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Artificial Neural Network Based Fault Detection in a Four Stroke Engine using Acoustic Signal

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***Abstract* – Fault detection and isolation technique have been developed for automated processes during the last few years. These methods include numerical methods, artificial intelligence methods or combinations of both. Condition monitoring and fault detection techniques are used to prevent early fault in a mechanical systems.**

The paper deals with the problem of fault detection in an automobile engine employing an artificial neural network (ANN). The fault detection is not an easy task for an inexperienced mechanic or driver because it needs a lot of knowledge for finding the fault. Many times the trial and error approach has been applied to detect the fault and because of that, the engine may get more damaged instead of getting repaired. To overcome such type of problem the new technique has been suggested to diagnose the fault correctly without opening the engine. Therefore, this paper presents the innovative technique to detect the Air Filter fault, Spark Plug fault, Insufficient Lubricants fault, Piston Ring fault and Rich Mixture fault, in a four stroke automobile engine, using a single sensor. The Artificial Neural Networks have been employed to classify the faults correctly. Performance of Multilayer Perceptron Neural Network and Support Vector Machine Neural Network has been compared on the basis of Average Classification Accuracy. The paper further justifies the use of Support Vector Machine Neural Network for classification of the faults.

***Keywords* - Four stoke Automobile Engine, Air Filter, Spark Plug, Insufficient Lubricants, Piston Ring, Rich Mixture, Artificial Neural Network, Classification Accuracy and Fault Detection Abbreviations – ACA - Average Classification Accuracy, AF - Air Filter Fault, SP - Spark Plug Fault, IL – Insufficient Lubricant Fault, PR – Piston Ring Fault, RM – Rich Mixture Fault, Nor – Normal Signal, MSE- Mean square error, NMSE - Normalize mean square error, MAE – Mean Absolute Error, r - Correlation Coefficient, ANN – Artificial Neural Networks and FDIE-fault detection, isolation and estimation.**

I. Introduction

There has been an increasing interest in fault detection in recent years, as a result of the increased degree of automation and the growing demand for higher performance, efficiency, reliability and safety in automotive systems [1]. Fault detection is a complex process but sound emission and vibration signals can be used in condition monitoring [2]. Fault detection technique can help to improve reliability, safety and economy by identifying the fault in an early stage [3]. One of the most popular techniques related to model-based fault diagnosis [4], which is claimed to be easy to implement and does not require additional hardware. Recently, various fault diagnostic models for automotive engines have been proposed [5, 6]. The more precisely the model represents the behavior of the internal combustion engine, the better its performance in detecting unusual conditions. However, an accurate and complete mathematical model of such a complex system is generally unavailable [7], mainly the assumptions introduced to condense mathematical complexity. Therefore, fault diagnosis systems based on physical engine models are difficult to develop [9]. The modern automotive systems have become more and more complex and it is becoming a challenging job for the researcher to provide the accurate fault detection system. A more promising approach was proposed by many researchers using neural networks [10]. The neural networks method emerged as the most suitable approach as it offers attractive feature for fault detection and diagnosis purposes [8]. This paper presents the generation of diagnostic model using the sound signal taken from normal and faulty condition of an automobile engine [11].

The four stroke engine has been used for experimentation because the four-stroke motor is the heart of most modern motorcycles. Although four-stroke motors are available in different displacements and cylinder arrangements, their basic components remain the same. The main parts of four stroke engines are Cylinders, Cylinder block, Piston and Connecting rods, Cylinder head Crankcase, Valves, Crank shaft Flywheel, Exhaust system, Camshaft Fuel system, Lubrication system and Ignition system.

The four stroke engine performs the four different operations that are intake, compression, combustion, and exhaust that occur during every two crankshaft rotations. The operation described in short as follows.

1. Intake stroke: Air and vaporized fuel are drawn in.
2. Compression stroke: Fuel vapor and air are compressed and ignited.
3. Combustion stroke: Fuel combusts and piston is pushed downwards.
4. Exhaust stroke: Exhaust is driven out. During the 1st, 2nd, and 4th stroke the piston is relying on power and the momentum generated by the other pistons.

With the rapid development of the signal processing techniques, the sound emission and vibration signals can be used in condition monitoring and fault diagnosis because they always carry the dynamic information of the mechanical system [12]. In this paper, analysis of faults in Air filter, Spark Plug, Piston Ring, Rich Mixture, Insufficient Lubricants have been carried out. The details of the faults are discussed below

A. Air Filter Fault

The air filter is connected on the intake system of automotive engines and the function of air filter is to

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provide the clean air to an automobile engine. Otherwise impurity such as dust in the air causes a very rapid wear of the engine, particularly of the cylinders, pistons and piston rings. Further, if the dirty air enters the crankcase; it contaminates the lubricating oil and ultimately damages the bearings and decreases the service period of the lubrication system. It is, therefore, necessary to have good quality air filter on the intake system of automotive engines.

