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Local Fault Assessment in a Helical Geared System via Sound and Vibration Parameters Using Multiclass SVM Classifiers

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A gear system transmits power by means of meshing gear teeth and is conceptually simple and effective in power transmission. Thus typical applications include electric utilities, ships, helicopters, and many other industrial applications. Monitoring the condition of large gearboxes in industries has attracted increasing interest in the recent years owing to the need for decreasing the downtime on production machinery and for reducing the extent of secondary damage caused by failures. This paper addresses the development of a condition monitoring procedure for a gear transmission system using artificial neural networks (ANNs) and support vector machines (SVMs). Seven conditions of the gear were investigated: healthy gear and gear with six stages of depthwise wear simulated on the gear tooth. The features extracted from the measured vibration and sound signals were mean, root mean square (rms), variance, skewness, and kurtosis, which are known to be sensitive to different degrees of faults in rotating machine elements. These characteristics were used as an input features to ANN and SVM. The results show that the multilayer feed forward neural network and multiclass support vector machines can be effectively used in the diagnosis of various gear faults.

Keywords: gear; ANN; SVM; vibration; sound.

1. Introduction

Condition monitoring of rotating machines is of crucial importance and has been studied for several decades. Vibration and sound signal analysis methods are widely used in condition monitoring of rotating machinery and structures. These techniques can help by detecting faults early, allowing parts to be replaced before a significant damage occurs. The application of fault classification tools viz. artificial neural networks (ANN), support vector machines (SVM), genetic algorithms, hidden Markov models to the condition monitoring of machinery has consequently been the subject of considerable research. Traditional pattern recognition includes a large collection of different types of mathematical tools (preprocessing, extraction of features, and final recognition). In many cases it is difficult to say what kind of tool would be the best for a particular problem (Wang, Mc Fadden, 1995; Murray, Penman, 1997, Mc Cormick, Nandi, 1997). Artificial neural networks (ANNs) are popular in pattern recognition applications including sound and vibration monitoring as they allow real-time condition monitoring at a fairly low cost. ANNs have capability to learn from the past data to classify machine's working condition. This information can be stored and employed for later use. The contributions of some authors (Li *et al.*, 2000; Samanta, 2004; Chen, Wang, 2002; Paya *et al.*, 1999) reveal the application of neural networks to condition monitoring of rotating machinery and its high success rates. ANNs consequently appear to be a possible solution to gear diagnostics problem as they could allow real-time online condition monitoring at a reasonably low cost (Yang *et al.*, 2002).

Chen, Wang, (2002) dealt with multi-layer perceptron (MLP) pattern classifiers for wavelet map interpretation and their application as a tool for mechanical fault detection. Features for neural networks were extracted from instantaneous scale distribution. This study was undertaken to simplify the difficulties in inspecting complicated wavelet patterns in time-scale domain. The authors highlighted the details of construction, boxing, and testing multilayer perceptron based classifiers for diagnosis of gear faults. Paya *et al.* (1999) carried out investigations to study both bearing and gear faults introduced separately as a single fault and then together as multiple faults in the drive line. The real time acceleration signals obtained from the driveline were preprocessed by wavelet transforms for the neural network to perform detection and identification of the exact kind of fault occurring in the model drive line. The authors summarised the results of their research for distinguishing between different kinds of faults viz. good gear, blip gear, shaved gear, and one with inner race defect bearing in a drive line. An overall success rate of 96% was achieved on test by back propagation network which gave the details of the fault in the driveline. Vyas, Kumar (2001) carried out experiments to automate the fault detection procedure in rotating machinery. A back propagation learning algorithm and a multilayer network were employed for fault detection. Five different types of faults were introduced in the experimental setup and five statistical moments of vibration signals were employed to box the network. An overall success rate of 90% was obtained in this work.

Wuxing *et al.* (2004) conducted experiments on a gearbox to classify the gear faults using cumulants and the radial basis function (RBF) network. The cumulants were calculated from the vibration signals collected from the inspected gearbox and were used as input features to an ANN. The radial basis function network was then used as a classifier for various operating conditions of the helical gearbox. e.g. normal, spalling, one worn tooth condition, and two worn teeth condition. The authors concluded that the method of fault classification by combining cumulants and the radial basis function network is promising and achieves better accuracy than many of the current methods available. Amarnath *et al.* (2013) used a C4.5 decision tree algorithm to classify faults in ball bearings. Sound signals were acquired from the bearing setup, descriptive statistical features were extracted from the sound signals to feed into decision tree algorithm. Results showed about 95.5% classification accuracy to diagnose various faults in ball bearings. However, machinery fault classification using artificial intelligence methods have developed based on empirical risk minimisation principle; hence these methods have some disadvantages viz. local optimal solution, low convergence rate, over fitting and poor generalisation when the fault classification samples are few. Support vector machine is a fairly new machine learning tool which is effectively used to minimise the aforementioned drawbacks. The main difference between SVMs and other classification tools is in their risk minimisation. The structural risk minimisation principle is used in SVMs to decrease an upper bound based anticipated risk. In the case of ANNs traditional risk minimisation procedure is used to decrease the error in training of datasets. Hence, the difference in risk minimisation results in a better generalisation performance for SVMs (Namdari, Hooshang, 2014; Banerjee, Das, 2012). The SVM classifier is extensively used for fault detection and classification in rotating machines/machine elements viz. bearings, gears, fan blades, cams, etc.

Samanta (2004) presented an experimental study to compare the performance of gear fault detection and classification using ANN and SVM. The time domain vibration signals of a rotating machine with normal and defective gears were preprocessed for feature extraction. The role of different vibration signals at normal and light loads were investigated in this work. SVM shows better classification accuracy than ANN. In addition, genetic algorithms (GA) were used to improve accuracy of fault classification. With GA based selection, the performance of ANN and SVM showed comparatively equal accuracy in results. Yang *et al.* (2005) presented a novel scheme to detect faults in reciprocating compressors of refrigerators. The vibration and noise signals were processed using wavelet transform to find diagnostic information. Further the statistical features of wavelets were used for fault classification using ANN and SVM techniques. A high accuracy in classification of faults was obtained using SVM technique.

