



Bearing Fault Diagnosis using Support Vector Machine with Genetic Algorithms Based Optimization and K Fold Cross-Validation Method.

Rahul Semil, Pratesh Jaiswal

Abstract: Moving component bearing is utilized to convey radial load and axial load or both just as. REB has nonlinear conduct make issue misalignment, surface waviness, fault happen at the inward race, external race, enclosure, ball or roller, so REB has a restricted life. Our concentration to evacuate fault diagnosis of bearing at the outer race has been investigating. For this purpose, REB vibration analysis is used. This paper present a support vector machine algorithm (SVM) approach with GA (Genetic algorithm) based optimization compare the result with SVM with cross-validation (CV) method along these lines, the information is processed correctly and an exact way. Time-domain Analysis, high pass and low pass filtering etc. used for feature extraction from vibration signal. Further, these feature extraction used as input to the SVM classifier. Support vector machine, a training given projected preparing information, the procedure yield perfect hyperplane. Feature extraction help to provides the actual condition of bearing. In this work, different signal processing techniques and process are used for fault diagnosis of bearing.

Keyword: Rolling element bearing, vibration analysis, SVM algorithm, feature selection, condition monitoring

I. INTRODUCTION

Conditioning monitoring is most important for rotating machine in the industry to enhancing reliability and decrease the loss of production. Vibration analysis of rotating machinery is the most common way in the field of condition monitoring. In which comparing the machine signals in defective and normal condition, recognition of fault in bearing like inner race, outer race, cage, ball defect etc. REB can carry radial load and axial load or both as well as. As a serious element, bearing life maximization is most important to decrease machine breakdown. REB has advantages to increase machine accuracy, reliability, etc. and reduce friction, maintenance cost, Loss of production, in industry. Fault happens in bearing lead a serious problem, so the proper bearing analysis is most important to decrease machine breakdown. Many works are happening in bearings analysis through vibration signals.

These signals use to find the incipient failure of m/c element through direct online monitoring to reduce the damage and machine downtime. The method of fault diagnosis of REB described in many steps: feature removal, signal analysis, data gathering, feature reduction, diagnostics [1, 2].

The serious step in this procedure to remove a decent feature, which describes the exact condition of REB. Rolling element bearing has a rotational motion in nature; periodic nature of vibration signal is the most essential characteristic, which grows up from bearing. As based on this outcome, many method and techniques related to the analysis of the periodic nature of bearings, such as analysis of spectrum [4, 5]. The wavelet analysis of periodic nature of vibration signal to fault diagnosis of bearing is important to find the best accuracy and reliability to the diagnosis of bearing [6]. Frequency-time analysis of bearing is an important characteristic to feature extraction of bearing represent the condition of rolling element bearing [7]. For many years both statistic first and second-order: mean, variance, power spectrum, kurtosis [11, 12] are common signal processing and analysis tools used widely for vibration analysis of the mechanical component. Bearing condition is often hidden by strong mechanical noise and the undesirable vibration-related element of the machine [8, 9]. The bi-spectrum study is not sensitive to find random noise and bi-spectrum analysis of peak, which only related to frequency and phase component [11, 12]. Support vector machine has not necessary to take the large size of the training sample, it gives a great performance in problemsolving of nonlinear and recognition of the pattern. Artificial neural network classifier developed in a fast manner in many years for solving the problem of fault diagnosis or other application and research problem [17, 19]. Hilbert and park transform used to fault diagnosis of mechanical vibration-related component, analysis the bearing failures and mechanical failure. Support vector machine is used Hilbert transform to fault diagnosis of a mechanical component and classify them [5]. Support vector machine (SVM) and artificial neural network (ANN) both are used for fault diagnosis. The optimum parameter and statistical feature selection based on the genetic algorithms, to classify the process of fault diagnosis SVM is used radial basis function [23]. Support vector machine has been used with continuous wavelet transform is simple, fast to conditioning monitoring of bearing and IMs. The main problem is associated with this technique to find the optimum parameter selection for wavelet fitter in bearing and other fault diagnosis problem [22].

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The SVM grouping (clustering) binary tree approach used for fault diagnosis of turbine gearbox, bearing fault detection [20]. Saidi has been used two high order spectra approach for fault detection of bearing and analysis of IMs and find out electrical failure using signals of the current [15]. Bearing condition improved using the combination of high order spectral analysis and cyclostationary.

