Multiple Fault Detection in typical Automobile Engines: a Soft computing approach

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Abstract: -Fault detection has gained growing importance for vehicle safety and reliability. For the improvement of reliability, safety and efficiency; advanced methods of supervision, fault detection and fault diagnosis become increasingly important for many automobile systems. Many times, the trial and error approach has been applied to detect the fault and therefore engine may get more damaged instead of getting repaired. To alleviate such type of problem, the idea of sound recording of engines has been suggested to diagnose the fault correctly without opening the engine.

In this paper, fault detection of two stroke engine, Hero Honda Passion four strokes and Maruti Suzuki Alto Automobile Engine have been proposed. The objective is to categorize the acoustic signals of engines into healthy and faulty state. Acoustic emission signals are generated from three different automobile engines in both healthy and faulty conditions. The paper proposes soft computing approach for detection of multiple faults in automobile engines which include signal conditioning, signal processing, statistical analysis and Artificial Neural Networks. The Statistical techniques and different Artificial Neural Networks have been employed to classify the faults correctly. Performance of Statistical techniques and ten types of Artificial Neural Networks have been compared on the basis of Average Classification Accuracy and finally, optimal Neural Network has been designed for the best performance.

Key-Words: - Artificial Neural Network, Automobile Engine, Classification Accuracy, Fault Detection and Stistical Techniques.

1 Introduction

During the last two decades many investigations have been made using analytical approaches, based on quantitative models. The idea is to generate signals that reflect in consistencies between nominal and faulty system operation. Such signals, termed residuals , are usually generated using analytical approaches, such as observers (Patton et al 2000, Chen & Patton,1999), parameter estimation (Isermann, 1994) or parity equations (Gertler, 1998) based on analytical(or functional) redundancy [1-5]. Neural networks have been successfully applied to many applications including fault diagnosis of non-linear dynamic systems (Wang, Brown & Harris, 1994[6]. MLP networks are applied to detect leakages in electro-hydraulic cylinder drive in a fluid power system (Watton & Pham, 1997) [7]. They showed that maintenance information can be obtained from the monitored data using the neural network instead of a human operator. The engine fault diagnosis system using the sound emission signal from automobile engine proposed by Jain-Da Wu and Chiu – Hong Liu (2008) but the few numbers of faults were considered [8]. Huang, et al (2008) suggested the Bayesian diagnostic models for fault cases with single and multiple symptoms. Particular considerations are also given to the determination of prior probabilities of root causes, and diagnostic procedure, but the proposed diagnostic model is found to be quite complex [9]. The detection, isolation and estimation of faults that occur in the intake air path of internal combustion engines are proposed by Matthew A. Franchek and et al (2007). The proposed model needed different types of sensors to detect the different faults [10].

In the recent years, a lot of technological advances have occurred in motor vehicular systems, pertaining to improve driving safety and comfort. But this entails making the vehicular systems more and more complex. At the same time, continuous increase in road traffic is a major problem in big metropolitan cities. There is also a scarcity of skilled mechanics in all over the world [11, 12]. It is therefore difficult to maintain the vehicle in good condition, not only in villages and towns but also in metropolitan cities. Determination of fault at an incipient stage and repairing them before it results into a larger fault is important, because it reduces the other damages, repairing cost and also reduces down-time of the engine [13].

The two-stroke petrol engine was very popular throughout the 20th century in motorcycles and small-engine devices, such as chainsaws and outboard motors, and was also used in some cars, a few tractors and many ships because of its simple design and high power-to-weight ratio and resulting low cost [14]. But the two stroke engine incredibly popular, until the Environmental Protection Agency (EPA) mandated more stringent emission controls in 1978 (taking effect in 1980) and in 2004 (taking effect in 2005 and 2010). The industry largely responded by switching to four-stroke petrol engines, which emit less pollution. Many designs use total-loss lubrication, with the oil being burnt in the combustion chamber, causing "blue smoke" and other types of exhaust pollution. This is a major reason why two-stroke engines were replaced by four-stroke engines in many applications.

Car technology has been advancing at amazing speed so it is no surprise that at least more than hundreds of car models are coming up in each year with newer technology and innovations. The new technologies are necessary to meet increased transport demands in future and satisfy the need for the safer, faster and more sustainable mobility of persons and goods. According to the news published by Maruti Suzuki New Delhi, on June 15th, 2012**:** "Maruti Suzuki Alto is the highest selling car, in the domestic Indian market since 7 years. It has also been rated as the highest selling small car in the world, since two years." In view of the popularity of Maruti Suzuki Alto Car, an Engine of this car has been specifically used for experimentation. In view of the above mentioned facts, the experimentation has been carried out on two stroke, Hero Honda Passion four stroke and Maruti Suzuki Alto automobile engine using statistical and ANN based classifiers. The experimental results revealed that the proposed method can extract the features and classify the different faults in an automobile engine. Further investigation has been carried out to detect the particular fault out of six different types of faults using a single sensor. Fig 1 shows the faulty parts of two strokes engine.

