Comparison of Vibration, Sound and Motor Current Signature Analysis for Detection of Gear Box Faults

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ABSTRACT

Gear box is used in automobiles and industries for power transmission under different working conditions and applications. Failure in a gear box at unexpected time leads to increase in machine downtime and maintenance cost. In order to overcome these losses, the most effective condition monitoring technique has to be used for early detection of faults. Vibration and sound signal analysis have been used for monitoring the condition of rotating machineries. Motor Current Signature Analysis (MCSA) has rarely been used in gearbox condition monitoring. This work presents a methodology based on vibration, sound and motor current signal analysis for diagnosis of gearbox faults under various simulated gear and bearing fault conditions. Statistical features were extracted from the raw data of these three transducer signals and the best features were selected from the extracted features. Then the selected features were given as an input to Artificial Neural Network (ANN) and Support Vector Machine (SVM) classifiers and their performances were compared. In recent years, Hybrid Electric Vehicles (HEV) are gaining more interest for their advances and this work had a scope in monitoring the power loss in hybrid electric vehicle gearbox using MCSA.

***Key words**:* Hybrid Electric Vehicle (HEV); Automobile Gear box; Fault diagnosis; Artificial Neural Network (ANN); Support Vector Machine (SVM).

1. INTRODUCTION

Hybrid electric vehicles are becoming more popular which uses electric motor and conventional Internal Combustion (IC) engine to drive the vehicle. HEV evolves due to limitations of the battery storage in fully electric drive vehicles and its main advantage is that it consumes less fuel with lesser CO_2 emission. Due to the continuous growth in population, the development in the field of HEV is necessary in order to increase fuel efficiency and reduce toxic emissions. The use of hybrid technology can downsize the engine (German, 2015); the downsized engine combined with electric motor produces an equal power as of a conventional engine. Gearbox is the important part in HEV for power transmission.

The majority of gearbox problems start from rolling – element bearing and it steps forward to the gear teeth. Gears and bearings are responsible for a majority of transmission power loss due to friction and gear oil interaction. Battery is also one of the major component in HEV and the motor consumes more power from battery when there is a power loss due to gearbox fault. So, monitoring the condition of the gear box is an important task to overcome power losses. This work uses an induction motor, automotive gearbox and a dynamometer setup used to study the behavior of gearbox using vibration, sound and Motor Current (MC) signals. Based on the obtained results, this work can be further extended for monitoring the power loss in HEV gearbox during motor drive and also in all motor operated mechanical systems.

A case study of a failed helical gear of a gearbox in a vehicle has concluded that misalignment of the gear and pitting in the tooth were the reasons for tooth breakage in the helical gear (Asi, 2006). Due to extreme operating stresses, surface defects are generated in the gear tooth which in turn cause faults in the gears such as gear tooth breakage and tooth wear (Praveenkumar, Sabhrish, Saimurugan & Ramachandran, 2018). The majority of problems in rotational mechanical system arise from faulty bearings which in turn affect other rotating components (Winder & Littmann, 1976). During operation, the sizeable part dislodges from the contact surface and creates ball damage, race defect and cage damage in bearing (Li & Wu, 1989). An air crash was caused by bearing failure which results in damage to the cage supporting the bearing balls (Smalley, Baldwin, Mauney, & Millwater, 1996). The author proposes an efficient approach for damage detection in multiple components which are analyzed using vibration signatures with an experimental set-up consists of combined gear –bearing faults (Dhamandea, Chaudhari, 2016). The

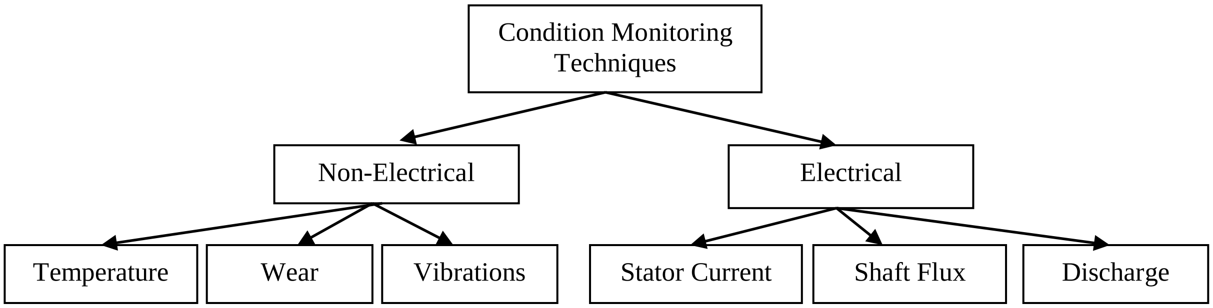

Figure 1. Classification of monitoring techniques (Negoita, Ionescu, 2010)

faults generate vibrations and increase in power consumption.

In order to avoid breakdown due to failures in the machines, fault diagnosis methods have been developed for condition monitoring (Lei & Sandborn, 2016). Condition monitoring techniques for motor operated rotating machineries are based on non-electrical and electrical signals which is shown in Figure 1. When a gearbox is running at different speeds and loading conditions, it is not possible to measure the severity of fault in the system, therefore some physical parameters such as vibration, sound, acoustic emission and wear debris has been considered for detection and diagnosis of faults (Amarnath, Sugumaran & Kumar, 2013).
Vibration signal analysis is one of the widely used method for detecting the condition of the gearbox in a continuous working atmosphere. Vibration and wear debris analysis were performed to find the correlation between these two analyses (Peng, Kessissoglou & Cox, 2005) and the vibration analysis was claimed to provide reliable and faster information. Thus, the varying vibration signals are used to detect the faults or air gaps between the gears (Fekia, Clercb & Velexa, 2013).

