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Robust Method for Fault Detection in an Motor Cycle Engines Using ANN Based Classifiers

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Abstract

Fault detection and isolation has gained growing importance for vehicle safety and reliability. In this paper Fault Detection in a Four Stroke (FS) motor Cycle engine has been proposed. Primary objective of this paper is to propose a smart as well as robust method for Fault Detection (FD) in automobile engines by using the Artificial Neural Network (ANN) based classifiers, which is able to detect the multiple faults in an incipient stage. Novelty of this proposed system is to reduce requirement of multiple sensors to a single sensor in order to detect multiple faults.

Keywords: *Automobile Engine, Digital Signal Processing, Artificial Neural Network & Classification Accuracy*

INTRODUCTION

The proposed method is based on parameter estimation, where a set of parameters is used to check the status of an engine and a model based approach is employed to generate several symptoms indicating the difference between faulty and non-faulty status. The research contribution in this area is as follows. Rolf Isermann, (2005), suggested the model based approach. Based on different symptoms, fault diagnosis procedures follow, determining the fault by applying classification or inference methods [1]. R. J. Howlett,(1996 &1999) described a neural network technique for determination of air-fuel ratio in the engine. The voltage waveforms across the spark plug were used for monitoring the engine and also for fault diagnosis or control [2, 3]. The soft computing (SC) methods were surveyed by R. J. Patton et.al. (2001), and SC methods was considered an important extension to the quantitative model-based approach for residual generation in FDI [4]. Wang Weijie, et.al (2004) proposed the engine vibration signals for fault diagnosis. A model of wavelet neural networks was constructed based on wavelet frame theory and neural networks technology [5]. The FDI system in dynamic data from an automotive engine air path using artificial neural networks was investigated by M. S. Sangha et.al. (2005). A generic SI mean value engine model was used for experimentation. Several faults were considered, including leakage, EGR valve and sensor faults, with different fault intensities. RBF neural network was used to detect and diagnose the faults[6].

Jian-Hua Zhang, et. al. (2010) proposed a fault diagnosis using Adaptive NeuroFuzzy Inference System (ANFIS) [8]. Zhe Wang, et. al. (2011) proposed a Fault Diagnosis Model for Automobile Engine using gradient descent genetic algorithm and optimization of system parameters have been carried out using neutral network learning algorithm [8]. Hamad A., et. al. (2012) proposed a RBF network to classify the faults. The performance of the developed scheme was assessed using an engine benchmark, the Mean Value Engine Model (MVEM) with Matlab/Simulink. Six faults have been simulated on the MVEM, including four sensor faults, one component fault and one actuator fault [9]. Ryan Ahmed et. al. (2015) proposed an engine fault detection and classification technique using vibration data in the crank angle domain is. These data are used in conjunction with artificial neural networks (ANNs), which are applied to detect faults in a four-stroke gasoline engine [10].

Kamal Jafarian and Mohammadsadegh Mobin, (2017), proposed a Misfire Fault Detection in the Internal Combustion Engine using the Artificial Neural Networks. Vibration signal analysis is introduced as the most effective approach for fault diagnosis [11]. Praveen Chopra et. al. (2015) proposed a technique using sparse-auto encoder for unsupervised features extraction from the training data. The training and testing data sets are then transformed by these extracted features, before being used by the softmax regression for classification of unknown engines into healthy and faulty class. This technique is tested on industrial IC engine data set, with overall classification performance of 183 correct classifications out of 186 test cases for four different fault classes [12]. Katsuba Yurii and Grigorieva Liudmila (2017), proposed an approach to increasing the safety of a vehicle's design with the help of artificial neural networks (ANNs) integrated in the vehicle's self-diagnostic system. ANNs will help to correct the values of self-diagnostic output signals for prompt maintenance and current repairs as well as safe operation of the vehicle [13]. Ran Zhang et. al. (2017), proposes a fault diagnosis model based on Deep Neural Networks (DNN). The proposed fault diagnosis approach is effective in recognizing the type of bearing faults [14]. Consequent to literature survey, the engine chosen for experimentation is a motor cycle four stroke engine. The five faults are considered for classification and it is explained in subsequent sections.

