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RESEARCH ARTICLE

Multiple Fault Detection in a Four Stroke Engine Using Single Sensor System

Shankar N. Dandare
Associate Professor in Electronics & Tele. Engg.
Electronics Department,
College of Engineering, Pusad, Maharashtra-State, India
Email: sndandare@rediffmail.com

S. V. Dudul
Professor & Head, Dept of Applied Electronics,
Sant Gadge Baba Amravati University, Amravati,
Maharashtra-State, India
Email: svdudul@gmail.com

Abstract

The proposed system follows a model–based approach based on Digital Signal Processing and Artificial Neural Network. Fault Detection and Isolation (FDI) of an Automobile Engine' have been carried out using acoustic signals which is captured from the engine. This 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.

In this work, experimentation is carried out on Hero Honda Passion Four Stroke (HHPFS) Engine. There are many more types of faults which may be developed because of wear and tear or lack of maintenance but, the database is generated only for five different types of faults and classification of the same is carried out. The signal normalization, signal conditioning, signal decompositions, analog to digital conversion and feature extraction were carried out by using the algorithm written in MATLAB R2010B. The paper describes the performance of statistical and Artificial Neural Network (ANN) based classifiers for individual and multiple faults and finally the optimal classifiers are proposed based on classification accuracy. It is observed from the experimental results that Artificial Neural Network (ANN) based classifiers are more appropriate than statistical classifiers. It is also observed that the magnitude of Mean Square Error (MSE) is under permissible limits and percentage Average Classification Accuracy (%ACA) is also reasonable.

Keywords: Digital Signal Processing Statistical Classifiers, Four Stroke Engine and ANN Based Classifiers

1. Introduction

Today, transportation technology, especially car, grows fast, but many drivers do not know how to work for their car. Fault Detection is not an easy for inexperienced mechanic or driver because it is needed a lot of knowledge for finding the fault. Therefore, they extremely depend on expert mechanic. Looking into this the FDI system is proposed to detect the fault in an incipient stage to avoid the inconvenience. The work carried out in this area is discussed below.

The classical approaches are limited for checking of some measurable output variables because they do not give a deeper insight and usually do not allow a fault diagnosis. Model-based methods of fault detection were developed by using input and output signals and applying dynamic process models. These methods are based, on parameter estimation, parity equations or state observers, Rolf Isermann, (2005), suggested the model based approach. The goal is to generate several symptoms indicating the difference between nominal and faulty status. Based on different symptoms fault diagnosis procedures follow, determining the fault by applying classification or inference methods [1]. The fault can be isolated if the residual associated with the matched isolation estimator remains below its corresponding adaptive threshold, whereas at least one of the components of the residuals associated with all the other estimators exceeds its threshold at some finite time [2]. R. J. Howlett,(1996 &1999), a neural network technique was described for determination of air-fuel ratio in the engine. The voltage waveforms across the spark plug were used for monitoring the engine and for fault diagnosis or control [3, 4]. The soft computing (SC) methods were surveyed by R. J. Patton et.al. (2001), in this study, the use of SC methods was considered an important extension to the quantitative model-based approach for residual generation in FDI [5].

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 [6]. 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 networks were trained to detect and diagnose the faults, and also to indicate fault size [7]. Jian-Hua Zhang, et. al. (2010), Proposed a fault diagnosis using Adaptive Neuro-Fuzzy inference system (ANFIS). ANFIS was applied to build a fault diagnosis model of automobile engine and induce cloud model of fan-out, outputting results were used to detect the performance parameter failure for the automobile engine [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 [9]. 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 [10]. Sensor fault detection, isolation and accommodation has been investigated by M. S. Sangha, et.al. (2012), along with detection of unknown faults for an automotive engine. Radial basis function (RBF) neural networks were used for fault diagnosis [11]. Madain M.,et.al.(2010), proposed the fault diagnosis using the sound samples. The fault under test was compared with the faults in the database according to their correlation, normalized mean square error, and formant frequencies values and the best match was considered fault detection. The developed system can be useful for the inexperienced technicians as a training module for them [12].

Based on the review of related literature the observation are made as under

- The fault diagnosis is not standardized among vehicle manufacturers.
- There is an uncertainty in scheduling vehicle.
- A complete diagnosis may need special equipments and trained technician’s help, which could make the diagnosis very expensive.
- Fault diagnosis is difficult because of hybrid control systems.
- Multiple sensors are required to detect the multiple faults and hence, the system may be complex.
- Sensitive Sensors with high accuracy and precision are required.
- Maintenance of sensors is difficult.