Microphones generally have wider band width, so that the sound signals will have more information compared to that of accelerometer (Benko, Petrovcic, Juricic, Tavcar & Rejec, 2005; Lu, Wang, He, Fang & Yongbin, 2016). A new intelligent monitoring system has been developed in thermal power plant for automatic monitoring of its machine components using sound signals. The sound signal analyzer detects the unusual sound and gives alarm when the sound level exceeds the threshold range (Oikawa, Tomizawa, & Degawa, 1997).

Previous research work reported (shibata, takahashi & shirai, 2000) the use of sound signal for fault diagnosis of rotating bearing element by visualizing measured sound signals. Local faults in rolling elements cause impacts and as a result transient excitation can be observed in sound signals (Amarnath, Sugumaran & Kumar, 2013). The vibration and sound signal analysis techniques have gained benefits in the emerging signal processing methods (Feng, Chu & Zuo 2011; Peng, Tse & Chu, 2005).

The stator current based motor current analysis has also been accepted by researchers for condition monitoring of electrical rotating machines owing to its advantages of being noninvasive and easy to use. Though vibration signal analysis is better suited for fault detection of mechanical systems, it can also be detected by means of motor current analysis since the induction motor current consumption is modified by the mechanical efforts and vibrational modes in rotating machines (Jose, Miguel, Antonio, Alfredo & Jesus, 2016). Motor current signature analysis (MCSA) has been the most recent addition as a nonintrusive and easy to measure condition monitoring technique. This analysis system can be used for measuring the characteristics for a perfectly working gearbox and use the data as a standard for measuring faults and defects in other gearboxes (Rajendra & Bhaskar, 2013). MCSA has been extensively used to detect bearing faults outside the induction motor (Singh, Amitkumar, & Navinkumar, 2014). In motor current signature analysis, the system can store certain data which can make decisions with high degree of accuracy (Rafiee, Rafiee & Tse, 2010). The concept of motor current signature analysis is such that the side band detection around the supply frequency (Benbouzid, 2000).

Condition monitoring process involves data acquisition, data processing and decision making to process maintenance methods. The processing of raw data takes more time for analysis and also it contains repeated values. In order to avoid the repetitiveness and reduce the processing duration, feature extraction has been done. Thus, feature extraction helps to convert the raw data into useful features such that it makes the process efficient (Saimurugan, Ramachandran, Sukumaran & Sakthivel, 2011).

For fault diagnosis of automobile gearbox, statistical features including Mean, Median, Mode, Skewness, Kurtosis, Standard deviation, Root mean square, Minimum, Maximum and Variance were extracted from time domain data and it provides a better classification accuracy (Praveenkumar, Saimurugan, Krishnakumar & Ramachandran, 2014). Research work reported that (Subrahmanyam & Sujatha, 1997) different statistical features are good indicators for bearing defect. The results showed that the trained neural networks were able to distinguish a normal bearing from defective bearings with 100% reliability using statistical features. Root mean square (RMS), crest factor, mean, standard deviation, variance and skewness are the statistical features used for gearbox fault diagnosis under realistic conditions (Pacheco, Oliveira, Sánchez, Cerrada, Cabrera, Li, Zurita, Artés, 2016). Recent research (Saimurugan & Nithesh, 2016) has been carried out in fault diagnosis of rotating machines using sound signal. The result clearly shows that the statistical features are good candidate for fault diagnosis than histogram features. Standard error, kurtosis, skewness, minimum, maximum and range are extracted from the time domain data for fault diagnosis of centrifugal pump using vibration signal. These extracted features from vibration signal is recommended for fault diagnosis (Sakthivel, Sugumaran, Babudevasenapathi, 2010). The electrical features such as line current, frequency, active power, power factor, V-rms, Total Harmonic Distortion (THD) voltage and THD current signals has been used in this study. The features extraction is further improved by a feature selection process. This process sorts out the features or parameters based on their accuracy. Thus, it increases accuracy further and also reduces the processing time.

Various algorithms are used for predicting the faults in the gearbox, so that faults are predicted before the structural damage. In recent days, neural networks have earned approval over other techniques as it is good in finding similarities among large quantity of data (Waqar, Demetgul & Kelesoglu, 2009). Research work reported (Samanta & Baulshi, 2003) that fault diagnosis of rolling element bearings through artificial neural network using time domain features is the best suitable method for on-line condition monitoring and diagnostics of rotating machines. Artificial neural network is like a human brain capable of taking decision like human and gives inference even if there is a high degree of complication (Gunal, Ece & Gerek, 2009). Neural network can analyze a wide range of data effectively and can give efficient results in short span of time (Gupta & Kaur, 2014). ANN has the ability to minimize errors by adjusting the weight function based on training values (Jaber & Bicker, 2016). The acquired result from the ANN is not only for detecting faults in a machine but it can also be used to find the severeness of the fault (Salem, 2012). The authors have performed condition monitoring on a spur gearbox using sound signal by extracting statistical features like kurtosis, RMS, maximum etc., and a classification accuracy of 97% was obtained using ANN (Kane, Andhare, 2016). Multi-layer perceptron trained with backpropagation learning algorithm is employed in this work to classify gearbox faults.