This approach gives a better result to reduce bearing failure [9]. Demodulation of resonance, the based approach has been used to diagnosis of faulty bearing [1]. Many techniques have been developed in the recent years such as empirical mode decomposition, continuous wavelet, Hilbert transform and cepstral analysis and many more to fault diagnosis of bearing and machine component [3, 9]. Many researchers have been used the spectral analysis of kurtosis for fault diagnosis of bearing in terms of optimal bands of frequency to improve the bearing life and reduce failure of the machine [10, 13]. Spectral kurtosis used to find optimal parameter based on the genetic algorithm (GA) but this approach requires large computation [14]. Many research recent year used the genetic algorithm in condition monitoring of machine based on automatic selection of feature. Genetic algorithm is used to optimize the parameter of SVM using radial basis function (RBF) to the diagnosis of faulty bearing in condition monitoring [3, 21, 22, 23]. The fast Fourier transformation and wavelet analysis and many more techniques used for fault diagnosis of bearing and machine condition monitoring to reduce the failure of the mechanical component using vibration analysis. The many tools past year used such as signal processing tools, statistical feature (mean-variance, skewness, root mean square etc.) EMD (empirical mode decomposition) used in condition monitoring of machine to improve the machine life. Conditioning monitoring is growing up in the recent year to improve the machine condition in the industry to reduce failure of the machine, loss of production, Diagnosis of a machine component, reduce maintenance cost and solving the problem of machine breakdown maintenance. Vibration analysis of machine condition is the simple and fast way uses for signal analysis and comparisons of normal and faulty condition to the diagnosis of machine component and reduce maintenance cost & total production cost [8, 9]. Condition monitoring is the best way to a diagnosis of machine component [8, 9]. The paper present a Support vector machine algorithm (SVM) approach with the GA (Genetic algorithm) based optimization compare the result with SVM with cross-validation (CV) method.

II. SUPPORT VECTOR MACHINE

In the year of 1960s, support vector machine learning theory presented and proposed by Vapnik. Further Since, the 1990s the support vector machine used algorithms with greater accuracy to solve a different complex problem in research and engineering field (Burges, 1998; Weston and Watkins, 1999) [1, 2]. The Support vector machine algorithm used to separate the two class of problem by a hyperplane. In which data separated by creating a line (hyperplane) between the two data sets. Support vector machine action easily explained in two-dimensional space condition with no loss of its generality. Fig 2 represent and show the two sets of different data classes series of points class A (circle) and class B (square), the dotted line represented margin. The

SVM tries to create a linear boundary between two sets of data of different classes to maximize the margin. SVMs try to create a hyperplane between two different series of points of the dataset to separate the different classes and an optimum hyperplane generate when a problem solved. Nearby points of data explain margin and are called a support vector of machine algorithms. The middle line represents the boundary situated between the margins. The grey circle and square represent the support vector in fig 2. A support vector machine is a classifier to separate the two classes by generating a hyperplane (solid line) between two sets of data points of different classes. Hyperplane dividing a plane into two parts in two-dimensional space each class lay in either side. The SVM basic fundamental phenomena deal with hyperplane separate the data described by support vectors.

SVM hyperplane equationis given as,
$$(w \cdot x) + b = 0 \quad w \in R^N, (1)$$

In the above equation W vector express the boundary, b is a bias (To add something left-hand side) in other words is scalar threshold and x is the input vector. Support vector are placed at margins, classes A and B equation are expressed in terms of respectively,

$$(w \cdot x) + b = 1(2)$$

And

$$(w \cdot x) + b = -1(3)$$

The data points limits correspond to support vector for a particular class, the decision function defines the following equation that can be good for entirely data points belongs to either class A and class B:

$$F(x) = \text{Sign}((w \cdot x) + b). (4)$$

To solve the optimization problem, the optimize hyperplane obtained then minimize by,

$$= \frac{1}{2} \|w\|^2$$

Subjected to,
$$y_i((w \cdot x_i) + b) \geq 1 \quad i = 1 \dots l \quad (5)$$

In the above equation,the total number of sets of training data is l. The optimization problem obtained at the result of constrained quadratic programming. The equationis given as,