Besides filtering the air, air filters also perform other functions as mentioned below.

It acts as a silencer for the carburetor system. i.e., it reduces the engine induction noise to an acceptable level.

 In case, the engine back-fires, the air filter also acts as a flame arrester.

The air filters offer a resistance to air flow, which is increased as the air filters get clogged with dirt. Consequently, air flow would get decreased, resulting in sluggish engine performance and higher consumption of fuel.

B. Spark Plug

A spark plug is an electrical device that fits into the cylinder head of some internal combustion engines and ignites compressed petrol by means of an electric spark. Spark plugs have an insulated centre electrode which is connected by a heavily insulated wire to an ignition coil circuit on the outside, forming, with a grounded terminal on the base of the plug, a spark gap inside the cylinder.

As the electrons flow from the coil, a voltage difference is developed between the centre electrode and side electrode. No current can flow because the fuel and air in the gap is insulator, but as the voltage rises further, it begins to change the structure of the gases between the electrodes. Once the voltage exceeds the dielectric strength of the gases, the gases become ionized. The ionized gas becomes a conductor and allows electrons to flow across the gap. Spark plugs usually require voltage in excess of 20,000 volts to fire properly.

B. a. Normal Spark Plug

Combustion deposits are slight and not heavy enough to cause any negative effect on engine performance. Brown to grayish tan color of the spark plug and minimal amount of electrode erosion clearly indicate that the plug is in the correct heat range and has been operating in a "healthy" engine.

C. Inappropriate Plug Gap

Inappropriate plug gap is developed because of routine damage like mechanical damage caused by a foreign object that has accidentally entered in the combustion chamber and that rough materials accumulating on the side electrode may melt to bridge the gap when the engine is suddenly put under a heavy load. Furthermore, because of the inappropriate plug gap, the voltage required to fire the plug has approximately doubled and will continue to increase with additional miles of travel. Even higher voltage requirements, as much as 100% above normal, when the engine is quickly accelerated. Poor engine performance and a loss in fuel economy are qualities of a worn or spoiled spark plug.

D. Insufficient Lubricants Fault

A lubricant is a substance introduced to reduce friction between moving surfaces. It may also have the function of transporting foreign particles.

A good lubricant possesses the following characteristics:

- High boiling point.
- Low freezing point.
- High viscosity index.
- Corrosion prevention.
- High resistance to oxygen.

One of the single largest applications of lubricants, in the form of motor oil is protecting the internal combustion engine of motor vehicles and powered equipment.

E. Rich Mixture Fault

Excessively rich or excessively lean mixtures decrease temperatures and combustion speed. Excess fuel, as in rich mixture, cools the engine somewhat, but the effect of unburned fuel as a coolant is generally overrated. The cooling is mainly due to other effects, like lower combustion speed. These are two very different conditions, as a lean mixture burns relatively slowly, and a rich mixture burns faster. It is indeed a key factor in ignition timing.

F. Piston Ring Fault

There are two types of piston rings, oil control rings and compression rings. Basically, the oil control rings keep oil OUT of the combustion chamber and compression rings keep the air/fuel mixture IN the combustion chamber.

Table 1A: Hero Honda Passion Engine Specifications
Engine Type : Single cylinder, four-stroke, Gear Box : 5- seed
Displacement: 97.50ccm(5.95 cubic inches)
Maximum Power : 7.37 HP (5.4 kW)) @ 8000 RPM
Compression Ratio : 9.0 : 1
Maximum Power : 7.37 HP (5.4 kW)) @ 8000 RPM
Maximum Torque : 7.95 Nm (0.8 kgf-m) @ 5000 RPM
Cylinder Bore : 50.0 mm
Stoke : 49.5 mm, Ignition : CDI

The piston slides up and down the cylinder. There is a small amount of clearance between the piston and the cylinder wall. The piston might be a fairly loosely fitted in the cylinder. If it were a tight fit, it would expand as it got hot and might stick tight in the cylinder. If a piston sticks (seizes), it could cause serious damage to the engine. On the other hand, if there is too much clearance between the piston and cylinder walls, much of the pressure from the burning gasoline vapour will leak past the piston (a condition known as blow by) and into the crankcase, and the push on the piston from combustion will be much less effective in delivering power.