Support vector machine was originally made for classification and nonlinear regression tasks (Swapna Vora, Jitendra, Gaikwad, Jayant & Kulkarni, 2015; Kocsis, Vamosi & Keviczki, 2014). Support vector machine creates a hyper plane between classes and that can classify data according to their classes using the biggest possible margin. Margin is the distance between two parallel hyper planes (Bacha, Souahlia & Gossa, 2012; Hong & Dhupia, 2014; Kar & Mohanty, 2006). The advantage of SVM is high precision and better generalization when there are less samples in counts (Chandran, Lokesha, Majumder & Raheemv, 2012; Chaari, Fakhfakh & Haddar, 2009; Thomson & Fenger, 2001; Hsu & Lin 2012). Recent research work (Praveenkumar, Saimurugan, Krishnakumar & Ramachandran, 2014) has been performed for fault diagnosis of spur gearbox using vibration signal by extracting statistical features from time domain signal like mean, sum, median, maximum, kurtosis, skewness etc. The classification accuracy of 97% was obtained using SVM classifier. The research claimed that the SVM classifier with RBF kernel function is a good candidate over other kernel functions such as linear, polynomial and sigmoid for fault diagnosis of rotational mechanical systems (Saimurugan, Ramachandran, Sukumaran & Sakthivel, 2011). SVM can also separate typical non-separable classes using kernel functions. This work uses SVM model with RBF kernel for diagnosis of gearbox faults.

Based on the literature review, vibration signals are widely accepted technique for rotating machine fault diagnosis. Motor current and sound signals are not well explored in the fault diagnosis of rotating machinery. This paper addresses the effectiveness of motor current and sound signals for fault diagnosis of gearbox in detail and then comparing its performance with well-established vibration signals. Rest of the work is as follows: The vibration, sound and motor current signals are captured for 4 different fault conditions such as good condition, face wear in gear, outer race fault bearing and combination of gear and bearing faults. The statistical features were extracted from all three signals and best features were selected using ranker selection method then it was classified using support vector machine with radial basis kernel function and artificial neural network. Then their classification performances are compared and discussed. Figure 2 shows the machine learning based fault diagnosis procedure in the form of flow chart.

2. EXPERIMENTAL STUDIES

The experimental studies contain experimental set up and experimental procedure.

2.1. Experimental Setup

The experimental set up consists of 3 major equipment’s:
1. 3-phase AC Induction motor (Variable speed, 1440rpm)
2. 4-speed synchronous gear box
3. Eddy current dynamometer

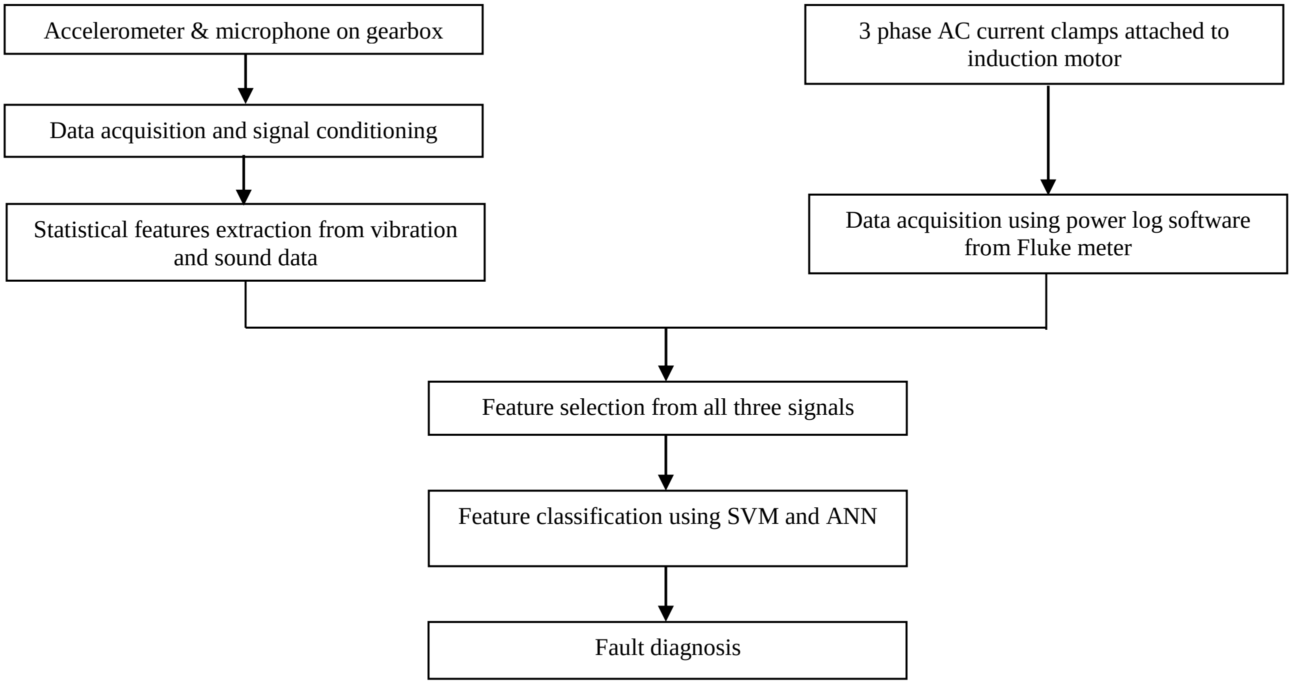

Figure 2. The methodology flow chart

The sensors and DAQ includes:

1. Piezo electric accelerometer
2. 40PH free field array microphone
3. Vib pilot DAQ
4. Fluke 435-ii series (real time power quality analyzer)

The experimental setup is designed particularly to diagnose faults in a HEV gearbox in a stationary test bench. The gear box was driven by an induction motor using flexible coupling. Flexible couplings help us to overcome misalignment between shafts and transmit power effectively to the gear box. Eddy current dynamometer is coupled with the gear box output shaft to apply load to the gear box and the load can be varied using torque controller in terms of Kg-m. The whole experiment set up is shown in Figure 3. Delta drive unit is employed which helps in controlling the speed of the motor between 0-1440 rpm. Dytran piezo electric type tri-axial accelerometer was mounted on the top surface of the gear box using adhesives and a 40PH free field array microphone is placed near to the bearing housing of the gearbox to acquire their corresponding signals. Both the sensors are connected to an 8-channel data acquisition system (DAQ) to acquire vibration and sound signals.