Typical Faults in two stroke and four stroke automobile engines considered for fault detection are as under [15].

- Air filter Fault(AF)
- Spark Plug Fault (SP)
- Rich Mixture Fault (RM)
- Gudgeon Pin Fault (GP)
- Insufficient Lubricants Faults (IL)
- Piston Ring Fault (PR)

Similarly, typical Faults considered in Maruti Suzuki Alto automobile engine for fault detection are as follows [16].

- Knocking Fault (KF)
- Insufficient Lubricant Fault (IL)
- Excessive Lubricants Fault (EL)
- High oil Level Fault (HOL)
- Piston Ring Fault (PR)
- Gudgeon Pin Fault (GP)

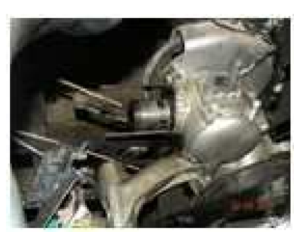
2 System Overview

The two strokes and four strokes engine is the heart of most modern motorcycles. Although four-stroke engines are available in different displacements and cylinder arrangements, their basic components remain the same. The acoustic signal emitting from engines are recorded as shown in fig 2A with recorded signal plot shown in fig 2B.

Fig 1: Faulty Parts of 2-Stroke Engine

Air Filter

Spark plug inside the cylender head



Damage Piston Ring

Gudgeon Pin with extended gap

Fig: 2 A: Signal Recording System

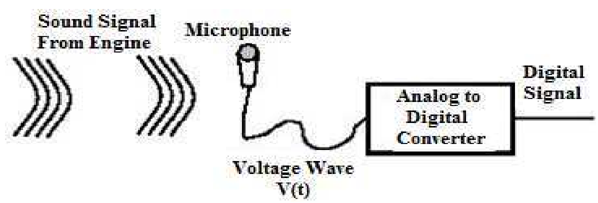
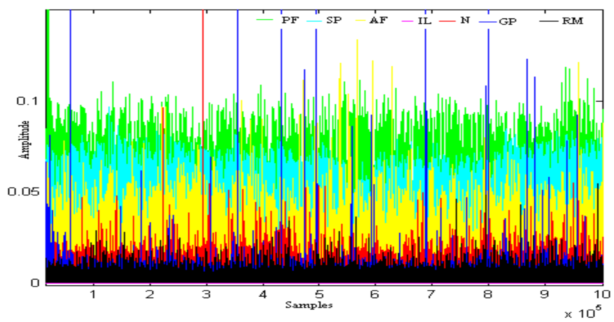


Fig 2B: Signal Plot for Healthy and Faulty State



The block diagram of the system is shown in Fig 3; it consists of an automobile engine along with the microphone is used as a sensor, signal recording, signal conditioning and signal processing system. Specifications of Microphone and MP3 Sound Recorder are shown in Table 1. The MP3 sound recorder is used to record the sound variations in '.wav' format at healthy and different faulty conditions of an automobile engine. The engine specifications are given as under

Specifications of Two Stroke Engine:
Peak power: 8.0 hp at 5500 rpm
Peak torque: 1.35 Kg-m at 3500 rpm
Engine Type: 5-port single cylinder, 2-stroke
Transmission: 4-speed gear box
Compression ratio: 6-10
Operating cycle: Two-stroke spark ignition
Engine: 150 cc engine
Engine Type: Single cylinder, four-stroke
Gear Box: 5- Speed Gear
Compression Ratio: 8.8: 1
Maximum Torque: 7.95 Nm, @ 5000 RPM
Cylinder Bore: 50.0 mm

Specifications of Maruti Suzuki Alto Engine:
Engine Displacement (cc): 796
Maximum Power: 46bhp@6200rpm
Engine Type: In-Line Engine, 3-Cylenders
Gear Box: 5 Speeds
Compression Ratio: 9:1
Maximum Torque: 62Nm@3000rpm
Valves per Cylinder: 4
The detailed analysis is carried out using algorithm developed in MALAB as given in section 3.

3 Data Acquisition

Initially, engines were started in healthy condition and four different signals were recorded in each gear position with 1200 rpm, 1500 rpm, 1800 rpm and 2100 rpm, respectively. The engine consists of neutral, and four different gears. The total 20 signals are recorded in each gear positions in healthy and faulty conditions. Nature of the recorded signal is found to highly complex as shown in fig 2B.
After that, one-by-one, fault is created in an automobile engine and the process of recording the signals was continued for six different faults. Finally, there will be a collection of total 140 recorded signals. The faults considered for analysis are given in section 1. The normalization, signal conditioning and analog to digital conversion carried out by using the algorithm written in MATLB.