By considering the different approaches for FDI system, the HHPFS Engine model is selected for experimentation. The specification of engine model is given in the Table 1. The proposed system follows a model–based approach based on Digital Signal Processing and Artificial Neural Network with single sensor system. The knowledge database is generated by recording the sound variation signals at different speeds and with each gear position in healthy and faulty conditions. The normalization, signal conditioning and analog to digital conversion were carried out by using the algorithm written in MATLAB R2010B. Statistical and ANN based classifiers are employed to classify the faults correctly.

The experimentation is carried out at “*Automobile Engineering Laboratory, Department of Electronic and Mechanical Engineering, Babasaheb Naik College of Engineering, Pusad. District Yavatmal. (M.S.)” and Research laboratory of Department of Applied Electronics, Faculty of Engineering and Technology, Sant Gadge Baba Amravati University, Amravati”*. The data acquisition system consists of an automobile engine along with the microphone as a sensor to capture the acoustic signal, signal recording, signal conditioning and signal processing system. There are many more types of faults which may be developed in the automobile engine but, the database is generated for only five different types of faults that are Air Filter Fault (FF), Spark Plug Fault (SP), Rich Mixture Fault (RM), Insufficient Lubricants Fault (ISL) and Piston Ring Fault (PR).

It is worthwhile to notice that the proposed system may be designed and attached to every newly produced engine, so that the fault can be detected at an incipient level. It is also suggested that the proposed FDI system can be extended to detect any number of faults. The proposed FDI system can be used as one type of tool to know the status of the engine and will act as a guide for maintaining the vehicle in good condition that will save our time and inconvenience. By considering the necessity of FDI system the broad objectives of proposed FDI system are listed as under.

- It is possible to detect the faults at an incipient stage.
- To improve productivity & reliability of an automobile.
- To facilitate unskilled or less skilled automobile staff to work more efficiently.
- To reduce the maintenance cost and down-time of an automobile.
- To avoid vehicular accidents because of inadequate maintenance.
- To prevent the monetary loss of customer (in the event of a wrong diagnosis).
- As a tool for training inexperienced people.
- To improve knowledge of driver in diagnosing the fault.
- The proposed FDI system is simple, reliable and flexible.
- It is single sensor system based on acoustic signal.

Table1: Specifications of Automobile Engines, Microphone and Sound Recorder

HHPFS Engine	Microphone	Sound Recorder
Displacement : 97.50cc	Unidirectional Cardioid	AD/DA conversion : 24 bits, 44.1 kHz
Maximum Power : 7.37 HP (5.4 kW) @ 8000 RPM	*Frequency : 50Hz -18KHz*	*Format : WAV*
Engine Type : Single cylinder, Four-stroke	*Impedance : 32 Ohm*	*Bit Rates : 64/96/128/ 160/192 /256/320 kbps*
Gear Box : 5- Speed Gear	*Sensitivity : 62 dB*	*Frequency Response : 20 Hz to 20 kHz*
Compression Ratio : 8.8 : 1	*Connector : 3.5 mm*	*USB Interface*
Maximum Torque : 7.95 NM, @ 5000 RPM	*Impedance : 1K ohm*	
Cylinder Bore : 50.0 mm		