Fluke power quality analyzer is used to acquire current and voltage signals and its real-time acquisition is shown in Figure 4. For acquiring the electrical signal, one end of the AC clamps is attached to the power input cable of the electric motor and the other end is connected to power quality analyzer for acquisition of electric signals at various speeds and loading conditions. Gear box provides different

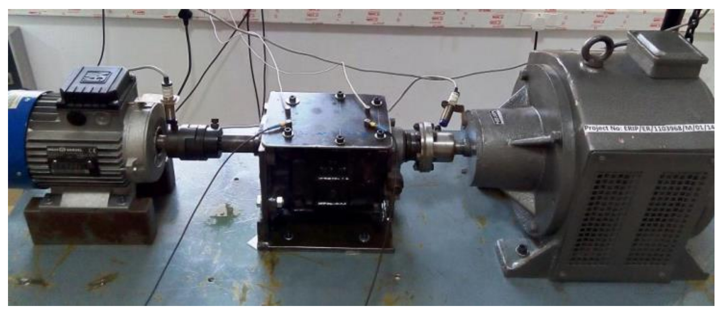

Figure 3. Experimental setup

Figure 4. Power quality analyzer

speed and torque conversions using different gear ratios. Number of teeth in main shaft and lay shaft for all four gears is shown in Table 1. The gear box used in this study is a 4-speed automotive manual transmission. Gears have been changed manually based on the speed of operation.

Gears	Main shaft	Lay shaft
Gear-1	28	11
Gear-2	24	19
Gear-3	18	25
Gear-4	14	30

Table 1. Number of teeth on gears

2.2. Experimental Procedure

The experiment was conducted based on different experimental conditions. There are 4 different combinations of gear and bearing classes in this experiment are:

1. Good Gear, Good Bearing (C1)
2. Good Gear, Fault Bearing (C2)
3. Fault Gear, Good Bearing (C3)
4. Fault Gear, Fault Bearing (C4)

The notations C1, C2, C3, C4 are defined for different fault conditions, such as Good gear good bearing with 0 Nm load as (C1-0), good gear fault bearing with 0Nm load as (C2-0), fault gear good bearing with 0Nm load as (C3-0) and fault gear fault bearing with 0Nm load as (C4-0) and similarly it follows for 5Nm load as C1-5, C2-5, C3-5 and C4-5. In this experiment 2 motor speeds, 2 loads, 4 gear fault conditions and 4 gear speeds with total of 64 conditions has been carried out and it is mentioned in Table 2.

Class	Engaged Gear	Motor Speed (rpm)	Torque (N-m)
C1, C2, C3, C4	1^{st}, 2^{nd}, 3^{rd}, 4^{th}	500	0,5
		750	0,5

Table 2. Experimental conditions

Initially for acquiring data, the gear box is incorporated with good gear and good bearing (C1) with 1^{st} gear and a speed of 500 rpm using induction motor and dynamometer running in neutral (0Nm). In all experimental conditions as given in Table 2 the setup is allowed to run some time to maintain the consistency in the signals, and the data acquisition was carried out. 8192 samples per second for a time period of 200 seconds (8192*200) was recorded and it is used for further operations. This procedure was followed for vibration and sound signals.

For acquiring electrical data same experimental conditions has been followed as per Table 2. Primarily the AC clamps were attached to the power input of the induction motor and output of the AC clamps is connected to the power quality analyzer to acquire electrical signals. Electrical data from the power quality analyzer was acquired by using power log software.

3. FEATURE EXTRACTION

The acquired raw time domain data set consists of information that is specific to a condition of a gearbox. Hence the analysis is performed on time domain data to extract information from the huge data set which pertains to the gearbox condition. Research work reported (Saimurugan, Ramachandran, Sugumaran & Sakthivel, 2011) fault diagnosis of bearing and shafts failures using time domain statistical features such as standard error, standard deviation, sample error, kurtosis, skewness etc., and classification using support vector machine model. The SVM model using RBF kernel gives a classification accuracy of 99% which clearly shows that the SVM model using statistical features is a good candidate for fault diagnosis of rotating machine elements. To extract information from huge amount of data, this work uses ten statistical features include mean, median, mode, skewness, kurtosis, standard deviation, root mean square, minimum, maximum and variance for vibration and sound signals. Matlab is used for statistical feature extraction and the input to the system is in the form of (8192 samples per sec * 200 seconds) and the output from the system after extraction is in the form of (200 data set * 10 features). The input Line current, frequency, active power, power factor, V-rms, Total Harmonic Distortion (THD) and voltage are the electrical features that has been directly acquired from the power quality analyzer.

4. FEATURE SELECTION

All features contribute to the classifications and there is a need for selecting the best features before classification. Research has been carried out to select the best feature selection technique makes it more robust across various classifiers. The classification accuracy increased by approximately 3–5% across a wide range of classifiers using ranker selection technique (Sarkar, Cooley & Srivastava, 2014). A feature selection approach using a combination of ranker selection method is employed which showed an increase in classification accuracy of about 10% which is higher for all classifiers when compared with previous results as specified in Ref. (Selvakuberan, Kayathiri, Harini, Devi, 2011).