Fig 3: Block Diagram of the System

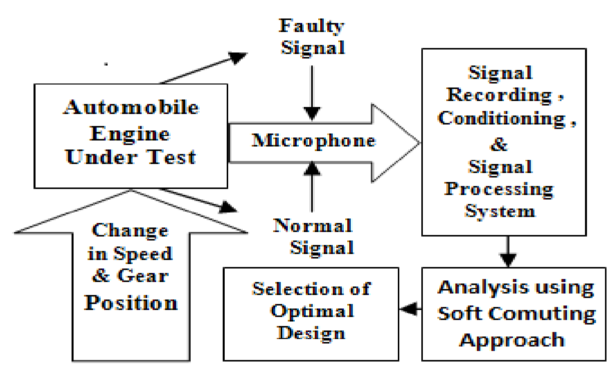
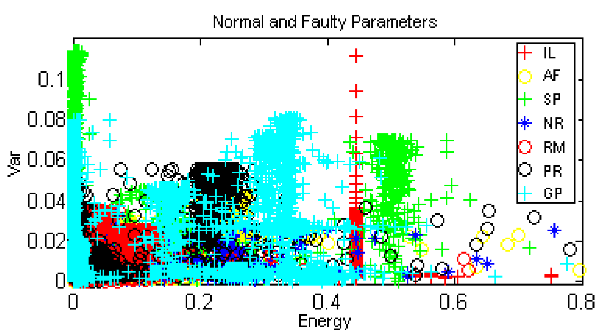


Table 1: Specifications of Microphone & Sound Recorder

Microphone Specifications	MP3 Recorder Specifications
Frequency: 20Hz-20KHz **Output Impedance** : ≤ 680Ω **SNR** : 58 db **Sensitivity**: -47db±2db **Operating Voltage**: 1-10V DC	**Frequency** : 20 Hz to 20 kHz **Format** : MP3 **Sampling Rate**: 22.05 kHz **Signal Format**: WAV

Later on, samples of each signal are partitioned into different 32 frames with 100,000 samples in it. The features of each frame have been extracted using MATLAB. The extracted seven features are Mean, Mode, Energy, Maximum Value, Minimum Value, Standard Deviation and Variance. The size of each feature matrix signal will be 32 x 20 x 8 with 7 inputs and one categorical output. After combining all six faults and healthy signal the size of feature matrix will be 4480 x 8 with seven inputs and one output. The extracted features are plotted as shown in fig 4. It is observed from the scatter plot that the faults are not linearly separable. Therefore the statistical and ANN classifier are employed to classify the faults as discuss in the following sections.

Fig 4: Scatter Plot for Healthy and Faulty Parameter



4 Classification Using Statistical Method

The Statistical analysis is carried out for each engine using XLSTAT. The classification and regression tree has been employed to classify the faults [11].

Table 2: Comparison of Statistical Technique in % ACA

Statistical Methods	Two-Stroke Engine	Hero Honda Passion	Maruti Suzuki Alto Engine
CHAID Pearson	81.50	60.52	53.89%
CHAID Likelihood	80.00	61.25	60.00%
EX- CHAID Pearson	81.50	60.52	53.89%
EX-CHAID Likelihood	80.00	61.25	53.89%
C&RT-Gini	76.00	64.90	57.78%
C&RT-Towing	69.50	47.81	41.11%
QUEST	80.00	16.67	16.67%

The feature matrix comprising of 4480 rows with 7 inputs and one output has been applied as an input to statistical classifiers. The performance of statistical classifier using CHAID Pearson, CHAID Likelihood, EX- CHAID Pearson, EX- CHAID Likelihood, C&RT Gini, C&RT Towing and QUEST has been observed. For two stroke engine, the performance of CHAID Pearson and EX-CHAID Pearson is found to be better than the other classifiers, for four stroke engine the performance of C & RT Gini is found to be better and for Maruti Suzuki Alto engine, the performance of CHAID Pearson is found to be better than other classifier as shown in table 2.

Table 3: Performance of CHAID Pearson and Ex- CHAID Pearson

% ACA for CHAID Pearson						2-Storke Engine Faults	% ACA for EX- CHAID Pearson					
TL-05	TL-06	TL-07	TL-08	TL-09	TL-10		TL-05	TL06	TL-07	TL-08	TL-09	TL-10
3.13	16.88	75.31	75.31	77.50	88.25	AF	47.81	69.69	81.56	82.81	82.50	83.81
95.94	85.31	75.63	83.44	83.13	88.25	GP	95.00	89.38	89.38	95.94	95.00	98.44
95.00	95.00	95.00	95.00	100.00	100.00	IL	95.00	95.00	95.00	95.00	95.00	99.69
0.00	14.69	14.69	15.00	24.69	50.19	NOR	0.00	23.75	33.44	38.44	48.44	56.50
98.75	98.75	79.06	84.38	84.38	88.21	PR	79.06	74.06	74.06	80.31	80.31	78.75
98.75	98.75	98.75	98.75	98.75	98.15	RM	98.75	98.75	98.75	98.75	98.75	98.75
14.06	17.19	30.63	30.31	47.19	57.47	SP	24.06	21.88	34.69	42.19	52.19	54.55
57.95	60.94	67.01	68.88	73.66	81.50	Total % ACA	62.81	67.50	72.41	76.21	78.88	81.50

The statistical analysis is carried out for tree depth varying from 5 to 10. The performance of CHAID Pearson, EX-CHAID Pearson, C & RT Gini and CHAID Likelihood is shown in table 4 and table 6 for 2stroke, four stroke and Maruti Suzuki Alto engine, respectively. It is learned that the classification accuracy is increased with increase in tree depth as shown in table 3 and table 4. As the result of Statistical Analysis is not encouraging, therefore the ANN has been considered for further analysis as discussed in following section.