2. Methodology

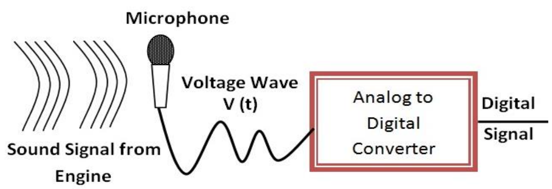

Fig 1: Signal Capturing System

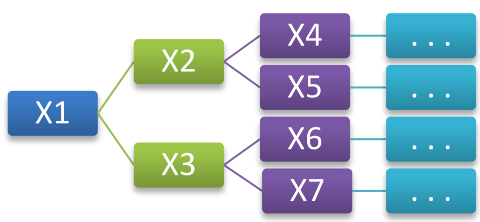

Fig 2: Signal Decomposition Technique

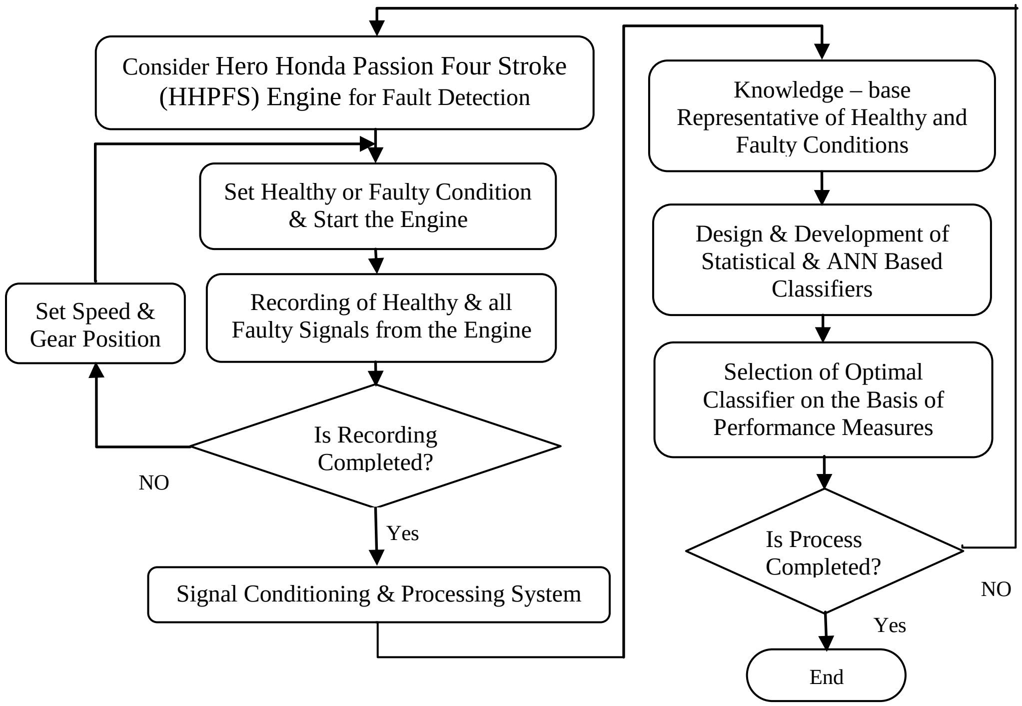

Fig 3: Working of Proposed FDI System

The unidirectional cardioid Microphone has been used as a sensor to acquire the sound variations from an automobile engine in normal and faulty conditions as shown in Fig 1. A unidirectional cardioid microphone is sensitive to sounds from only one direction, which it is facing only. These microphones are more commonly used for live vocal, speech & instrument performances as they are good at rejecting background sounds from other unwanted directions. The MP3 sound recorder is used to record the sound variations of an Automobile Engine in a wave format. The specifications of Microphone and MP3 recorder are also given in Table 1. Signal is divided into different frames by using the signal decomposition technique is shown in Fig 2.

Initially, the engine is started in healthy (normal) condition and signals are recorded at different speed and each gear positions. The HHPFS engine consists of five different gears including one neutral gear. The four signals were recorded in each gear position at 1200, 1500, 1800 and 2100 RPM. Therefore, there will be a collection of 140 recorded signals for five different faults and one neutral condition. The feature extraction is also carried out of each frame of the signal. These extracted features will be considered as a knowledge base for classification of different faults. The detail working of Fault Detection system is shown in Fig 3.

3. Observations of Recorded Signals and Pattern of Features

The nature of recorded signals is observed in time domain and features are extracted of each signal before and after decompositions of the signals. The recorded signals are plotted as shown in Fig 4A and Fig 4B. It is noticed from the signal plot that the most of the signals are overlapped and their nature is found to be highly complex and also the amplitude of the faulty signal is greater than that of the healthy condition signals.

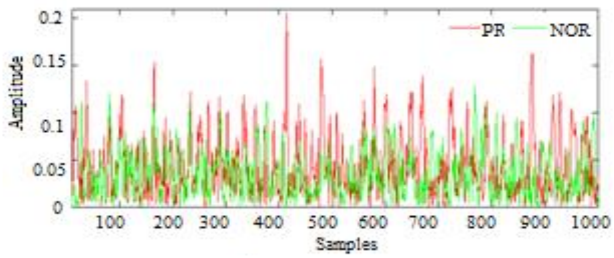

Fig 4A : Engine' Signals for Normal and PR Fault

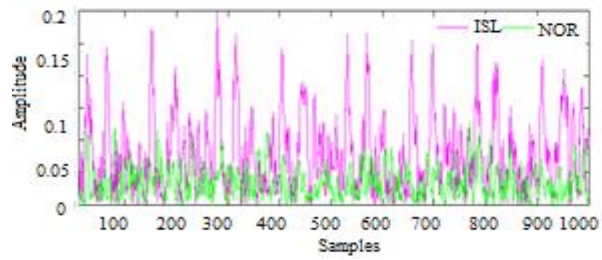

Fig 4B: Engine' Signals for Normal and ISL Fault

The knowledge base is generated by extracting the features of healthy and faulty conditions signals. The extracted features are Mean, Energy, Maximum Value, Minimum Value, Standard Deviation, Variance and Mode for five different types of faults and out of which Minimum vs. Energy and Mean vs. Energy features are plotted as shown in Fig 5A & Fig 5B. After observing the overlapping nature of features and non separable decision boundaries, the decision is taken to employ the soft computing approach to classify the faults. At the beginning the statistical classifiers are employed to classify the faults which are explained in the subsequent section.

