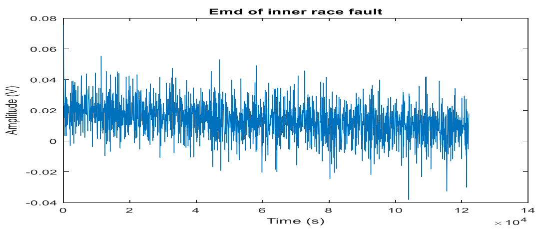

Figure 12 EMD of Inner race Fault signal

Figure 12 shows the EMD of outer race fault signal which is obtained by removing all noises in the signal using empirical mode decomposition with denoising technique.

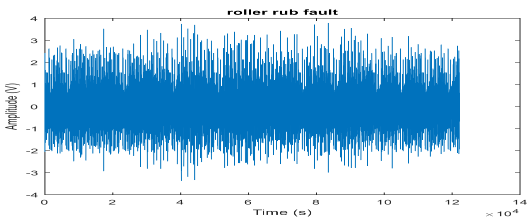

Figure 13 Roller rub Fault signal

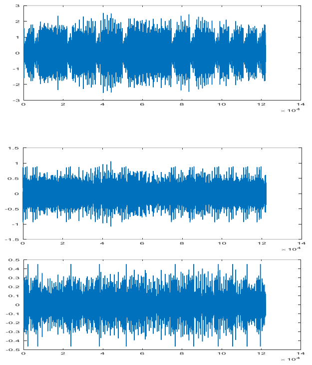

Figure 14 IMFs of Roller rub Fault signal

Figure 13 shows the signal obtained from the accelerometer having the roller rub fault with diameter 0.07 and the fault depth 0.014 which runs in 1750rpm and samples at 12 KHz and Fig 14 shows their extracted IMFs of roller rub fault vibrating signal by sifting process in several iterations on satisfying the required conditions.

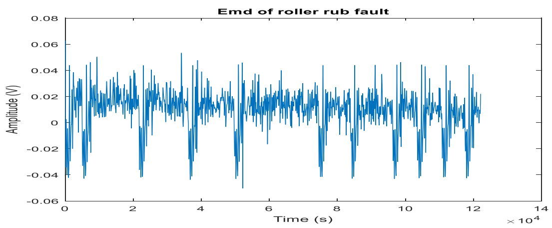

Figure 15 EMD of Roller rub Fault

Figure 15 shows the EMD of roller rub fault signal which is obtained by removing all noises in the signal using empirical mode decomposition with denoising technique.

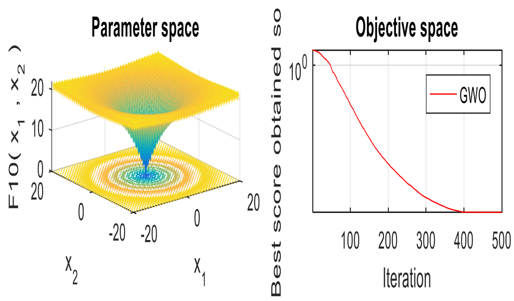

Figure 16 IGWO optimized parameter for bearing design

Figure 16 shows the result for optimization procedure of IGWO which is benchmarked for bearing design problem which is running in particular speed with some inner race faults having the fault diameter of 0.07 and the fault depth of 0.014 . The optimized parameter is helpful in selecting the desired factors for the classification. The features are selected based on the optimization technique which makes the problem easier. The fitness strength and the local optimal solution for this optimization procedure is higher than other traditional optimization procedures.

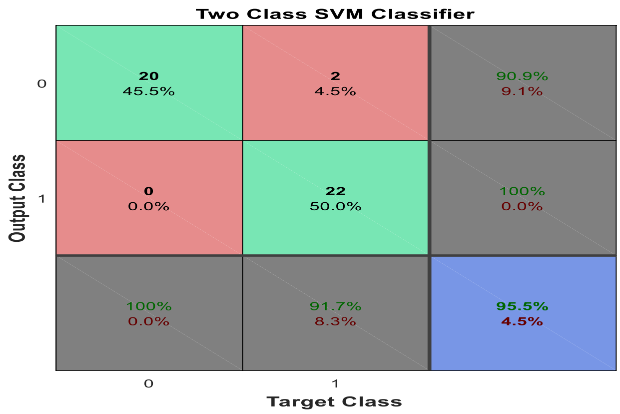

Figure 17 Two class WSVM classifier output

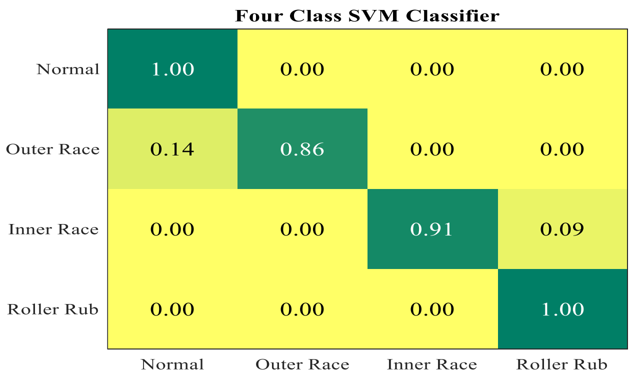

Figure18 Four class WSVM classifier output

Figure 17 shows the two classes SVM classifier output which shows the sensitivity, specificity, accuracy, border error of the signals calculated with the help of SVM confusion matrix. Figure 18 shows that the four classes WSVM classifier. Here the normal vibrating signal and roller rub fault signals are classified correctly but the outer race fault and inner race fault signal are classified with 14% and 9% error. The accuracy of the classifier will be 95.5%. 14% of outer race fault signal is classified as normal vibrating signal. 9% of inner race fault signal is classified as roller rub fault signal. The error of the classifier will be 4.5%.