Best features selected in vibration signals are

1. Sum
2. Median
3. Standard deviation
4. Variance
5. Skewness

Best features selected in sound signals are

1. Mean
2. Sum
3. Median

4. Minimum
5. Standard Deviation

Best features selected in electrical signals are

1. V-rms ph-ph L1,L2,L3 avg
2. THD V L1N,L2N,L3N avg
3. THD A L1,L2,L3,N avg
4. Power factor total average

5. FEATURE CLASSIFICATION

The feature classification process splits the data points depending on the percentage of data given for training and testing sets. Training sets means learning the data points to perform the correlation tasks, that is storing the data by giving set of rules to perform further operations. Testing sets helps to find the classification accuracy of the trained data points. Cross fold validation technique is used to evaluate the predictive models by partitioning the original samples into training set to train the model and the testing set to evaluate the model. In K-fold cross validation, the original samples were randomly classified into K equal size subsamples. The single subsample is retained as validation data for testing the model and the remaining K-1 subsamples were used as training data. The K results from the folds can be averaged to produce a single estimation result. The main advantage of this method is that all subspaces were used for both the training and validation and each subspace is used for validation once. The data sets were given as an input to the algorithm for training and testing which gives out the confusion matrix and classification accuracy for different conditions. Artificial Neural Network (ANN) and Support Vector Machine (SVM) are the two classifiers used for this study.

5.1 ARTIFICIAL NEURAL NETWORK (ANN)

ANN is the non-linear mapping system and it is a replication of neurons of human brain. ANN consist of three-layer structure that is input, hidden and output layer, each consist of one or more neurons. Numerical input values are given to input layer, each neuron in input layer will take only one input value. Number of input neurons depends on number of input features and this value is transferred to the hidden layer. Hidden layers are interconnected by weights to output layer. Every single neuron of hidden layer is connected to their corresponding single neuron of output layer and it provides response in terms of numerical values.

The training of ANN is accomplished by adapt the weights of the connections between three layers. ANN makes response based on decision variables. A network can be constructed without any hidden layer or more than one hidden layer based on decision variables, input data, and number of process parameters (Samanta & Balushi, 2013). The number of hidden layers should be selected properly where too many neurons will make over-fitting and very less neurons will cause under-fitting (Mia & Dhar, 2016). The selection of hidden layers is based on input vector size and input-output vector space classification.

Training algorithm, network structure, training time, training data size, value of weight, test data size and learning functions are the important factors which validates the performance of ANN (Samanta & Balushi, 2013). The accuracy in level of prediction is based on number of layers, nodes and their relation in neural networks (Hajar, Raad & Khalil, 2012). The best possible architecture of ANN model has to be developed and test the model for higher accuracy and lower root mean square error (RMSE). The implementation of the ANN involves the formation of network topologies or architecture that consists of layers of neurons that are arranged sequentially. The neural network topology used in the present study is illustrated in Figure 5. It has an input layer, hidden layer and output layer. In the present study, the features of vibration, sound and motor current signals form the input layer and four different fault classes form the output layer. Each neuron in the hidden layer receives information from all neurons in the layer above, processes the data and sends the output to all the neurons in the layer below. This type of network architecture provides a feed-forward path to the output.

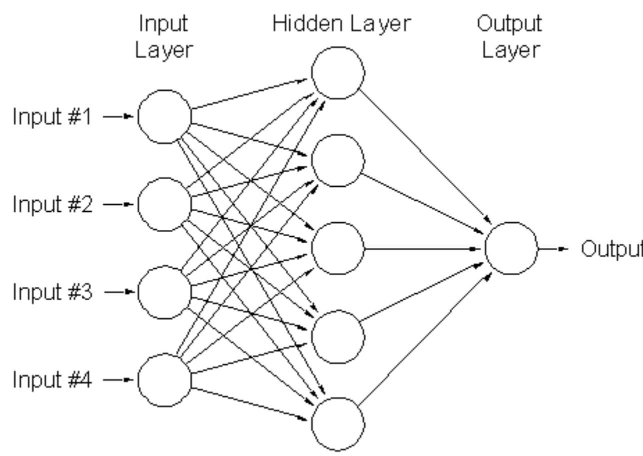

Figure 5. Artificial Neural Network Topology

5.2 SUPPORT VECTOR MACHINE (SVM)

Support vector machine is also known as support vector networks and it belongs to the class of supervised learning algorithm. It constructs a hyper plane and it tries to attain maximum possible separation between two classes. Two planes which passes through points in the data set on either side of the hyper plane is called bounding plane and the distance between two bounding planes are called as margin. Main objective of SVM is to choose a correct hyper plane in order to obtain a maximum margin. The points which lie on the bounding planes are called support vectors. Generalization error occurs when separating the classes with large margin. When new examples arrive for classification, the chance of error occurring in prediction based on the learned classifier should be minimum, which minimize the generalization error (Saimurugan, Ramachandran, Sukumaran & Sakthivel, 2011).

If the optimal hyper plane separates the training vectors without error (Vapnik, 1999, Mohandes, Halawani, Rehman & Hussain, 2004), then the error rate of test sample depends on the ratio of support vectors to number of training vectors. A small set of support vectors leads to good generalization. SVM allows a small training error to get a better test accuracy. A pictorial representation of SVM is shown in Figure 6. This work uses SVM model using RBF kernel for diagnosis of gearbox faults.

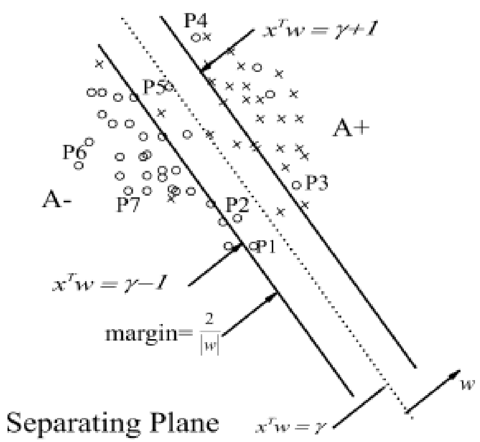

Figure 6. Pictorial representation of SVM (Saimurugan, Ramachandran, Sukumaran & Sakthivel, 2011).