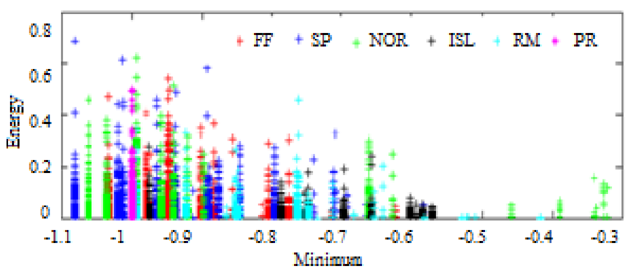

Fig 5A: Scatter Plot for Minimum Vs Energy

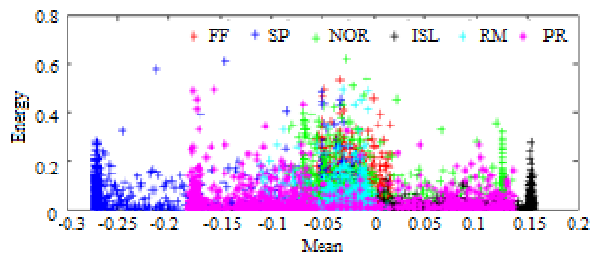

Fig 5B: Scatter Plot for Mean Vs Energy

4. Classification of Faults Using Statistical Classifiers

The statistical classification is carried out using *XLSTAT* and the Process Flow Diagram for Statistical Classifiers is shown in Fig 7. In this the classification and regression trees have been employed to classify the faults. The feature matrix comprising of 7 inputs and one categorical output has been applied to statistical classifiers. The size of each feature matrix is 20×8 including seven inputs and one categorical output. Therefore, knowledge database consists of 40 rows and 8 columns. The performance has been observed with respect to *CHAID-Pearson, CHAID-Likelihood, Exhaustive-CHAID-Pearson, Exhaustive-CHAID-Likelihood, C&RT Gini, C&RT-Towing and Quest* Methods and results are depicted in Table 2, for each fault, with the %ACA of each method. It is observed that for FF condition and the maximum %ACA is found to be *85%* for *C&RT Gini* method, for SP Fault condition the maximum %ACA is found to be *87.50%* for *C&RT Gini* method, for PR Fault condition the maximum %ACA is found to be *80.00% for all types of statistical classifiers*, for ISL Fault condition and the maximum %ACA is found to be *77.50%* for *all types of statistical classifier*, for Rich Mixture RM Fault condition and the maximum %ACA is found to be *85.00% for all types of statistical classifiers*.

