OPTIMIZATION OF FEATURE SELECTION DATA FOR TRAINING ANN BASED GEARBOX FAULT DIAGNOSIS

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Abstract

Gearboxes are one of the complex machinery used widely in all process industries as speed reducers. Condition monitoring and fault diagnosis play an important role in increasing availability of machinery. In order to increase the reliability of fault diagnosis an effort has been made in this work to develop an ANN based diagnosis system with two prominent fault conditions of gears worn-out and broken tooth are being simulated. Vibration signal is collected and five feature parameters are extracted based on vibration signals and used as input features to the ANN diagnosis system developed in MATLAB, a three layered feed forward network using back propagation algorithm. The ANN system has been trained and tested with the learning rate, number of hidden layer neurons is varied one after the other and fixed optimal training parameters are identified.

Key Words: Gearbox Fault Diagnosis, Vibration signal, Artificial Neural Networks, Training data, optimization, Back propagation Algorithm.

I. INTRODUCTION

Gear boxes are widely used in all process industries as a speed reducer and it is a complex machinery where many rotating elements are in action with one another. Depending on the criticality of machine the condition monitoring and fault diagnosis becomes important, and related to reliability of condition monitoring also. Amongst many condition monitoring methods, vibration monitoring detects nearly 70% of faults.

Fault detection and diagnosis consists of feature extraction and decision making and the reliability of diagnosis depends on the expertise of relating vibration features to the fault detection, where sometimes signatures are contaminated by noise, contradicting symptoms, the limitations on the ability of human beings when multiple features are applied. An effort has been made to develop an ANN based system for gear fault diagnosis and giving the emphasis of optimizing the training parameters.

Vibration based diagnosis is mostly employed because of ease of measurement and accuracy of detection with original TSA signal with phase modulation and amplitude modulation (Wilson Wang, 2001). Efficient maintenance scheduling can be planned if accurate information about machine condition is known and to improve the reliability of diagnostics either combining two technologies or data fusion and intelligent systems (Farrar and Duffey,1999) . The key factor for proper fault classifying system is to select the best suitable input values, which would be the base classifying system (Walter Bartelmus, 2003).

The training parameters play a vital role in deciding the operational efficiency of the neural network, like the number of neurons in the hidden layer and learning rate, number of epochs (Amarnath, 2005). The detection accuracy of Support Vector Machines is better than ANN without Genetic Algorithm, With GA both are comparable (Samantha, 2003).

II. EXPERIMENTAL SETUP

A gearbox with 16/14 helical teeth as gear and pinion is considered for study. The vibration signature is collected from the signal generator using an Accelerometer of PCB peizotronics make with a sensitivity of 100mV/g. A schematic of the setup is shown in fig. 1.

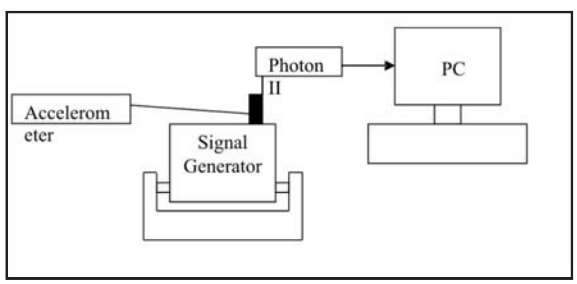


Fig. 1. Experimental Setup

Different sets of data are collected when the gearbox was operating at two fault conditions viz., worn out case and broken tooth case . A total of 30 sets of data are collected for each operating condition and signals are sampled at 12 kHz. The accelerometer outputs are inherently amplified as the accelerometer employed is of

ICP type and are fed directly into the USB powered LDS Dactron Photon II , a 4-channel analyzer acts as the data acquisition system. The response of the system is averaged over 10 measurements with a Hanning window facility.

III. OPTIMIZATION OF FEATURE DATA TO TRAIN ANN

The vibration signature is preprocessed in order to obtain the required features of mean, root mean square (rms), variance, skewness and kurtosis. These features act as the input parameters to the artificial neural network was developed using Mat Lab neural network toolbox. A three layer feed forward network is employed and trained using the back propagation algorithm. The training parameters play a vital role in deciding the operational efficiency of the neural network. Training of a neural network involves selection of some key parameters like the number of epochs, number of neurons in the hidden layer and learning rate. After training the network is validated using the testing data. Among the 30 sets of data collected 20 were used for training the network and 10 sets were used as the testing data. The learning rate is varied while keeping the number of hidden layer neurons constant at 9 and in turn the number of epochs to obtain an optimal design. The learning rates used are 0.05, 0.1, 0.15, 0.2 and 0.25. The classification performance obtained for various cases as given in the Table1. Fig. 3 shows the variation in the mean square error with respect to the number of epochs while reaching the target value of 0.0001 during training of the network.