$$w = \sum \alpha_i x_i (6)$$

In equation x_i are the support vector. Putting equation (6) in equation (4) the decision function given by,

$$f(x) = \text{sign}(\sum_{i=1}^l \alpha_i (x \cdot x_i) + b) (7)$$

In SVMS, the linear boundary of the two classes does not separate the classes correctly in the input space. Then in higher dimensional, linear separation is possible to create a hyperplane that can be separate the class properly is possible. In support vector machine, with the help of transformation $\phi(x)$ transforms the data input space in N-dimensional to featured space in Q dimensional,

$$s = \phi(x) (8)$$

In the above equations $s \in R^Q$ and $x \in R^N$. Fig 1 represents the transformation of data in input space in N dimensional to featured space in Q dimensional.



The transformation substitution in equation (7) given as follow:

$$f(x) = \text{sign} \left(\sum_{i=1}^l \alpha_i (\phi(x) \cdot \phi(x_i)) + b \right) \quad (9)$$

To transform or converts the data input space to featured space in higher dimensional space is very intensive relative to computation. Kernel function can use to an originally map the data in higher dimensional space from the transformation of data. The dot product provided in a single step to reduce the computational load and that in higher dimensional space, transformation reduces the effect of remembering. The kernel function $K(x, y)$ is given by equation as,

$$K(x, y) = \phi(x) \cdot \phi(y) \quad (10)$$

The modification of decision function given as,

$$f = \text{sign} \left(\sum_{i=1}^l \alpha_i K(x, x_i) + b \right) \quad (11)$$

The input vector is actually a support vector is governed by the parameter α_i is a weighted factor ($0 < \alpha_i < \infty$). In SVM, some different types of kernel function used such as, radial basis function, sigmoid, polynomial etc. In current work, radial basis function kernel, given by the following equation,

$$k(x, y) = (-|x - y|^2 / 2\sigma^2). \quad (12)$$

Full feature set based used the RBF parameter(σ). An iterative process selects the optimum value of the RBF kernel parameter. If the data is not separate, the overlap between the data sets point of classes. The α_i parameter range decrease the boundary outlier's affect which support vectors can describe. In case of not separate the data, modified constrained of the problem is ($0 > \alpha_i > C$). For in case of separate the data value of C is infinity but data is not separable the value of c is varied, which depend on a number of error in training. If the training error are, few the value of C is high but in case the low value of C permitted higher error in the training solution. To handle the support vector generalized capability. Few parameter like, High regularized parameter C and RBF kernel parameter width σ . In this current work, C value taken, as 100 and RBF kernel parameter σ and selection of feature based on Genetic algorithms (GA) based approach. Denoted view and geometric view of REB shown in fig. 3.

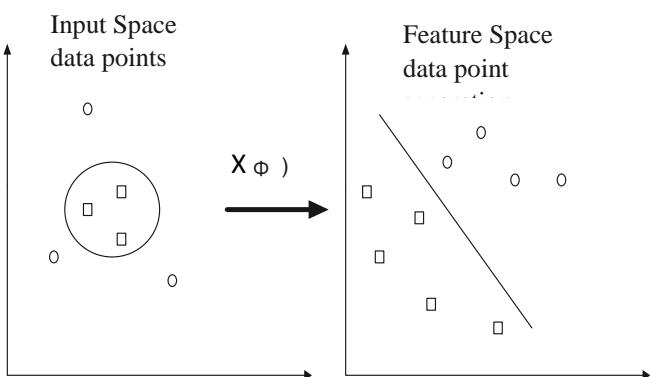


Fig. 1. Separation of input and feature space

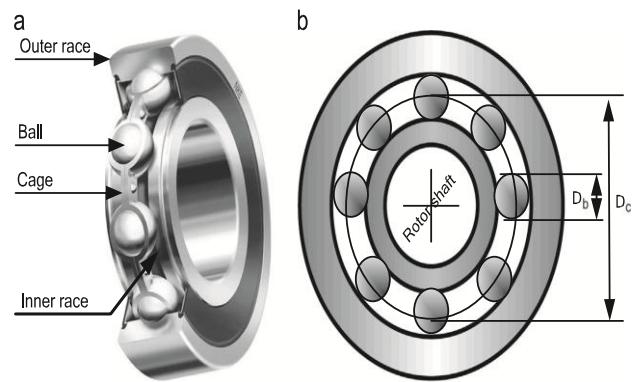


Fig 3. (a) Detonated view and (b) geometry of rolling-element bearing [27]