Shin *et al.* (2005) adopted SVM technique for detection and classification of faults in electro mechanical machinery using vibration signal parameters. Multilayer perception (MLP) of ANN technique was also included in the diagnosis program. The results concluded that the classification of faults using SVM was superior to that of MLP of ANN techniques. Yuan, Chu (2006) carried out fault diagnosis of turbo pump rotor using SVM with multiclass algorithm and ANNs. SVM based fault classification was proved to be more effective and correct in comparison with ANN algorithm. Sugumaran *et al.* (2007) employed proximal support vector machines (PSVM) and SVM to classify faults in bearings. The authors compared the results of PSVM and SVM. PSVM was found to have fewer iterations and faster learning as compared to SVMs in fault classification. A novel method to diagnose faults in rotating machinery was proposed by Hu *et al.* (2007). Improved wavelet package transform was used to extract the salient frequency band features from the vibration signals. SVM ensemble technique was adopted in fault classification, which provides promising results in diagnosis of machinery. Aditya *et al.* (2016) have considered ANN and SVM classification techniques to diagnose simulated faults in roller bearings using statistical features of raw vibration signals. The authors have considered different fault severity levels in bearings operating under various speeds and load conditions. The results showed the suitability of ANN and SVM for detecting bearing faults. In our recent work, (Amarnath, Praveen Krishna, 2014) experimental investigations have been carried out to detect localised gear tooth faults of a two stage helical gearbox. EMD based statistical parameters of sound and vibration signals were used to diagnose the severity of faults in helical geared system. Although the analysis of temporal and frequency features of sound and vibration signals is adequate to detect and diagnose the simulated faults on gear tooth, there is a need for reliable fast automated diagnostic procedure for gear fault detection.

Artificial neural networks have potential applications to classify faults in machine elements viz. gears, bearings, cams, rotors, etc. The present work is continuation of our recent work (Amarnath, Praveen Krisshna, 2014), where statistical parameters of sound and vibration signals were considered for gear fault detection. In this work, attempts are made to classify and diagnose the simulated faults in helical gears of a two stage helical gearbox. Gear fault classification was carried out using ANNs, the statistical parameters extracted from the vibration and sound signals of a two stage helical gearbox were used to train and test the ANN, results obtained from this classification method showed 92% classification accuracy. However, in order to improve the fault classification accuracy, the vibration and sound signal datasets were processed using multiclass SVMs. Result obtained from the SVM classification technique showed about 97.1% accuracy, which highlighted the suitability of the method to classify the localised faults in the helical geared system.

2. Experimental setup

Figure 1 shows the experimental setup. The setup consists of a 5 HP two stage helical gearbox, whose specifications are given in Table 1. The gear box is driven by a 5.5 HP, 3-phase induction motor with a rated speed of 1440 rpm. The speed of the motor is controlled by an inverter drive and for the present study the motor is operated at 80 rpm. In other words, the speed of the gear is 1200 rpm. With a step up ratio of 1:15, the speed of the pinion shaft in the second stage of the gear box is 1200 rpm. The pinion is connected

Table 1. Dimensions, specifications, and test conditions of the gears.

	First stage	Second stage
Number of teeth	43/13	73/16
Pitch circle diameter (mm)	198/65	202/48
Pressure angle 0°)	20	20
Helix angle 0°)	20	15
Modules	4.5/5	2.75/3
Speed of shafts	80 rpm (input)	1200 rpm (output)
Mesh frequency	59 Hz	320 Hz
Step up ratio	1:15	
Rated power	5 HP	
Power Transmitted	2.6 HP	

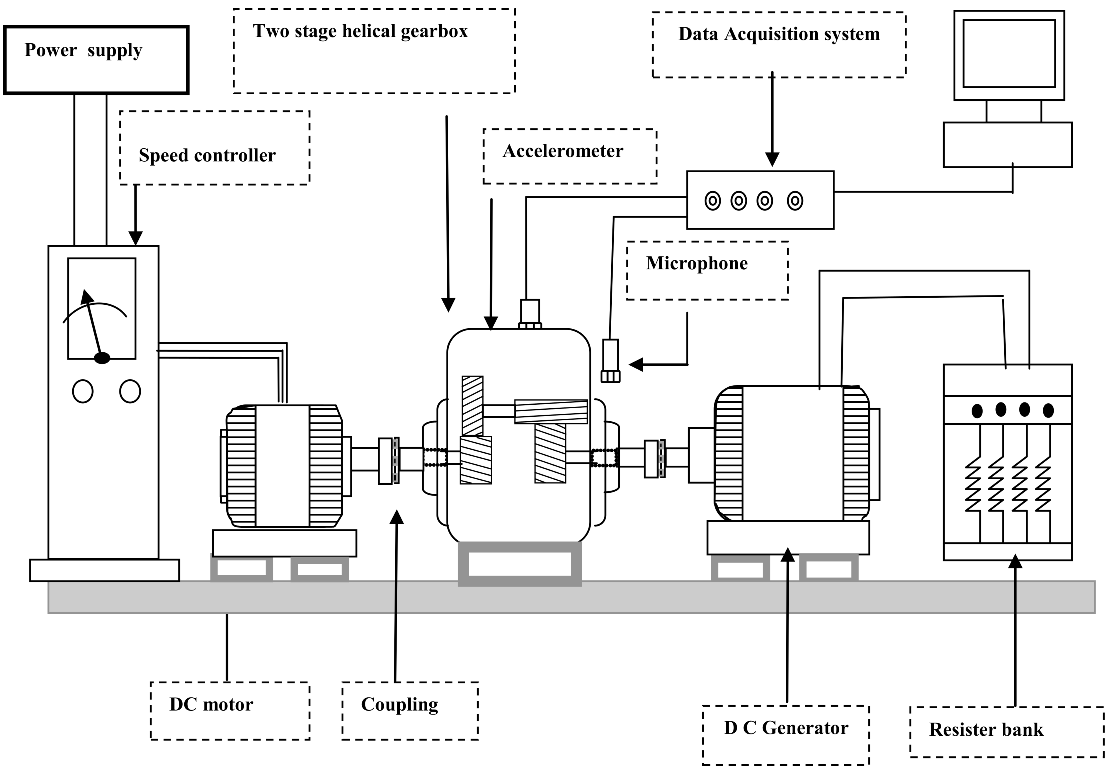

Fig. 1. Experimental setup of two stage helical gearbox.

