Fault Identification in IC Engine using DSP and ANN

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ABSTRACT
The incipient faults in IC engine can be detected by conventional methods using various sensors. In this proposed paper the use of audio signal from engine is employed for fault detection. The use of audio signal for fault diagnosis in Internal Combustion Engine has grown significantly due to advances in the progress of digital signal processing algorithms and Artificial Neural Network. A fault diagnosis in internal combustion engine using digital signal processing & Artificial Neural Network uses MATLAB is proposed. The present paper discusses a methodology where a set of parameters is used to checks the status of an engine as either healthy or faulty This method based on parameter estimation, also signal modal approaches are developed to generate several symptoms indicating difference between normal and faulty status.

Keywords- Internal Combustion Engine, Digital Signal Processing, Artificial Neural Network, Parameter Estimation

1. INTRODUCTION
The conventional methodes are limited or trend checking for supervision, fault detection and fault diagnosis. As they do not give a deeper insight and usually do not allow a fault diagnosis so, a model-based method of fault detection has to be developed [2].

Determination of fault at an early stage and repairing them before it leads to larger fault is important, because it reduces the other damages, repairing cost and also reduces down time of the engine [3].

This paper discusses the faults due to spark plug, the details of spark plug fault as under.

2. 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 center 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 center electrode and side electrode. No current can flow because the fuel and air in the gap is an 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. Because the spark plug is inside the engine and is the only easily removable part it can be used as an indicator to the Faults in Spark Plug.

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 and minimal amount of electrode erosion which clearly indicates the plug is in the correct heat range and has been operating in a "healthy" engine.

B. Inappropriate Plug Gap
In appropriate plug gap is developed because of routine damage like mechanical damage caused by a foreign object that has accidentally entered the combustion chamber. This condition may also be due to inappropriate reach spark plugs that permit the piston to contact or collide with the firing end.

The gap may also because the plug has served its useful life and should be replaced. 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, may occur when the engine is quickly accelerated. Poor engine performance and a loss in fuel economy are qualities of a worn or spoiled spark plug.

The main cause of inappropriate spark plug is because of rough materials that accumulate on the side electrode may melt to bridge the gap when the engine is suddenly put under a heavy load.

The normal and faulty spark plug with inappropriate gap is shown in Fig.1.

Normal Inappropriate Gap.

Fig. 1: Normal and Faulty Spark Plug.

If the spark plug are found faulty, it can be easily replaced or repaired. Thus maintaining a high level of engine reliability by efficient fault diagnosis is thus important for several reasons.

- The down time of the engine is expensive.
- Certain malfunctioning conditions can be threat to the safety of both human being and environment.

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 [2, 5].

3. ARTIFICIAL NEURAL NETWORK

In this paper we have tested the performance of all the types of neural networks for fault detection in an automobile engine. The brief introduction of all neural networks is as follows.

a. Multilayer perceptron:

Multilayer perceptrons (MLPs) are layered feedforward networks typically trained with static backpropagation. These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data (typically three times more training samples than network weights).

b. Generalized feedforward networks:

Generalized feedforward networks are a generalization of the MLP such that connections can jump over one or more layers. In theory, a MLP can solve any problem that a generalized feedfoward network can solve. In practice, however, generalized feedforward networks often solve the problem much more efficiently. A classic example of this is the two spiral problem. Without describing the problem, it suffices to say that a standard MLP requires hundreds of times more training epochs than the generalized feedforward network containing the same number of processing elements.

c. Modular feedforward networks:

Modular feedforward networks are a special class of MLP. These networks process their input using several parallel MLPs, and then recombine the results. This tends to create some structure within the topology, which will foster specialization of function in each sub-module. In contrast to the MLP, modular networks do not have full interconnectivity between their layers. Therefore, a smaller number of weights are required for the same size network (i.e. the same number of PEs). This tends to speed up training times and reduce the number of required training examples.

d. Jordan and Elman networks:

Jordan and Elman networks extend the multilayer perceptron with context units, which are processing elements (PEs) that remember past activity. Context units provide the network with the ability to extract temporal information from the data. In the Elman network, the activity of the first hidden PEs are copied to the context units, while the Jordan network copies the output of the network. Networks which feed the input and the last hidden layer to the context units are also available.

e. Principal component analysis networks (PCAs):

Principal component analysis networks (PCAs) combine unsupervised and supervised learning in the same topology. Principal component analysis is an unsupervised linear procedure that finds a set of uncorrelated features, principal components, from the input. A MLP is supervised to perform the nonlinear classification from these components.