III. EXPERIMENTAL WORK

The defective and normal bearing signals acquired from the Case Western Reserve University [22]. The experimental arrangement showed in Fig. 4, contains a 2 HP induction motor with accelerometers, dynamometer and torque transducer. An accelerometer used to collect vibration data at drive end in the normal and faulty condition of bearing running at the outer race (signal x). Then accelerometer used at fan end for collect vibration signal normal and faulty condition of bearing running at the outer race (signals y). The pc based data acquisition system is used to data are collected using accelerometer which is attached through charge amplifiers. The further signal was associated with the data acquirement system. With the help of EDM, machine fault generated on bearing an outer race. In the test, the type of bearing is SKF 6025. The number of samples collected for each channel was 1,000. At a Sampling rate of 48000/s, measurement taken. In the current work, the time-domain analysis of bearing vibration signals are used to data pre-processed to excerpt the features for use as inputs to the classifier to SVM. Bearing runs continuously at a different speed with the test rig.

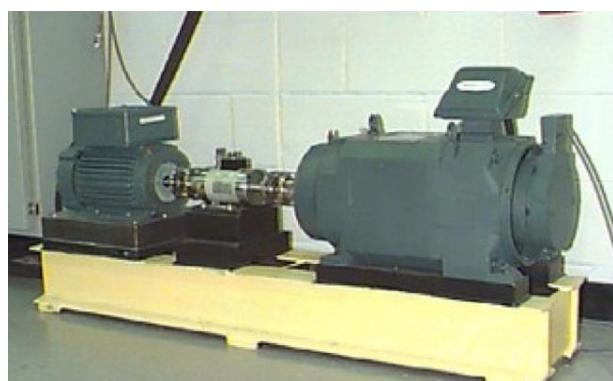


Fig 4. Experimental set up of bearing. [28]