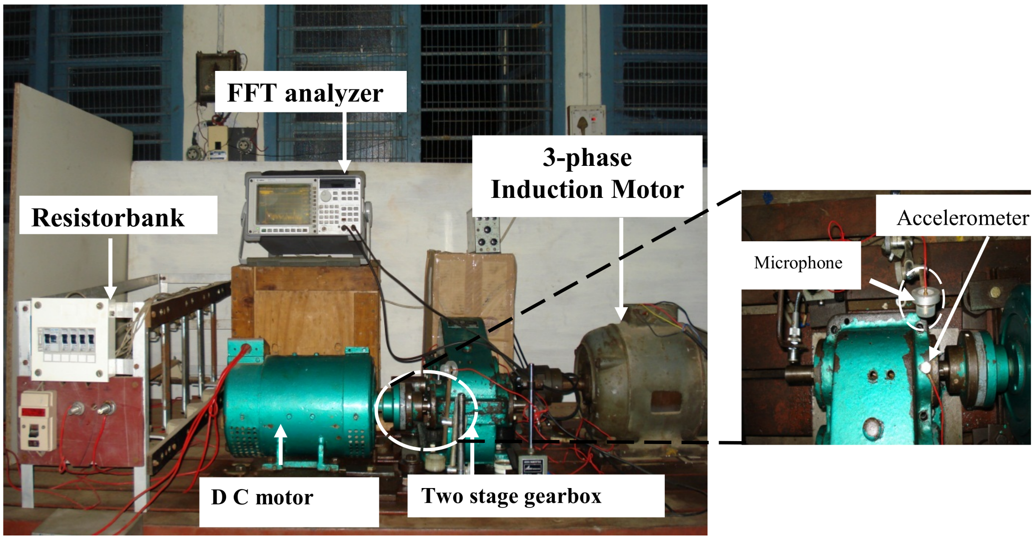

Fig. 2. Photograph of the experimental setup with sensors and equipments.

to a DC motor (which is used as generator) to generate 2 kW power which is dissipated in a resistor bank. This loading arrangement minimises additional torque fluctuations. Tire couplings are fitted between the electrical machines and gear box so that the backlash in the system can be restricted to the gears.

The motor, gear box, and generators are mounted on I-beams which are anchored to a massive concrete block. A B&K 4332 accelerometer was stud-mounted to measure the vibration signals generated on the bearing housing of pinion shaft. The accelerometer outputs were conditioned using B&K 2626 charge amplifier.

The acoustic signals were measured by a B&K 4117 microphone which was installed close to the test pinion. Position of the microphone is important in acoustic measurements. Initially the measurements are taken at different distances and directions. Maximum useful frequency for the measured sound signal is 4.1 kHz, at this frequency the maximum distance for near field assumption (assuming 1 wavelength) is around 8.1 cm, in the present study microphone has been placed at a distance of 5.5 cm (near field condition), this procedure was successfully used in our previous work (Amarnath, Praveen Krishna, 2014). The experimental setup with sensors and equipment is shown in Fig. 2.

2.1. Fault simulation

Overhaul time of a new gearbox is more than one year. It is very difficult to study the fault detection procedures without seeded fault trials. Local faults in a gear can be classified into three categories viz. surface wear spalling, cracked tooth, and loss of a part of tooth due to breakage of tooth at root or at a point on working tip (broken tooth or chipped tooth). There are various methods to simulate faults in a geared system. The simplest approach is partial tooth removal. This simulates the damage due to breakage at a point on the working tip. This type of fault is common in many industrial applications (Staszewski *et al.*, 1997). In the present experiment, depthwise damage was simulated on the helical gear tooth by grinding operation. Figure 3 shows seven cases of the gear damage considered for experiments: healthy gear and gear with six stages of depthwise tooth removal, i.e. 0%, 10%, 20%, 40%, 60%, 80%, and 100% tooth removal conditions. Figure 4 depicts photographs of healthy and worn gears.

For controlled power transmitted by the gearbox, vibration signals and sound signals were picked up by the accelerometer and microphone and were acquired using Agilent 35670A FFT analyser. Statistical features were extracted from the acquired datasets to classify different faults simulated in a gear tooth. The vibration and sound signals were truncated to 3 kHz using a low pass filter and sampled at 8.16 kHz. The sampled signals were then processed using MATLAB 6.5 neural network toolbox (Demuth, Beale, 1998). SVM torch, a freely available C++ based object oriented machine learning library was used for training and testing model (Collobert, Bengio, 2001).

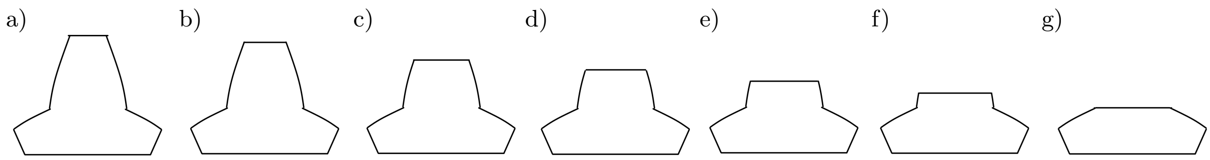

Fig. 3. Details of gear damage for the experiment (a) healthy gear, (b)–(g) tooth removal from 10% to 100%.

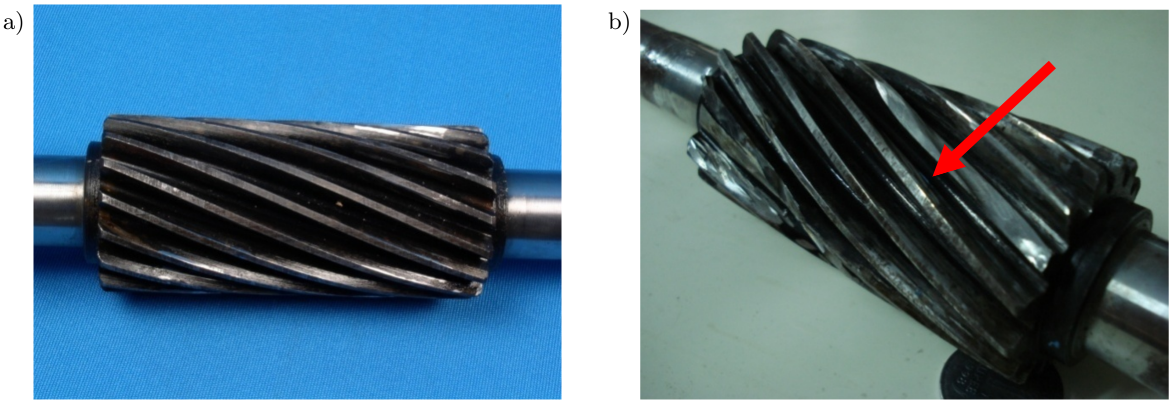

Fig. 4. Test pinions: a) healthy pinion, b) defective pinion.