From the results shown in Table 1 learning rate of 0.15 is deduced to be the most optimal one considering the number of epochs and also the accuracy of the outputs. In the next step learning rate was kept constant at 0.15 and the number of hidden neurons was varied from 5 to 15.

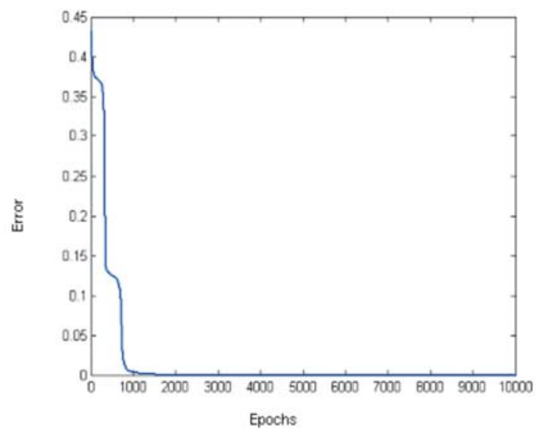
Table 1. Number of the epochs Vs. Accuracy of the Outputs by varying Learning rate value

SL. No.	Learning rate	Epochs	Case1 [1 0]	Case2 [0 1]
1	.05	26,914	[0.94 0.03]	[0.04 0.93]
2	0.1	14,263	[0.93 0.02]	[0.04 0.94]
3	.15	9,500	[0.98 0.01]	[0 0.99]
4	0.2	5938	[0.95 0.05]	[0.05 0.96]
5	.25	3126	[0.94 0.03]	[0.04 0.95]

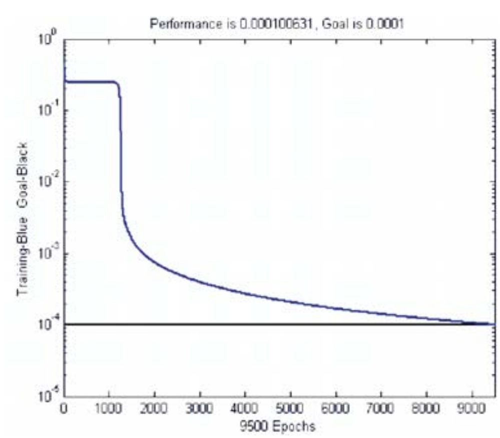
Table 2 shows the outputs of the network while varying the number of hidden layer neurons. It can be clearly seen that number of hidden layer neurons of 9 forms the most optimal one. In this way, the optimum training parameters have deduced and the network was trained and tested for these values.

Table 2. Variation in outputs by varying the number of neurons in the hidden layer

SL. No.	Hidden layer Neurons	Epochs	Worn out case output	Cracked case output
1	5	12,138	[0.9941 0.0111]	[0.0113 0.9968]
2	9	9500	[0.9894 0.0082]	[0.0002 0.9958]
3	15	6583	[0.9919 0.0088]	[0.0104 0.9889]



(a)



(b)

Fig. 2. Variation of errors with respect to epochs

Closeness of the target vectors and outputs obtained for our network are shown in Table 3. A five dimensional vector consisting of mean, kurtosis, rms, skewness and variance represents each data set.

Table 3: Closeness of the output obtained and Target for learning rate of 0.15

Type of fault	Output Obtained	Target
Worn out gear	[0.998 0.008]	[1 0]
Cracked gear	[0.0002 0.998]	[0 1]

IV. RESULTS AND DISCUSSION

An Artificial Neural Network was used to perform fault diagnosis using the time domain features extracted from vibration signal. Operating conditions involved worn-out gear case and cracked tooth case. The design parameters of the neural network are carefully selected as they play a vital role in the construction of the model. When the inputs are applied to the network as the output pattern appears [0 1], then the network indicates that the inputs belong to the worn-out case and if the output pattern appears as [0 1] then the network indicates that the inputs belong to the broken tooth case. The output pattern is shown in Table 4.

Table 4. Output pattern for First experimental Investigation

Worn out Case	Broken tooth Case
[1 0]	[0 1]

V. CONCLUSION

In this way ANN will be effectively able to identify and at the same time easily communicate the error to the user. Thus it can be deduced that with selection of optimum features and parameters and proper training procedures the neural network can diagnose gear faults with high accuracy.

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