IV. FEATURE EXTRACTION

A. Signal statistical features-

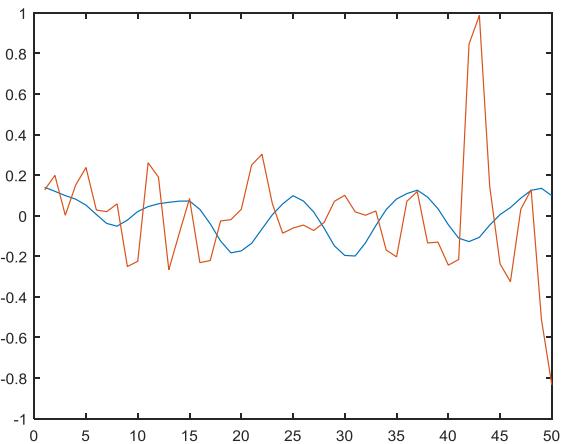
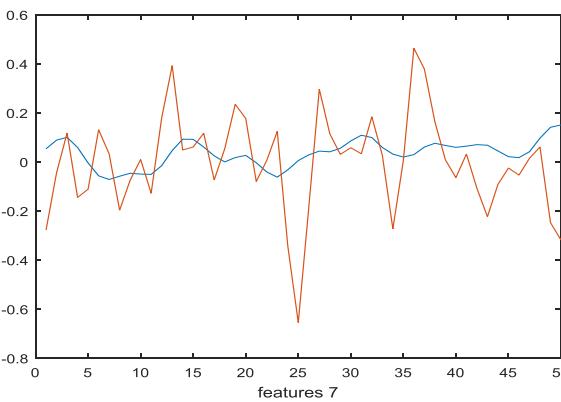
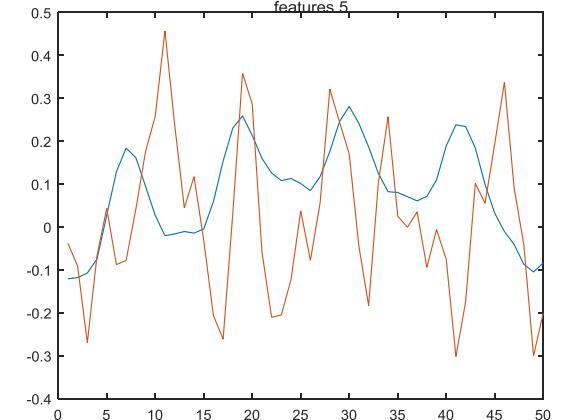
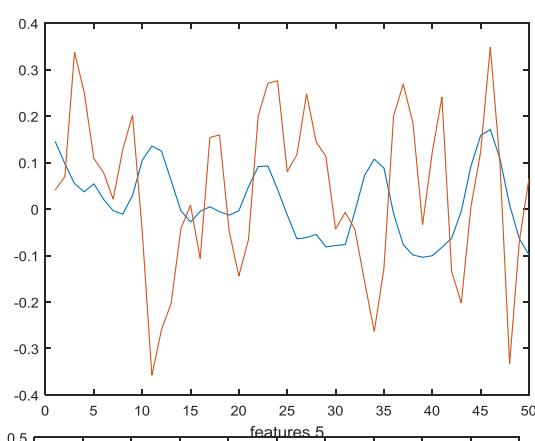
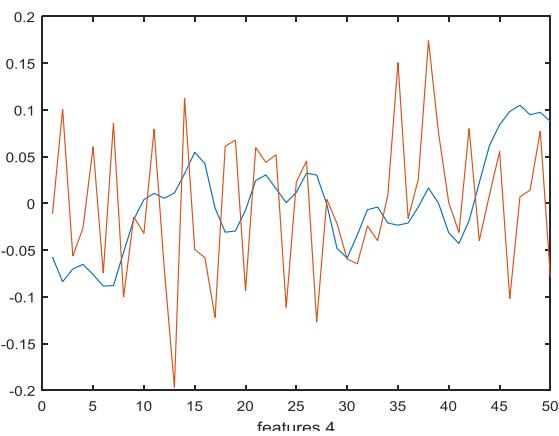
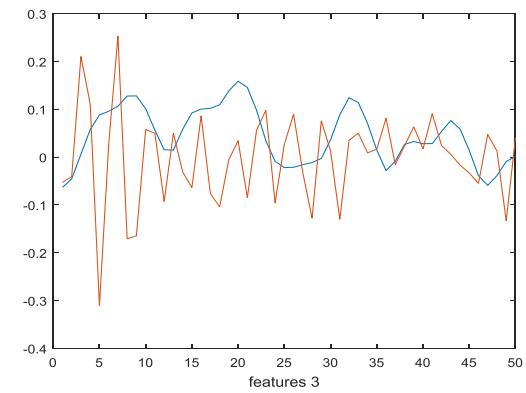
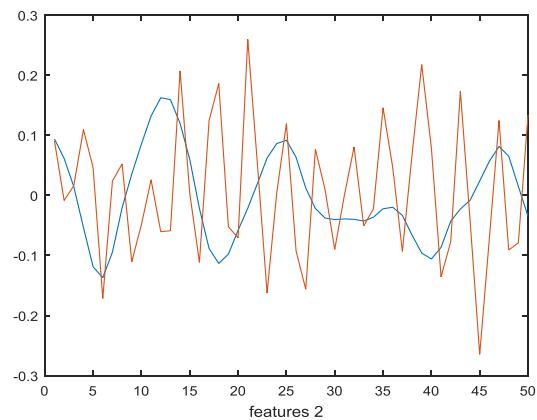
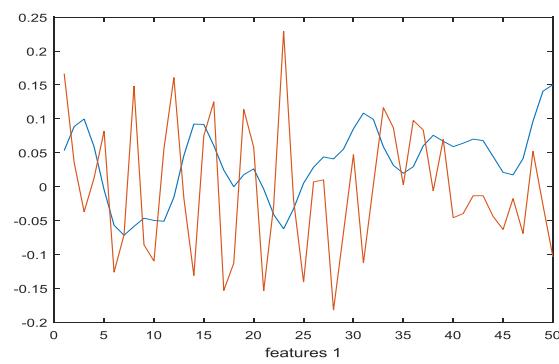
Normal and faulty bearing data of one set of each considered an experiment. Vibration signals in normal and faulty condition consisting of 1000 samples (q_i) are taken using the accelerometer to monitor the condition of the machine. Vibration signals of drive end and fan end resultants is defined by the equation, $w = \sqrt{(x^2 + y^2)}$. In this current work, samples alienated into 50 bins of 200 (n) samples for each. These bins used to extract the features, mean, variance, skewness, kurtosis, root mean square, range etc. Fig 3 show the plot of remove the features from vibration signals. Some of the features presented of the full features set. The feature extraction is show the actual bearing condition of the machine to find the failure of the bearing. The bearing run continuously with test rig to high speed to improve the bearing life, feature extraction help to reduce the failure of the bearing. These features is also describe the bearing behaviour. From these vibration signals extract the features set (1-9).