2.2. Test procedure

The experiments were conducted for two load conditions: 1 kW and 2 kW load, i.e. 50% and 100% load capacity of the resistor bank. The vibration and sound signal datasets were collected when the helical gearbox was operating at 0%, 10%, 20%, 40%, 60%, 80%, and 100% tooth removal conditions. A total of 30 datasets were collected for each tooth removal condition. Vibration and sound signals acquired from the gearbox were used to classify faults using ANNs and SVMs. Figure 5 shows a flow chart of the signal analysis and fault classification procedure.

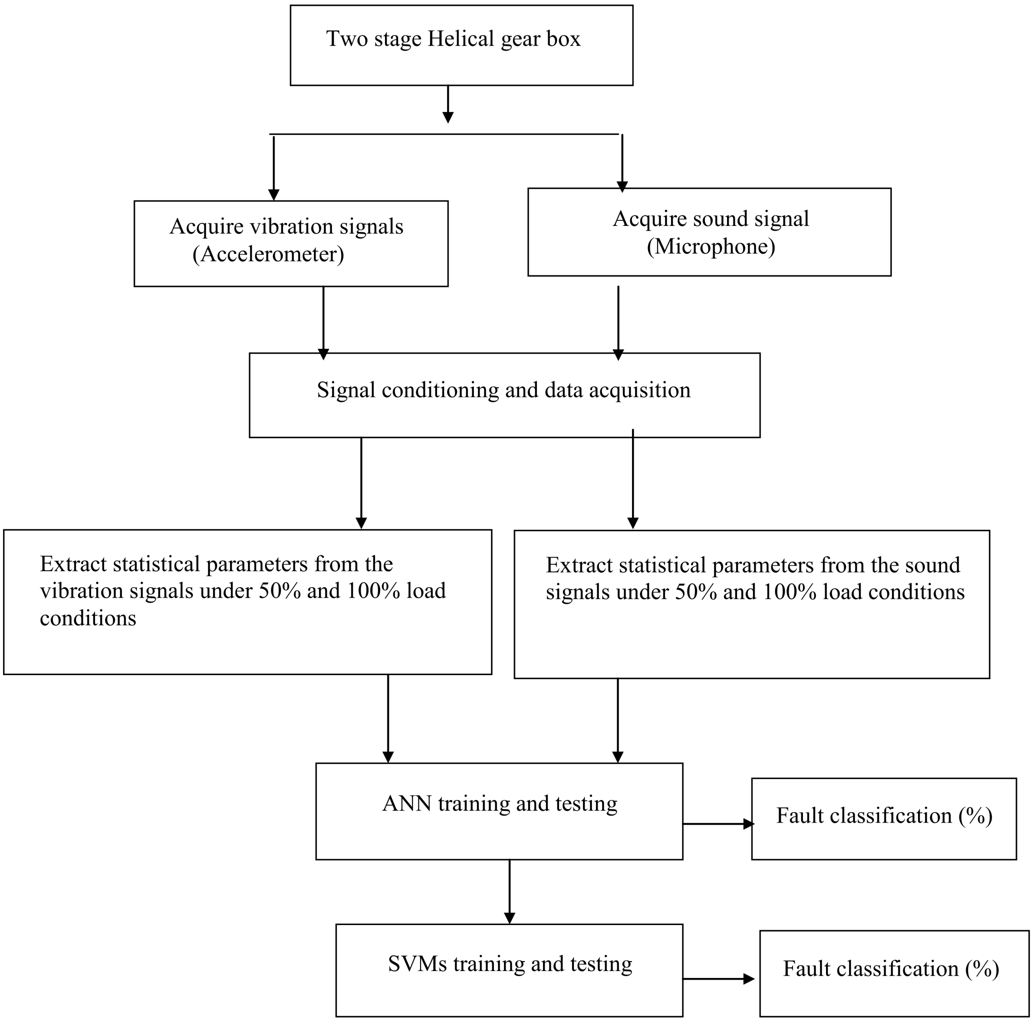

Fig. 5. Flow chart of gear fault diagnostic procedure.

3. Neural networks in fault classification of rotating machines

ANNs are practical to use because they are nonparametric. It has been reported that the accuracy of a neural classifier is better than that of the traditional ones. Artificial neural networks offer advantages for automatic detection and diagnostics of rotating machines since they do not require an in-depth knowledge of the behavior of the operating machines or their internal vibration mechanisms. However, they require a large number of boxing examples. Artificial neural networks are inspired by biological findings relating to the behavior of the brain as a network of units called neurons and have been found to be an effective tool for pattern recognition in many situations where data are fuzzy or incomplete. They are based on models of human neurons and have been used to perform tasks that previously relied on human judgment to take decisions (Murray, Penman, 1997; Mc Cormick, Nandi, 1997; Samanta, 2004; Hu *et al.*, 2007). The basic building block for an artificial neural network is the neuron. Each neuron consists of many inputs and outputs. A typical neuron model is as shown in Fig. 6.

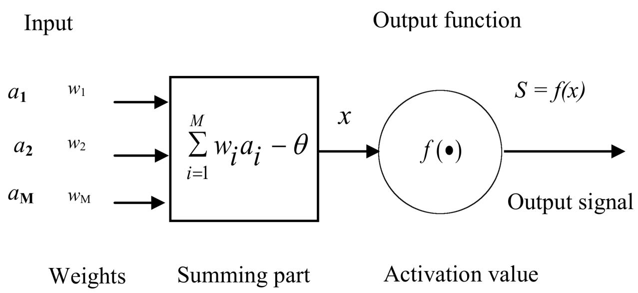

Fig. 6. Typical neuron model.

3.1. Test procedure

In the model the activation value (x) is given by the weighted sum of its M input values (a_i) and a bias term (θ_N). The output signal (S) is typically a nonlinear function $f(x)$ of the activation value. The following equations describe the typical neuron model.

Activation:

$$x = \sum_{i=1}^{M} w_i a_i - \theta_N . \tag{1}$$

Output signal:

$$s = f(x). \tag{2}$$

A common differentiable output function used in the back propagation learning process is one which possesses a sigmoid nonlinearity. Two examples of nonlinear functions are the logistic function and hyperbolic tangent function. These two functions are shown in Figs. 7a and b.