Table 4: Performance of CHAID Likelihood and C & RT Gini

% ACA for CHAID Likelihood for Maurti Suzuki Alto Engine						
Faults	TL-05	TL-06	TL-07	TL-08	TL-09	TL-10
HOL	36.67	50.00	60.00	60.00	60.00	60.00
IFS	10.00	10.00	10.00	10.00	10.00	10.00
ISL	96.67	96.67	96.67	96.67	96.67	96.67
KF	83.33	83.33	83.33	83.33	83.33	83.33
Nor	83.33	90.00	90.00	90.00	90.00	90.00
PF	50.00	50.00	56.67	56.67	56.67	56.67
GP	35.67	50.00	64.00	64.00	64.00	64.00
%ACA	60.00	63.33	66.11	66.11	66.11	66.11

% ACA for C & RT Gini for Hero Honda Passion Engine						
Faults	TL-05	TL06	TL-07	TL-08	TL-09	TL-10
FF	65.00	70.63	70.63	70.63	70.63	70.63
IL	53.13	63.13	63.75	66.25	68.75	68.75
Nor	73.75	73.75	73.75	73.75	73.75	73.75
PF	59.38	52.50	55.00	53.75	51.88	51.88
RM	66.25	66.25	66.25	66.25	66.25	66.25
SP	71.88	71.88	71.88	71.88	71.88	71.88
GP	55.38	52.50	55.00	53.88	53.88	53.88
% ACA	63.54	64.38	65.18	65.20	65.29	65.29

5 Classification using ANN

Subsequent analysis is continued using different configuration of Artificial Neural Networks such as Multilayer Perceptron (MLP), Gernalised Feedforward (GFF), Modular Neural Network (MNN), Jorden & Elman Network (JEN), Radial Basis Function (RBF), Self Organizing Feature Map (SOFM), Principal Component Analysis (PCA), Time Lagged Recurrent Network (TLRN), Recurrent Network (RN) and Support Vector Machine (SVM)[12]. The percentage Classification Accuracy has been observed for all ten types of ANN. The feature matrix consists of 4480 rows with 7 inputs such as: *Mean, Mode, Energy, Maximum Value, Minimum Value, Standard Deviation and Variance* and one output which are applied as an input to the ANN. The input layer of the ANN contains seven neurons pertaining to seven inputs. Output is categorical, which represents a type of fault or healthy condition of an engine. As there are six different types of faults and one healthy condition. The number of neurons in the output layer should be seven (Six neurons corresponding to six different faults and one neuron to indicate healthy condition). Three data partitions namely, Training, Cross Validation (CV) and Testing were used with different tagging order. The first 50 % samples (1:2240) are used for training, the second 25 % samples (2241: 3360) are used for cross validation and third 25 % samples (3361:4480) are used for testing of the classifier. Each ANN is retrained three times with different random intialization of connection weights and biases. The performance of all ten types of ANN classifier has been observed for all three types of an automobile engine as shown in table 5. It is observed that the performance of classifiers MLP NN (7-35-40-7) and SVM NN is found to be better amongst ten neural network classifiers used for the analysis. Further, performance of MLP NN has been observed for one and two hidden layers in subsequent sections.

Table 5 : Classification of faults using ANN

ANN	**% ACA for two Stroke Engine**			**% ACA Hero Honda Passion Engine**			**% ACA Maruti Suzuki Alto**		
	Test	**CV**	**Training**	**Test**	**CV**	**Training**	**Test**	**CV**	**Training**
MLP	94.38474	94.66995	97.35761	86.618616	90.94709	92.048232	55.46415	55.73544	58.40767
GFF	91.85029	92.1579	94.08542	83.160309	89.21164	91.201743	55.77485	56.19408	57.90048
MNN	90.61682	91.25747	94.84375	84.178653	85.449735	82.616151	58.7721	59.437	61.57078
JEN	88.99437	89.61069	93.98324	82.385866	86.243386	83.887383	57.13754	58.5818	60.07232
SOFM	91.82685	93.6714	94.6862	80.719199	89.608466	86.034954	52.70591	51.68064	53.05507
TLRN	77.35093	76.57056	82.62689	78.280175	89.68254	86.490851	58.30167	57.91153	60.55084
PCA	91.09804	93.9433	94.07634	81.678653	84.328042	87.65597	56.66088	57.33402	58.38295
RN	72.13725	71.76931	69.15831	67.632687	72.973545	79.810718	51.39181	52.08884	53.54042
RBF	84.88235	82.62952	82.63668	81.178653	79.749735	80.516151	53.97779	53.86846	55.88928
SVM	95.51961	93.92815	96.01961	92.45414	94.17989	93.4008	84.99111	85.51761	98.6426