II. Data Collection

The block diagram of the system is shown in Fig 1. It consists of an automobile engine along with the

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microphone, signal recording and signal processing system. The Specifications of an Automobile Engine, Microphone and MP3 Sound Recorder are given in Table 1A, 1B and 1C respectively. The MP3 sound recorder is used to record the sound vibrations, in ".wav" forms. Firstly the engine is started in normal condition and sound vibrations are recorded for different speed and different gear positions. The microphone is mounted closer to the engine. As sound vibrations carries the dynamic information of the engine, therefore this recorded signal has been used to detect the particular fault in an automobile engine.

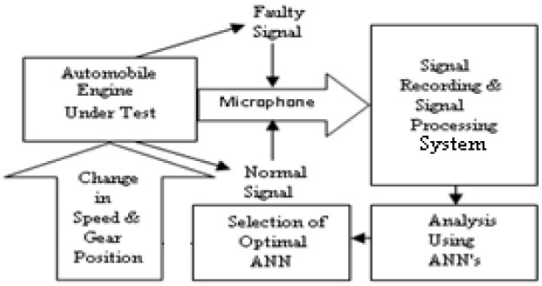


Fig 1: Block Diagram of the system

Table 1B : Microphone Specification	
Type	Over the Ear
Specification	
Frequency	20Hz-20KHz
Drive Unit	40 mm
Impedance	32 Ohm
Sensitivity	110dB3dB
Microphone-Sensitivity	58db2db
Connector	3.5 mm

Table 1C : Sound Recorder Specification	
AD/DA conversion	24 bits, 44.1 kHz
Data Type	
Format	MPEG 1, Audio Layer 3 (MP3)
Sampling Rate	44.1 kHz
Bit Rates	64/96/128/160/192/256/320 kbps
Format	WAV
Frequency Response	20 Hz to 20 kHz
USB Interface	Mini-B type connector (support USB 1.1/2.0 mass storage device class)
AD/DA conversion	24 bits, 44.1 kHz

III. Features Extraction

The five set of signal were recorded in different speed & different gear positions i.e. at 1000 rpm, 2000 rpm, 3000 rpm, 4000 rpm, & 5000 rpm for approximate 30 sec duration of each signal. The signals were converted in to discrete samples and then divided into 32 frames with each frame consisting of 1000 samples. The features were extracted for each frame using MATLAB software. The extracted parameters are Mean, Mode, Energy, Maximum Value, Minimum Value, Standard Deviation and Variance. Therefore, the data files consisting of 960 x 8 samples which can be applied to an ANN to classify the faults.

A. Preparation of training, cross validation, test data partitions

Sets of features from Normal, Filter Fault, Spark Plug fault, Insufficient Lubricant Fault, Piston Fault and Rich Mixture Fault signals of an automobile engine were collected in a data file. The data file is consists of 960 x 8 records with 7 inputs and 1 output. These 960 sets of features are then used as inputs to the neural network for the classification of the fault in an automobile engine. Three different data partitions were used with different tagging orders. In the first case, the first 50 % samples (1:480) are used for training, the second 25 % samples (240:480) for cross validation, and the third 25 % samples (720:960) for testing of the classifier. In the second case, the last 50 % samples (480:960) are used for training, the second 25 % (240:480) for cross validation, and first 25 % samples (1:240) for testing of the classifier.

A. a. Experimentation

A. a. a. Design of MLP NN Classifier

The primary advantage of using the MLP NN for approximation of the mapping from input to the output of the system is its simplicity and suitability for real time applications. The choice of the number of hidden layers and the number of units in each of the hidden layers is critical. It has been established that a MLP NN that has only one hidden layer, with a sufficient number of neurons, acts as universal approximations of non-linear mappings. Experimentally, it can be verified that the addition of extra hidden layer can enhance the discriminating ability of the NN model. However, it does so at the cost of the added computational complexity. The trade-off between accuracy and complexity of the model should be resolved carefully. The single and two hidden layer MLP NN were designed by adopting independent validation method. The learning and generalization ability of the estimated Neural Network based classifier is assessed on the basis of certain performance measures such as ACA, MSE, NMSE and correlation coefficient.