B. Low pass and high pass filtering-

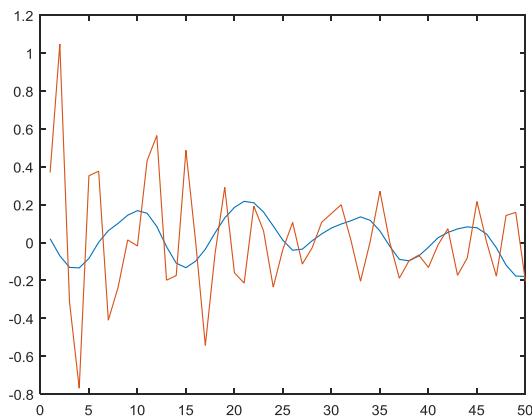
The raw vibration signals further handled directly through high pass filters and low pass filters. The frequency cut off is taken ($f/5$) according to the sampling rate ($f = 48000/s$). From the low pass and high pass filtering process, the vibration signal to extract the 21 features set(10-30). Low pass and high filleting are efficient and effective to manage the vibration signal to monitor the bearing condition continuously run with high speed with the machine.

C. Normalization-

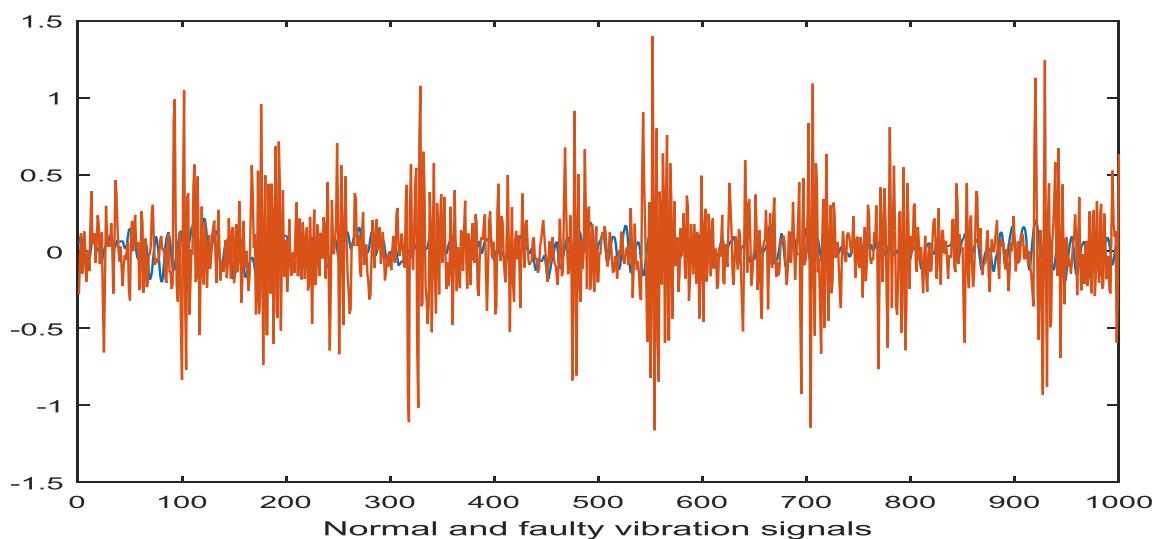
From the vibration signals, features are extracted is normalized for improved the training of network success. All sets of normalized features are divided into $30 \times 90 \times 2$ row and columns. Where row defines the features and columns represented per signal of bins. These further multiplied by 3 signals and two conditions of bearings, normal & faulty. The normal and faulty condition of REB at the outer race investigated in this work. Vibration signals of REB have been analysed to fault diagnosis of REB with different feature selection. Feature selection gives a more efficient and effective condition of REB



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**Fig. 5. Time-domain analysis features of learnt signals:
normal, faulty.**