5.1 Single hidden layer MLP NN classifier for two stroke engine

The comprehensive analysis of single hidden MLP NN is continued by varying the Epochs, Processing Elements (PEs), Learning Rule (LR) and Transfer Function (TF). The feature matrix comprising of 4480 records was split into three parts in the ratio 2:1:1. First part of data was used for training the network, second used for cross validation and the third part used for testing the network. The process was repeated by varying hidden layer PEs from 5 to 100 for default supervised learning epochs 1000. The MLP was further refined by changing the number of Epochs, different variants of back propagation Learning Rule Algorithms such as STEP, Momentum (MOM), Conjugate Gradient (CG), Levenberg Marquardt (LMQ), Quick Propagation (QP) and Delta-Bar-Delta (DBD). The performance of one hidden layer MLP NN is shown in Fig 5A and Fig 5B. It is found that the Maximum Average Classification Accuracy (ACA) is observed for PE equal to 90 and Epochs equal to 4100. Fig 5C & 5D shows the performance of 1HL MLP with reverse tagging order in which Maximum ACA obtained for 1HL MLP at PE equal to 45 and for 2 HL MLP L1 PE equal to 40 and L2 PE equal to 45. The Average Classification Accuracy is found to be nearly same for forward and reverse tagging order.

Fig 5A: ACA for 1HL MLPNN

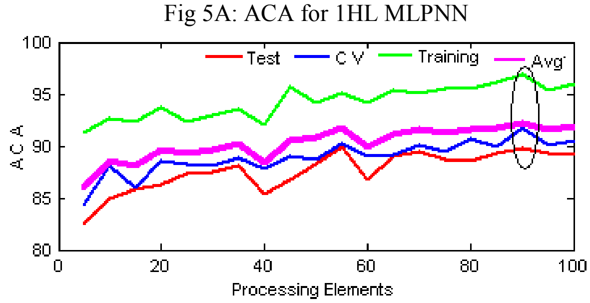


Fig 5B: MSE for 1HL MLP NN

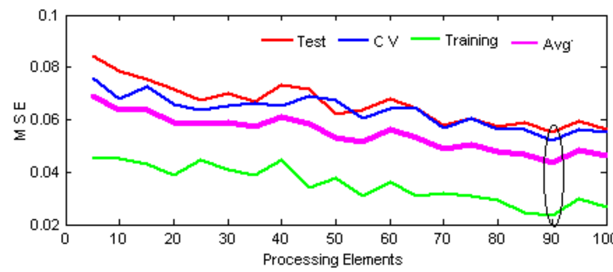


Fig 5C: 1HL MLP with Reverse Tagging for 2 – stroke (PE-45)

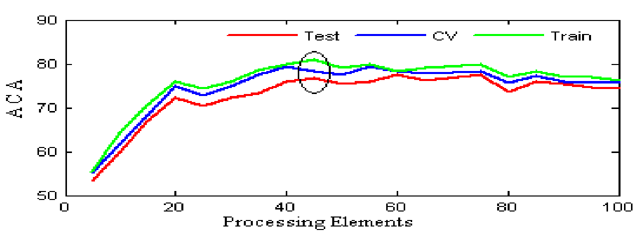
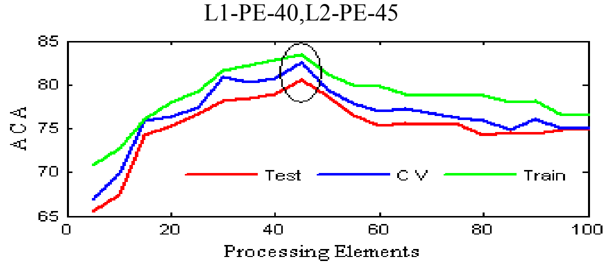


Fig:5D HL MLP with Reverse Tagging for 2 – stroke, L1-PE-40,L2-PE-45



5.2 Two hidden layer MLP NN classifier for two stroke engine

The two hidden layer MLP was retrained for three times with different random weight initialization by feature matrix as an input to the neural network. Total dataset of size 4480 x 8 was divided into three parts in the ratio 2:1:1. First part is used as training dataset, second as cross validation and third as testing dataset. As the number hidden layers in a neural network increases, the complexity of computation is also seen to increase. Here, the network is designed by keeping Hidden layer #1 (L1) PE fixed to 5 and by varying Hidden layer #2 (L2) PE from 5-100 in steps of 5. The ACA maximum is obtained for Epochs equal to 4100 for 1HL MLP. Then step-by-step, the L1 PE was also varied from 5-100 in steps of 5 with varying simultaneously the L2 PE. After training the network three times with each set of PEs, the network was tested for test dataset, cross validation dataset and training dataset.