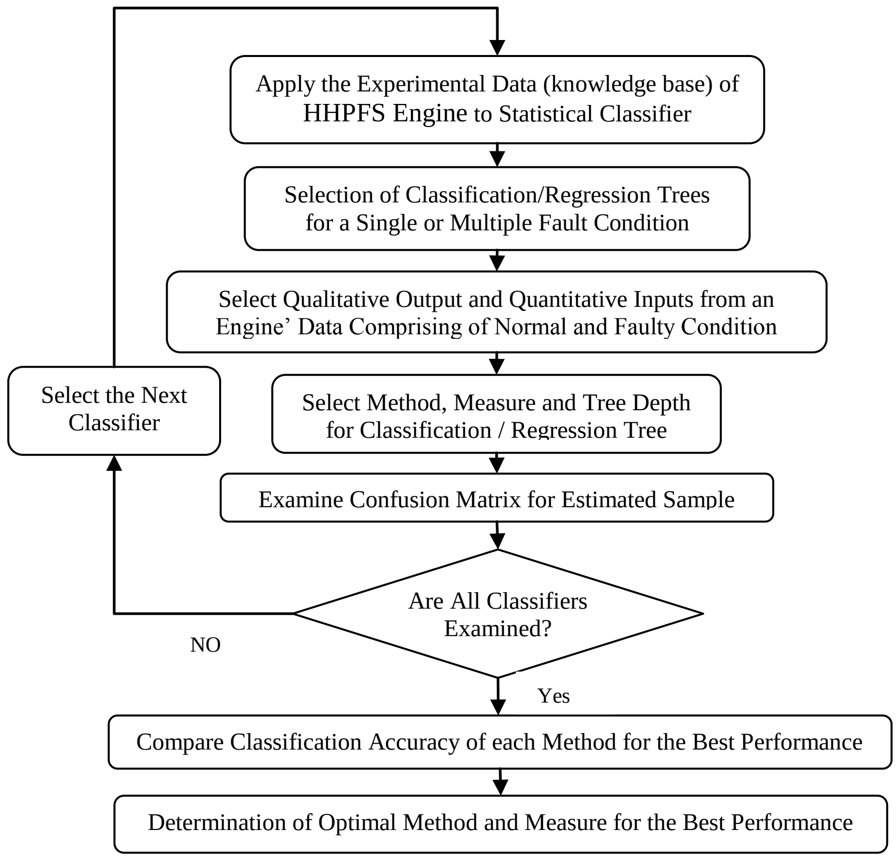

Fig 6: Process Flow Diagram for Statistical Classifiers

Table 2: Percent ACA for Individual Faults Using Statistical Classifiers

Method	Measure	% ACA for FF	% ACA for SP	% ACA for PR	% ACA for ISL	% ACA for RM
CHAID & Exh. CHAID	*Pearson*	*82.5.00%*	*70.00%*	*80.00%*	*77.50%*	*85.00%*
CHAID & Exh. CHAID	*Likelihood*	*82.5.00%*	*70.00%*	*80.00%*	*77.50%*	*85.00%*
C&RT	*Gini*	*85.00%*	*87.50%*	*80.00%*	*77.50%*	*85.00%*
C&RT	*Towing*	*77.50%*	*70.00%*	*80.00%*	*77.50%*	*85.00%*
Quest		*50.00%*	*70.00%*	*80.00%*	*77.50%*	*85.00%*

4.1 Classification of Multiple Faults in HHPFS Engine

The knowledge base of combined five different faults is applied to the Statistical Classifier for classification. The size of each feature matrix is 20×8 including seven inputs and one categorical output. Therefore, knowledge database consists of 120 rows and 8 columns. The performances of all statistical classifiers were observed and results are depicted in Table 3. It is observed that the percentage classification accuracy for *C&RT Gini* is found to be maximum amongst all statistical classifier and it is 63.33 % which is not reasonable. Therefore, the analysis is pursued by using ANN based Classifiers for possibility of improvement in performance and which is explain in subsequent section.

Table 3: Performance of Statistical Classifier for Combined Five Faults

Faults	*CHAID &Exh. CHAID*		*C&RT*		*Quest*
	Pearson	*Likelihood*	*Gini*	*Towing*	
FF	*75.00%*	*80.00%*	*65.00%*	*75.00%*	*65.00%*

ISL	*50.00%*	*65.00%*	*75.00%*	*65.00%*	*65.00%*
NOR	*35.00%*	*35.00%*	*75.00%*	*20.00%*	*25.00%*
PR	*85.00%*	*85.00%*	*60.00%*	*20.00%*	*20.00%*
RM	*35.00%*	*35.00%*	*65.00%*	*45.00%*	*70.00%*
SP	*30.00%*	*40.00%*	*40.00%*	*20.00%*	*20.00%*
Total % ACA	*51.67%*	*56.67%*	*63.33%*	*40.83%*	*44.17%*