2. SYSTEM OVERVIEW

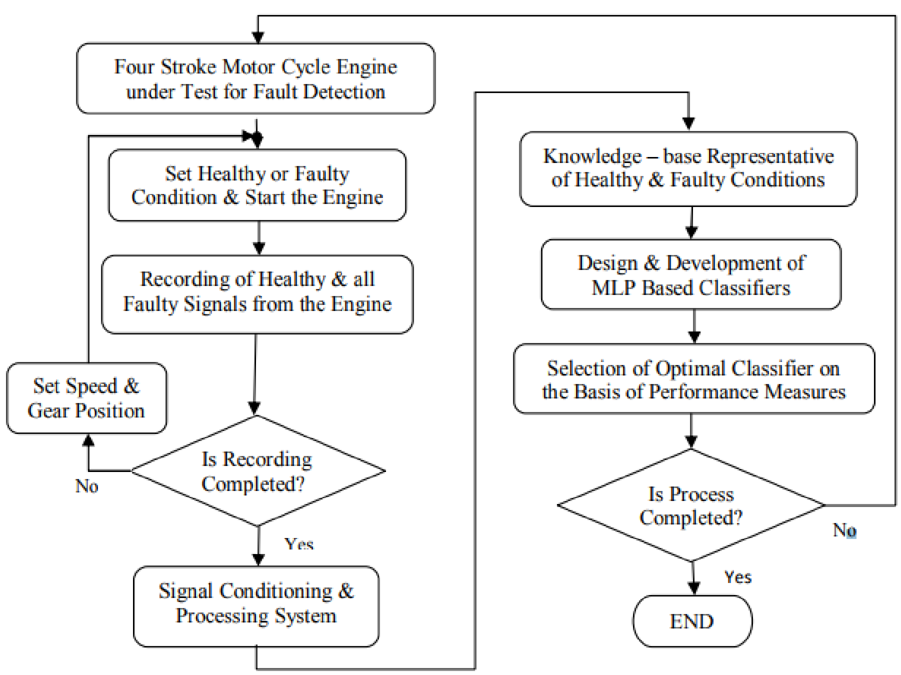

Fig1: Working of the system

The system consists of an automobile engine along with the microphone as a sensor to capture the acoustic signal from the motor cycle engine. The Unidirectional Cardioid microphone was employed as a sensor. The signals are recorded by creating one fault at a time so that the working of the engine will not be affected by any other fault.

Four strokes Motorcycle engine was used for experimentation 1. The specification of this engine is shown in Table 1. The data collection is carried out for five different faults, like Air filter Fault (AFF), Spark Plug Fault (SPF), Rich Mixture Fault (RMF), Insufficient Lubricants Fault (ILF) and Piston Ring Fault (PRF).

Initially, the engine is started in normal condition and signals are recorded at five different speed and four different gear positions. The five signals are recorded in each gear position at 1200, 1500, 1800, 2100 and 2400 RPM. Therefore, there will be a collection of 120 recorded signals for five different faults with one normal condition of the automobile engine.

The working of the system is shown in fig 1. The signal was recorded in wave format. Signal Decomposition and Computation of Feature Matrix The size of the feature matrix depends upon the number of fault signals and the number of frames of the signals considered at a time as shown in Table 2. The signal decomposition techniques are employed to divide the signal into different frames. Initially, 1, 50, 000 discrete samples are considered as a single frame. Then these 1, 50, 000 samples are then divided into two parts i.e. in two different frames. Later on, each frame in turn is divided into two parts resulting in four frames. This process of signal decomposition is continued up to 128 numbers of frames.

Features extraction and the signal conditioning of each frame have been done using the algorithm written in MATLAB software. The extracted seven futures are mean, energy, minimum, maximum, standard deviation, variance and mode from each frame of recorded signals. The extracted futures are employed for classification of faults using one and two hidden layer Multilayer Perceptron (MLP) neural network.