Further, the network was also refined by varying the Epochs 100 to 5000 for best classification accuracy. The performance of 2 hidden layers MLPs is shown in Fig 7A and Fig 7 B. It is also noticed that L1 PE is 35 whereas L2 PE is 50 with TANH-AXON - transfer function, Learning Rule-Momentum and Epochs-2500. The comparison details of 1HL MLP and 2HL MLP is also given in Bar Chart of fig 6A and Fig 6B. The optimal parameter for one and two hidden layer MLP is also shown in table 7. The Classification Accuracy of 2H-Layer MLP is found to be more than 1H-Layer MLP.

Fig 6 A Transfer Function Vs ACA for MLP

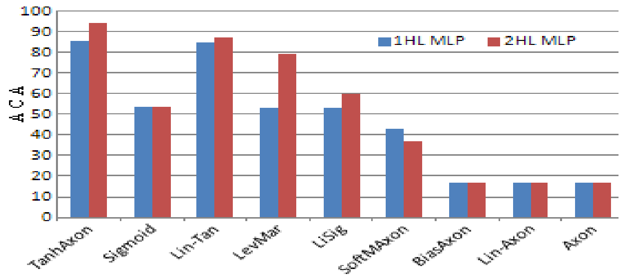


Fig 6 B Learning Rule Vs ACA for MLP

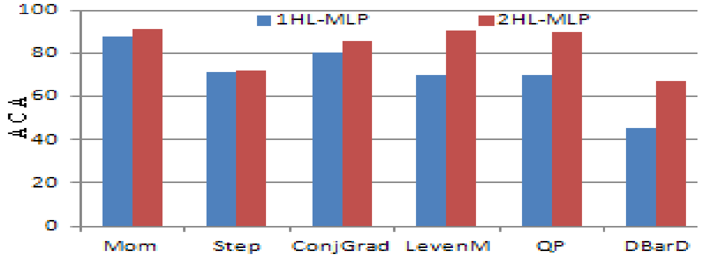


Fig 7A: ACA for 2 HL MLP L1 PE 35, L2 PE 50

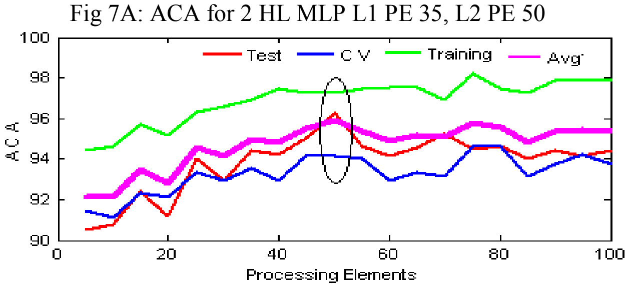


Fig 7B: MSE for 2 HL MLP L1 PE 35, L2 PE 50

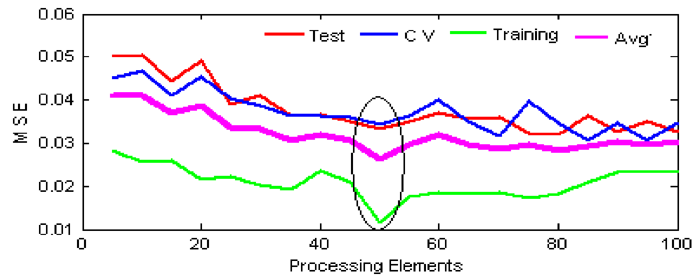


Table 7 : Optimal parameters for MLP NN Classifier for Two stroke Engine

1 HL MLP NN with Epochs 4100			2 HL MLP NN with Epochs 2500		
Parameter	Hidden Layer	Output Layer	Hidden Layer-1	Hidden Layer-2	Output Layer
PE	90	1	35	50	1
TF	TANH-AXON	TANH-AXON	TANH-AXON	TANH-AXON	TANH-AXON
LR	Mom	Mom	Mom	Mom	Mom
Step Size	1.0	0.1	1.0	0.1	0.01
MOM	0.7	0.7	0.7	0.7	0.7

5.3 One and Two hidden layer MLP NN classifier for Four Stroke Engine

Similarly, thorough analysis is also carried out by one and two hidden layer MLP NN classifier to classify the faults in four stroke engine with same type of data partitioning schemes. That is the feature matrix of size 4480 x 8 was divided into three parts in the ratio 2:1:1. First part was used as training dataset, second as cross validation and third as testing dataset. 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 feature matrixes. Further, the network was also refined by varying the Epochs 100 to 5000 for best classification accuracy. The performance of one and two hidden layers MLPs with ACA and MSE is shown in Fig 8A and Fig 8B. It is found that for one hidden layer MLP the maximum ACA is obtained for L1 PE are 40 with Epochs-4000. For two hidden layer MLP L1 PE is 35 and L2 PE is 95 with TANH-AXON - transfer function, Learning Rule-Momentum and Epochs-2000 as shown in table 8.