Radial basis function (RBF) networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements (PEs). This layer uses gaussian transfer functions, rather than the standard sigmoidal functions employed by MLPs. The centers and widths of the gaussians are set by unsupervised learning rules, and supervised learning is applied to the output layer. These networks tend to learn much faster than MLPs.

f. Generalized Regression (GRNN) / Probabilistic (PNN):

If a generalized regression (GRNN) / probabilistic (PNN) net is chosen, all the weights of the network can be calculated analytically. In this case, the number of cluster centers is by definition equal to the number of exemplars, and they are all set to the same variance (which may be optimized if a cross validation setis specified). This type of RBF usually performs best when the number of exemplars is small (<1000) or so dispersed that clustering is ill-defined.

g. Self-organizing feature maps (SOFMs):

Self-organizing feature maps (SOFMs) transform the input of arbitrary dimension into a one or two dimensional discrete map subject to a topological (neighborhood preserving) constraint. The feature maps are computed using Kohonen unsupervised learning. The output of the SOFM can be used as input to a supervised classification neural network such as the MLP. This network's key advantage is the clustering produced by the SOFM which reduces the input space into representative features using a self-organizing process. Hence the underlying structure of the input space is kept, while the dimensionality of the space is reduced.

h. Time lagged recurrent networks (TLRNs):

Time lagged recurrent networks (TLRNs) are MLPs extended with short term memory structures. Most real-world data contains information in its time structure, i.e. how the data changes with time. Yet, most neural networks are purely static classifiers. TLRNs are the state of the art in nonlinear time series prediction, system identification and temporal pattern classification.

i. Recurrent Networks:

Fully recurrent networks feed back the hidden layer to itself. Partially recurrent networks start with a fully recurrent net and add a feedforward connection that bypasses the recurrency, effectively treating the recurrent part as a state memory. These recurrent networks can have an infinite memory depth and thus find relationships through time as well as through the instantaneous input space. Most real-world data contains information in its time structure. Recurrent networks are the state of the art in nonlinear time series prediction, system identification, and temporal pattern classification.

j. CANFIS (Co-Active Neuro-Fuzzy Inference System):

The CANFIS (Co-Active Neuro-Fuzzy Inference System) model integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions. Fuzzy inference systems are also valuable as they combine the explanatory nature of rules membership functions) with the power of "black box" neural networks.

k. The Support Vector Machine (SVM):

The Support Vector Machine (SVM) is implemented using the kernel Adatron algorithm. The kernel Adatron maps inputs to a high-dimensional feature space, and then optimally separates data into their respective classes by isolating those inputs which fall close to the data boundaries. Therefore, the kernel Adatron is especially effective in separating sets of data which share complex boundaries. SVMs can only be used for classification, not for function approximation.

3. EXPERIMENTAL SETUP

Figure 2.Shows the Experimental Setup with four stroke IC engine and Audio signal capturing and Recording system. The Carbon microphone is placed near the engine head so that it will capture the audio signals from the engine. Audio signal carry valuable information about the engine behavior and status of engine.

Fig.2: Experimental Setup with audio signal capturing system.

The engine was started and firstly the audio signals are recorded for normal state of engine at different speed i.e. 1000rpm to 5000rpm with 1000rpm interval. Then the normal spark plug is replaced by faulty spark plug and signals are recorded again at same speed.
The engine used is a four stroke IC engine of Hero Honda Passion the detail specification is as in table :1

Performance		
Peak power	**7.37 hp at 8000 rpm**	
Peak torque	**7.95 Nm (0.8 kgf-m or 5.9 ft.lbs) @ 5000 RPM**	
Engine		
Type	**Single cylinder, four-stroke** Displacement : **97.50 ccm (5.95 cubic inches)**	
Transmission	**4-speed gear box**	**Smooth easy shifting**
Operating cycle	**Fore-stroke spark ignition,**	
Compression ratio	**6-10**	
Bore	**50.0 mm**	
Stroke	**49.5 mm**	

Table 1: Specification of Hero Honda Passion Engine

4. BLOCK DIAGRAM OF SYSTEM

It will be acceptable for vehicular system that it must have vehicle information system. To develop such system, detail analysis of the fault is required. The working of the system is shown in the block diagram Fig 3. The MP3 sound recorder has been used to record the sound signals along with the carbon microphone. The parameters of recorded sound signals are extracted using the MATLAB software. The detailed analysis is carried out using neural networks and finally the optimal neural network is designed.