Table 1 shows the constrained benchmarks applied for the bearing design problem, wear design problem, pressure vessel design problem and.vibrated signals obtained from the acceleromater are to optimize the parameters by using Improved Grey Wolf Optimization Technique and results are compared with the previous optimization algorithms.The motor allows to run in various speeds like 1730rpm,1750rpm,1772rpm,1797rpm with different fault signal strengths.

Table 2 shows that the signal with different data sets which includes the training and testing samples have some defects. This results was obtained in different speeds while the motor is running with different fault diameter of inner and outer races fault. The defects are of in varying size and nature. The bearing is allowed to run in normal condition and also in fault condition. By the classifier the fault signal can be classified from the original signal.

Table 3 shows that the algorithm which optimize the benchmarks of several parameters. Here the IGWO algorithm provides good optimal solution and fitness strength higher than all other algorithms.

Problem	**Sinusoidal**	**Cubic**	**Chebyshev**	**Circle**	**Bernoulli**	**Iconic**	**Singer**	**Logistic**
G1	14.2549	14.9102	14.8208	10.1674	13.1992	14.4305	13.276	12.9501
G2	0.37927	0.61969	0.79234	0.24179	0.42098	0.475368	0.33464	0.567539
G3	0.89358	0.67743	0.9631	32272.6	0.83895	0.114244	0.89996	0.508566
G4	31042.9	31662.7	54912.1	19775.2	33950.9	33473.2	30602.2	32905.7
G5	45557.1	39697.2	6493.28	6301.74	53972.1	23913.7	65623.1	40975.8
G6	6259.18	6562.48	6493.28	6301.74	6299.29	6447.32	6369.35	6349.51
G7	659.2649	36.6793	60.2228	60.3272	130.1939	38.363	228.2640	629.2659
G8	0.02662	0.06348	503.023	0.05272	0.04591	0.09213	0.06365	0.075205
G9	639.153	626.40	676.620	612.330	602.193	665.641	614.264	612.465
G10	7113.17	7036.43	7046.23	6027.24	6994.93	7060.14	7029.66	6045.15
G11	0.6580	0.6690	0.6612	0.6402	0.6269	0.6682	0.6256	0.6255

Table 1 Results of grey maps of IGWO for benchmark functions

Data set	Training samples number	Testing samples number	Defect size of samples	Operating condition	Classification label
A	16	16	0/0	Normal	1
	16	16	0.006/0.006	Outer race	2
	16	16	0.006/0.006	Inner race	3
	16	16	0.006/0.006	Roller rub	4
B	16	16	0.006/0.022	Inner race	3
	16	16	0/0	Normal	1
	16	16	0.006/0.022	Roller rub	4
C	16	16	0.006/0.020	Roller rub	4
	16	16	0.006/0.020	Inner race	3
	16	16	0/0	Normal	1
	16	16	0.006/0.020	Outer race	2
D	16	16	0.006/0.014	Inner race	3
	16	16	0/0	Normal	1
	16	16	0.006/0.014	Outer race	2
	16	16	0.006/0.014	Roller rub	4

Table 2 Fault Classification for different data sets

Algorithm	Worst	Mean	Best	Standard
IGWO	6187.120	5732.450	5023.753	252.480
GWO	6294.426	6149.354	6023.679	368.453
CSA	7323.438	6324.765	6057.231	384.285
ABC	N.A	6245.934	6059.723	252.567
PSO	1406.452	8745.456	6674.365	1465.53
PSO-DE	N.A	6059.213	6059.213	N.A
HPSO	6288.577	6099.942	6059.231	86.1001
GA3	6303.785	6297.675	6235.673	7.41334
BA	N.A	6059.213	6059.213	N.A
CPSO	6363.126	6145.246	6154.342	86.2431
UPSO	9543.342	8012.453	6234.753	7236.31
GA4	6469.022	6177.25	6059.946	130.642

Table 3 Comparison results for bearing design problem

7. CONCLUSION

IGWO algorithm provides high optimal fitness strength for WSVM to classify four different types of faults. WSVM classifier was used to classify the normal and fault signal using IGWO algorithm. The statistical features are extracted from IMF shifting process in measured vibrating signal was used as input for the classifier. The measured vibrating signal is denoised using EMD denoising technique. The performance IGWO based WSVM classifier is compared and analyzed with GWO, PSO, GSA, DE and FEP based SVM classifier. IGWO based WSVM classifier provides better performance due to adaptive fitness function, gain flexibility and good sample-out-of generalization capability.

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