Table 8 : Optimal parameters for MLP NN Classifier for Four stroke Engine

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 8A: Processing Element Vs. ACA for MLP

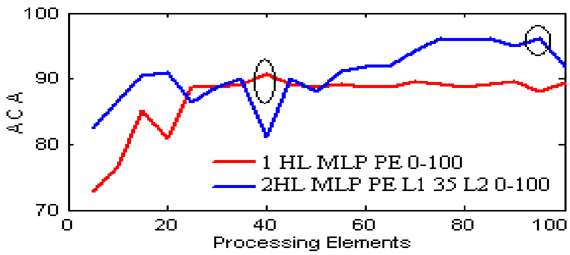
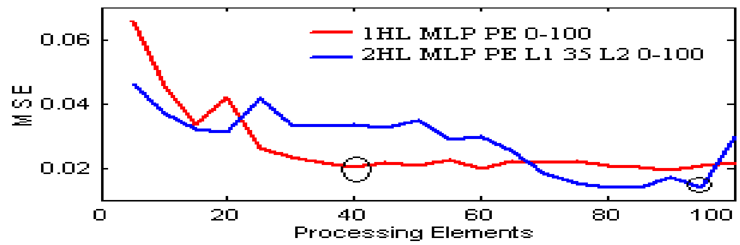


Fig 8B: Processing Elements Vs. MSE for MLP



5.4 Design of Support Vector Machine NN Classifier for two stroke, four stroke and Maruti Suzuki Alto Engines

As it is observed from the performance comparison of different ANN classifiers, the performance of SVM classifier is found to be superior to all other classifiers; therefore, the exhaustive analysis is carried out for SVM NN classifier for all three types of automobile engines [16]. The Kernel Adatron algorithm is specifically used for Support Vector Machine NN classifier. The dataset of 4480 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 used for cross validation and the third part used for testing the network. The SVM is trained and tested by varying the Epochs from 10 to 200. The performance of SVM for two stroke engine is shown in Fig 9A and Fig 9B. The Classification Accuracy is found to be Maximum at Epochs equal to 95.

Fig 9A : Performance of SVM for 2 stroke engine

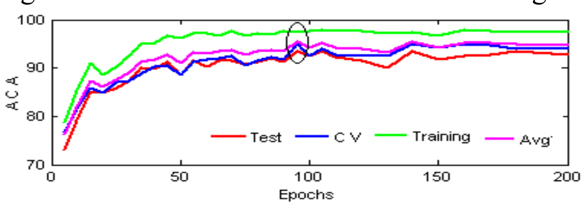


Fig. 9B : MSE for SVM for 2 stroke engine

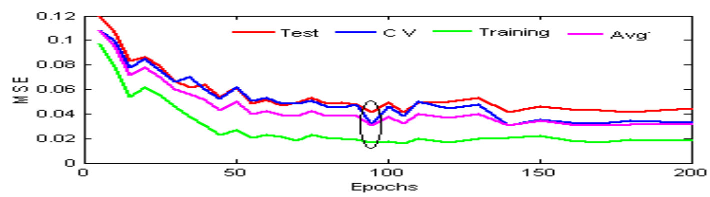


Fig 9C: Performance of SVM for 4 stroke engine

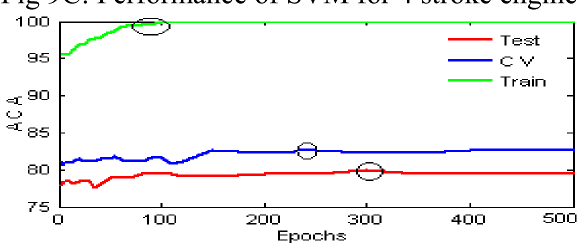
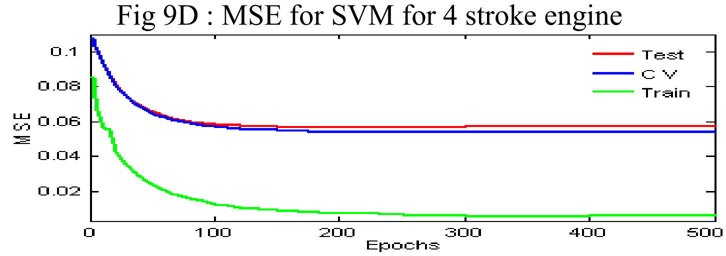
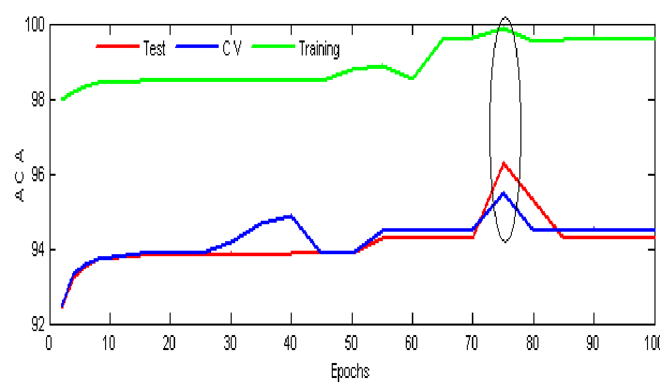


Fig 9D : MSE for SVM for 4 stroke engine



With the same types of data partitioning scheme, the performance of SVM for four stroke engine was also observed. It is found that the maximum ACA is observed with corresponding Minimum MSE for epochs equal to 70 for training data sets as shown in Fig 9C and Fig 9D. Similarly, with the same types of data partitioning scheme the performance of SVM for Maruti Suzuki Alto Engine was also observed. It is found that the maximum ACA is observed with corresponding Minimum MSE for epochs equal to 75 for training, cross validation data sets, and testing data sets as shown in Fig10.