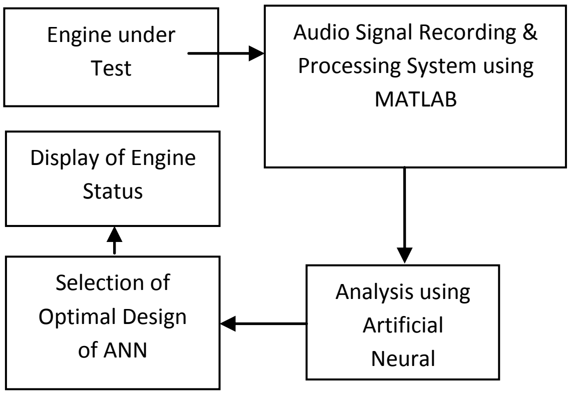
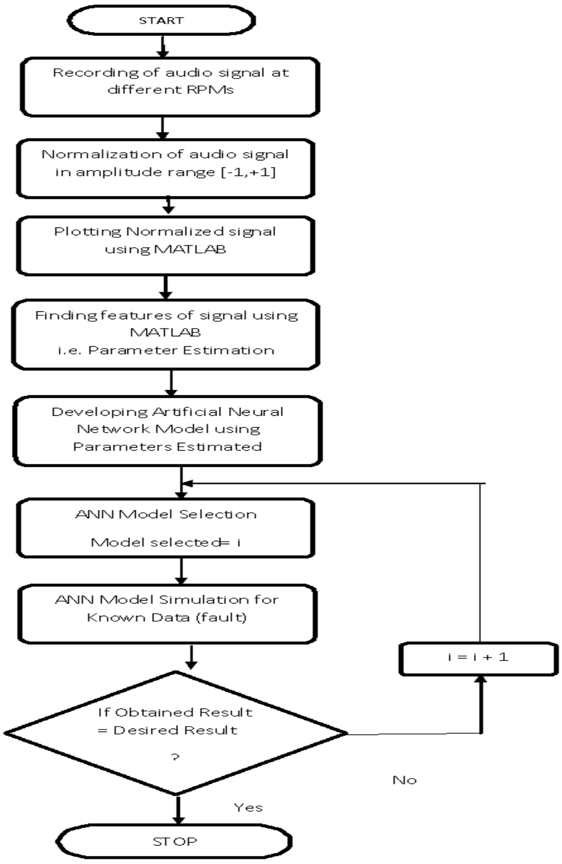


Fig. 3: Block Diagram of the System

5. FLOW OF THE SYSTEM

The Fig.4 shows, the complete flow for the process of fault identification in four stroke IC engine using audio signal.



6. RESULTS AND OBSERVATIONS

The recorded audio signals are normalized and plotted as shown in fig.4.

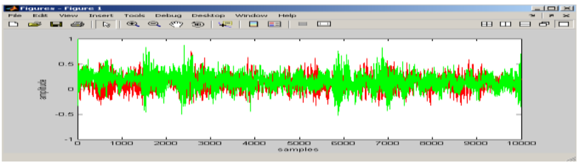


Fig.4 (a): Faulty (Red) and Non Faulty (Green) Audio Signals at 1000 rpm

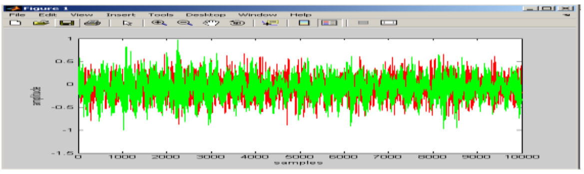


Fig.4 (b): Faulty (Red) and Non Faulty (Green) Audio Signals at 2000 rpm

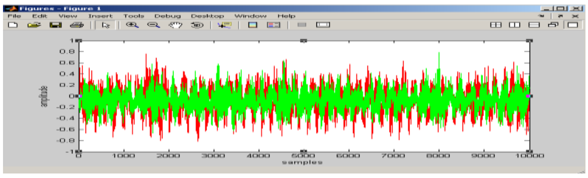


Fig.4 (c): Faulty (Red) and Non Faulty (Green) Audio Signals at 3000 rpm

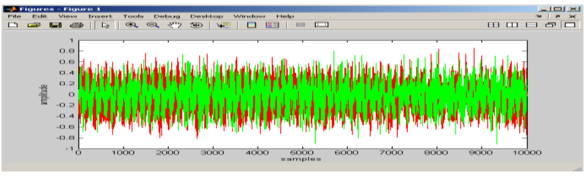


Fig.4 (d): Faulty (Red) and Non Faulty (Green) Audio Signals at 4000 rpm

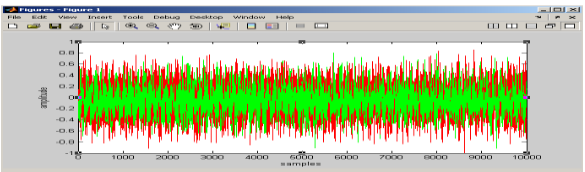


Fig.4 (e): Faulty (Red) and Non Faulty (Green) Audio Signals at 5000 rpm

It is observed from the plots that

i. The amplitudes of the signal for Faulty Spark Plug is smaller than that for Non Faulty Signals.
ii. It is also observed that there no separation between faulty and normal signals.
iii. The mean value of faulty signal is shifted down as compared to the mean value of non faulty signal.
iv. The maximum and minimum values of non faulty and faulty signal are different.