The decision function after obtaining 'w' and 'γ' is given by

$$f(x) = sign(w^T \mathbf{x} - \gamma) \quad (1)$$

For a new point, the sign of $w^T \mathbf{x} - \gamma$ is assigned as a class value. The above Figure 6 shows a two class SVM problem A+ and A-, where point P3 and P4 belongs to class A- are misclassified to class A+. The data points P1, P2, P3, P4, and P5 belonging to A- are support vectors. A small amount of training error is required to minimize the generalization error.

6. RESULTS AND DISCUSSION

The data set for the various conditions of the gearbox as mentioned in the Table 2 was acquired for 200s from the sensors mounted on different locations of the gearbox. Features such as mean, median, mode, skewness, kurtosis, standard deviation, root mean square, minimum, maximum and variance have been extracted from time domain data of vibration and sound signals. Then the best features have been selected from the extracted statistical features of vibration and sound signals and then the electrical features from motor current signal. The best selected features were then used for feature classification. Classification is normally a two-phase problem namely training and testing. In training phase, the data sets were learned. The testing phase identifies how well labeling unseen examples. ANN and SVM are the two classifiers used to classify the feature sets. The test result of the classifier for 4^{th} gear 750rpm of electrical signal is shown in the form of confusion matrix in Table 3.

The interpretation of confusion matrix is as follows:

- The diagonal elements in the confusion matrix show the correctly classified instances. The first row first element belongs to "C1-0 good class with 0Nm load". 99 instances out of 100 instances were correctly classified in class "C1-0", one instance got misclassified in class "C2-0 gear fault with 0Nm load".
- All the instances from class C1-5 and C2-5 were classified correctly. The confusion matrix for an eight-class problem is shown in Table 3 and this particular class yields a classification accuracy of 98.375%.

The classification accuracy is calculated using.

$$Classification\ accuracy = \frac{Sum\ of\ total\ instances\ in\ the\ diagonal\ element}{Total\ number\ of\ instances} * 100 \quad (2)$$

Category	**C1-0**	**C2-0**	**C3-0**	**C4-0**	**C1-5**	**C2-5**	**C3-5**	**C4-5**
C1-0	**99**	1	0	0	0	0	0	0
C2-0	0	**98**	0	2	0	0	0	0
C3-0	0	0	**98**	0	1	0	0	1
C4-0	0	0	1	**98**	0	0	0	1
C1-5	0	0	0	0	**100**	0	0	0
C2-5	0	0	0	0	0	**100**	0	0
C3-5	0	0	0	0	0	0	**98**	2
C4-5	0	0	0	0	0	0	4	**96**

Table 3. SVM confusion matrix for gear-4 at 750 rpm of electrical data

The classification accuracy of SVM for all three vibration, sound and electrical signals is shown in Table 4. The electrical signal lower band accuracy is of 98.32% and upper band accuracy of 100%. Whereas vibration signal yield lower band accuracy is of 95.2% and upper band accuracy of 100%. But the sound signal yield lower band accuracy is of 74.88% and upper band accuracy of 92.33% and it is comparatively lower than the other two signals. Both vibration and electrical signal outperforms sound signal. SVM gives a better accuracy for vibration and electrical signals, but electrical signal performs better than vibration signal.

GEARS	SVM Electrical Signal %		SVM Vibration Signal %		SVM Sound Signal %	
	500 rpm	750 rpm	500 rpm	750 rpm	500 rpm	750 rpm
Gear-1	99.75	100	96.12	100	75.0	74.88
Gear-2	100	100	99.75	99.75	77.19	90.94
Gear-3	100	100	100	99.75	83.33	92.33
Gear-4	100	98.37	95.26	99.75	77.17	82.52

Table 4. SVM classification accuracy of Electrical, Vibration and Sound signals

The comparison of classification accuracy of ANN for all three signals is shown in Table 5. The classification accuracy of electrical signal for ANN almost gives 100% and it is far better when compared to vibration and sound signals.

GEARS	ANN Electrical Signal %		ANN Vibration Signal %		ANN Sound Signal %	
	500 rpm	750 rpm	500 rpm	750 rpm	500 rpm	750 rpm
Gear-1	99.62	100	96.12	97.62	73.37	69.12
Gear-2	100	100	99.94	99.62	69.50	88.12
Gear-3	100	100	99.88	100	71.12	88.75
Gear-4	100	100	92.82	94.50	73.62	86.37

Table 5. ANN classification accuracy of Electrical, Vibration and Sound signals

From the above result, one can easily conclude that electrical signals perform better in both the classifiers over the other two signals. ANN classifier with electrical signals yield overall classification accuracy of 99.95 which is good enough to automate the fault diagnosis process in gearbox.

7. CONCLUSION

Fault diagnosis of gearbox using vibration signal is the major research area in the field of condition monitoring. This work compares the classification accuracy of vibration, sound and electrical signals for early detection of gearbox faults. Statistical features have been extracted from the acquired signals of eight gearbox fault classes and the best features from these three signals are selected using ranker selection method. The selected feature sets were classified using SVM and ANN classifiers. While comparing the classification accuracy of all three signals, electrical signals performs better than sound and vibration signals in both the classifier models. Motor current signals can be used for replacement of vibration signals in motor operated rotating machine fault diagnosis process. This work can be further extended for monitoring the power loss in HEV gearbox during motor drive.

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REFERENCE

German, J. (2015). Hybrid vehicles technology development and cost reduction. *International Council on Clean Transportation*, ICCT Technical Brief, No. 1, July 2015.