5. Classification of Faults using ANN Based Classifiers

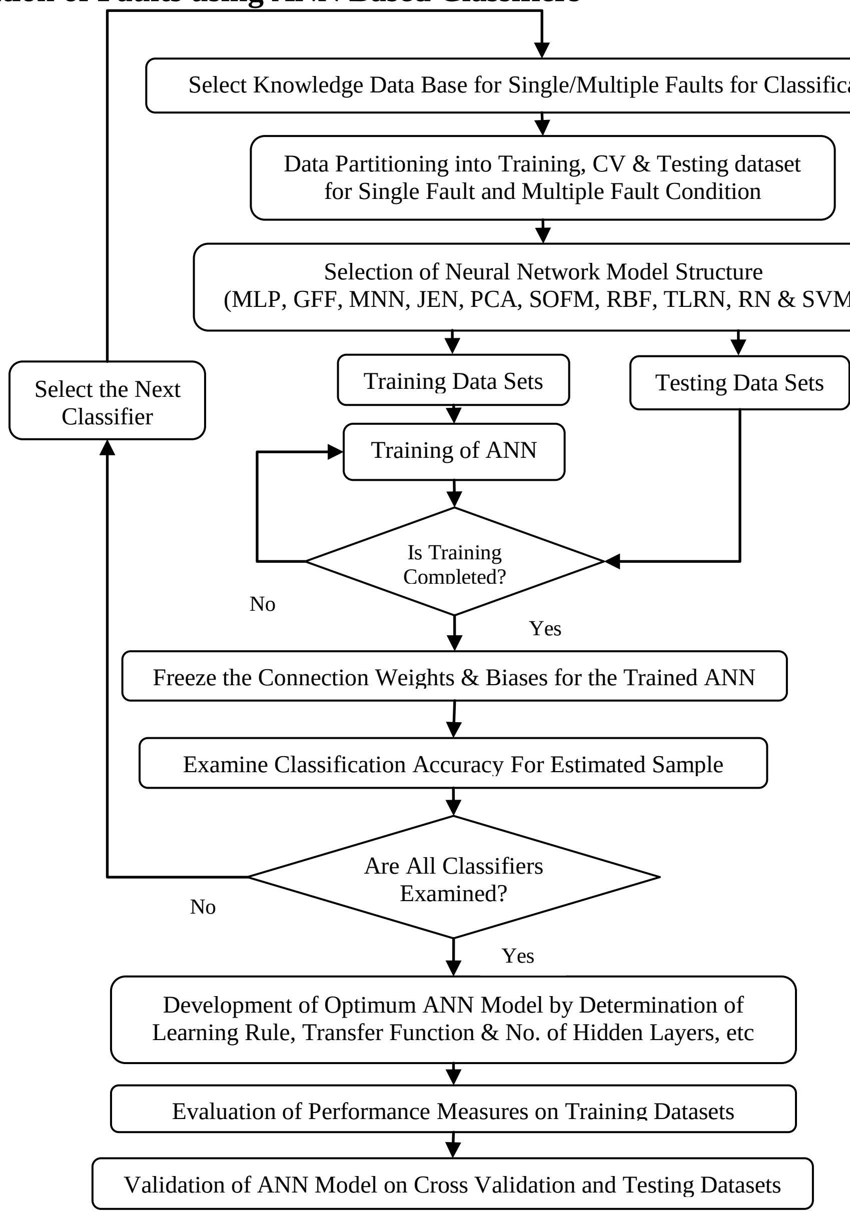

Fig 7: Working of ANN Based Classifiers for Classification of Faults in a HHPFS Engine

Subsequently, the analysis is continued using different configuration of ANN based classifiers such as *Multilayer Perceptron (MLP), Generalized 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)*. The working of ANN based classifiers is shown in Fig 7. The %ACA has been observed for all ten types of ANN based classifiers. The input layer of the ANN contains seven neurons corresponding to seven inputs. One categorical output denotes a type of fault or healthy condition of an engine. As there are five different types of faults and one state indicating healthy condition, the number of neurons in the output layer must be six (five neurons corresponding to five different faults and one neuron corresponding to healthy condition). Three data partitions, namely, Training, Cross Validation (CV) and Testing were used with different tagging order. Every time, ANN is retrained three times with different random initialization of connection weights and biases with a view to ensure true learning and generalization.

5.1 Classification of Single Fault in a HHPFS Engine

Table 4: Performance of ANN Based Classifiers for Single Fault

ANN	*FF*		SP		ISL		RM		PR	
	Testing	*CV*	*Testing*	*CV*	*Testing*	*CV*	*Testing*	*CV*	*Testing*	*CV*
MLP	*92.9*	*85.7*	91.7	*100.0*	*100.0*	*91.7*	*100.0*	*100.0*	*100.0*	*100.0*
GFF	*85.7*	*61.9*	58.3	*92.9*	*100.0*	*91.7*	*100.0*	*100.0*	*100.0*	*100.0*
MNN	*52.4*	*71.4*	66.7	*61.9*	*100.0*	*91.7*	*100.0*	*100.0*	*100.0*	*100.0*
JEN	*78.6*	*59.5*	83.3	*61.9*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*
PCA	*85.7*	*78.6*	58.3	*69.0*	*100.0*	*91.7*	*100.0*	*100.0*	*100.0*	*100.0*
RBF	*78.6*	*50.0*	50.0	*76.2*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*
SOFM	*52.4*	*71.4*	87.5	*85.7*	*100.0*	*100.0*	*91.7*	*62.5*	*100.0*	*100.0*
TLRN	*54.8*	*21.4*	62.5	*85.7*	*83.3*	*83.3*	*100.0*	*100.0*	*75.0*	*80.0*
RN	*38.1*	*69.0*	45.8	*66.7*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*
SVM	*59.5*	*57.1*	83.3	*76.2*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*

The size of the feature matrix for a single fault with single frame is 40×8; i.e. 20×8 matrix for healthy (normal) signal and 20×8 matrix for each Faulty Signal. The feature matrix was fragmented into three parts in the ratio of 2:1:1 indicating training dataset: CV dataset: testing dataset. The classification accuracy of each faulty condition for testing and CV data set has been depicted in the Table 4. It is observed that the classification accuracy of MLP based classifier is better amongst all classifiers for FF and SP faults. Further it is also observed that classification accuracy for all ANN based classifiers is reasonably good for single fault. Therefore, the analysis is pursued by combining the multiple faults and it is explained in the subsequent sections.