These audio signals are processed using MATLAB to find the parameters as minimum value, maximum value, mean value, energy, standard deviation and variance.
Various Artificial neural networks are tested for their classification efficiency for classifying the parameters of faulty and non-faulty status of internal combustion engine as shown in table 2.

Artificial Neural Networks	Spark Plug Fault
MLP	86.27
GFF	73.22
MNN	66.17
SOFM	90.16
PCA	82.73
JEN	74.30
RBF	74.21
RN	58.48
TLRN	64.19
SVM	94.16

Table.2: Classification Efficiency of various ANN

The classification efficiency of MLP, SOFM, and SVM is found to be good for classifying faults in engine. The performance of Support Vector Machine (SVM) is observed from the table 2 and table 3. The SVM neural network is giving the best performance as compared to SOFM and all other neural networks. The classification accuracy and Mean Square Error along with the other parameter are also shown in the Table 3. The Average MSE, Training MSE and Cross validation MSE are decrease as epochs are increased as shown in Fig 8.

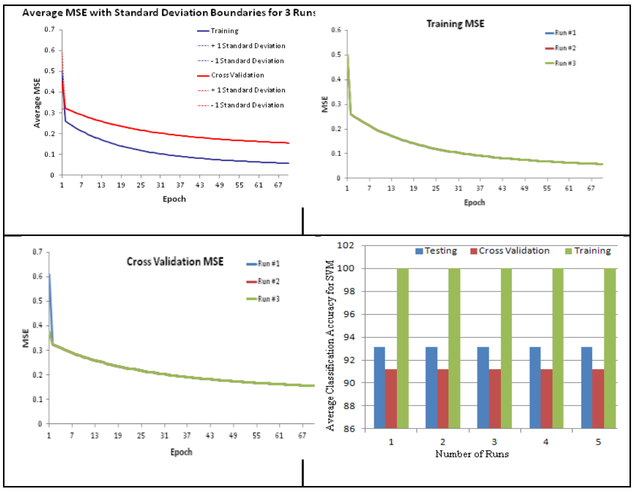


Fig.5: Performance of SVM and ACA for five runs

Performance	*SYMBOL(NORMAL)*	*SYMBOL(FDAF)*	*SYMBOL(FSSP)*
MSE	0.017983566	0.01592459	0.016699036
NMSE	0.081706407	0.071221086	0.074913024
MAE	0.107095211	0.092876184	0.098657467
Min Abs Error	0.000150851	0.000154145	6.46459E-05
Max Abs Error	0.444764822	0.523945691	0.482128395
r	0.974395655	0.975858309	0.976181116
Percent Correct	100	100	100

Table.3: Performance of SVM

The Support Vector Machine is developed which uses kernel function as linear support vector machine classifier which classify the given data into faulty and non faulty.

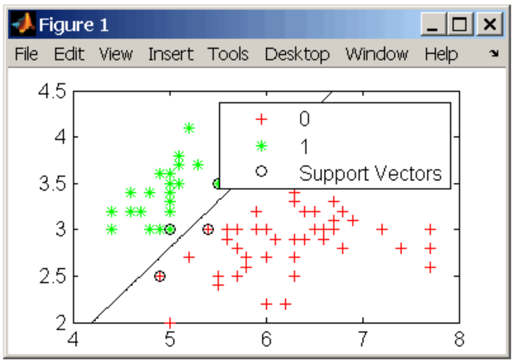


Fig.6: linear support vector machine classifier

The developed neural network is first trained by using benchmark data and then the test signal is applied to the neural network. The audio signal for Air filter fault is applied the neural network as 'unknown' signal , the result of the system is shown in fig.7: giving Filter fault in the Engine

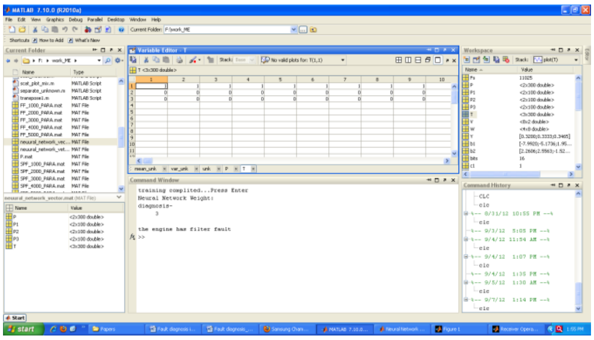


Fig.7: Output of the system showing spark plug fault

7. CONCLUSION

In view of the importance of spark plug, it is possible to detect the fault at an early stage so that the component can be replaced before its failure.

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