Table1: Specifications of Four Stroke Motor Cycle Engine

Max. Torque : 7.95 NM,, @ 5000 RPM	Gear Box : 4 - Speed Gear
Maximum Power : 7.37 HP (5.4 kW), @ 8000 RPM	Compression Ratio : 8.8 : 1
Engine Type : Single cylinder, Four-stroke	Displacement : 97.50cc

Table 2: Computation of Feature Matrix

Signal	Signal Frames							
	1	2	4	8	16	32	64	128
NOR	20×8	40×8	80×8	160×8	320×8	640×8	1280×8	2560×8
AFF	20×8	40×8	80×8	160×8	320×8	640×8	1280×8	2560×8
SPF	20×8	40×8	80×8	160×8	320×8	640×8	1280×8	2560×8
PRF	20×8	40×8	80×8	160×8	320×8	640×8	1280×8	2560×8
ILF	20×8	40×8	80×8	160×8	320×8	640×8	1280×8	2560×8
RMF	20×8	40×8	80×8	160×8	320×8	640×8	1280×8	2560×8
Total	120×8	240×8	480×8	960×8	1920×8	3840X8	7680×8	15360×8

3. WORKING OF ANN BASED CLASSIFIERS

These frames consist of all faulty and non-faulty signals which were used as input to MLP for classification after data partitioning into testing, cross validation and training datasets. The classification of faults using one and two hidden layer MLP based classifier is shown in fig 1 in the form of flow chart.

After training the network, the test data are applied to trained neural network for classification of multiple faults. MLP are assessed on the basis of percentage Average Classification Accuracy (%ACA) and Mean Square Error (MSE).

4. DESIGN OF OPTIMAL CLASSIFIER

The performance of one and two hidden layer MLP is observed and compared. Then optimal classifier has been designed by considering the Learning Rule, Transfer Function, No. of Hidden Layers, etc. Evaluation of Performance Measures on Training Dataset, Validation of ANN on Cross Validation and Testing Datasets has been completed as shown in fig 2. The classification accuracy in percentage for training, cross validation and testing are recorded at each stage and average of these classification accuracy i.e. %ACA is plotted for each transfer function and learning rule which is explain in subsequent section.