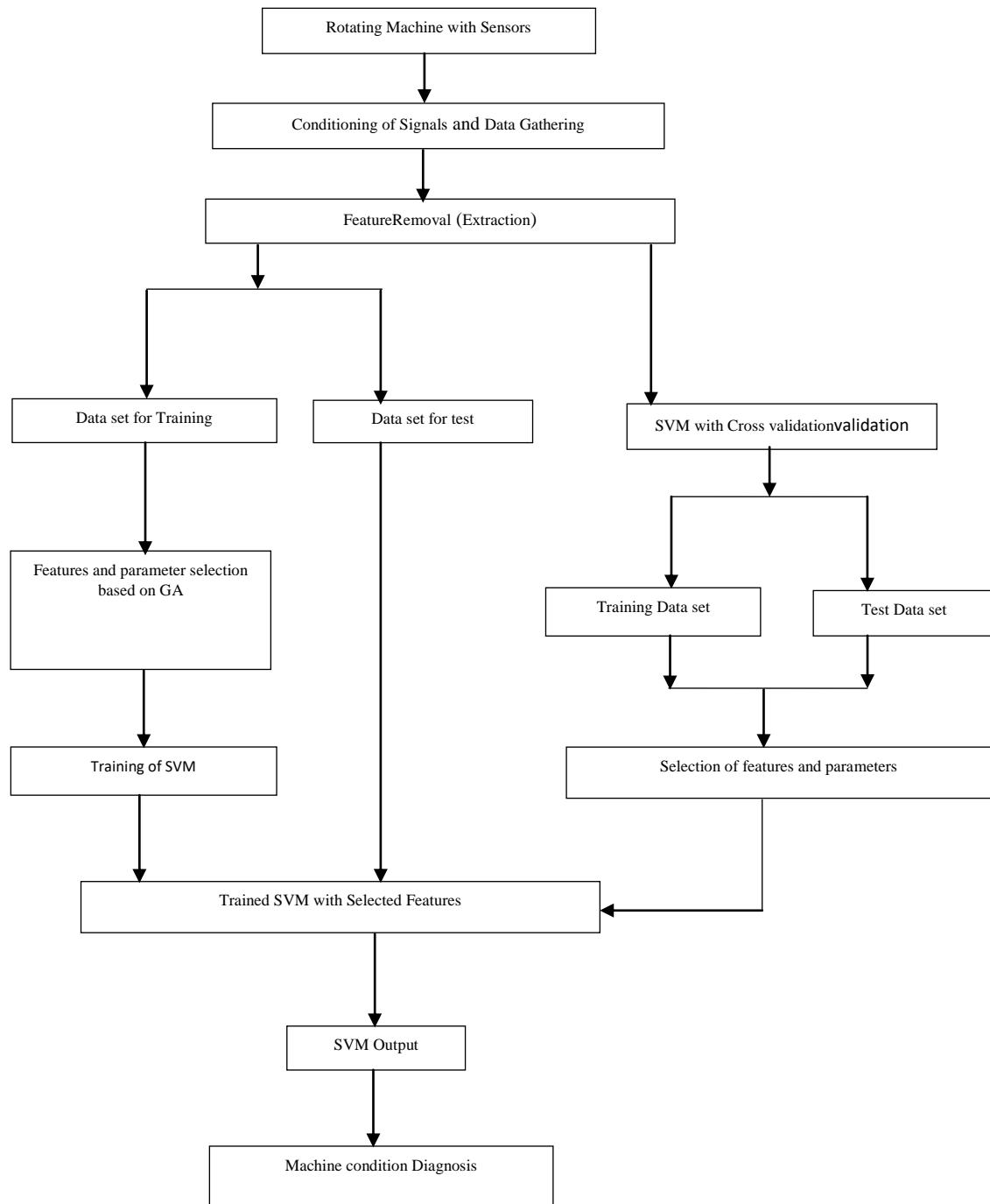


Fig. 6. Flow chart of machine diagnosis procedure.