Praveenkumar, T., Saimurugan, M., Krishna kumar, K., & Ramachandran, K. I. (2014). Fault diagnosis of automobile gearbox based on machine learning techniques. *Procedia Engineering*, vol. 97, pp. 2092-2098.

Negoita, A., Scutaru, Gh., & Ionescu, R.M. (2010). A brief review of monitoring techniques for rotating electrical machines. *Bulletin of the Transilvania University of Brasov*, vol. 3 (52), Series I.

Saimurugan, M., Ramachandran, K.I., Sugumaran, V., & Sakthivel, N. R. (2011). Multi component fault diagnosis of rotational mechanical system based on decision tree and support vector machine. *Expert Systems with Applications*, vol. 38, pp. 3819-3826.

Fekia, N., Clercb, G., & Velexa, P. (2013). Gear and motor fault modeling and detection based on motor current analysis. *Electric power R&D*, vol. 95, pp. 28-37.

Feng, Z. P., Chu, F. L., & Zuo, M. J. (2011). Time-frequency analysis of time-varying modulated signals based on improved energy separation by iterative generalized demodulation. *Journal of Sound and Vibration*, vol. 330, pp. 1225-1243.

Peng, Z. K. Tse, P.W., & Chu, F.L. (2005). An improved Hilbert-Huang transform and its application in vibration signal analysis. *Journal of Sound and Vibration*, vol. 286, pp. 187-205.

Benko, U., Petrovcic, J., Juricic, D., Tavcar, J., & Rejec, J. (2005). An approach to fault diagnosis of vacuum cleaner motors based on sound analysis. *Mechanical Systems and Signal Processing*, vol. 19, pp. 427-445.

Siliang Lu., Xiaoxian Wang., Qingbo He., Fang Liu., & Yongbin Liu. (2016). Fault diagnosis of motor bearing with speed fluctuation via angular resampling of transient sound signals. *Journal of Sound and Vibration,* vol. 385, pp. 16-32.

Rafiee, J., Rafiee M.A., & Tse P.W. (2010). Application of mother wavelet functions for automatic gear and bearing fault diagnosis. *Expert Systems with Applications*, vol. 37 (6), pp. 4568-4579.

El Hachemi Benbouzid M. A. (2000). Review of Induction Motors Signature Analysis as a Medium for Faults Detection. *IEEE Transactions on Industrial Electronics*, vol. 47, (5), pp. 984- 993.

Tayyab Waqar., Mustafa Demetgul., & Cemal Kelesoglu. (2012). Fault Diagnosis on bevel gearbox with neural networks and feature extraction. *Elektronika ir Elektrotechnika*, vol. 21.

Gunal, S., Ece, D. G, & Gerek. (2009). Induction Motor Condition Monitoring Using Notch Filtered Motor Current. *Mechanical Systems and Signal Processing,* vol. 23, pp. 2658-2670.

Kanika Gupta., & Arunpreet Kaur. (2014). A review on fault diagnosis of induction motor using artificial neural networks. *IJSR*, vol. 3, pp. 680-689.

Samira ben salem. (2012). Support vector machine-based decision for induction motor fault diagnosis using air-gap torque frequency response. *IJCA*, vol. 38, pp. 4696-4702.

Alaa Abdulhady Jaber., & Robert Bicker. (2016). Fault Diagnosis of Industrial Robot Bearings Based on Discrete Wavelet Transform and Artificial Neural Network. *International Journal of Prognostics and Health Management*, ISSN 2153-2648, 2016 017.

Swapna Vora., Jitendra, A., Gaikwad, Jayant., & Kulkarni, V. (2015). Fault diagnosis of bearing of electric motor using wavelet transform and fault classification based on support vector machine. *AREEE*, vol. 2, pp. 41-46.

Krisztian deak, Imre kocsis, Attila vamosi, & zoltan keviczki, Failure diagnostics with svm in machine maintenance engineering. *Annals of the oredea university*, vol. 1(1).

Bacha, K., Souahlia, S., & Gossa, M. (2012). Power transformer fault diagnosis based on dissolved gas analysis by support vector machine. *Electric Power Systems Research*, vol. 83, pp.73-79.

Liu Hong., & Jaspreet Singh Dhupia. (2014). A time domain approach to diagnose gearbox fault based on measured vibration signals. *Journal of Sound and Vibration*, vol. 333, pp. 2164-2180.

Kar, C., & Mohanty, A.R. (2006). Monitoring gear vibrations through motor current signature analysis and wavelet transform. *Mechanical Systems and Signal Processing*, vol. 20, pp. 158-187.

Chandran, P., Lokesha, M., Majumder, M.C., & Raheemv, K.F. A. (2012). Application of Laplace Wavelet Kurtosis and Wavelet Statistical Parameters for Gear Fault Diagnosis. *International journal of multidisciplinary sciences and engineering,* vol. 3(9), pp. 1-8.

Chaari, F., Fakhfakh, T., & Haddar, M. (2009). Analytical modeling of spur gear tooth crack and influence on gear mesh stiffness. *Europen Journal of Mechanics- A/ Solids*, vol. 28, pp. 461-468.

Thomson, W., & Fenger, M. (2001). Current signature analysis to detect induction motor faults. *IEEE Industry Applications Magazine*, vol. 12, pp. 26-34.

Hsu, C.W., & Lin, C. J. (2012). A comparison of methods for multiclass support vector machines. *IEEE Trans. Neural Networks,* vol. 13, pp. 415-425.

Samanta, B., & Al-Balushi, K. R. (2013). Artificial Neural Network based fault diagnostics of rolling element bearings using time-domain features. *Mechanical Systems and Signal Processing*, Vol. 17, pp. 317-328.

Mozammel Mia., & Nikhil Ranjan Dhar. (2016). Prediction of surface roughness in hard turning under high pressure coolant using Artificial Neural Network. *Measurement*, vol. 92, pp. 464-474.