5.2 Classification of Combined Three Faults (PR, FF & ISL) and (RM, SP & FF)

Table 5: Classification of Combined Three Faults (PR, FF & ISL) and (RM, SP & FF)

ANN	PR, FF & ISL			RM, SP & FF		
	Testing	*CV*	*Training*	*Testing*	*CV*	*Training*
MLP	*78.33333*	*91.66667*	*90*	*100*	*93.75*	*89.39394*
GFF	*70*	*67.91667*	*70*	*70.83333*	*83.33333*	*84.84848*
MNN	*57.5*	*61.11111*	*73.33333*	*77.08333*	*79.16667*	*82.57576*
JEN	*55.83333*	*70.83333*	*83.33333*	*79.16667*	*77.08333*	*91.28788*
PCA	*56.66667*	*70.83333*	*72.5*	*79.16667*	*75*	*80.30303*
RBF	*73.33333*	*69.16667*	*83.33333*	*75*	*79.16667*	*75*
SOFM	*62.5*	*66.66667*	*68.33333*	*90.75*	*87.5*	*89.39394*
TLRN	*55.83333*	*39.30556*	*67.5*	*75*	*75*	*75*
RN	*53.33333*	*67.91667*	*65.83333*	*75*	*79.16667*	*77.27273*
SVM	*78.33333*	*81.66667*	*100*	*93.75*	*88.75*	*100*

Further, analysis is continued for considering the combined three faults togather in two groups. In one group the faults considered are PR, FF & ISL and in another group the faults considered are RM, SP & FF. The extracted features are combined for three faults along with the features of normal signal. The size of the feature matrix for single frame is 80×8, i.e. 20×8 matrix for normal signal, 20×8 matrix for each faulty signals. The same types of data partitioning is employed(2:1:1) as explained earlier. The performances of all ten types of ANN based classifiers are depicted in Table 5. From the classification, it is observed that the performance of MLP and SVM based classifiers is found to be impressive amongst all ten types of classifiers. It is observed that the classification accuracy of ANN based classifiers for combined three faults is decreased as compared to single fault. The process of classification is also continued for combined five faults together, which is explained in the subsequent sections.

5.3 Classification of Combined Five Faults Using MLP Based Classifier

The knowledge base is combined for five faults along with the healthy condition signal. The performance of MLP based classifier is observed for 1 to 128 frames. Classification Accuracy is plotted for 1 to 128 frames for test, CV and training datasets as shown in Fig 8. It is observed that the %ACA is found to be Maximum for eight numbers of frames for each signal and 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.