V. SUPPORT VECTOR MACHINE WITH CROSS VALIDATION

Cross-validation is an average method for regulating hyperparameters of predictive models. In the cross-validation method (CV), the accessible data divided into K subgroups. Individually data point in is arbitrarily allotted to one of the subgroups such that these are of practically equal size. Further, we describe as the unification of all data points except those in. For individually an individual model constructed by applying the algorithm to the exercise data. This model, then calculated through a cost function by means of the test data in. The type of the K products of the model valuations called cross-validation (test) performance

or cross-validation (test) error and is used a predictor of the presentation of the algorithm when applied to Usual values for K are to select and using K-fold CV, we first divided the available data into K subgroups. Then we calculate the cross-validation error using this divided error for the SVM classifiers using dissimilar values for and lastly we have to choose the C and σ with the lowest CV error and use it for the training of SVMs the whole data set. In the present work, we have to use 1000 sample of the faulty and normal bearing signal at sampling rate 48000/sec.



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Further features removed from the vibration signals used as the input to the SVM classifier. In the cross-validation, based approach data divided into K subsets and radial kernel function parameter used to an originally map the data in higher-dimensional space. In addition, get the best accuracy with different features selection.

VI. SUPPORT VECTOR MACHINE WITH GENETIC ALGORITHMS

Genetic algorithm recently and last year used in many engineering application and research field. Genetic algorithms used, genetic operator to solve both linear and nonlinear problem. The problem solved by finding space of all-region, which we can state, and exploring the possible area by the help of selection, mutation, and crossover. The possible area exploring with help of genetic operator of the problem, which applied in population for individuals. The consideration of six concerns is the basic need of genetic algorithm to solve the problem. Genome (chromosome) representation, function selection, operators like a

crossover, the mutation for function imitation, initial population size, criteria of termination and the valuation function (Michal wiz, 1999 Tang et al. 1996, Goldberg, 1989). These six basic concern described in detail in this current work. A Size of the population of ten individuals used to generate chromosome in a random manner. Chosen the size is on the basis to different genomes has high interchange. The size also was chosen to reduce the chance of convergence within the population. Genetic algorithms are used selected features and used for specific classifier one variable parameter. Radial basis function width (σ) for SVM. Set of Q possible inputs are used in training of SVM to give N different inputs, the chromosome (genome) contain N+1 real numbers. The range $1 \leq x_i \leq Q$ of the constrained (x_i , i = 1, N) is first N number in the genome SVM.

$$X = (x_1 x_2 \dots x_N x_{N+1})^T \quad (13)$$

The number x_{N+1} has to be within the range $s_{min} \leq x_{N+1} \leq s_{max}$: The boundss_{min} and s_{max} represent the lower and the higherboundaries on the SVM classifier parameter

VII. EXPERIMENTAL RESULTS

Experimental result of SVM with GA and cross-validation based approach are discussed below in table 1, table 2, table 3

Table 1.Presentation of classifier without feature assortment for dissimilar signal pre-processing

Data groups input features (%)	Accuracy	Filtering 10-30 94.25
SVM ($\sigma = 0.6$)		
Signals 1-9	87.28	

Table 2. Presentation of SVM with GA based feature assortment for dissimilar signal pre-processing

Datagroups Algorithms) with SVMs	GA (Genetic	Signals 3, 4, 5	0.25 0.4186.22
Input features	width(σ)	Average time (s)	Filtering 12, 18, 22 0.40 11.292.68
Accuracy(%)			

Table 3. Presentation of SVM with Cross-validation based feature assortment for dissimilar signal pre-processing

Cross-validation with SVMs		
Data groups	Input features	Width (σ)
Accuracy (%)		Average time (s)
Signals 1, 2, 60.200.3587.5		
Filtering	15, 22, 260.60	6.597.5

VIII. CONCLUSION

In this paper, we presented the REB fault diagnosis of bearing using a support vector machine (SVM) algorithm using GA based optimization and cross-validation approach.

Most of the cases the accuracy of the cross-validation approach is higher than the GA based approach and the simplicity of GA is lower than the CV based approach. The GA based approach is used to parameter selection and optimization.



In this case, C picked as 100 because the C is minimum, the test error minimized then test success is high and the sigma width takes different for both approach GA and CV approach. Both techniques give the best result for SVM but cross-validation method is using with SVM is simple and under stable easily. The input feature acquired from time-domain vibration signal analysis, Low pass and high pass filtering etc. The importance of dissimilar signal processing and vibration signal analysis investigated.

Further research work analysis is using the best parameter optimization technique to optimize a parameter of SVM.

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