Logistic function:

$$f(x) = \frac{1}{1+e^{x}}, \qquad -\infty < x < \infty. \tag{3}$$

Hyperbolic tangent function:

$$f(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}, \qquad -\infty < x < \infty. \tag{4}$$

For the logistic function the limit is $0 \le F(x) < \infty$ and for the hyperbolic tangent function the limit is $-1 \le f(x) \le 1$. A typical feed forward neural network is discussed in the next section.

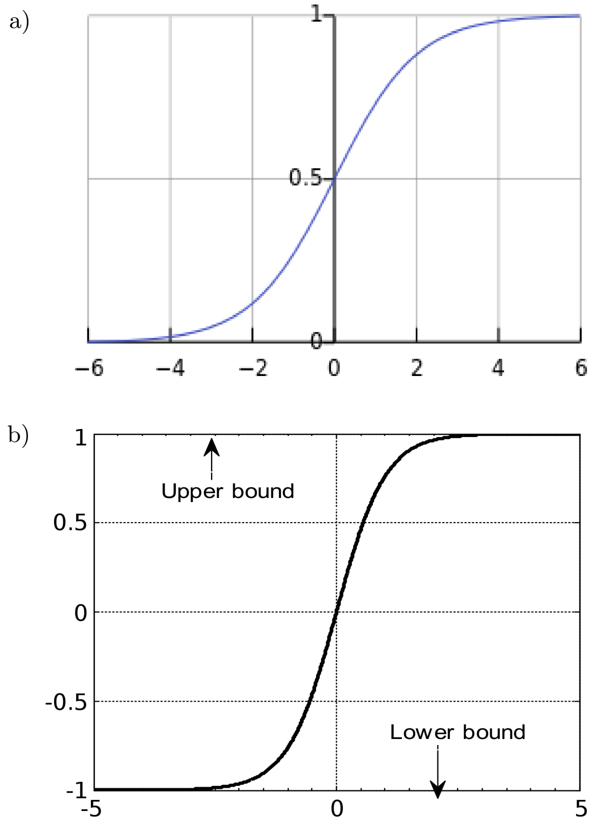

Fig. 7. Nonlinear function: a) logistic function, b) hyperbolic tangent function.

3.2. Multilayer feed forward neural network model

A three layered feed forward neural network is as shown in Fig. 8. The network consists of three layers:

i. The input layer that receives preprocessed data.
ii. The hidden layer which processes the data.
iii. The output layer that provides the result of the analysis, i.e. healthy or damaged.

The input layer has **I** linear input units indexed by **i**, the hidden layer has **J** nonlinear units indexed by **j**, and the output layer has **K** nonlinear units indexed

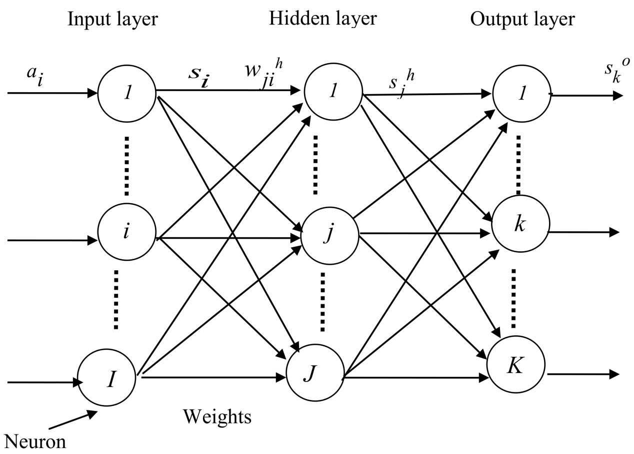

Fig. 8. Three layered feed forward neural network.

by **k**. For simplicity, only one layer (the second layer) of hidden units is considered here. Extension of learning to a network consisting of several hidden layers is trivial. Since the vector $a(m)$ is given at the input layer and the desired output $b(m)$ is available at the output layer, the error between the desired output vector $b(m)$ and actual output vector $b'(m)$ is available only at the output layer. Using this error, it is necessary to adjust the weights (w^h_{ji}) from the input units to the hidden units, and the weights (w_{kj}) from the hidden units to the output units (Yegnanarayana, 1999).

3.3. Configuring the neural network

The neural network design parameters play an important role in the development of classification models. The activation function used at the hidden layer and the output layer in the network was a hyperbolic tangent function. The hidden layer was implemented with 10, 15, and 18 neurons. The ANN was optimised for best accuracy by arriving at the best possible combination of number of epochs, hidden layers, and learning rate at constant momentum rate. The learning rates used were 0.1 and 0.15 and the number of epochs 5, 10, 15, 20, and 25. To improve generalisation and to avoid overboxing, the cross validation method was applied during the boxing.

Optimal design parameters were obtained using cross validation for verification. The optimal parameters were obtained as number of epochs: 10, number of nodes in the hidden layer: 25, and learning rate: 0.1 for 50% load. The corresponding values for 100% load were 25, 15, and 0.1. The preprocessing is performed on the whole signal to extract the required features. The most commonly used fault diagnostic parameters of vibration/sound signals viz. mean (μ), root mean square (rms), variance (σ^2), skewness, and kurtosis were used as input features to the ANN. The boxing of the neural network with boxing data was performed using MATLAB 6.5.

The three-layered feedforward neural network was boxed for the back propagation algorithm using 20 sets of data corresponding to each fault condition. Each dataset consisted of 30 time domain signals, each time domain signal consisting of the average of 16 time history plots obtained over 5 revolutions of the gear tooth. The model after boxing captures the discriminating hyper surface. The mean squared error on the boxing data after each epoch was plotted as shown in Fig. 9. It should be noted that change in error is significantly low after 18 epochs.

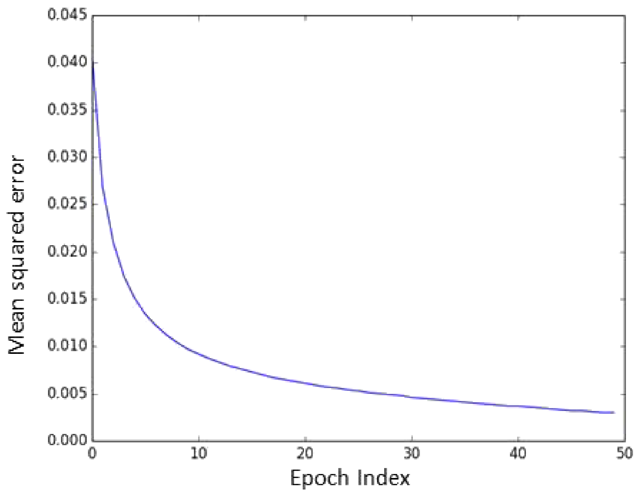

Fig. 9. Training error curve of three layer neural network model.