Mayssa Hajar., Amani Raad., & Mohamad Khalil. (2012). Bearing and gear fault detection using artificial neural networks. *ACTEA*, vol. 1, pp. 101-106.

Vapnik, V.N. (1999) The nature of statistical learning theory. *Springer-Verlag,* (1999), pp. 138-146.

Mohandes, M. A., Halawani, T. O., Rehman, S., & Ahmed A. Hussain. (2004). Support vector machines for wind speed prediction. *Renewable Energy*, vol. 29, pp. 939-947.

M, Amarnath., V. Sugumaran., & Hemantha Kumar. (2013). Exploiting sound signals for fault diagnosis of bearings using decision tree. *Measurement*, vol. 46, pp. 1250-1256.

T, Praveenkumar., B, Sabhrish., M, Saimurugan., & K.I, Ramachandran. (2018). Pattern Recognition based On-line Vibration Monitoring System for Fault Diagnosis of Automobile Gearbox. *Measurement*, Vol. 114, pp. 233-242.

Juan Jose Saucedo-Dorantes., Miguel Delgado-Prieto., Juan Antonio Ortega-Redondo., Roque Alfredo Osornio-Rios., & Rene de Jesus Romero-Troncoso. (2016). Multiple-Fault Detection Methodology Based on Vibration and Current Analysis Applied to Bearings in Induction Motors and Gearboxes on the Kinematic Chain. *Shock and Vibration*, Article ID 5467643.

N.R, Sakthivel., V, Sugumaran.,& S.Babudevasenapati. (2010). Vibration based fault diagnosis of monoblock centrifugal pump using decision tree. *Expert Systems with Applications,* Vol. 37, pp. 4040-4049.

P.V, Kane., & A.B, Andhare. (2016). Application of psychoacoustics for gear fault diagnosis using artificial neural network. *Journal of Low Frequency*

Noise, Vibration and Active Control, Vol. 35, pp. 207-220.

Chandrima Sarkar., Sarah Cooley., & Jaideep Srivastava. (2014). Robust Feature Selection Technique using Rank Aggregation. *Applied Artificial Intelligence*, Vol. 28(3), pp. 243–257.

K, Selvakuberan., D, Kayathiri., B, Harini., & M, Indra Devi. (2011). An efficient feature selection method for classification in health care systems using machine learning techniques. IEEE Xplore, 3rd International Conference on Electronics Computer Technology (ICECT).

M, Saimurugan., & R, Nithesh. (2016). Intelligent Fault Diagnosis Model for Rotating Machinery Based on Fusion of Sound Signals. *International Journal of Prognostics and Health Management*, ISSN 2153-2648, 2016 018.

Laxmikant S, Dhamandea., & Mangesh B. Chaudhari. (2016). Detection of Combined Gear-Bearing Fault in Single Stage Spur Gear Box Using Artificial Neural Network. *Procedia Engineering*, Vol. 144, pp. 759 – 766.

Winder, R. L., & Littmann, W. E. (1976). Bearing damage analysis. National Bureau of Standard Publication.

Smalley, A. J., Baldwin, R. M., Mauney, D. A., & Millwater, H. R. (1996). Towards risk based criteria for rotor vibration. In International proceedings of the institute of mechanical engineers—Vibrations in rotating machinery pp. 517–527.

James Li, C., & Wu, S. M. (1989). Online detection of localized defects in bearing by pattern recognition analysis. *ASME Journal of Engineering for Industries*, Vol. 111, pp. 331–336.

O, Asi. (2006). Fatigue failure of a helical gear in a gearbox. *Engineering Failure Analysis*, Vol. 13, pp. 1116–1125.

Barshikar Raghavendra Rajendra., & Santosh.V, Bhaskar. (2013). Condition Monitoring of Gear Box by Using Motor Current Signature Analysis. *International Journal of Scientific and Research Publications*, Vol. 3, Issue 8.

Sukhjeet Singh., Amit Kumar., & Navin Kumar. (2014). Motor Current Signature Analysis for Bearing Fault Detection in Mechanical Systems. *Procedia Material Science*, Vol. 6, pp. 171-177.

Katsuhiko Shibata., Atsushi Takahashi., & Takuya Shirai. (2010). Fault diagnosis of rotating machinery through visualisation of sound signals. *Mechanical Systems and Signal Processing*, Vol. 14(2), pp. 229-241.

T, Oikawa., M, Tomizawa., & S, Degawa. (1997). New Monitoring System for Thermal Power Plants using Digital Image Processing and Sound Analysis. *Control Engineering Practice*, Vol. 5, No. 1, pp. 75-78.

Shi, X. Z., Xu, Z. Q., & Xu. (1988). A Study on the automatic recognition of vibration signal for ball bearing faults – The FFTAR feature extraction and classification methods. In Proceedings of ieee international workshop on applied time series analysis (pp. 318–321). World Scientific.

Fannia Pacheco., José Valente de Oliveira., René-Vinicio Sánchez., Mariela Cerrada., Diego Cabrera., Chuan Li., Grover Zurita., & Mariano Artés, (2016). A statistical comparison of neuroclassifiers and feature selection methods for gearbox fault diagnosis under realistic conditions. *Neurocomputing*, Vol. 194, pp. 192–206.

M, Subrahmanyam., & C, Sujatha. (1997). Using neural networks for the diagnosis of localized defects in ball bearings. *Tribology International*, Vol. 30, No. 10, pp. 739–752.

Xin Lei., & Peter A. Sandborn. (2016). PHM-Based Wind Turbine Maintenance Optimization Using Real Options. *International Journal of Prognostics and Health Management*, ISSN 2153-2648, 2016 008.