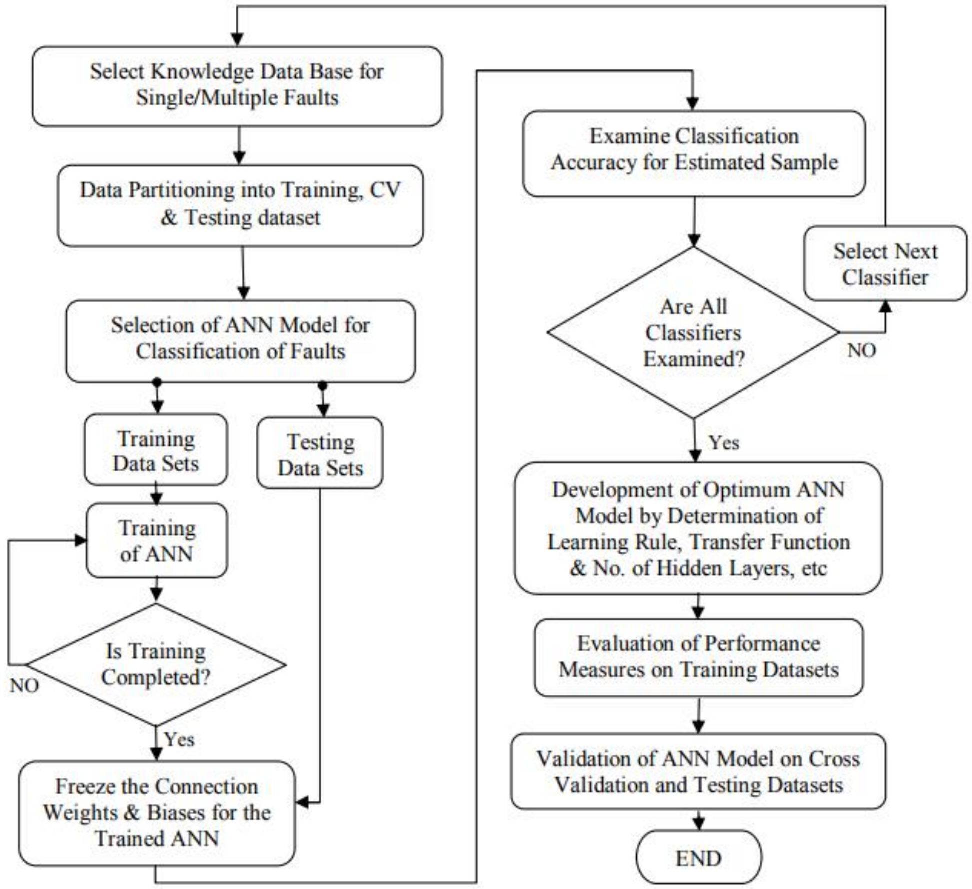

Fig 2: Design of Optimal Classifier

5. RESULTS

The performance of MLP based classifier is observed for 1 to 128 frames as shown in Fig 3 in the form of a Bar-Chart. In the classification the feature matrix was divided into three parts in the ratio of 2:1:1. The first parts of data were used for training the network, the second one was used for cross validation and the third one was used for testing the network. It is observed that the %ACA is found to be Maximum for the feature matrix with eight frames of each signal and lowest for two frames of the signals. It is also observed that further increase in frame number does not seem to improve the performance. Therefore, further analysis is continued by considering the eight frames of each signal.

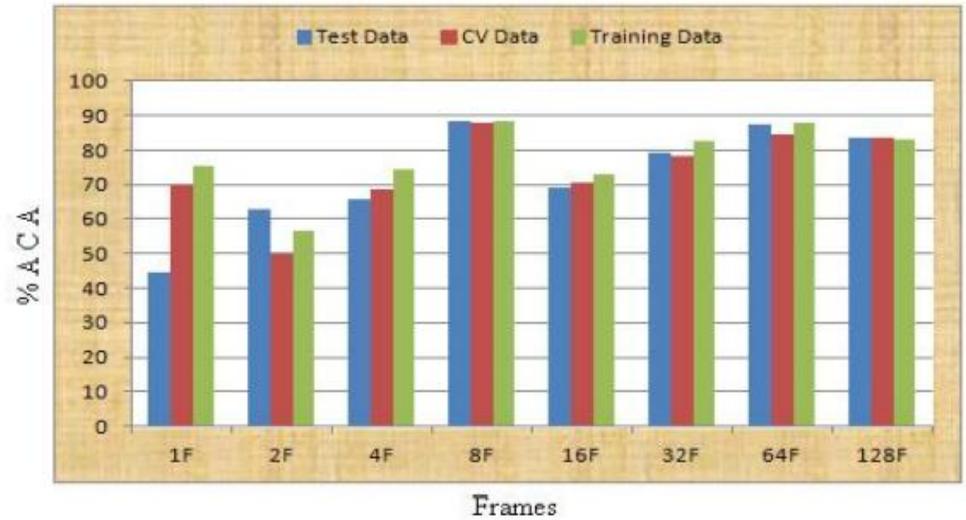

Fig 3: Performance of MLP Based Classifier

As there are 20 signals recorded for each fault and normal signal, the size of the feature matrix is 960×8, i.e. 960 rows and 8 columns by considering the eight frames of each signal. The eight columns contain seven features and one categorical output.