3.4. Fault classification using support vector machines

In order to obtain classification performance better than what was got using ANNs, SVMs were used. The SVM is a linear classifier pioneered by VAPNIK. It has emerged as a pattern classifier that can learn even from a small boxing dataset for each class (Shin *et al.*, 2005). The main idea of an SVM is to construct a hyperplane as a decision surface in such a way that the separation between positive and negative examples

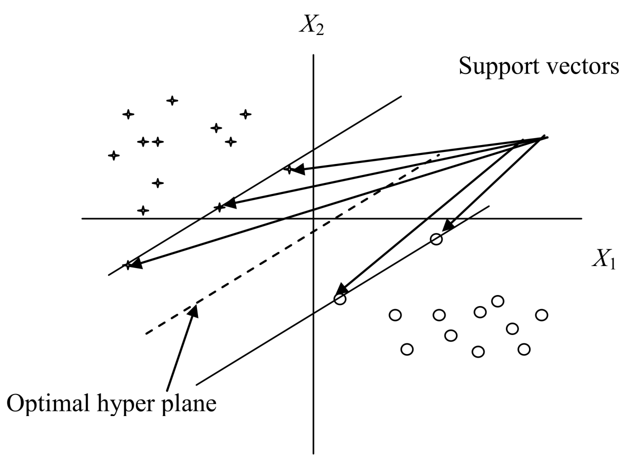

Fig. 10. Classification of two classes by SVM.

(margin) is maximised (Yaun, Chu, 2006). Figure 10 shows the classification of a series of points into two different classes of data, class A (asterisk) and class B (circles).

The notion that is central to the construction of the support vector learning algorithm is obtaining the inner-product kernel between a support vector X_1 and another vector X_2 drawn from the input space. The support vectors constitute a small subset of the boxing data extracted from the support learning algorithm. The separation between the hyperplane and the closest data point is called the margin of separation, denoted by 'ρ'. The goal of a support vector machine is to find a particular hyperplane for which the margin of separation 'ρ' is maximised. Under this condition the decision surface is referred to as optimal hyperplane (Yang *et al.*, 2005; Hu *et al.*, 2007).

The SVM is based on the following two mathematical operations:

(a) Nonlinear mapping of an input pattern vector into a higher dimensional feature space.

(b) Construction of an optimal hyper plane for separating the patterns in the higher dimensional space.

Operation (a) is performed in accordance with Cover's theorem on the separability patterns. For an input pattern space made up of nonlinearly separable patterns, Cover's theorem states that such a multidimensional space may be transformed into a new feature space where the patterns are linearly separable with a high probability, provided the transformation is nonlinear, and the dimension of the feature space is high enough. These two conditions are embedded in operation (a). The separating hyperplane is defined as a linear function of the vectors drawn from the feature space. Construction of this hyperplane is performed in accordance with the principle of structural risk minimisation that is rooted in Vapnik–Chervonenkis (VC) dimension theory.

The optimal hyperplane is defined as

$$\sum_{i=0}^{N_L} \alpha_i d_i k(X, Xi) = 0, \tag{5}$$

where $\{\alpha_i\}_{i=1}^{N_L}$ and $\{d_i\}_{i=1}^{N_L}$ are the Langrange multiplier and desired response (target output) respectively, $d_i \in \{1, -1\}$ and $K(X, Xi)$ are inner product kernels and defined by

$$\begin{aligned} K(X, X_i) &= \varphi^{\mathrm{T}}(X)\varphi^{\mathrm{T}}(X_i) \\ &= \sum_{j=1}^{m_1} \varphi_j(X)\varphi_J(X_J) = 1, 2, \ldots, N_L \,. \end{aligned} \tag{6}$$

Here X is an m-dimensional vector drawn from the input space, and $\{\varphi_j(X)\}_{j=1}^{m_1}$ denotes a set of nonlinear transformations from the input space to the m1 dimensional feature space. From Eq. (5) it is seen that the construction of the optimal hyperplane is based on the evaluation of an inner product kernel $K(X, Xi)$ which is used to construct the optimal hyperplane in the feature space without having to consider the feature space itself explicitly. Since the design of an SVM involves finding an optimum hyperplane, it is necessary to find the optimal Lagrange multipliers which are obtained from the given boxing samples $\{(X_i\, d_i)\}_{i=1}^{N_L}$.

4. Results and discussions

4.1. Fault classification using neural networks

Figures 11a and b and Fig. 12a and b show typical raw time domain vibration and sound signals acquired from healthy and faulty gears respectively. X axis in the plots show time in seconds and Y axis corresponds to acceleration in m/s^2 and sound level in mPa for vibration and sound time domain plots, respectively.

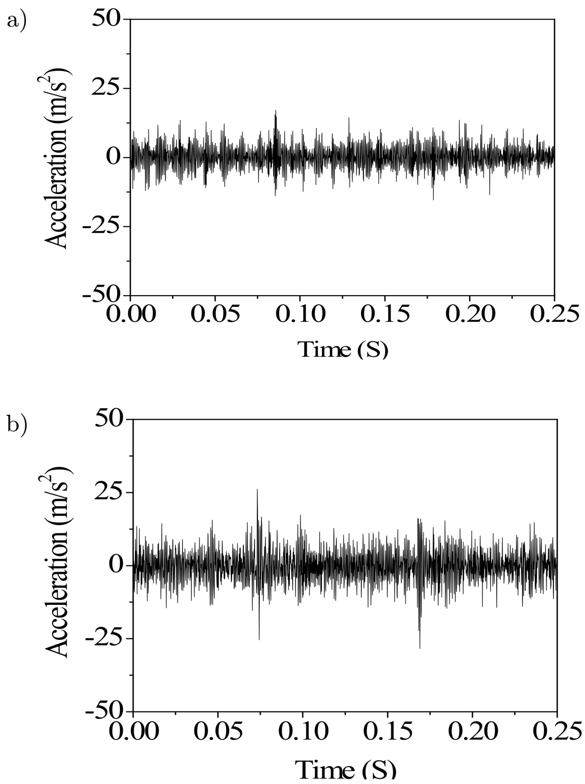

Fig. 11. Vibration signals in time domain: a) healthy gear, b) worn gear.