Fig 10: Performance of SVM Classifier for Maruti Suzuki Alto Engine.



6. Conclusion

In this paper, a technique for Multiple Fault Detection in a two stroke, Hero Honda Passion four stroke and Maruti Suzuki Alto Automobile Engines using sound signal has been proposed. Fault detection has been carried out only for six different faults. The main advantage of this system is its simplicity, low cost and compactness having a single sensor system. From the meticulous analysis using statistical and ANNs classifier, it is learned that ANN classifiers are more appropriate for fault diagnosis. The comparative analysis of 10 different Artificial Neural Networks depicts that the classification Accuracy of MLP and SVM are found to be greater amongst the group of ANNs used for the analysis. Also, the classification accuracy of two hiddden layer-MLP is found to be greater than that of one hidden layer. It is also depicted that the 2HL MLP NN and SVM NN can be used as reasonable classifier for multiple fault detection in a two stroke, four stroke automobile engine and Maruti Alto engine. However, SVM NN classifier is seen to be more appropriate classifier for two stroke, Hero Honda Passion four stroke and Maruti Suzuki Alto Automobile Engines as its classification accuracy is much higher than other classifiers.

References

[1] Patton R J, Frank P M & Clark R N, *Issues in Fault Diagnosis for Dynamic Systems*, Springer, April 2000

[2] Chen J & Patton R J, *Robust Model-Based Fault Diagnosis for Dynamic Systems*, March 1999, Kluwer

[3] Rolf Isermann R, (1994a), Fault diagnosis of machines via parameter estimation and knowledge processing - a tutorial paper, Automatica , 29, (4),815-835.

[4] Gertler, J., Fault Detection and Diagnosis in Engineering Systems, *Marcel Dekker, Inc., New York, 1998.*

[5] C. Angeli , A. Chatzinikolaou, On-line Fault Detection Techniques for Technical Systems: A survey (2004), International journal of computer science & applications, vol I, No I, pp. 12-30

[6] Wang, H., Brown, M. and Harris, C.J. (1994) Fault Detection for a Class of Unknown Nonlinear Systems via Associative Memory Networks. *Proc. I Mech E, J. Systems and Control Engr.*, 208, (12), 101--108.

[7] Watton, J.; Pham, D.T. (1997). An artificial neural network based approach to fault diagnosis and classification of fluid power systems, Proceedings of the Institution of Mechanical Engineers. Part I, Journal of systems and control engin211 I 4 307-317.

[8] Jain-Da Wu, Chiu – Hong Liu, "Investigation of engine fault diagnosis using discrete wavelet transform and neural network". Expert System with Applications 35(2008) 1200-1213.

[9]Huang, Yingping, McMurran, Ross, Dhadyalla, Gunwan t and Jones, R. Peter (2008) Probability based vehicle fault diagnosis: Bayesian network method.Journal of IntelligentManufacturing, Vol.19 (No .3). pp. 301-311. ISSN 0956-5515.

[10] Matthew A. Franchek, Patrick J. Buehler & Imad Makki, "Intake Air Path Diagnostics for Internal Combustion Engine" Journal of Dynamic Systems, Measurement, and Control, January 2007, Vol, 129/33.

[11] M. B. Celik and R. Bayir, "Fault detection in internal combustion engines using fuzzy logic." Proc. IMechE Vol. 221 Part D: J. Automobile Engineering 2007.

[12] Kadarsah Suryadi & Eri Ricardo Nurzal, " A Decision Support System for Car Fault Diagnosis Using Expert System" International Journals of Information Science for Decision Making N02, April 1998.

[13] Shubhalxmi Kher, P.K.Chande, & P.C.Sharma, "Automobile Engine Fault Diagnosis Using Neural Network" IEEE Intelligent Transportation Systems Conference Proceeding- Oakland (CA), USA – August 25-29 2001.

[14] S. N. Dandare and S. V. Dudul "Neural Network based Air Filter Fault Detection in an Automobile Engine from Sound Signal" In First International Conference on Sunrise Technologies SSVPS BSD College of Engineering, Dhule, on 14-&15th Jan 2011.

[15] S.N.Dandare and S.V.Dudul "Consistency of MLP & SVM for Air Filter Fault Detection in an Automobile Engine from Sound Signal" International Journal of Computer Information Systems, Vol. 2, No. 3, 2011.

[16] S. N. Dandare and S. V. Dudul "Novel technique for multiple fault detection in an automobile engine using sound signal" Int. Jou. of Ele.Com.and Com. Science, Vol 3, Issue 5, ISSN 2278-4209, 2012.