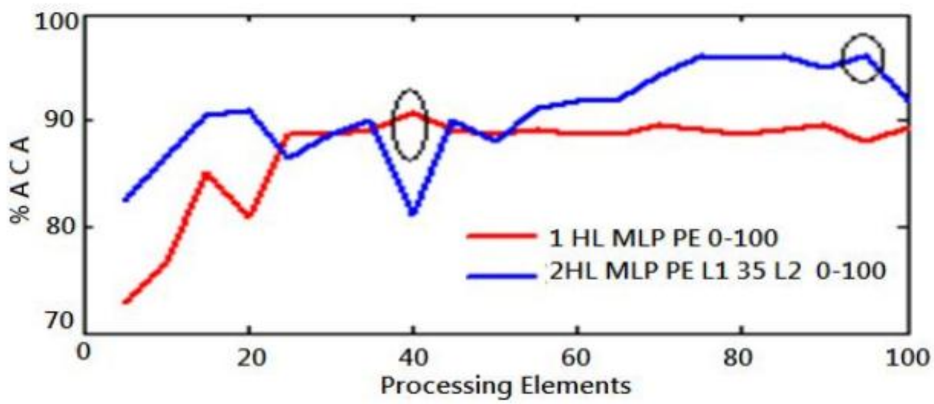

Fig 4: Performance of 1 & 2 HL-MLP Based Classifier

The single hidden layer MLP NN was re-trained three times and tested for classification accuracy for test, cross validation, and training datasets. The process was repeated by varying the number of hidden layer PEs from 2 to 100 for default number of epochs set to 1000. The MLP based classifier was further investigated by changing the Learning Rule Algorithms such as STEP, MOM, CG, LMQ, QP and DBD. The performance of one and two hidden layer MLP NN has been shown in Fig 4. It is observed from the performance of 1HL-MLP based classifier that the Maximum classification accuracy is achieved at 40 PEs. Further, MLP based classifier is refined by changing the Transfer Function, Learning Rule and Epochs. The performance is shown in Fig 5.

The optimal transfer function is TANH-AXON, Learning Rule is Momentum and other optimal parameter for the one and two HL-MLP are depicted in Table 3. It is observed that for two hidden layer accuracy is maximum for PE's equal to 95 with transfer function is TANH-AXON and Learning rule Momentum as shown in table 2.

Table 3: Optimal Parameters for one and two Hidden Layer MLP Based Classifier

One-HL-MLP NN with Epochs - 4000			Two-HL-MLP NN with Epochs - 2000		
Optimal Parameter	*Hidden Layer*	*Output Layer*	*Hidden Layer-1*	*Hidden Layer-2*	*Output Layer*
PE's	*40*	*5*	*35*	*95*	*5*
Transfer Function	*TANH-AXON*	*TANH-AXON*	*TANH-AXON*	*TANH-AXON*	*TANH-AXON*
Learning rule	*Momentum*	*Momentum*	*Momentum*	*Momentum*	*Momentum*
Learning Rate	*1.0*	*0.1*	*1.0*	*0.1*	*0.01*

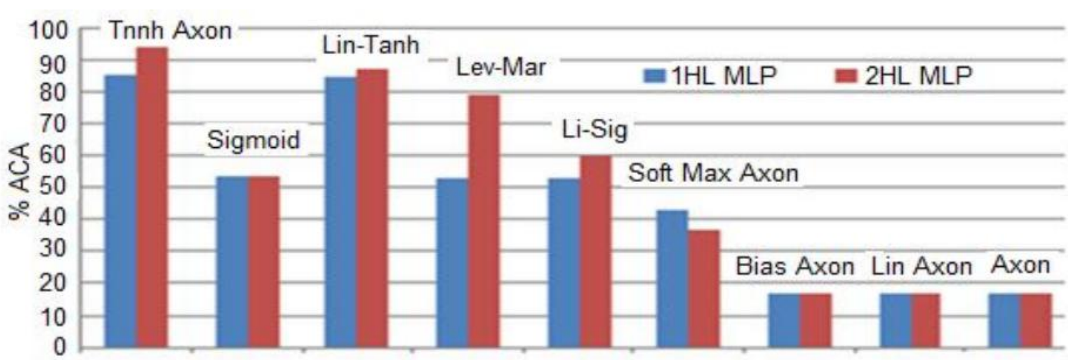

Fig 5: Comparison of Different Transfer Functions

The different learning rules are also compared and % ACA is calculated.