Although some impulses are observed under fault advancement of worn gear, it is hardly possible to evaluate the gear fault condition only through such a temporal signal. Mean (μ), root mean square (rms), variance (σ^2), skewness, and kurtosis of the measured acceleration and sound signals were used as input fea-

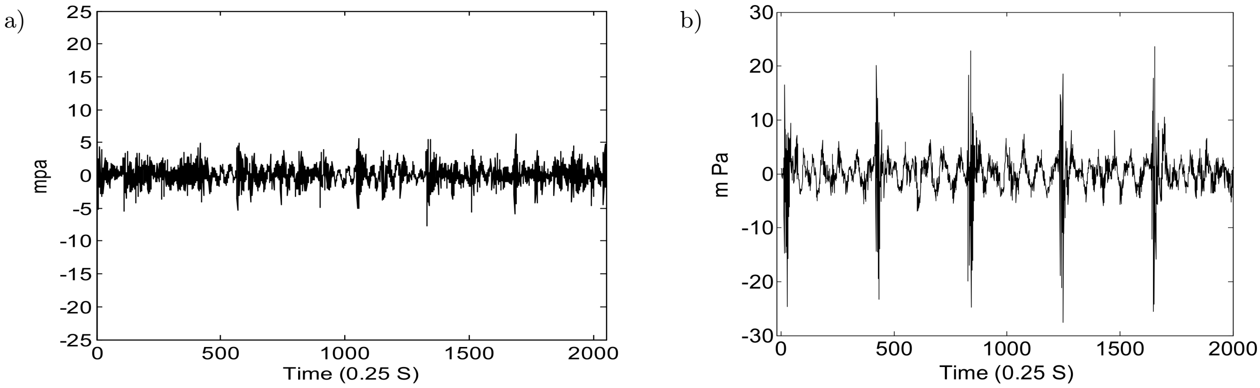

Fig. 12. Sound signals in time domain: a) healthy gear, b) worn gear.

tures to an ANN with five input nodes, fifteen/twenty-five nodes (for 100% or 50 % loads respectively) in the hidden layer and seven output nodes to classify the seven categories of faults in the gearbox.

After boxing, the network was tested using testing examples, 10 datasets were used for testing. Thus boxing dataset consisted of 140 values and the testing data consisted of 70 values. The classification performance obtained for the gearbox operating at 50% and 100% loads under various cases is given in Tables 2 and 3, respectively.

The input data gave rise to 100% training success. However, the results obtained from testing show that the classification performance of the ANN yielded a maximum accuracy of 89.87% (for 50% load condition) and 91.4% (for 100% load condition) for the chosen range of defect stages. Further, the sound signals acquired from the gearbox under above mentioned operating conditions were considered for fault classification. Table 4 shows the results of training testing capabilities of the ANN for statistical parameters data extracted from the sound signals. Though input data showed 100% training success, the test successes of the input data varied from 90.4% to 44.2% and 92.8% to 37.14% for 50% and 100% load conditions respectively. In the case of 50% load condition, the sound signals acquired from the gearbox provided significant contribution to classify the local faults in the gear pair under the best combination of epochs, hidden layers and learning rate as given in Table 4, the testing success rates of 63/70 (90.4%), 60/70 (85.%), and 56/70 (80%) were obtained.

Table 2. Classification performance for different ANN configurations for diagnosis of gear faults with 50% of maximum load (vibration data).

No. of epochs	No. of neurons in the hidden layer	Learning rate	Number of defects correctly identified							No. of examples identified correctly	Success rate %
			0% Fault	10% Fault	20% Fault	40% Fault	60% Fault	80% Fault	100%Fault		
5	10	0.1	9	6	5	4	3	3	5	28/70	40
10	10	0.1	9	10	4	8	10	7	8	55/70	78.57
15	10	0.1	3	6	10	6	10	6	4	48/70	68.71
10	10	0.1	7	10	4	8	10	7	8	55/70	78.57
10	15	0.1	8	7	8	8	7	8	10	58/70	82.71
10	20	0.1	7	10	8	7	8	10	7	60/70	85.71
10	**25**	**0.1**	10	**9**	**7**	**10**	**10**	**8**	**9**	**63/70**	**89.87**
10	25	0.15	10	8	7	7	6	9	9	56/70	80.37
10	20	0.18	**10**	7	7	6	5	8	8	51/70	72.84
30	30	0.15	10	6	8	7	5	7	3	45/70	64.28
15	20	0.15	10	5	4	4	4	8	10	43/70	61.42

Table 3. Classification performance for different ANN configurations for diagnosis of gear faults with 100 % of maximum load (vibration data).

No. of epochs	No. of neurons in the hidden layer	Learning rate	Number of defects correctly identified							No. of examples identified correctly	Success rate %
			0% Fault	10% Fault	20% Fault	40% Fault	60% Fault	80% Fault	100%Fault		
5	10	0.1	0	0	1	8	7	7	0	23/70	24.2
10	10	0.1	8	3	8	6	4	10	7	46/70	65.57
15	10	0.1	10	7	8	6	8	10	4	53/70	75.71
20	10	0.1	10	10	8	7	8	10	7	60/70	85.71
25	10	0.1	9	8	9	5	5	10	7	53/70	75.71
20	10	0.1	10	10	8	7	8	10	7	60/70	85.71
20	**15**	**0.1**	**8**	**9**	**8**	**9**	**10**	**10**	**10**	**64/70**	**91.42**
20	18	0.1	10	10	7	7	7	10	8	59/70	84.28
20	15	0.15	8	9	8	6	5	10	8	54/70	77.14
15	15	0.15	10	10	9	7	2	7	0	45/70	64.28
20	20	0.15	9	5	4	1	1	8	9	36/70	51.14

Table 4. Classification performance for different ANN configurations for diagnosis of gear faults with 50% of maximum load (sound data).