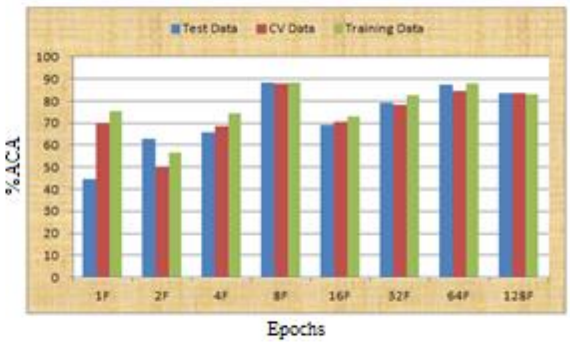

Fig 8: Performance of MLP Based Classifier

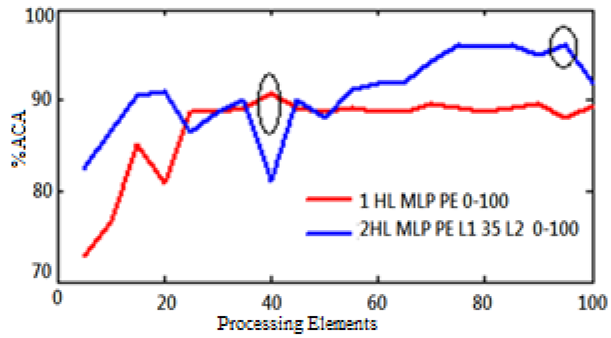

Fig 9: Performance of #1 & #2HL-MLP

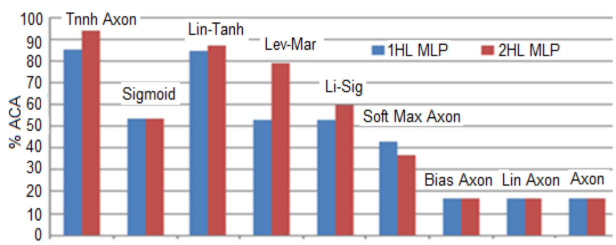

Fig 10A: Comparison of Transfer Functions

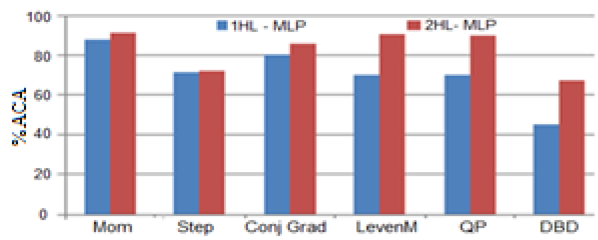

Fig 10B: Comparison of Learning Rules

Further analysis is continued by using MLP base classifier with 8 frames of each signal. As there are 20 signals recorded for each fault and normal signal, the size of the feature matrix will be (20 x 6 x 8) 960×8, i.e. 960 rows and 8 columns by considering the eight frames of each signal. 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 5 to 100 for default number of epochs set to 1000. The two hidden layer MLP based classifier was also retrained three times with different random weight initializations. The feature matrix was applied to the 2HL-MLP with the same type of data partitioning scheme. As the number of hidden layers in a neural network increases, the complexity of computation is also seen to increase. Here, the network was designed by keeping a number of Hidden layer #1 (L1) PEs fixed to 5 and by varying Hidden layer #2 (L2) PEs from 5 to 100 in step of 5. Then step-by-step, the number of L1 PEs was also varied from 5 to 100 in step of 5 by varying simultaneously the L2 PEs. After retraining the network three times with each set of PEs, the network was tested for test, cross validation and training dataset. The MLP based classifier is further investigated by changing the Learning Rule Algorithms such as STEP, MOM, CG, LMQ, QP and DBD. The performance of one & two hidden layer MLP NN has been shown in Fig 9, Fig 10A and Fig 10B. It is observed that the % ACA is Maximum at 4000 Epochs for 1HL-MLP and at 2000 Epochs for 2HL-MLP. The optimal transfer function is TANH-AXON, Learning Rule is Momentum and other optimal parameter for the one and two HL-MLP are also depicted in Table 6.

Table 6: 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	*HL*	*Output Layer*	*HL-1*	*HL-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*

5.4 Classification of Faults in a HHPFS Engine Using SVM Based Classifier

The detailed analysis is also carried out for Support Vector Machine using the Kernel Adatron algorithm. The Kernel Adatron algorithm transforms inputs into a higher 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. Therefore, the performance of SVM based classifier is examined for different frames and the performance are plotted in Fig 11. The knowledge base for combined five faults with 8 frames comprising of 960x8 records was split into three parts in the ratio of 2:1:1. The first part of data was used for training the network, second one was used for cross validation and the third part was used for testing the network. A total dataset has a size 960 × 8 with 7 inputs and 1 categorical (symbolic) output (translated into 6 binary outputs). The SVM is retrained three times with healthy & faulty feature matrix derived from an automobile engine. The SVM based classifier is trained and tested by varying the no. of Epochs from 1 to 500. The performance of SVM based classifier is exhibited in Fig 11 and Fig 12. It is observed that at the 90th epoch, the classification accuracy on the training dataset is found to be reasonable and average MSE is also reasonably less.

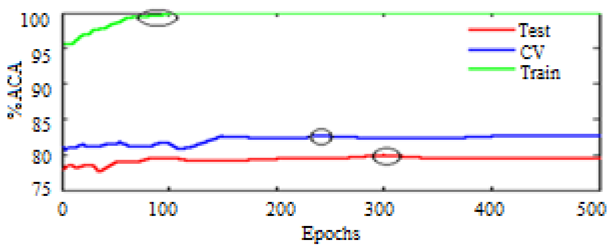

Fig 11: %ACA of SVM Based Classifier

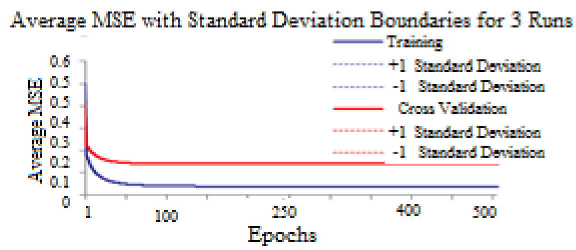

Fig 12: MSE of SVM Based Classifier

Conclusion

From the relative study and scrupulous comparison of all statistical and ANN based classifiers for automobile engine, it is concluded that the proposed FDI system can provide the best possible solution to early detection of faults in an automobile engine. The main advantage of this system is its simplicity, reliability, cost-effectiveness and compactness requiring a single sensor system. From the meticulous analysis using statistical and ANN based classifiers, it is inferred that ANN based classifiers are more appropriate for fault diagnosis. From the comparative analysis of all ten different types of ANN based classifiers, it is noticed that the Classification Accuracy of MLP and SVM based classifier is found to be reasonably acceptable amongst the group of ten ANN based classifiers used for the analysis. Also, the classification accuracy of two hidden layer MLP is found to be greater than that of a single hidden layer MLP. It is also seen that the 2HL-MLP NN and SVM can be used as reasonable classifiers for multiple faults detection in a HHPFS engine. However, MLP and SVM based classifier are seen to be more appropriate classifier for HHPFS Engines as its classification accuracy is higher than all other classifiers. In future, the work can be extended to any number of faults by generating the knowledgebase for respective faults.

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