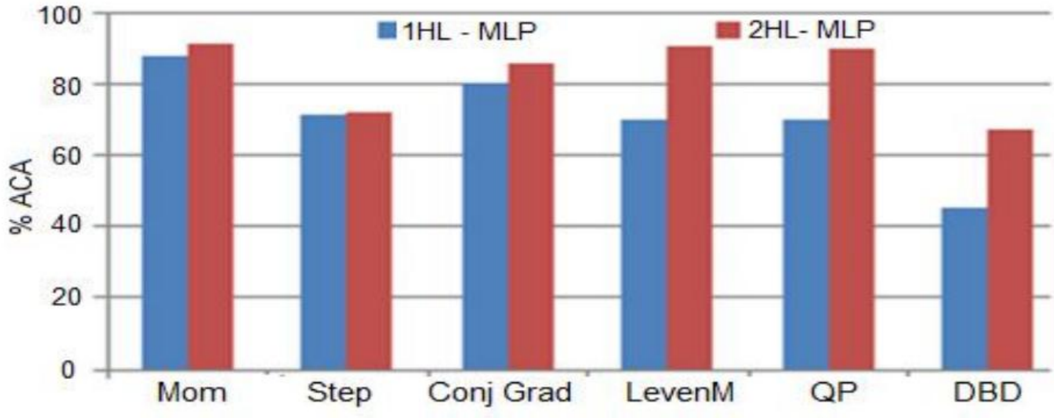

Fig 6: Comparison of Different Learning Rules

The Plots for Epochs Vs Average MSE for 2HL-MLP is shown in Fig 7, respectively. The % ACA is Maximum at 4000 Epochs for 1HL-MLP and at 2000 Epochs for 2HL-MLP. It is found that Average MSE decreases as the number of Epochs are increased and it is observed that the training MSE is always less than that of CV MSE. The average MSE is obtained very closer to zero for two hidden layer MLP with transfer function is TANH-AXON and Learning rule Momentum as shown in fig 7.

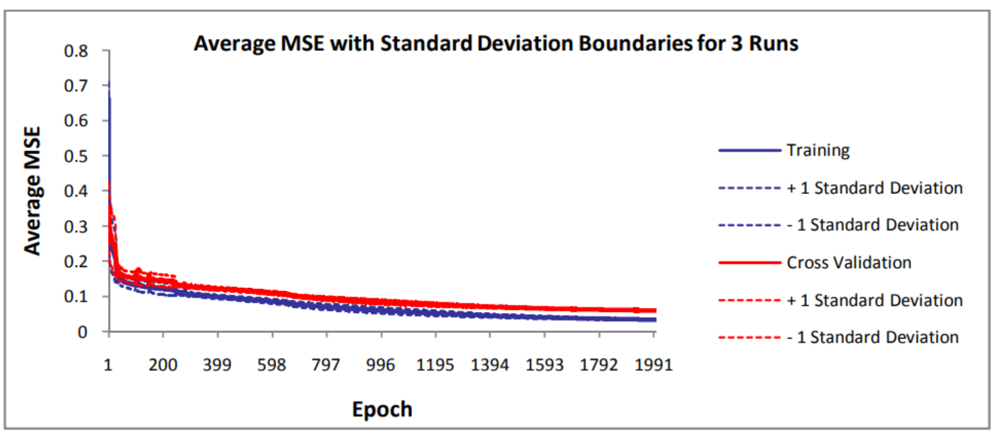

Fig 7: Average MSE for 2HL-MLP Based Classifier

CONCLUSION

A technique has been proposed for Multiple Fault Detection in a Motor Cycle Four Stroke engine using an acoustic signal. Only five faults are considered for classification. It is possible to extend the work for any number of faults.

The novelty of the work is that using customized signal processing algorithm; only seven simple statistical features are extracted from each recorded sound signal of an automobile engine. Therefore, these seven features with appropriate values can represent a specific automobile engine fault. The input layer of neural network has seven processing elements, as there are seven extracted features from the recorded sound signal. The number of processing elements in the output layer is determined according to the number of different fault conditions in an automobile engine. The neural networks MLP is designed very meticulously following a systematic network growing approach. Topology of the neural network, learning rule, transfer function (activation function) of processing elements in input layer, hidden layer, output layer; number of hidden layers, number of processing elements in each hidden layer are varied gradually in order to optimize the performance measures of classifier, such as minimization of MSE and maximization of the classification accuracies for each fault condition. For two layers MLP the percent average classification accuracy is obtained above 95% which is very desirable result.

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