A. a. b. Single Hidden layer MLP NN Classifier

Single hidden layer MLP NN is designed to give optimal performance on the basis of the best ACA. The dataset of 960 records was divided into three parts in the ratio 2:1:1, first part of data was used for training the network, second part of the data was used for cross validation and the third part of the data was used for testing the network. The network with 7 inputs and 1 output, PEs with TANH-AXON transfer function (TF) and Momentum Learning Algorithm (LR) was trained three times and tested for classification accuracy for test, cross validation, and training datasets. The process was repeated by varying hidden layer PEs from 2 to 100 for default epochs 1000. The MLP was further refined by changing the Learning Rule Algorithms such as STEP, MOM, CG, LMQ, QP and DBD. The performance of one hidden layer MLP NN has been shown in Table 2, Fig 2A, Fig 2B, Fig 3A and Fig 3B

A. b. c. Two Hidden layer MLP NN Classifier

A two hidden layer MLP NN was designed for the best classification accuracy. The MLP NN having 2 hidden layers, TANH-AXON TF and MOM LR at hidden layers and output layer with 7 inputs and 1 output respectively. The MLP was trained for three times by giving faulty and normal feature matrix derived from an automobile engine as input to the neural network. Total dataset of size 960 x 8 was divided into three parts in the ratio 2:1:1, first part used as training dataset, second as cross validation and third as testing dataset. As the hidden layers in a neural network increases, the complexity of computation also increases. Here the network is designed by keeping L1 PE fix to 5 and varying L2 PE from 5-100 in steps of 5. Then step by step the L1 PE was also varied from 5-100 in steps of 5 with varying simultaneously the L2 PE. Separate networks were designed to compare the performance of MLP NN while L1 & L2 PE are varied. After training the network three times with each set of PEs, the network was tested for test dataset, cross validation dataset and training dataset. The performance of the network was recorded as percentage classification accuracy and MSE for various datasets. Further the network was also refined by varying the Epochs 100 to 5000 for best classification accuracy. The performance comparison of 1 & 2 hidden layers MLPs is shown in Table 2, Fig 2A, Fig 2B, Fig 3A and Fig 3B.

A. b. d. Design of Support Vector Machine NN Classifier

The Kernel Adatron is specifically used for Support Vector Machine NN and is designed to give optimal performance on the basis of the best ACA. The dataset of 960 x 8 records was divided into three parts in the ratio 2:1:1, first part of data was used for training the network, second part of the data was used for cross validation and the third part of the data was used for testing the network. Total dataset of size 3840 x 8 with 7 inputs and 1 output were trained for three times by giving faulty and normal feature matrix derived from an automobile engine as input to the network. The SVM is trained and tested by varying the Epochs from 10 to 5000. The performance of SVM is shown in Fig 4A and Fig 4B.

IV. Result

It has been found that the maximum ACA 91 % and 97.5 % is obtained in one hidden layer MLP for PEs 40 and in two hidden layer MLP for PEs at L1 35, PEs at L2 95 respectively. The Transfer Function - TANH-AXON, Learning Rule – Momentum, along with the Learning rate 1.0 and 0.1 for hidden layer and for output layer respectively and also the momentum is 0.7 for both hidden layer and output layer is found to be same in one & two hidden layer MLP as shown in table 4. Other optimal parameters and performance of 1 hidden and 2 hidden layer MLP are also shown in Fig 2A, Fig 2B, Fig 3A and Fig 3B. The small circle shown on the graph indicates the maximum value of ACA and minimum value of MSE for processing elements corresponding to one and two hidden layer MLP.

It has been also found that the SVM converges after 300 Epochs but at Epochs equal to 70, 250 and 300 the ACA is found to be maximum for Test datasets, CV datasets and Training datasets respectively as shown if Fig 4A. The small circle shown on the graph in Fig 4A indicates the maximum value for ACA for three different datasets. The ACA for training dataset is found to be 100 % for Epochs 70. The performance of SVM is also shown in Fig 4A and Fig 4B.

Table 2: Optimal Parameter for one and two Hidden Layer MLP

One Hidden Layer MLP NN with Epochs - 4000			Two Hidden Layer MLP NN with Epochs - 2000		
Optimal Parameter	Hidden Layer	Output Layer	Hidden Layer-1	Hidden Layer-2	Output Layer
Processing Elements	40	1	35	95	1
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
Momentum	0.7	0.7	0.7	0.7	0.7