No. of epochs	No. of neurons in the hidden layer	Learning rate	Number of defects correctly identified							No. of examples identified correctly	Success rate %
			0% Fault	10% Fault	20% Fault	40% Fault	60% Fault	80% Fault	100%Fault		
5	10	0.1	5	4	3	5	4	7	3	31/70	44.2
10	10	0.1	10	8	6	9	9	5	7	54/70	77.14
15	10	0.1	7	5	9	10	7	8	4	50/70	71.42
10	10	0.1	6	9	10	7	4	8	9	53/70	75.71
10	15	0.1	7	10	9	6	7	10	5	55/70	78.57
10	20	0.1	10	10	6	8	7	10	6	60/70	85.71
10	**25**	**0.1**	**9**	**8**	**10**	**9**	**9**	**9**	**9**	**63/70**	**90**
10	20	0.18	8	6	9	10	9	6	8	56/70	80.0
10	25	0.15	8	10	8	9	6	4	6	51/70	72.85
30	30	0.15	6	8	7	4	10	9	3	47/70	67.14
15	20	0.15	4	7	10	8	4	6	9	43/70	61.42

Table 5. Classification performance for different ANN configurations for diagnosis of gear faults with 100 % of maximum load (sound data).

No. of epochs	No. of neurons in the hidden layer	Learning rate	Number of defects correctly identified							No. of examples identified correctly	Success rate %
			0% Fault	10% Fault	20% Fault	40% Fault	60% Fault	80% Fault	100%Fault		
5	10	0.1	0	4	3	7	8	4	0	26/70	37.1
10	10	0.1	2	4	7	8	3	7	4	35/70	50
15	10	0.1	8	10	6	7	6	4	6	47/70	67.14
20	10	0.1	4	6	9	10	8	9	8	54/70	77.14
25	10	0.1	6	9	7	6	4	10	8	50/70	71.14
20	10	0.1	7	9	10	8	9	8	8	53/70	75.71
20	**15**	**0.1**	**10**	**9**	**8**	**7**	**9**	**10**	**10**	**65/70**	**92.8**
20	18	0.1	9	7	8	6	9	9	9	57/70	81.42
20	15	0.15	4	8	9	7	8	9	9	55/70	78.57
15	15	0.15	9	8	10	6	5	4	8	50/70	71.42
20	20	0.15	4	7	10	8	4	6	9	42/70	68.57

Further, for 100% load condition the success rates of 65/70 (92.8), 57/70 (81.42), 55/70 (78.57) were obtained under the best combination of number of epochs, hidden layers, and learning rates given in Table 5.

4.2. Results of fault classification using support vector machines

Support vector machines are extensively used for data classification and regression problems. However, application to classification has been considered in this work. The procedure of gear fault classification based on multilayer classification consists of three steps:

1. Extract the statistical features from the vibration and sound signals acquired under healthy and faulty conditions of the gearbox.
2. Training SVMs.
3. Identify the gear faults with the trained classifier.

The same set of data as used for ANNs has been processed using SVMs. Table 6 shows the details of datasets, while Tables 7 and 8 give the classification performance of vibration and sound respectively.

The dataset corresponding to case A in Table 6 consists of 210 data values for seven different operating conditions at 50% load condition. Similarly, the dataset corresponding to Case B consists of another 210 data values for seven tooth removal conditions at 100% load condition. The datasets A and B were split into 140 boxing and 70 testing classes each. A multiclass SVM with the Gaussian kernel function, which

Table 6. Details of datasets of both vibration and sound signals.

Case A: 50% load		Case B: 100% load		% of tooth removal	Labels of classification
No. of training samples	No. of testing samples	No. of training samples	No. of testing samples		
20	10	20	10	0	0
20	10	20	10	10	1
20	10	20	10	20	2
20	10	20	10	40	3
20	10	20	10	60	4
20	10	20	10	80	5
20	10	20	10	100	6

was proved to be the best one in machinery fault diagnosis (Yang *et al.*, 2005), was used in the present work in the following form:

$$K(X, X_i) = \exp\left[\frac{\|X - X_i\|}{2\sigma^2}\right]. \tag{7}$$

The parameter σ denotes the constant width kernel parameter, $\|X - X_i\|$ is the Euclidean distance between the vectors X and X_i. The optimum value of constant width kernel parameter σ was selected based on an iterative trial and error process and datasets. For the vibration signals obtained from the gearbox, the SVM showed best classification performance for $\sigma = 8$ and

Table 7. Performance of SVM in gear fault classification using vibration signals.

50% load		100% load	
σ	Classification performance (%)	σ	Classification performance (%)
2	40 (28/70)	2	73 (51/70)
3	68 (47/70)	3	56 (39/70)
5	52 (36/70)	5	83 (58/70)
6	87 (61/70)	**6**	**94.2 (66/70)**
8	**91.4 (64/70)**	8	79 (55/70)

$\sigma = 6$ for 50% and 100% load cases respectively as seen in Table 7. Further, SVM based gear fault classifications is continued using sound signals of gearbox acquired under 50% and 100% load conditions. Table 8 gives the best classification results for $\sigma = 8$ and $\sigma = 6$ for 50% and 100% load conditions respectively.

Table 8. Performance of SVM in gear fault classification using sound signals.

50% load		100% load	
σ	Classification performance (%)	σ	Classification performance (%)
2	51.4 (36/70)	2	70 (49/70)
3	67.1 (47/70)	3	74.2 (52/70)
5	71.4 (50/70)	5	81.4 (57/70)
6	82.5 (58/70)	**6**	**97.1 (68/70)**
8	**94.2 (66/70)**	8	79 (54/70)

5. Summary and conclusions

An artificial neural network and support vector machine fault classification methods have been used to perform gear fault diagnosis based on the extracted statistical features from the sound and vibration signals of two stage helical gearbox. The operating conditions involved a healthy gear and gear with simulated faults consisting of depthwise removal of tooth in six stages. The vibration and sound datasets were collected from the gearbox in real time and were then applied to perform initial testing and subsequent validation. The following conclusions were drawn from the experimental observations.

1. ANN fault classification method based on the statistical features extracted from the vibration signals showed classification performances of over 89.87% for 50% load condition and 90% for 100% load conditions.
2. Further, ANN method based on statistical features of sound signals resulted in a slight improvement in gear fault classification performance, results showed over 91.4% for 50% load condition and 94.2% for 100% load conditions.
3. In order to improve the classification performance, SVM method was used to process the statistical features. The vibration signal statistical parameters processed using the multiclass SVM based on multiclass class strategy showed better performances of 92% for 50% load and 95% for 100% load conditions.
4. For the sound signals, the SVM based on multiclass strategy showed the classification performances over 94.2% for 50% load and 97.1% for 100% load conditions.
5. The better classification performance was obtained by SVM based on multiclass strategy which can serve as a promising alternative for intelligent gear fault diagnosis applications using the vibration and sound signals.

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