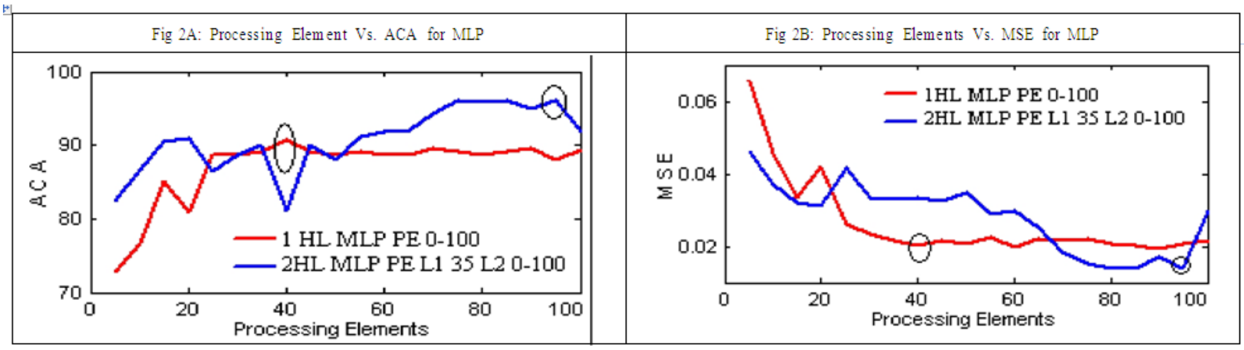


Fig 3A Transfer Function Vs ACA for MLP

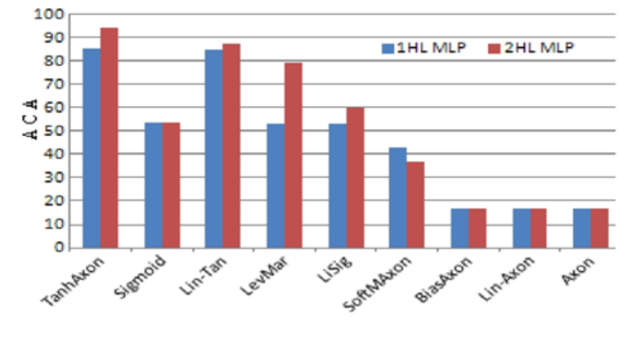


Fig 3B Learning Rule Vs ACA for MLP

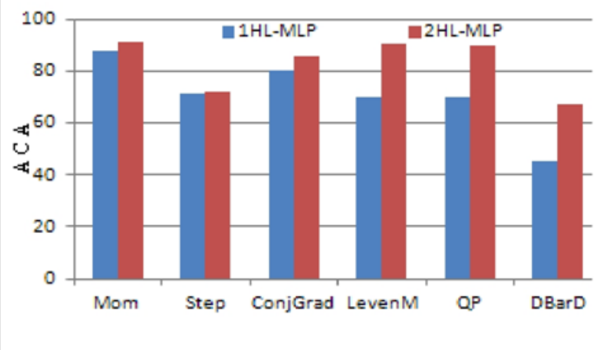


Fig 4A Epochs Vs ACA for SVM

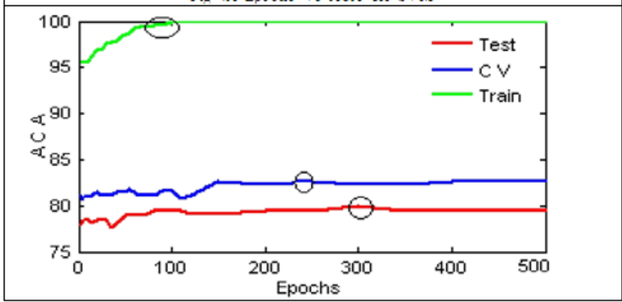
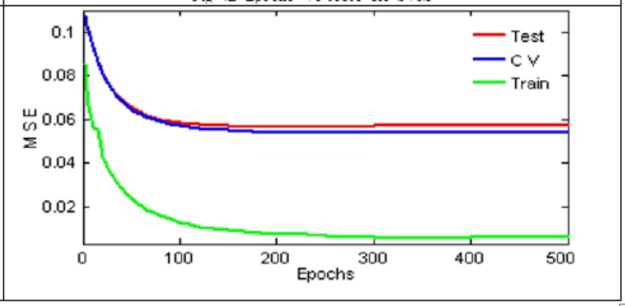


Fig 4B Epochs Vs ACA for SVM



V. Conclusion

Experimentation has been done on Hero Honda Passion four stroke automobile engine using MLP NN and SVM NN. The experimental results indicated that the proposed method can extract the feature and classify the different faults in a four stroke automobile engine. Further investigation has been carried out to detect the particular fault out of Air Filter Fault, Spark Plug Fault Insufficient Lubricants fault, Piston Ring fault and Rich Mixture fault, using a single sensor. It is not a complete automatic fault detection system but it can be extended to any number of faults. The main advantage of this system is its simplicity and compactness having a single sensor system.

The comparative analysis of Artificial Neural Networks depicts that the performance of SVM NN is found to be superior to 2Hidden Layer MLP NN with Epochs – 4000, L1 PE - 35, L2 PE – 95 and 1 Hidden Layer MLP with Epochs – 4000, PE-40. The SVM NN with Epochs -70 the ACA for training dataset is found to be 100 %. Therefore SVM can be used as a reasonable classifier for fault detection in a four stroke automobile engine.

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